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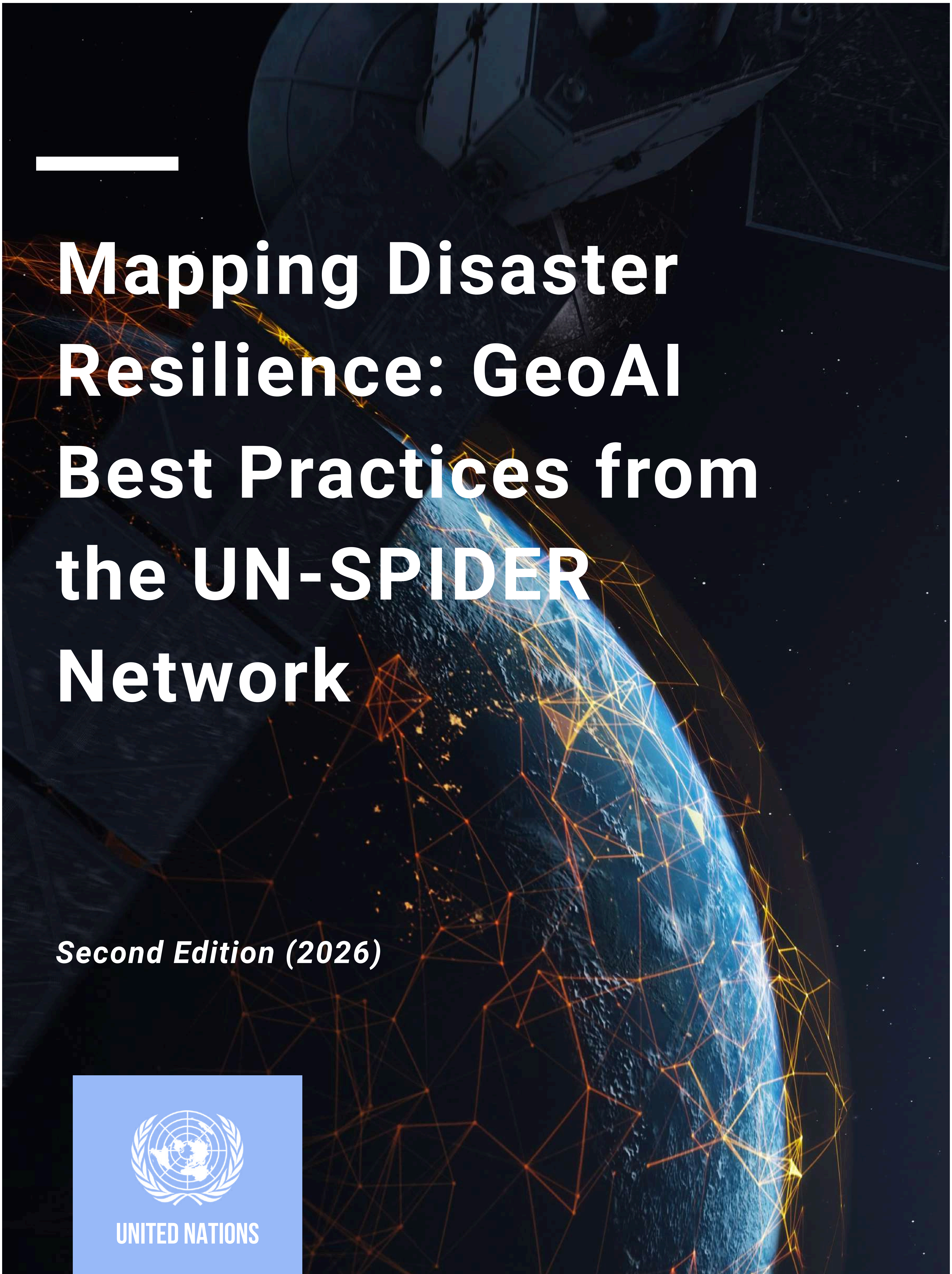

Mapping Disaster Resilience: GeoAI Best Practices from the UN-SPIDER Network

Second Edition (2026)

UNITED NATIONS

UNITED NATIONS PLATFORM FOR SPACE-BASED INFORMATION FOR DISASTER MANAGEMENT AND EMERGENCY RESPONSE

UNITED NATIONS OFFICE FOR OUTER SPACE AFFAIRS

Mapping Disaster Resilience:

GeoAI Best Practices from the UN-SPIDER Network

UNITED NATIONS
Vienna, 2026

ACKNOWLEDGEMENTS

This Compendium is the result of a collaborative effort bringing together expertise from across six continents and a broad range of technical and institutional backgrounds. The United Nations Office for Outer Space Affairs (UNOOSA) and the UN-SPIDER Programme would like to express their sincere appreciation to the **Regional Support Offices** whose analysts, experts, and managers contributed case studies, technical inputs, and peer review to this publication. Their practical experiences and on-the-ground insights highlight the growing role of GeoAI in supporting disaster risk reduction and emergency response efforts worldwide.

We also extend our gratitude to the national space agencies, disaster management authorities, research institutions, and academic partners that supported the Regional Support Offices throughout the data collection, analysis, and validation processes.

Under the guidance of **Lorant Czaran**, Chief of the Space Application Section, **Hamid Mehmood** led the writing and production team. The core team consisted of **Jumpei Takami** and **Thilanka Seneviratne**. Research and editing was provided by a multidisciplinary team of interns: **Erguge Su**, **Mehraveh Sakhaei**, **Sarah Schädel-Höpfner** and **Qianyi Cao**.

FOREWORD

Ms. Aarti Holla-Maini
Director, United Nations Office
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From the vantage point of outer space, disasters reveal themselves with a clarity that ground-level observation rarely affords. Floodwaters spreading across a delta, the scar of a wildfire moving along a mountainside, a coastline retreating season by season: each can now be seen, measured and understood from orbit. Geospatial Artificial Intelligence (GeoAI) is what allows us to turn that vantage into action, converting the steady stream of satellite observations into decisions that shorten evacuation times, guide responders, protect livelihoods and inform the long work of recovery.

Through its UN-SPIDER Programme and the worldwide network of Regional Support Offices, the United Nations Office for Outer Space Affairs is proud to present this Compendium of GeoAI best practices. Building on the inaugural edition, it gathers proven approaches from across the network, spanning wildfire and flood risk, landslide and coastal-erosion monitoring, and the management of scarce water resources. Each case makes the same quiet point: when algorithms are shared, when data are open, and when local expertise is respected, even a modestly resourced emergency-operations centre can wield analytic power that was once the preserve of the world's largest space agencies. That is a profound shift in who is able to anticipate and respond to disaster, and it is precisely the shift UN-SPIDER exists to advance.

Yet technology alone is not enough. The Sendai Framework for Disaster Risk Reduction and the 2030 Agenda for Sustainable Development remind us that resilience is, in the end, a human endeavour, built on partnerships that cross borders and disciplines, on trust in science, and on policies grounded in evidence rather than hindsight. This Compendium therefore offers more than workflows and accuracy metrics. It distils lessons on data equity, on ethics and transparency, and on the capacity-building required so that every Member State, and in particular the least developed and most hazard-exposed, can take part in this transformation on its own terms.

The publication arrives at a consequential moment. Following the climate negotiations in Belém and on the road toward the 2030 stock-take of the Sendai Framework and the realisation of the Early Warnings for All initiative, the demand for timely, trustworthy and locally relevant evidence has never been greater. The practices collected here show that GeoAI is no longer a boutique research interest. It is becoming a backbone technology for the decade of action that lies ahead, and a practical means of putting space-based information at the service of those who need it most.

I extend my sincere gratitude to the analysts, planners and innovators across the Regional Support Office network who contributed the insights compiled here; to the national space agencies, disaster management authorities and research institutions that opened their data and expertise; and to the academic and private-sector partners whose open models and computing support continue to lower the barriers to entry. Their collective work is a reminder that this Office achieves the most when it convenes and coordinates, rather than acts alone.

It is my hope that this Compendium will inspire new collaborations, accelerate the integration of GeoAI into early-warning systems, and help turn satellite observations into safer lives and more resilient livelihoods for communities everywhere.

- Aarti Holla-Maini
Director, United Nations Office for Outer Space Affairs (UNOOSA)

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II. EXECUTIVE SUMMARY

Key Messages

Geospatial Artificial Intelligence (GeoAI), the convergence of satellite-derived data with modern machine-learning techniques, has become a decisive factor in disaster-risk governance. The active Earth-observation fleet continues to expand, and open models now convert large volumes of imagery into decision-ready layers in minutes rather than days. This Compendium consolidates proven GeoAI practice from across the UN-SPIDER Regional Support Office (RSO) network into a single practical reference, documenting the methods, data, partnerships and measurable outcomes behind each case so that other offices and national agencies can replicate or adapt them. Its scope spans the end-to-end workflow, from data acquisition and model development through validation, deployment and governance, and covers rapid-onset hazards such as wildfire and flood alongside slow-onset stresses including landslide, coastal erosion and water scarcity.

For disaster risk reduction and emergency response, the significance of GeoAI lies less in any single technical advance than in who can now use it. Capability that was once the preserve of the largest space agencies is increasingly available to offices with modest resources, open data and sponsored cloud credits. Hazards can be detected in near-real time, their impacts forecast in advance, and policy responses grounded in defensible evidence rather than retrospective estimate. Crucially, the practices in this edition show that computationally efficient and transparent methods can match the performance of far heavier models while remaining reproducible in data-scarce settings, which is precisely what allows GeoAI to serve the least-resourced and most hazard-exposed States that lie at the centre of the UN-SPIDER mandate.

Highlights of RSO Contributions

The case studies in this edition illustrate the breadth of operational GeoAI now in use across the network:

- **Wildfire fuel mapping (Cyprus).** A Random Forest framework in Google Earth Engine fused Sentinel-1 and Sentinel-2 data with terrain and vegetation variables to produce fuel-model maps at 10 to 30 metre resolution, a substantial improvement over the coarser regional datasets previously available for local fire-behaviour planning.
- **Flood susceptibility in data-scarce basins (Cyprus).** Comparing four machine-learning models across eight watersheds, the work showed that a simplified Random Forest model using only land use, slope, elevation and flow accumulation achieved around 95 per cent agreement with flood-inventory data, offering authorities a rapid, low-cost screening tool in place of fully detailed hydrodynamic models.
- **AI-enhanced landslide susceptibility (Cyprus).** Climate Hazards Group InfraRed Precipitation with Station (data-CHIRPS) were fused with sparse rain-gauge observations using machine learning, then combined with geomorphological factors in a multi-criteria framework, producing high-resolution susceptibility maps that captured more than 30 per cent of known landslide occurrences within the highest-risk classes.
- **Coastal erosion monitoring (Cyprus).** An unsupervised Pulse Coupled Neural Network extracted shorelines from Sentinel-2 imagery (validated to an RMSE of 9.21 metres) and quantified the downdrift impact of a coastal breakwater, establishing a repeatable, low-cost workflow transferable to other Mediterranean coasts and small island developing States.
- **Water reuse planning across the Middle East and North Africa (MENA) region.** The Water-REPEAT framework combined Earth Observation, computer vision and large language models to map wastewater infrastructure and demand across Egypt, Saudi Arabia and the United Arab Emirates. In Egypt alone, AI-based detection identified approximately 164 treatment plants beyond the 552 already documented, a thirty per cent increase in known infrastructure, supporting evidence-based, climate-resilient water planning.
- **Coastal water-quality assessment (Cyprus).** A Random Forest classifier applied to Sentinel-2 imagery in Google Earth Engine generated turbidity-probability maps along the coastline, enabling near-real-time detection of rainfall-driven water-quality changes for environmental monitoring and coastal management.

Strategic Takeaways

Several lessons cut across these practices. Automation is necessary but not sufficient; the trust of decision-makers depends on rigorous validation and clearly communicated uncertainty. Global models must be localised, since performance degrades in landscapes and climates unlike those they were trained on, and the fusion of satellite data with whatever local ground truth exists is often what makes the difference in data-scarce settings. Efficiency and transparency matter as much as raw accuracy, because reproducible and interpretable workflows are the ones that other offices can adopt and that authorities are willing to act upon. And capability endures only when it is anchored in institutions rather than in a single grant or individual.

These lessons point to a clear set of next steps for the period ahead. UN-SPIDER and its partners should pool open models, reference pipelines and compute resources so that less-resourced offices can participate on equal terms; embed standardised documentation, validation and ethical safeguards from the outset rather than retrofitting them; and work toward sustainable financing that carries proven workflows beyond pilot cycles and into permanent national services. Pursued together over the coming triennium, and against a policy calendar that includes Conference of the Parties (COP) 31, the 2027 Sustainable Development Goal (SDG) review and the 2030 stock-take of the Sendai Framework, these actions would help GeoAI mature from an early-adopter toolset into dependable infrastructure for disaster resilience.

III. INTRODUCTION AND CONTEXT

Background and Rationale

The past year has only sharpened a trend that the inaugural edition of this Compendium identified in 2025: the volume of space-borne data and the maturity of the artificial-intelligence techniques able to exploit it are advancing in tandem, and faster than most disaster management institutions can absorb. As of early 2026, independent tracking services and the European Space Agency count approximately 14,500 active satellites in Earth orbit up from roughly 2,000 in 2019 with a substantial and growing share dedicated to Earth-observation missions that stream petabytes of imagery each day. The European Space Agency (ESA) projects that some 100,000 satellites could be in orbit by 2030. This data abundance has outpaced conventional analytic workflows; many national disaster management agencies still depend on manual photo-interpretation or ad-hoc scripting that cannot keep pace with multi-sensor, multi-temporal archives.

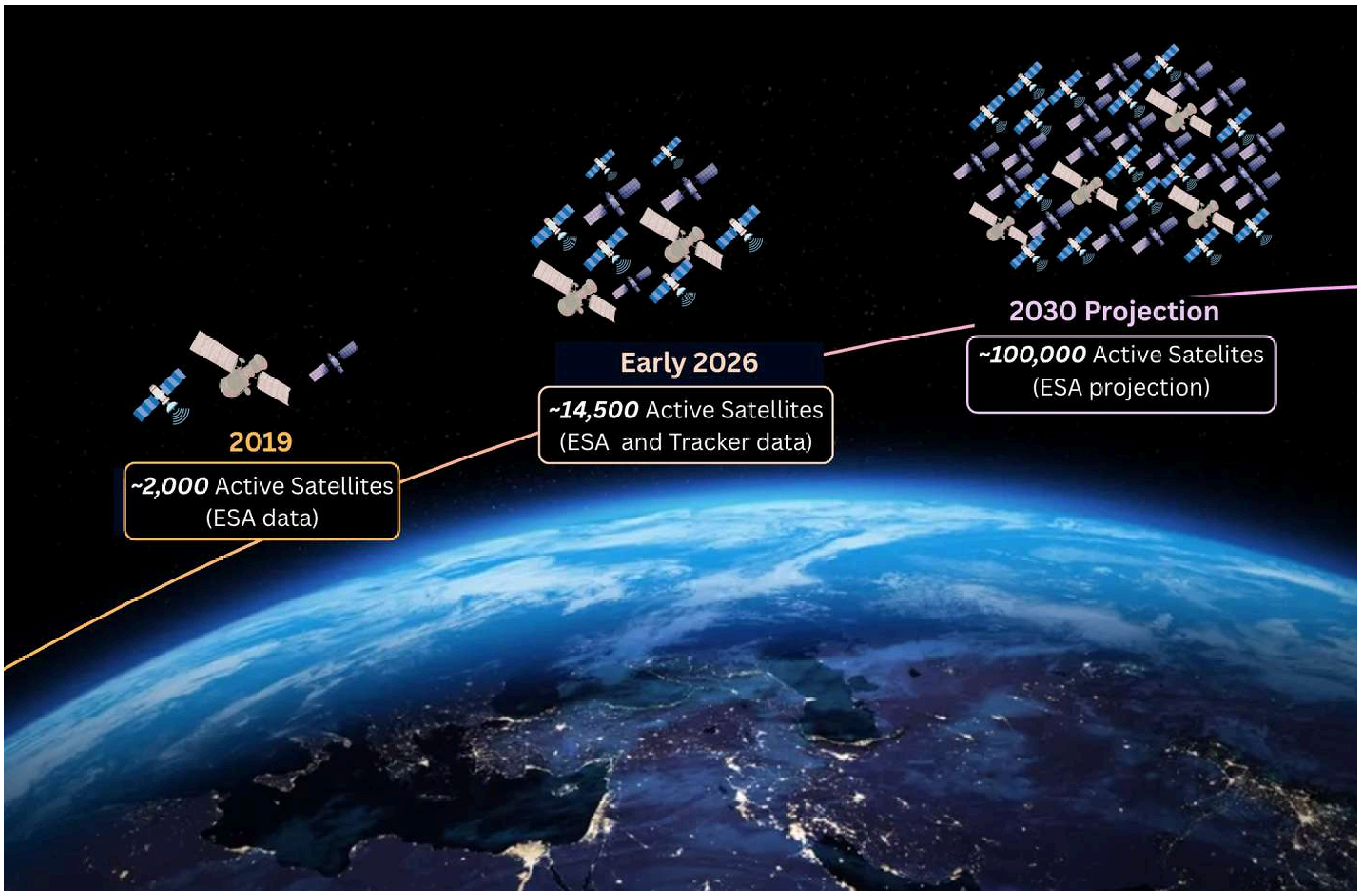


Figure 1: Increasing Trend in Satellite Numbers

Data Source: ESA; **Background Image Credit:** Buradaki/Shutterstock

GeoAI—artificial-intelligence methods purpose-built for spatial data closes that gap. Deep convolutional networks, U-Net derivatives and, increasingly, vision transformers and open-weight foundation models fine-tuned on planetary-scale corpora now deliver pixel-accurate land-cover maps, object detections and change analyses in near-real time. Cloud-native platforms allow these models to ingest terabytes of Sentinel-1 Synthetic Aperture Radar (SAR) or Sentinel-2 optical imagery and return decision-ready layers within minutes, even over bandwidth-constrained regions. The operational payoff is concrete: automated GeoAI pipelines now generate national-scale water-extent maps, burn scars and damage masks within hours of a hazard event—an order-of-magnitude improvement over manual approaches, and a critical input for early warning and impact assessment.

This technological leap meets an increasingly urgent risk landscape. Climate-related hazards already account for the majority of global disaster losses, and their frequency is projected to rise through the 2030s, while rapid urbanisation and infrastructure expansion in exposed areas continue to amplify vulnerability. Meeting the targets of the Sendai Framework for Disaster Risk Reduction therefore hinges on transforming raw Earth-observation data into timely, location-specific intelligence that local authorities can trust and act upon. UN-SPIDER was created precisely to "ensure that all countries, and in particular developing countries, have access to and develop the capacity to use all types of space-based information for disaster management." GeoAI now stands out as the most powerful and, increasingly, the most accessible pathway to that mandate.

This second edition of the Compendium arrives at a decisive moment in the international policy calendar. COP 30 concluded in Belém in November 2025 with the adoption of the Belém Political Package, which signalled a threefold increase in adaptation finance by 2035, agreed a set of indicators for tracking progress on the Global Goal on Adaptation, and issued new guidance to the Fund for Responding to Loss and Damage. The window now extending through COP 31 in 2026, the 2030 stock-take of the Sendai Framework, the 2027 target of the Early Warnings for All initiative, and the 2027 SDG Summit will determine whether GeoAI matures from an early-adopter toolset into standard operating infrastructure for disaster-risk governance. By consolidating proven practice from across the Regional Support Office network, this Compendium aims to accelerate that transition.

UN-SPIDER and GeoAI

GEOAI REFERS TO THE INTEGRATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES WITH GEOGRAPHIC INFORMATION, EARTH OBSERVATION DATA AND SPATIAL ANALYSIS. IT ENCOMPASSES METHODS SUCH AS MACHINE LEARNING, DEEP LEARNING, COMPUTER VISION AND EMERGING GEOSPATIAL FOUNDATION MODELS TO EXTRACT, ANALYSE AND INTERPRET PATTERNS, RELATIONSHIPS AND TRENDS WITHIN GEOSPATIAL DATASETS. BY ENABLING THE AUTOMATED PROCESSING OF LARGE AND COMPLEX VOLUMES OF SPATIAL DATA, GEOAI ENHANCES THE SPEED, SCALE AND ACCURACY OF GEOSPATIAL INSIGHTS AND SUPPORTS A WIDE RANGE OF APPLICATIONS, INCLUDING ENVIRONMENTAL MONITORING, URBAN PLANNING, DISASTER RISK MANAGEMENT, CLIMATE ADAPTATION AND HUMANITARIAN RESPONSE.

UN-SPIDER was created to “ensure that all countries, particularly developing countries, have access to and develop the capacity to use space-based information for disaster management”. In this context, GeoAI is emerging as an increasingly powerful and accessible means of transforming growing volumes of Earth Observation data into actionable information for disaster risk management. Its relevance stems from three interrelated developments:

1. Scalability at Marginal Cost

Cloud-based GeoAI services leverage pay-as-you-go infrastructure, allowing a provincial emergency operations centre to access analytical capabilities that were once limited to major space agencies and research institutions, without requiring significant investment in dedicated high-performance computing infrastructure. Advances in cloud computing and geospatial foundation models have substantially reduced the cost and time required to process large volumes of Earth Observation data, making national- and regional-scale analyses increasingly accessible to resource-constrained institutions and low-income countries.

2. Reduction of Technical Barriers

Pre-trained geospatial foundation models such as Prithvi and Satlas, together with cloud-based development environments and low-code notebooks, have significantly lowered the technical barriers to applying GeoAI. Many of these tools provide documented APIs, pre-trained weights and transfer-learning capabilities that enable users to adapt models to new tasks without building complex machine-learning pipelines from scratch. Experiences across the UN-SPIDER network suggest that, with targeted training and access to appropriate datasets, practitioners can increasingly apply advanced GeoAI methods to disaster management challenges without requiring extensive expertise in deep learning.

3. Catalyst for Inclusive Innovation

Many GeoAI tools, model weights, datasets and analytical workflows are increasingly being shared through open-source and collaborative platforms, supporting the principles of open science and enabling knowledge exchange across regions. As a trusted convener within the disaster risk management and space communities, UN-SPIDER is well positioned to facilitate the sharing of methodologies, promote access to benchmark datasets, and support collaborative initiatives among its Regional Support Offices and partner institutions. Through activities such as technical workshops, knowledge-sharing events and joint projects, the network can help identify and adapt GeoAI solutions to regional contexts, for example for storm-surge modelling in coastal environments, flood mapping in data-scarce regions, or glacier-lake outburst flood monitoring in mountainous areas.

Integrating GeoAI across UN-SPIDER's advisory, capacity-development, and emergency-response lines of work will:

Accelerate Early Warning

Model-driven now-casting can feed directly into national multi-hazard early-warning systems, shaving crucial hours off evacuation timelines.

Elevate Evidence in Policy Dialogue

Robust, reproducible analytics underpin funding requests to mechanisms such as the Green Climate Fund and the Loss and Damage Fund, strengthening developing countries' negotiating positions.

Future-Proof Capacity-Development

By training local institutions on modular, open-source GeoAI toolkits rather than platform-locked software, UN-SPIDER ensures that skills and workflows remain adaptable as technology evolves.

In summary, GeoAI has the potential to advance UN-SPIDER's founding vision beyond facilitating access to satellite data towards enabling more timely, actionable and user-oriented information for disaster risk management. Integrating these capabilities into technical advisory missions, knowledge resources and rapid mapping mechanisms can strengthen the programme's ability to support Member States in addressing increasingly complex disaster risks driven by climate change, environmental degradation and socio-economic pressures.

Objectives and Scope

The GeoAI Compendium is conceived as a practical reference that consolidates emerging methods, case studies and policy guidance on geospatial artificial intelligence. It is designed to help Regional Support Offices, national disaster management agencies and development partners systematise GeoAI adoption moving from pilot demonstrations to routine operations that directly support disaster risk reduction (DRR) and sustainable-development objectives.

The thematic scope spans the end-to-end GeoAI workflow, from data acquisition and preprocessing through model development, validation, deployment and governance. Rapid-onset hazards such as floods, earthquakes, landslides and wildfires sit alongside slow-onset stresses including drought, coastal erosion and water scarcity. While the methods presented are global in applicability, the case studies draw on the operational experience and ground truth contributed by the RSO network. The intended audience ranges from RSO analysts and space-agency engineers to disaster management officials and academic researchers; purely commercial use-cases that remain proprietary fall outside the Compendium's remit.

Each case study combines narrative text with figures, call-out boxes and, where available, annotated workflow descriptions rather than raw data dumps, so that readers receive context, methodology and reproducible assets in a single package. Content is updated on a twelve-month cycle timed to feed new material into the annual RSO coordination meeting, with major breakthroughs released as interim technical notes between editions. All submissions undergo peer review by an editorial panel of RSO representatives, external experts and UN-SPIDER staff, and are published under permissive licences that respect privacy, data-protection regulations and open-science principles.

Objectives

The Compendium pursues **four interlocking objectives**:

1. Promote Knowledge Exchange and Peer Learning

Catalogue state-of-the-art algorithms, cloud platforms and open datasets in a format that RSOs can replicate or adapt, and document operational lessons successes and challenges alike to shorten the learning curve for new adopters.

2. Strengthen Institutional Capacity

Provide implementation blueprints, sample workflows and training modules that can be embedded in UN-SPIDER technical-advisory missions, and offer modular teaching materials that can be localised to national languages, data policies and connectivity conditions.

3. Anchor GeoAI Innovation in Global Frameworks

Link each practice to the instruments it advances—the Sendai Framework (notably Targets B and C on reducing disaster mortality and economic loss, and Priority 1 on understanding risk), the Paris Agreement and its provisions on adaptation and loss and damage, the Early Warnings for All initiative, and the Sustainable Development Goals, with particular emphasis on SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action) and SDG 9 (Industry, Innovation and Infrastructure).

4. Facilitate Partnership and Resource Mobilization

Provide the evidence impact indicators, cost-benefit metrics and success stories that underpin funding proposals and South–South cooperation, and identify priority research gaps suitable for joint investment by governments, academia and the private sector.

Methodology

To ensure that the Compendium captures a balanced, evidence-based portrait of GeoAI practice across the UN-SPIDER network, content was gathered through a two-step call for contributions consisting of (i) a formal invitation e-mail and (ii) a structured submission template. The invitation was circulated to all twenty-nine Regional Support Offices that were part of the UN-SPIDER network at the time on 18 March 2026 and outlined the purpose of the Compendium and the submission process. Contributions were accepted until 21 April 2026. RSOs were encouraged to nominate up to six projects that demonstrated diversity in thematic focus, geographic setting and GeoAI techniques.

The Best-Practice Form included in Annex I was used as the main tool for collecting information on submitted initiatives. Contributors were asked to provide a concise description (200–300 words) of the challenge being addressed, the GeoAI approaches and satellite data utilized, key implementation partners, achieved results, and the relevance of the initiative to UN-SPIDER objectives or specific Sustainable Development Goals (SDGs). The template also requested information on lessons learned as well as references to relevant publications, platforms, or repositories. Using a common submission format helped ensure consistency in the information provided, facilitated comparison across cases, and enabled the collection of both technical and contextual details in a structured manner.

Screening and Appraisal

All forms received by the deadline underwent a two-tier review:

1. **Completeness check** – Submissions were verified for mandatory fields (problem definition, technical approach, outcomes). Incomplete entries were returned to the originating RSO for clarification within seven days.
2. **Qualitative assessment** – An editorial panel—comprising UN-SPIDER staff, remote sensing, GIS and disaster management experts, scored each practice against four criteria:

- Innovative use of GeoAI (novel models, data fusion, automation gains);
- Documented impact on disaster risk reduction or sustainable development goals;
- Replicability in data- or resource-constrained contexts;
- Contribution to local capacity-development (training components, open-source outputs).

Projects meeting at least three criteria at a "high" or "very high" level advanced to the Compendium. Where multiple entries covered similar hazards or methods, the panel selected the example with the stronger evidence base to avoid redundancy and maintain geographic balance.

Data Verification and Synthesis

For shortlisted practices, the editorial team performed light fact-checking—consulting publicly available datasets, peer-reviewed articles or partner-agency reports—to confirm quantitative claims such as accuracy scores or reductions in response time. Verified entries were then harmonised into a common narrative format that mirrors the Compendium's house style: context, methodology, results, enabling factors and policy linkage. Where appropriate, graphics and code snippets supplied by RSOs were edited for clarity and inserted as boxed elements.

Limitations

While the questionnaire approach delivered consistent, high-quality inputs, it relied on the self-reporting capacity of RSOs and therefore may under-represent emerging practices still in pilot phase or those constrained by data-sharing restrictions. The annual update cycle will provide opportunities to incorporate such projects as they mature.

By coupling a rigorous, template-driven survey with a transparent peer-review process, the Compendium ensures that only validated, policy-relevant and scalable GeoAI practices are showcased—laying a credible foundation for knowledge exchange, capacity development and future collaboration across the UN-SPIDER community.

GeoAI: Opportunities and Challenges

The convergence of high-resolution Earth-observation satellites, cloud-native data infrastructures and foundation-scale AI models is opening a new strategic frontier for disaster risk reduction (DRR) and climate resilience. For the UN-SPIDER community, GeoAI promises not only faster and more accurate hazard analytics but also fundamentally different ways of organising knowledge, partnerships and resources. These gains, however, arrive alongside a parallel set of technical, institutional and ethical concerns that must be managed if GeoAI is to deliver equitable and sustainable impact. This section sets out the principal opportunities the technology presents, followed by the challenges that the practices in this Compendium have brought to light.

Opportunities

a. Speed-to-Insight

Vision transformers and generative models now ingest terabytes of multi-sensor imagery and return decision layers such as flood extents, burn scars and damage masks in minutes rather than days. This compression of the sensor-to-action timeline transforms emergency operations, allowing civil-protection agencies to issue evacuation orders during the first hours of a coastal storm rather than after water has already reached urban cores.

b. Global Coverage at Local Detail

Constellation growth means that even small island developing States now receive frequent, metre-scale imagery. With cloud processing, an RSO can train a single segmentation model on regional data and deploy it simultaneously across dozens of provinces. This scalability lets countries move from isolated pilot demonstrations to routine, nationwide monitoring of hazards such as landslides, wildfire fuel build-up or drought-driven crop failure.

c. Multimodal Fusion

Contemporary GeoAI architectures reason jointly over optical and SAR imagery, digital elevation models, in-situ sensor networks and meteorological forecasts. This fusion yields richer and more resilient outputs, for example flood maps that integrate ground observations to correct cloud-obscured satellite scenes, or earthquake-impact layers that blend Sentinel-1 interferometry with building-stock inventories.

d. Lower Entry Barriers

Open-weight models and low-code notebooks have narrowed the skills gap considerably. An analyst with basic Python proficiency can fine-tune a landslide or flood-susceptibility model in a single afternoon, often using free or sponsored cloud credits. As several practices in this edition demonstrate, computationally efficient approaches such as Random Forest can match the performance of far heavier models while remaining transparent and reproducible, an advantage that aligns squarely with UN-SPIDER's mandate to serve least-developed and disaster-prone countries.

e. Evidence for Finance and Policy

GeoAI outputs, including damage tallies, exposure heatmaps and susceptibility indices, translate directly into quantified loss-and-damage claims, climate-adaptation proposals and SDG indicator submissions. By standardising these analytics, RSOs can help ministries strengthen their case for concessional finance from facilities such as the Green Climate Fund and the Fund for Responding to Loss and Damage, whose role was reinforced at COP 30.

Challenges

a. Data Inequity and Ground-Truth Scarcity

The same regions that face the highest disaster risk often hold the least validation data. Sparse and unevenly distributed in-situ networks, incomplete hazard inventories and limited historical records constrain both model training and accuracy assessment. Several practices in this Compendium addressed this constraint directly, for example by fusing satellite precipitation estimates with the few available rain gauges, but the underlying scarcity remains a structural barrier to reliable hazard mapping at fine spatial scales.

b. Compute and Infrastructure Constraints

Although cloud platforms have lowered the cost of entry, sustained access to processing capacity, reliable connectivity and storage is far from universal. Bandwidth limitations slow the transfer of large archives, and the recurring cost of commercial cloud compute can exceed the budgets of the agencies that would benefit most, leaving capability concentrated in better-resourced institutions.

c. Model Generalisation and Drift

Models trained in one geographic or ecological setting frequently underperform when applied to landscapes with different land-cover classes, terrain or climate regimes. Performance can also degrade over time as conditions on the ground change. Robust validation, spatially aware cross-validation and periodic retraining with local samples are therefore essential, yet they add to the data and labour burden that resource-constrained offices already face.

d. Data Sovereignty and Governance

Cross-border hazards demand models trained on diverse geographies, but raw imagery and derived layers often cannot cross national boundaries because of security statutes and data-residency laws. In the absence of agreed protocols for sharing models rather than data, valuable training signal stays locked within jurisdictions, limiting the collective benefit that federated approaches could otherwise unlock.

e. Ethics, Transparency and Trust

High-resolution analytics can intersect with personally identifiable information, raise questions of bias, and produce outputs that decision-makers are reluctant to act upon when the reasoning is opaque. Without clear documentation of how a model was built, what data it used and where it is reliable, even accurate outputs may fail to inform policy. Explainability, bias auditing and transparent provenance are prerequisites for operational credibility, not optional refinements.

f. Capacity and Sustainability

Many promising deployments remain dependent on short-term project funding, the presence of a few skilled individuals, or external partnerships that may not endure. Translating pilots into permanent services requires recurring budget lines, defined institutional roles and career pathways for geospatial and machine-learning expertise, so that workflows survive the end of any single grant or collaboration.

The Structure of this Compendium

The sections that follow present who is doing the work, what they are achieving, and how those achievements can be scaled and governed. Section IV profiles each Regional Support Office (RSO), providing the institutional context behind every case study. Section V then presents the heart of the Compendium—twenty-five best-practice GeoAI applications—grouped along the disaster management cycle from risk assessment and hazard mapping, through EWS and preparedness, rapid damage assessment to recovery, reconstruction, and resilience-building as well as cross-cutting applications. Finally, Section V ends by highlighting common elements of success and concludes with lessons learned. Section VI distils forward-looking recommendations that emerged across the GeoAI applications, while Section VII concludes with the strategic implications for UN-SPIDER and its partners. Finally, Section VIII contains annexes with the data-collection template and the glossary.

IV. RSO PROFILES

Regional Support Offices (RSOs) assist in implementing UN-SPIDER's mission to ensure that all countries can access and use space-based information to support disaster risk reduction and emergency response. Hosted by national or regional institutions with expertise in remote sensing, geospatial technologies, and applied research, RSOs operate across diverse geographic regions. They contribute technical expertise, local knowledge, and institutional capacity to develop and implement tools using satellite data and GeoAI for disaster risk reduction. Through targeted research and training initiatives, RSOs integrate global scientific advancements into national policies and local disaster management strategies. Their efforts support the Sendai Framework and the Sustainable Development Goals by enhancing preparedness, early warning systems, and recovery planning at national and regional levels.

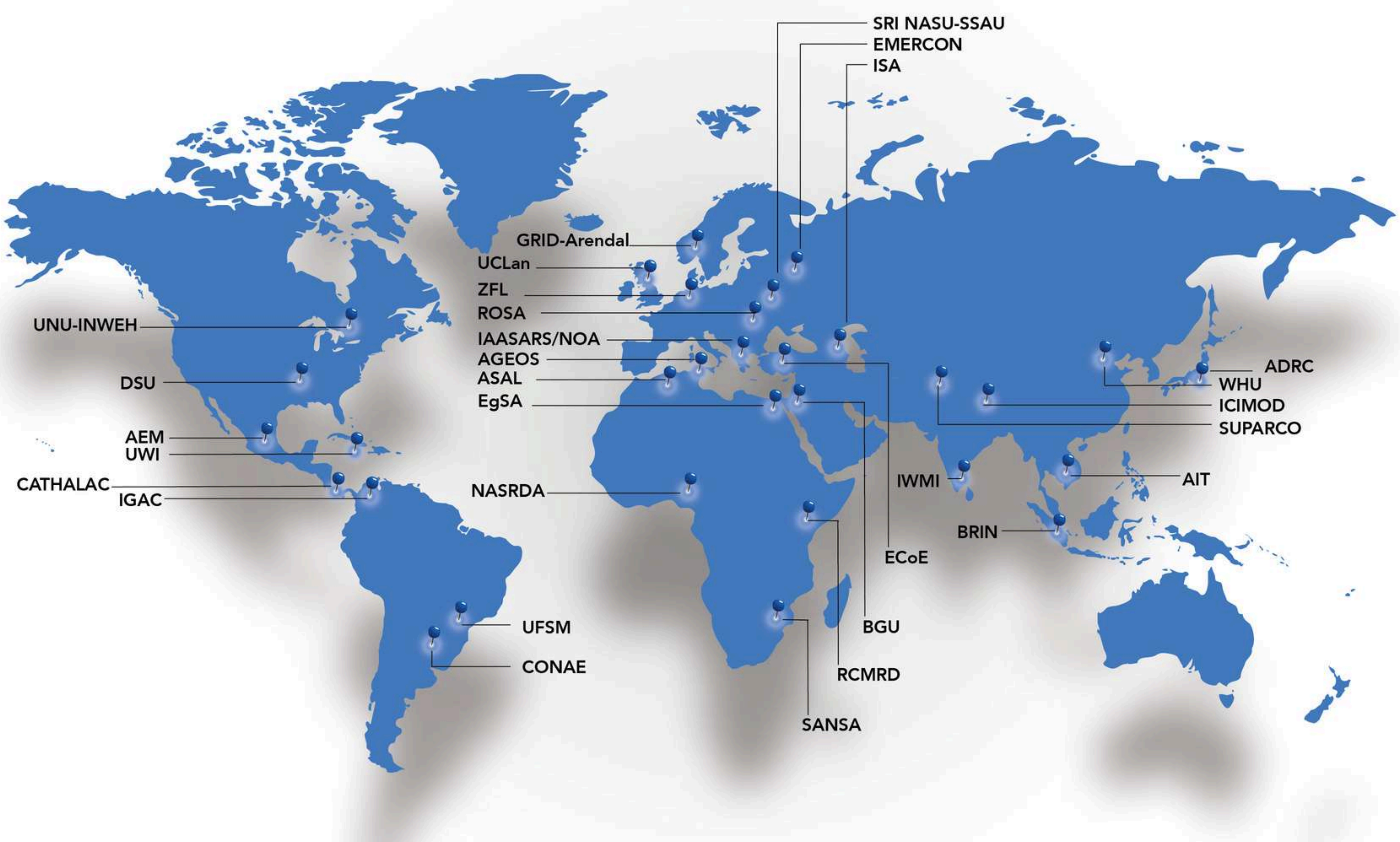


Figure 2: UN-SPIDER Regional Support Offices Map 2026

Figure 3: UN-SPIDER Regional Support Offices Meeting 2025

Ben-Gurion University of the Negev (BGU)

The UN-SPIDER Israel Regional Support Office at Ben-Gurion University of the Negev (BGU) advances research, capacity-building, and international cooperation in the application of space technologies for disaster risk reduction, climate resilience, public health, and sustainable development. Anchored within a multidisciplinary research environment, the RSO promotes the concept of Orbital Resilience—the integration of Earth Observation, satellite communications, navigation systems, ground-based sensors, and data-driven decision support to strengthen preparedness, early warning, response, and recovery capabilities.

The RSO operates in close collaboration with the Israeli Space Agency, strengthening national and international partnerships to advance the use of space technologies for societal resilience. The BGU RSO supports research, innovation, and training across diverse disciplines, including remote sensing, geoinformatics, engineering, public health, environmental sciences, and artificial intelligence. Drawing on Ben-Gurion University's expertise in satellite applications and innovation, the RSO develops next-generation methodologies and decision-support solutions that enhance resilience to natural hazards, climate change, and complex emergencies through the effective use of space-derived information.

Center for Interdisciplinary Geospatial Information Technologies (GIT), Delta State University

Delta State University's Center for Interdisciplinary Geospatial Information Technologies (GIT) became a member of the UN-SPIDER network of Regional Support Offices on 1 October 2018. As a University-hosted RSO, the Center focuses on education, technical training, and applied research in geographic information systems (GIS), remote sensing, global positioning systems (GPS), and spatial analysis. Its facilities include dedicated GIT workstations, including spatial data servers, large-format plotters, high-resolution scanners, and advanced GPS equipment, with site licenses for ESRI, ENVI, and Leica products.

The Center supports disaster response and risk reduction globally by providing technical advisory missions, expert deployments to UN-SPIDER programmes, and capacity-building activities. By adding a North American location to the RSO network, GIT strengthens UN-SPIDER's ability to deliver timely geospatial support and training across the region.

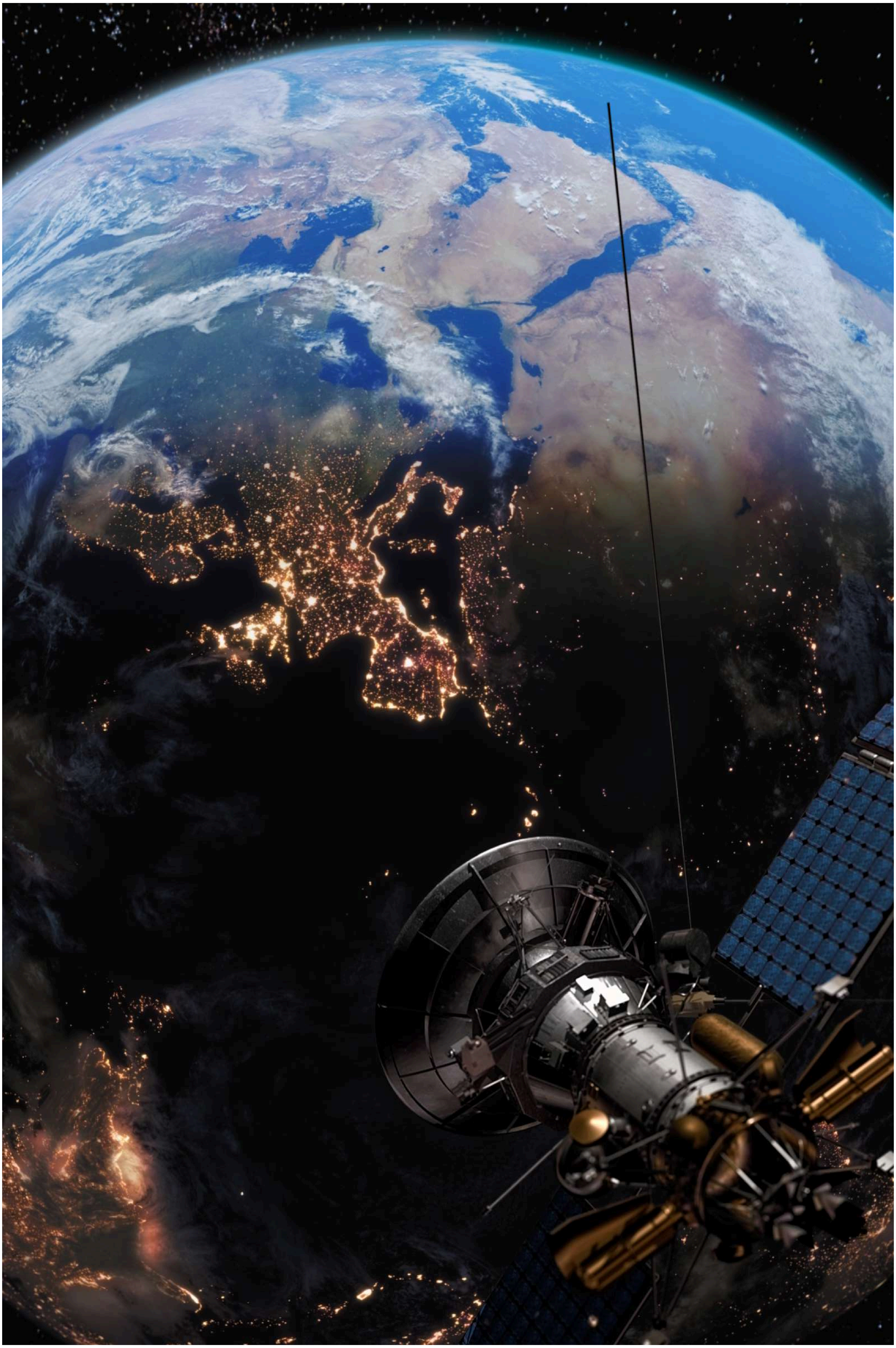
Center for Remote Sensing of Land Surfaces (ZFL)

The Center for Remote Sensing of Land Surfaces (ZFL) is an interdisciplinary center of the University of Bonn dedicated to research and teaching in the fields of remote sensing, geoinformation sciences and spatial modelling. It was founded with the objective to strengthen interdisciplinary collaboration within the University of Bonn and to foster research and teaching activities in its field.

In a complementary fashion to their academic activities, ZFL staff offer advice concerning general remote sensing questions and assist in solving complex problems. Due to the centralization of the remote sensing facilities of several institutions, a high degree of scientific exchange is guaranteed.

ZFL focuses on three key topics: risks, water and geomatics. Advanced courses, workshops and lectures referring to specific topics of remote sensing are organized regularly. Additionally, ZFL staff conduct their own research projects in various subjects and locations financed by external funding organizations. Furthermore, ZFL conducts advanced courses, workshops and lectures referring to specific topics of remote sensing regularly upon request.

In 2019, the United Nations Office for Outer Space Affairs (UNOOSA), through its UN-SPIDER Programme, and the ZFL have launched the SPEAR project (Spaceborne Earth Observation Applications for Emergency Response and Disaster Risk Reduction) to understand needs, develop solutions and strengthen national capacities in using space-based information for disaster monitoring and prevention in Africa in line with international and regional frameworks.



ERATOSTHENES Centre of Excellence (ECoE)

The ERATOSTHENES Centre of Excellence (ECoE) is a research centre operating as a Digital Innovation Hub for Earth Observation, Space technology, and geospatial information for multi-hazard risk assessment and climate resilience. ECoE is a member of various international networks, such as Copernicus Academy, ISPRS, GEO, MedRIN (NASA), ACTRIS/EARLINET, EARSeL, NEREUS, etc., and aspires to serve as a reference point in the Eastern Mediterranean, the Middle East, and North Africa region.

The ECoE integrates remote sensing, data management and processing technologies, applied research, educational services, and entrepreneurship support. Its operations are underpinned by two critical infrastructures: an Earth Observation Satellite Data Acquisition Station (DAS) and a Ground-Based atmospheric remote sensing Station (GBS). The Centre uses satellite data from Copernicus, Unmanned Aerial Vehicles (UAV)-derived data, and national-scale datasets to support environmental monitoring and decision-making. Finally, ECoE has developed and operates the Cyprus Earth Observation Data Cube (https://cyprusdatacube.com/) that manages various datasets from ESA (Sentinel-1, Sentinel-2) and NASA (MODIS) missions.

The activities of the Disaster Risk Reduction Cluster of the ERATOSTHENES CoE include the systematic monitoring of hazards, the development of Early Warning and Decision Support Systems dealing with earthquakes, landslides, coastal/soil erosion, forest fires, floods, drought, and epidemics.

Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing (IAASARS/NOA)

The Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing (IAASARS) is one of the three institutes of the National Observatory of Athens (NOA), the oldest research institution in Greece. IAASARS/NOA serves as a UN-SPIDER Regional Support Office, supporting disaster risk reduction through space-based information. IAASARS/NOA hosts the BEYOND Center of Earth Observation Research and Satellite Remote Sensing, a European Centre of Excellence positioning the Institute as a dynamic actor for multi-hazard management at regional, Mediterranean, European and global levels. BEYOND systematically provides disaster risk assessment, monitoring, and mapping products and services primarily for South-Eastern Europe, North Africa, the Middle East, but also worldwide.

Through the Operational Unit BEYOND, IAASARS operates 24/7 observational infrastructures for receiving and archiving Earth Observation data, such as the Copernicus Data Hub Relay and the Hellenic Mirror Site with a number of satellite acquisition stations, while deploying advanced modeling capacities and integrated Earth Intelligence solutions for real-time multi-hazard assessment, including fire, flood, earthquake, volcanic, and landslide risk assessment, smart farming, renewable energy and climate-related disease outbreaks.

International Water Management Institute (IWMI)

The International Water Management Institute (IWMI), a CGIAR Research Center, is a global leader in water management, sustainable agriculture, climate resilience, and disaster risk reduction. IWMI is headquartered in Colombo, Sri Lanka, with regional offices across Asia and Africa. IWMI works in partnership with governments, civil society, and the private sector to develop scalable agricultural water management solutions that have a real impact on poverty reduction, food security, and ecosystem health.

The institute actively works to apply knowledge by collaborating with other research centers, policymakers, donors, partners, and communities to increase its impact. IWMI's scientists come from diverse fields, including water management, hydrology, economics, engineering, irrigation, GIS and remote sensing, software development, information management, communications, monitoring and evaluation, and uptake coordination.

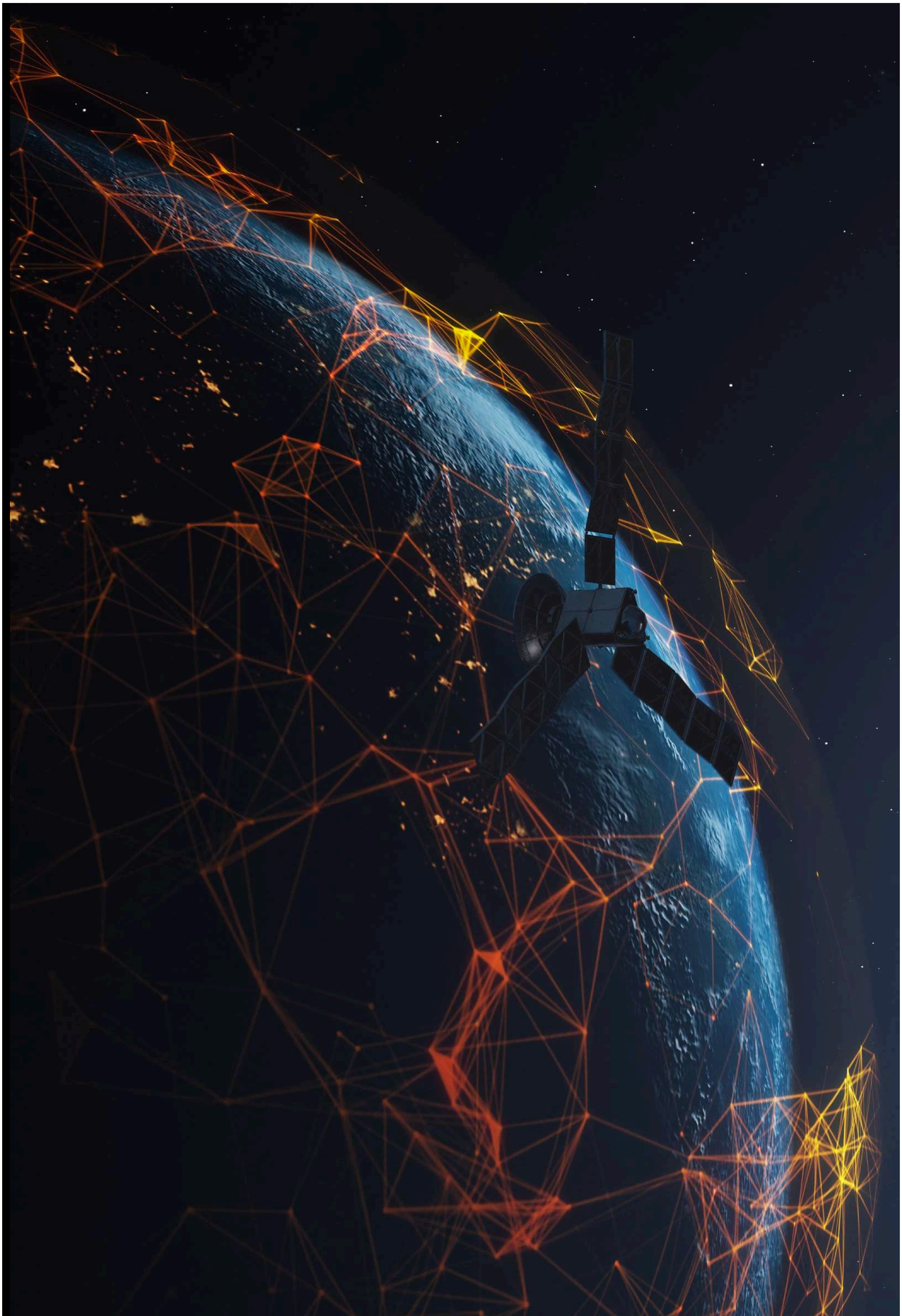
IWMI develops AI-powered tools that integrate Earth Observation, geospatial analysis, and stakeholder engagement to enhance early warning, anticipatory action, and climate adaptation in vulnerable regions.

Space and Upper Atmosphere Research Commission (SUPARCO)

The Pakistan Regional Support Office (Pak-RSO) is hosted by the Space Application Center for Response in Emergency and Disasters (SACRED) under the Pakistan Space and Upper Atmosphere Research Commission (SUPARCO). Supported by the National Disaster Risk Management Fund (NDRMF), SUPARCO applies national-scale practices to enhance urban planning, disaster risk reduction, exposure assessment, and sustainable development.

SUPARCO is mandated to conduct research and development in space science, space technology, and their peaceful applications in the country. It works towards developing indigenous capabilities in space technology and promoting space applications for the socio-economic uplift of the country.

SUPARCO's GeoAI-driven practices demonstrate how Earth Observation and AI can improve disaster preparedness and sustainable development outcomes across Pakistan's diverse landscapes.



Space Research Institute of the National Academy of Sciences of Ukraine and the State Space Agency of Ukraine (SRI NASU-SSAU)

The Space Research Institute of the National Academy of Sciences of Ukraine and the State Space Agency of Ukraine (SRI NASU-SSAU) is one of the country's leading institutions in geospatial intelligence, Earth Observation, and space-based environmental monitoring. To support Ukraine's environmental security, SRI NASU-SSAU creates AI-driven geospatial systems for disaster management, climate adaptation, and land use monitoring.

SRI NASU-SSAU contributes to national and international scientific communities through new Land Cover/Land Use (LC/LU) datasets, harmonized data representations, and pilot simulations that support strategic policy, sustainability, and post-war recovery planning. Their practices improve evidence-based decision-making for recovery, adaptation, and land management by empowering stakeholders with tools for scenario-based analysis.

University of Lancashire

The University of Lancashire focuses on advancing disaster risk reduction and climate resilience through geospatial technologies and AI. With a strong emphasis on international collaboration, the University of Lancashire brings together researchers, students, and institutions to co-develop innovative solutions that address global environmental challenges. Their work includes applications in mangrove conservation, hydro-disaster management, and sustainable agriculture.

The University of Lancashire combines expertise in space-based technologies and disaster risk management, with a focus on applying Earth Observation, remote sensing, and geospatial tools to support disaster preparedness, response, and recovery. The Centre works on developing practical solutions that integrate satellite data, mapping, and spatial analysis to monitor hazards, assess risks, and inform decision-making.

Through visiting scholar and student initiatives, University of Lancashire strengthens capacity in GeoAI, satellite data use, and resilience-building. These collaborative efforts support both scientific advancement and the generation of policy-relevant knowledge, particularly in regions vulnerable to coastal disasters, flooding, and climate stress.

V. GEOAI BEST PRACTICES AND INNOVATIVE APPLICATIONS

Section A: Risk Assessment and Hazard Mapping

Overview

Hazard profiling and risk analytics are essential for identifying high-risk areas and guiding proactive, data-driven disaster management aligned with the SDGs. Advances in AI/ML (e.g., Random Forest, U-Net, LSTM) combined with satellite data (e.g., Sentinel-1, CHIRPS) enable accurate, scalable multi-hazard risk assessments. This integration helps governments and responders act quickly, protect infrastructure, and build community resilience.

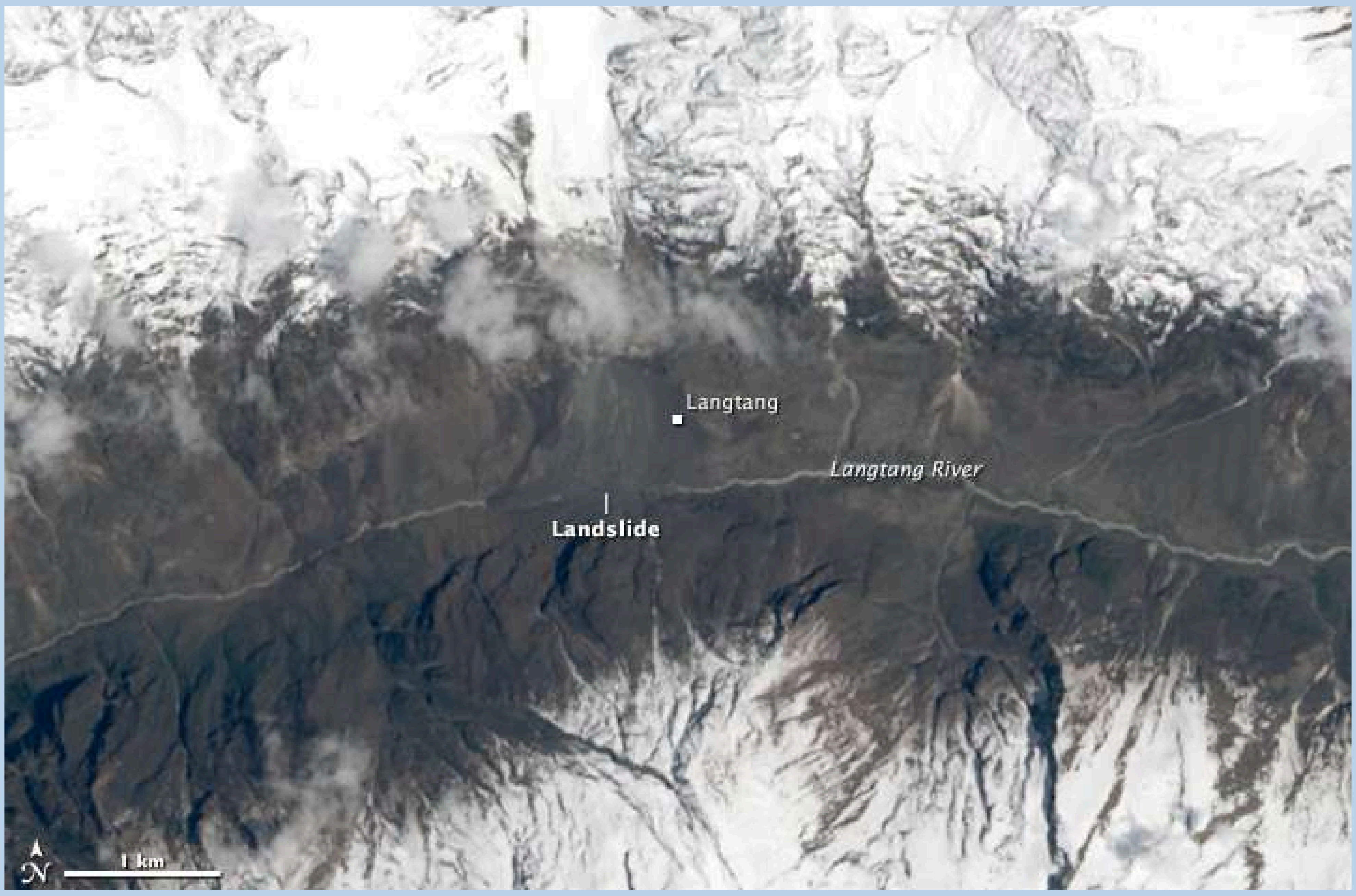


Figure 4: Landslide in Langtang Valley following 25 April 2015 earthquake in Nepal
(c) UN-SPIDER Knowledge Portal

Delta State University - GeoAI for Spatial Bias and Aggregation Risk Detection

Title of GeoAI Practice

GeoAI for Spatial Bias and Aggregation Risk Detection

Challenge or Problem Addressed

Many disaster management and GeoAI systems rely on administrative zones or aggregated datasets that may distort real-world hazard conditions. Flood risk, social vulnerability, and infrastructure exposure often vary continuously across space, yet decision systems frequently force these phenomena into discrete boundaries. This practice addresses the challenge of identifying and mitigating aggregation bias, zoning distortions, and misleading GeoAI outputs that can negatively affect disaster preparedness and emergency response.

Brief Description

This GeoAI practice was developed through Delta State University's GeoAI Risks curriculum to help students, researchers, and practitioners understand how spatial aggregation and zoning distortions influence disaster-risk modeling and GeoAI decision systems. The initiative focuses on the Modifiable Areal Unit Problem (MAUP), ecological fallacy, and governance-induced spatial bias that can emerge when AI systems rely on aggregated or administratively defined geographic units. Through hands-on laboratories using ArcGIS Pro, Python, and Google Earth Engine, participants evaluate how different spatial resolutions and administrative boundaries alter hazard interpretation, vulnerability analysis, and resource prioritization. The practice emphasizes governance-aware spatial analytics and operational decision quality rather than solely model accuracy. It supports more transparent and resilient disaster-risk analysis workflows while helping organizations recognize hidden distortions that may emerge in GeoAI-enabled emergency management systems.

BY ADDRESSING THESE CRITICAL ANALYTICAL BLIND SPOTS, THE EDUCATIONAL FRAMEWORK CULTIVATES HIGHLY TRANSPARENT, GOVERNANCE-AWARE WORKFLOWS. THIS ENSURES THAT EMERGENCY RESOURCE PRIORITIZATION AND VULNERABILITY ASSESSMENTS ARE GUIDED BY UNDISTORTED, REAL-WORLD CONDITIONS RATHER THAN MISLEADING ADMINISTRATIVE BOUNDARIES.

Implementation and Collaborations

The initiative was implemented through the Delta State University GIT curriculum as part of an interdisciplinary GeoAI and disaster-risk education framework. The project incorporates classroom instruction, applied laboratory exercises, and collaborative discussions involving students, geospatial practitioners, and emergency-management stakeholders. The curriculum emphasizes reproducible workflows and scalable educational approaches that can be adapted internationally.

Delta State University - GeoAI for Spatial Bias and Aggregation Risk Detection

Technical Approach and Methods

The practice integrates spatial statistics, machine learning workflows, multiscale geospatial analysis, and Earth Observation datasets. Students and practitioners use ArcGIS Pro, Python, GeoPandas, raster analysis, interpolation methods, and Google Earth Engine to evaluate how spatial resolution and aggregation influence GeoAI outputs. Synthetic and real-world hazard datasets are analyzed across parcel, block, tract, county, and regional scales to demonstrate how GeoAI interpretations shift across spatial resolutions.

Impact and Outcomes

The practice improved participant understanding of spatial uncertainty, aggregation effects, and governance-related distortions in GeoAI systems. Students developed stronger analytical awareness regarding the limitations of AI-driven hazard mapping and gained practical experience evaluating decision-system reliability. The work also supports broader discussions regarding trustworthy AI, transparent disaster analytics, and resilient spatial decision-making.

Alignment with SDGs

This practice supports UN-SPIDER's mission by strengthening the responsible use of space-based information and GeoAI for disaster risk reduction. It aligns with SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 16 (Peace, Justice, and Strong Institutions) by promoting more equitable, transparent, and resilient geospatial decision systems.

THIS PRACTICE CHAMPIONS THE **RESPONSIBLE USE** OF SPACE-BASED INFORMATION BY BUILDING AN ADAPTABLE, MULTISCALE ANALYTICAL FRAMEWORK THAT IS ACCESSIBLE EVEN IN **RESOURCE-CONSTRAINED ENVIRONMENTS**.

Lessons Learned and Recommendations

- This project demonstrates that many GeoAI errors originate from AI algorithms themselves, not from the structure of spatial data and governance systems. Future implementations should integrate uncertainty analysis, multiscale evaluation, and governance-aware validation into GeoAI workflows. Educational programs should emphasize spatial reasoning and operational interpretation alongside technical AI skills.
- Operational examples included comparisons of parcel-, census tract-, and county-level flood exposure outputs using Sentinel-2 imagery, digital elevation models (DEMs), and socioeconomic vulnerability indicators to demonstrate how aggregation alters GeoAI interpretations.
- The framework was intentionally designed using both commercial and open-source geospatial tools, including ArcGIS Pro, QGIS, Python, OpenStreetMap, and Google Earth Engine, to support adoption in resource-constrained environments and international training programs.

Delta State University - GeoAI for Spatial Bias and Aggregation Risk Detection

Additional References or Resources

- Delta State University Geospatial Information Technology (GIT) Program
- GeoAI, GIS, Remote Sensing, Disaster Risk Reduction, and Governance-Aware Spatial Analytics Educational Initiatives Website: https://www.deltastate.edu/college-of-business-and-aviation/geospatial-information-technology/ Forthcoming Publication
- Alexander, D., & Brooks, T. J. GeoAI Risks: The New Geography of Uncertainty Forthcoming publication through Amazon Kindle Direct Publishing (KDP). Final ISBN and publication URL pending release.
- GeoAI Risks Companion Educational Resources
- Applied GeoAI laboratories and instructional workflows supporting:
  - Disaster Risk Reduction
  - Multiscale Flood Modeling
  - Adversarial Geography and Stress Testing
  - GeoAI Governance and Ethics
  - Spatial Bias and Aggregation Analysis
  - Feedback Loop Detection in Spatial Decision Systems
  - Earth Observation and Remote Sensing Integration
  - Earth Observation and Geospatial Data Sources
- Sentinel-1 SAR Imagery : European Space Agency (ESA) synthetic aperture radar imagery supporting flood detection, disaster monitoring, and all-weather Earth Observation. Sentinel-1 Mission Overview
- Sentinel-2 Optical Imagery : High-resolution multispectral optical imagery used for land-cover analysis, flood mapping, vegetation monitoring, and disaster assessment. Sentinel-2 Mission Overview
- Landsat 8/9 : NASA/USGS Earth Observation program supporting long-term environmental monitoring and disaster analysis. Landsat Missions
- NASA Earth Observation Products :NASA Earth Observation datasets supporting environmental monitoring, climate analysis, and disaster-risk applications. NASA Earthdata
- Copernicus Programme Datasets :European Union Earth Observation and environmental monitoring services. Copernicus Programme
- OpenStreetMap (OSM) : Open-source global geospatial data supporting mapping, humanitarian operations, and disaster response. OpenStreetMap
- Digital Elevation Models (DEMs) :Elevation datasets used for hydrologic analysis, terrain modeling, and flood-risk assessment. Representative sources include NASA SRTM and Copernicus DEM products. NASA SRTM Data
- ArcGIS Living Atlas : Curated geospatial content and Earth Observation layers supporting GIS and GeoAI workflows. ArcGIS Living Atlas
- Google Earth Engine :Cloud-based planetary-scale geospatial analysis platform supporting remote sensing and GeoAI workflows. Google Earth Engine
- Public instructional repositories, companion materials, and additional educational resources will be released following publication of the instructional text.

Delta State University - GeoAI for Spatial Bias and Aggregation Risk Detection

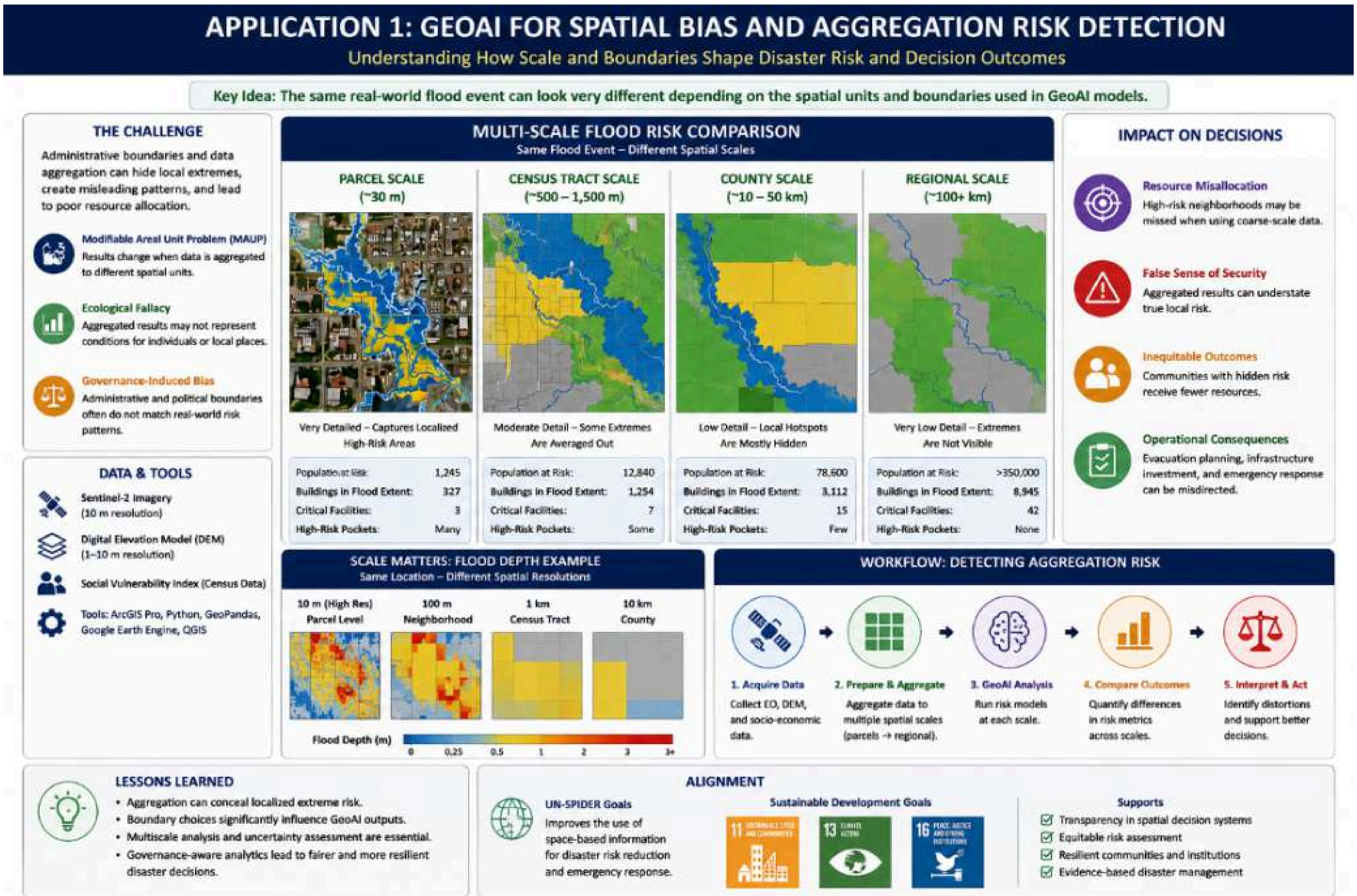


Figure 5: GeoAI for Spatial Bias and Aggregation Risk Detection

Delta State University - Adversarial Geography and Stress Testing of GeoAI Systems

Title of GeoAI Practice

Adversarial Geography and Stress Testing of GeoAI Systems

Challenge or Problem Addressed

Many GeoAI systems are optimized for ideal operating conditions but are not designed to account for manipulated, incomplete, or intentionally distorted spatial information. During disasters or crises, adversarial conditions can compromise situational awareness and create cascading decision failures. This practice addresses the need for resilient GeoAI systems capable of operating under uncertainty and degraded information conditions.

Brief Description

This GeoAI practice explores how disaster management systems and geospatial AI models can fail under adversarial or degraded geographic conditions. Developed through Delta State University's GeoAI Risks curriculum, the initiative introduces students and practitioners to adversarial geography concepts including manipulated spatial inputs, incomplete datasets, boundary distortions, misinformation, and intentional geographic deception. Through scenario-based stress testing exercises, participants evaluate how GeoAI-enabled decision systems respond to corrupted or misleading spatial information during emergency-management operations. The practice emphasizes operational robustness, resilience, and trustworthy AI principles within disaster risk reduction environments.

THIS PRACTICE INTRODUCES AN ESSENTIAL PARADIGM SHIFT IN DISASTER RISK MANAGEMENT BY MOVING BEYOND IDEAL DATA CONDITIONS TO **STRESS-TEST GEOAI SYSTEMS** AGAINST REAL-WORLD ADVERSARIAL THREATS AND INFORMATION DEGRADATION. UTILIZING TOOLS LIKE ARCGIS PRO, PYTHON, AND OPEN-SOURCE FRAMEWORKS, THE CURRICULUM SIMULATES COMPLEX CHALLENGES SUCH AS **DATA CORRUPTION**, **BOUNDARY MANIPULATION, FALSE HOTSPOTS, AND INTENTIONAL GEOGRAPHIC DECEPTION.**

Technical Approach and Methods

The practice combines geospatial simulation, spatial statistics, machine learning workflows, and adversarial stress-testing scenarios. Participants use ArcGIS Pro, Python, and open-source geospatial frameworks to simulate data corruption, boundary manipulation, false hotspots, and degraded Earth Observation inputs. GeoAI outputs are evaluated under varying operational conditions to identify system vulnerabilities and resilience gaps.

Delta State University - Adversarial Geography and Stress Testing of GeoAI Systems

Implementation and Collaborations

The initiative was implemented through classroom laboratories, operational simulations, and governance-focused GeoAI exercises within the Delta State GIT program. The framework integrates interdisciplinary perspectives from GIS, emergency management, AI ethics, and spatial decision support. The approach is scalable and designed to support broader disaster-resilience education and capacity-building initiatives.

Impact and Outcomes

Participants gained practical experience identifying vulnerabilities in GeoAI systems and understanding how adversarial conditions influence disaster-response operations. The initiative strengthened awareness of trustworthy AI principles, resilience engineering, and operational risk assessment in geospatial environments. The practice also contributes to emerging discussions regarding resilient AI architectures for emergency management.

Alignment with SDGs

This practice aligns with UN-SPIDER objectives by supporting resilient disaster risk reduction capabilities and improving operational use of geospatial technologies under uncertain conditions. It contributes to SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action).

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

11 SUSTAINABLE CITIES AND COMMUNITIES

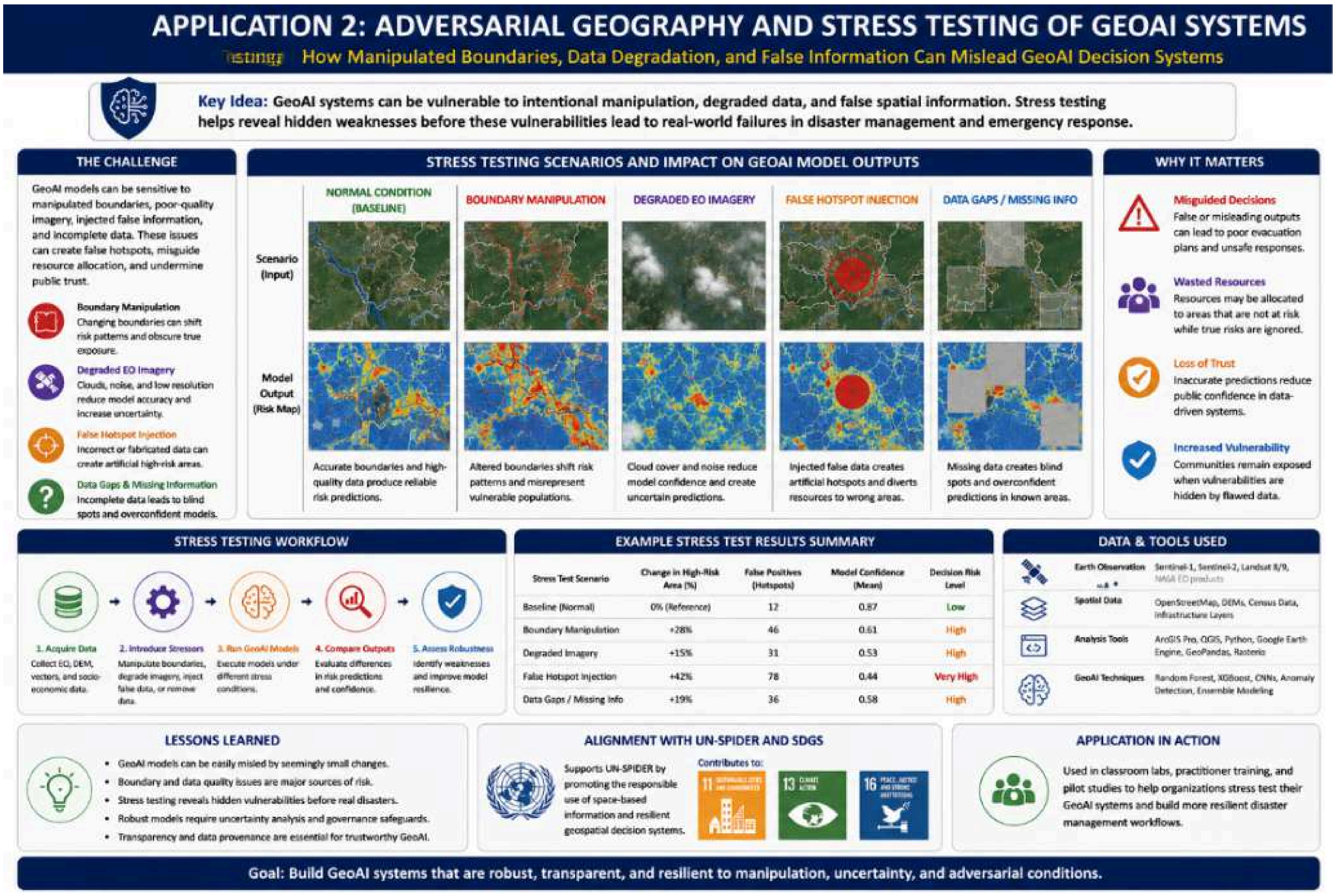
13 CLIMATE ACTION

Lessons Learned and Recommendations

- GeoAI systems should be evaluated not only for accuracy but also for resilience under degraded or manipulated conditions. Future GeoAI programs should incorporate adversarial testing, uncertainty modeling, and governance-aware validation into operational workflows and educational curricula.
- Scenario-based exercises included simulated false flood hotspots, degraded satellite imagery, manipulated evacuation-zone boundaries, and incomplete damage-assessment datasets to evaluate GeoAI resilience during disaster-response operations.
- The methodology integrates Earth Observation sources such as Sentinel-1 SAR imagery, Sentinel-2 optical imagery, and open geospatial datasets to support scalable and internationally transferable resilience-testing workflows.

Delta State University - Adversarial Geography and Stress Testing of GeoAI Systems

Additional References or Resources



Stress Test Scenario	Change in High-Risk Area (%)	False Positives (Hotspots)	Model Confidence (Mean)	Decision Risk Level
Baseline (Normal)	0% (Reference)	12	0.87	Low
Boundary Manipulation	+28%	46	0.61	High
Degraded Imagery	+15%	31	0.53	High
False Hotspot Injection	+42%	78	0.44	Very High
Data Gaps / Missing Info	+19%	36	0.58	High

Figure 6: Adversarial Geography and Stress Testing of GeoAI Systems

Delta State University - GeoAI-Based Multi-Scale Flood and Vulnerability Modeling

Title of GeoAI Practice

GeoAI-Based Multi-Scale Flood and Vulnerability Modeling

Challenge or Problem Addressed

Disaster management organizations frequently rely on flood-risk products generated at incompatible spatial scales. Differences in resolution and aggregation can produce inconsistent interpretations of hazard exposure, infrastructure vulnerability, and emergency-planning priorities. This practice addresses the need for scale-aware GeoAI workflows capable of supporting transparent and operationally meaningful flood-risk analysis.

THIS PRACTICE TRANSFORMS FLOOD-RISK ANALYSIS BY DIRECTLY ADDRESSING THE CRITICAL **INCONSISTENCIES** THAT ARISE WHEN DISASTER MANAGEMENT ORGANIZATIONS RELY ON **INCOMPATIBLE SPATIAL SCALES.**

Brief Description

This GeoAI practice demonstrates how flood-risk assessments and vulnerability analyses change dramatically across spatial scales and data resolutions. Developed through Delta State University's GeoAI Risks educational framework, the project uses multiscale geospatial analysis to examine how parcel-level, neighborhood-level, and regional-scale modeling produce different interpretations of exposure and risk. The initiative integrates Earth Observation data, spatial interpolation, machine learning, and geospatial visualization to support disaster preparedness and resilient infrastructure planning.

Technical Approach and Methods

Participants use ArcGIS Pro, raster analysis, digital elevation models, interpolation methods, hydrologic modeling techniques, and Google Earth Engine workflows to compare flood-risk outputs across multiple geographic scales. Synthetic and real-world datasets are evaluated to demonstrate how changes in resolution affect GeoAI predictions and spatial decision-making.

Implementation and Collaborations

The practice was implemented through classroom laboratories and applied geospatial analysis exercises within the Delta State University GIT curriculum. Students and practitioners completed multiscale flood modeling activities designed to simulate operational disaster-planning environments and improve understanding of spatial uncertainty.

Impact and Outcomes

The initiative improved participant understanding of scale sensitivity, spatial uncertainty, and flood-risk interpretation. Students developed practical experience using Earth Observation data and GeoAI tools to support resilient planning and disaster preparedness. The project also reinforced the importance of transparent multiscale analysis in emergency-management decision systems.

Delta State University - GeoAI-Based Multi-Scale Flood and Vulnerability Modeling

Alignment with SDGs

This practice supports UN-SPIDER's mission to improve access to geospatial technologies for disaster risk reduction. It aligns with SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 9 (Industry, Innovation, and Infrastructure).

Lessons Learned and Recommendations

- GeoAI workflows should incorporate multiscale evaluation and uncertainty analysis to avoid misleading disaster-risk interpretations. Future initiatives should prioritize scalable educational frameworks and reproducible geospatial workflows for disaster-resilience training.
- Operational exercises compared flood-risk outputs derived from Landsat, Sentinel-2, and DEM-based hydrologic models across parcel, neighborhood, watershed, and regional scales to demonstrate scale-driven variation in GeoAI decision outputs.
- The instructional framework was designed to support adaptation by universities, emergency-management agencies, and disaster-risk organizations operating in both developed and resource-constrained environments.

Delta State University - GeoAI-Based Multi-Scale Flood and Vulnerability Modeling

Additional References or Resources

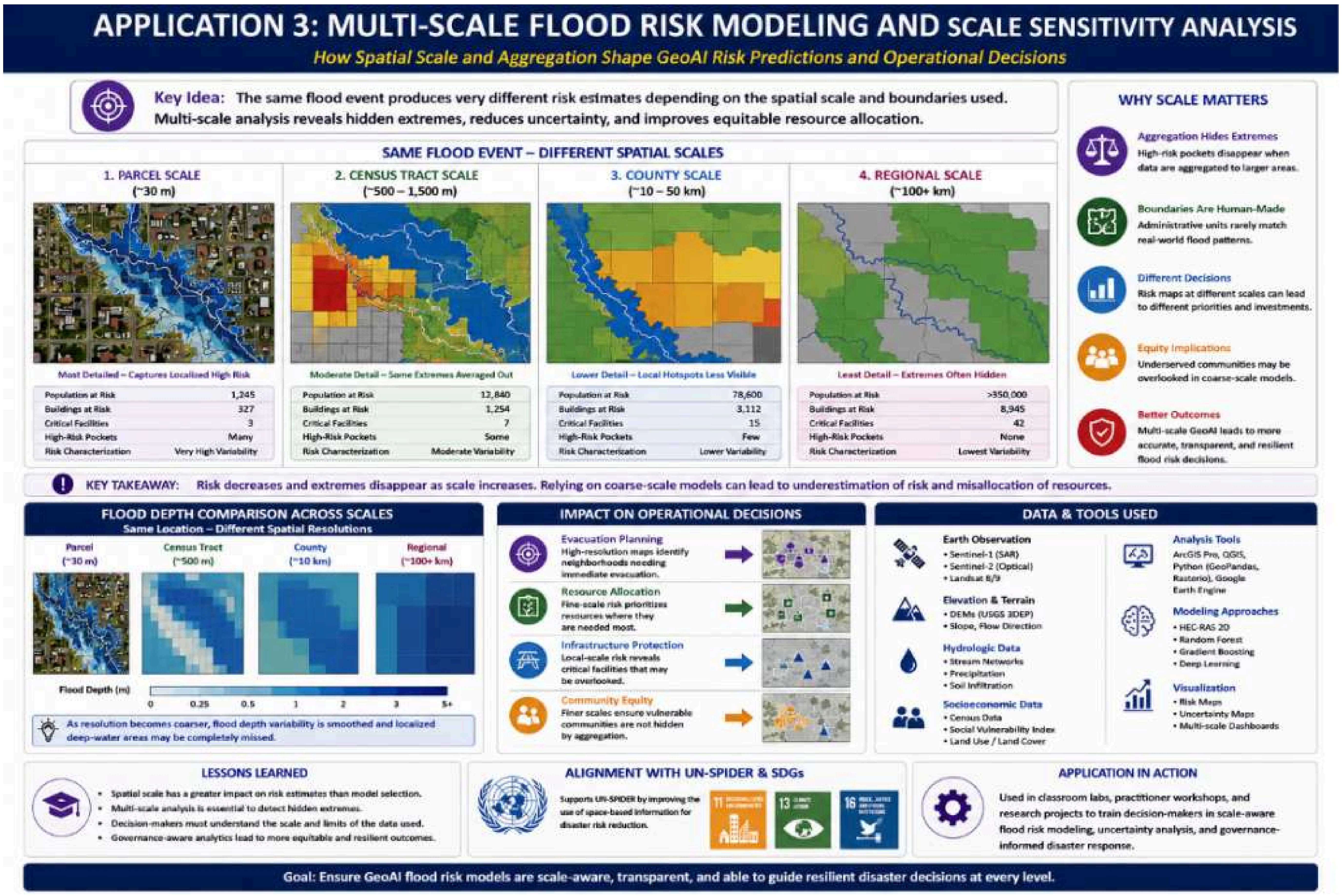


Figure 7: Multi-Scale Flood Risk Modeling and Scale Sensitivity Analysis

Delta State University - GeoAI Feedback Loop Detection in Spatial Decision Systems

Title of GeoAI Practice

GeoAI Feedback Loop Detection in Spatial Decision Systems

Challenge or Problem Addressed

GeoAI systems may unintentionally reinforce biased decision patterns through repeated operational feedback loops. In disaster-response environments, these effects can distort resource allocation, infrastructure prioritization, and emergency-response planning. The practice addresses the need to identify and mitigate self-reinforcing errors in AI-enabled spatial systems.

Brief Description

This GeoAI practice investigates how spatial decision systems can unintentionally reinforce errors, inequalities, and biased operational patterns over time. Developed through the Delta State University GeoAI Risks curriculum, the initiative explores feedback loops in disaster management, emergency response, and resource allocation systems. Participants examine how repeated GeoAI-driven decisions can amplify existing spatial disparities and create self-reinforcing patterns of vulnerability. The practice emphasizes the importance of governance-aware monitoring and resilient system design in operational GeoAI environments.

Alignment with SDGs

This practice supports UN-SPIDER's goals by promoting resilient and equitable use of geospatial technologies for disaster risk reduction. It aligns with SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 16 (Peace, Justice, and Strong Institutions).

Technical Approach and Methods

Participants use spatial simulation, temporal analysis, machine learning workflows, and geospatial visualization tools to model feedback loops within disaster management systems. ArcGIS Pro, Python, and Google Earth Engine are used to evaluate how repeated decision cycles influence spatial outcomes and risk patterns over time.

Implementation and Collaborations

The initiative was implemented through laboratory exercises and applied simulations within the Delta State University GIT curriculum. The project integrates interdisciplinary instruction involving GIS, AI ethics, emergency management, and spatial systems analysis.

Impact and Outcomes

Participants gained practical understanding of how GeoAI systems can unintentionally amplify vulnerability and inequality over time. The initiative improved awareness of resilient system design, governance-aware monitoring, and operational transparency within disaster management environments.

11 SUSTAINABLE CITIES AND COMMUNITIES

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16 PEACE, JUSTICE AND STRONG INSTITUTIONS

Delta State University - GeoAI Feedback Loop Detection in Spatial Decision Systems

Lessons Learned and Recommendations

- GeoAI systems should be continuously evaluated for unintended reinforcement effects and long-term operational consequences. Future GeoAI implementations should incorporate governance-aware monitoring, transparency mechanisms, and iterative validation workflows.
- Operational simulations demonstrated how repeated GeoAI-driven resource allocation decisions could unintentionally reinforce unequal disaster-response coverage and create persistent spatial disparities in emergency preparedness outcomes.
- The methodology integrates Earth Observation datasets, temporal geospatial analysis, and open-source geospatial workflows to support scalable international implementation and resilient decision-system monitoring.

Additional References or Resources

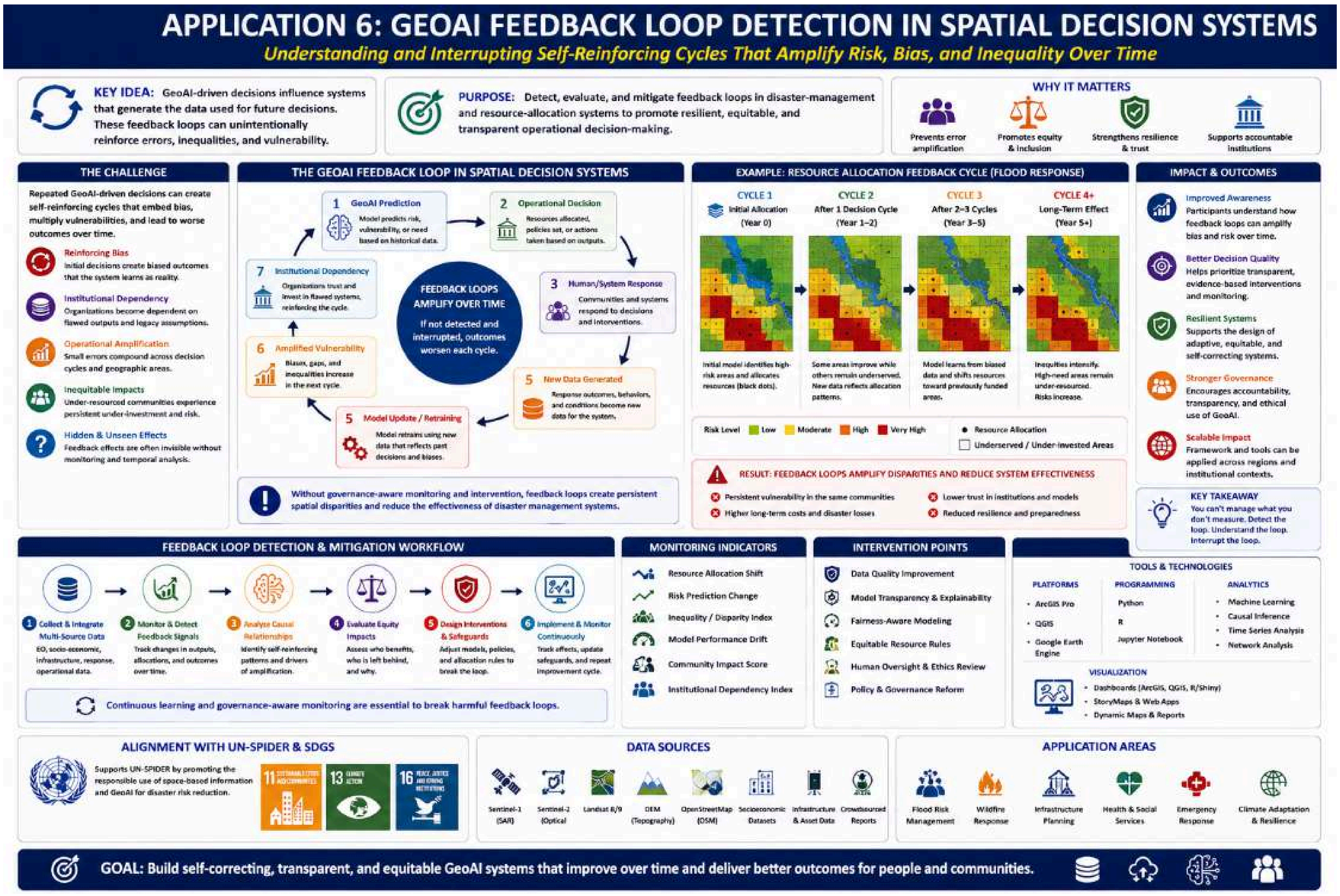


Figure 8: GeoAI Feedback Loop Detection in Spatial Decision Systems

ECoE - Habitat-Based Fuel Model Mapping Using Random Forest in Google Earth Engine: A Case Study of Cyprus

Title of GeoAI Practice

Habitat-Based Fuel Model Mapping Using Random Forest in Google Earth Engine: A Case Study of Cyprus

Brief Description

Accurate characterization of fuel types is essential for understanding wildfire behavior and supporting effective fire management strategies, particularly in fire-prone Mediterranean ecosystems. This study presents a novel GeoAI-based framework for fuel type mapping in Cyprus by integrating multi-source Earth Observation (EO) data with machine learning techniques. Building upon an existing habitat classification approach, dominant habitat types were reclassified into ecologically meaningful fire behavior fuel models based on vegetation structure, biomass, and expected fire dynamics, following the Scott and Burgan framework. The analysis was conducted in Google Earth Engine (GEE), combining Sentinel-2 optical imagery, Sentinel-1 SAR data, spectral indices (e.g., NDVI, NDMI, NBR), topographic variables, and tree density layers to capture both structural and biophysical properties of vegetation. A Random Forest classifier was applied to generate high-resolution fuel model maps, demonstrating improved discrimination of fuel types compared to traditional habitat-based classifications. The proposed framework provides a scalable and transferable solution for wildfire risk assessment, fire behavior modeling, and decision support in Mediterranean environments.

THIS HIGHLY SCALABLE APPROACH **SEAMLESSLY TRANSLATES** INTRICATE SPATIAL RELATIONSHIPS INTO ACTIONABLE, INTUITIVE MAPS, EQUIPPING LOCAL DECISION-MAKERS WITH THE CRITICAL, LOCALIZED DETAIL REQUIRED FOR ACCURATE FIRE SIMULATION, RISK ASSESSMENT, AND TARGETED MITIGATION PLANNING IN **VULNERABLE MEDITERRANEAN** ECOSYSTEMS.

Challenge or Problem Addressed

Wildfires pose a major threat to ecosystems, infrastructure, and human life, particularly in Mediterranean regions such as Cyprus, where climate conditions (high temperatures, low precipitation, and strong winds) favor fire ignition and spread. A key limitation in wildfire risk assessment is the lack of high-resolution, spatially explicit fuel type information. Existing datasets, such as the European Forest Fire Information System (EFFIS), provide fuel maps at coarse spatial resolution (~250 m), which are insufficient for local-scale decision-making. This practice addresses the need for high-resolution, accurate, and spatially detailed fuel characterization, enabling improved wildfire risk mapping, fire behaviour simulation, and mitigation planning.

ECoE - Habitat-Based Fuel Model Mapping Using Random Forest in Google Earth Engine: A Case Study of Cyprus

Technical Approach and Methods

The proposed approach integrates GeoAI, remote sensing, and ecological knowledge for high-resolution fuel model mapping in Cyprus. Multi-source Earth Observation (EO) data were utilized, including Sentinel-2 multispectral imagery, Sentinel-1 SAR data (Radar), and derived spectral indices (e.g., NDVI, NDMI, NBR), combined with topographic variables (elevation, slope, aspect) and tree density datasets to capture both structural and biophysical characteristics of vegetation. The analysis was implemented on the GEE platform, enabling efficient large-scale data processing. A stratified training dataset was developed using expert interpretation of dominant species in the selected study area, supported by high-resolution imagery from Google Earth and georeferenced digital aerial orthophotos provided by the Department of Lands and Surveys for the years 2014 and 2019. Subsequently, habitat types were translated into fire behavior fuel models based on vegetation structure, following the Scott and Burgan framework. A Random Forest classifier was applied due to its robustness and high performance in heterogeneous environments. Model performance was evaluated using standard accuracy metrics and cross-validation techniques. The overall workflow emphasizes the identification of dominant fuel characteristics to support wildfire risk assessment and management.

Implementation and Collaborations

The study was implemented using Google Earth Engine, enabling efficient large-scale data processing and analysis. The work was conducted within the research activities of the ERATOSTHENES Centre of Excellence (Cyprus) under the EXCELSIOR Horizon 2020 project (https://excelsior2020.eu/), integrating expertise in remote sensing, GIS, and wildfire risk assessment. The proposed approach is designed to be transferable and can be readily adapted by governmental authorities, such as the Department of Forests, the Cyprus Fire Service, and the Cyprus Civil Defence, as well as by research institutions and international organizations involved in disaster risk management and environmental monitoring.

Impact and Outcomes

The proposed GeoAI-based fuel type mapping framework enhances wildfire risk assessment by providing better spatial resolution (10–30m) on fuel types, improving the identification of fire-prone areas and enabling more targeted prevention and mitigation strategies. The approach strengthens situational awareness and operational decision-making by allowing authorities to prioritize high-risk zones, optimize resource allocation, and improve preparedness and response planning, potentially reducing response times and increasing suppression efficiency. In addition, it supports capacity-building through the adoption of advanced GeoAI methods and provides a scientific basis for policy development and risk-informed wildfire management. Overall, the framework contributes to reducing economic losses associated with wildfires, including damage to ecosystems, infrastructure, and tourism, while enhancing community resilience and protecting human lives, property, and critical natural resources.

Lessons Learned and Recommendations

- Integrating multi-source EO data significantly improves fuel classification accuracy.
- Machine learning models such as Random Forest provide robust performance in heterogeneous Mediterranean landscapes.
- Elevation and environmental gradients influence fuel structure and should be considered as contextual variables.

ECoE - Habitat-Based Fuel Model Mapping Using Random Forest in Google Earth Engine: A Case Study of Cyprus

Alignment with SDGs

This GeoAI tool directly addresses the following Sustainable Development Goals (SDG):

- SDG 3: Good Health and Well-being.
- SDG 11: Sustainable cities and economies
- SDG 13: Climate action
- SDG 15: Life on land

3 GOOD HEALTH AND WELL-BEING | 11 SUSTAINABLE CITIES AND COMMUNITIES | 13 CLIMATE ACTION | 15 LIFE ON LAND

ROOTED IN A RIGOROUS FOUNDATION OF PEER-REVIEWED SPATIOTEMPORAL RESEARCH, THIS GEOAI FRAMEWORK TRANSLATES COMPLEX EARTH OBSERVATION DATA INTO **ACTIONABLE CLIMATE RESILIENCE STRATEGIES**

Additional References or Resources

- Prodromou, M., Theocharidis, C., Gitas, I. Z., Eliades, F., Themistocleous, K., Papasavvas, K., Dimitrakopoulos, C., Danezis, C., & Hadjimitsis, D. (2024). Forest Habitat Mapping in Natura2000 Regions in Cyprus Using Sentinel-1, Sentinel-2 and Topographical Features. Remote Sensing, 16(8), 1373. https://doi.org/10.3390/rs16081373.
- Prodromou, M.; Gitas, I.; Mettas, C.; Tzouvaras, M.; Danezis, C.; Hadjimitsis, D. Comparative Analysis of Supervised Machine Learning Algorithms for Forest Habitat Mapping in Cyprus. Sustainability 2025, 17, 6021. https://doi.org/10.3390/su17136021.
- Prodromou, M., Gitas, I., Mettas, C., Tzouvaras, M., Themistocleous, K., Konstantinidis, A., Pamboris, A., & Hadjimitsis, D. (2025). Remote-Sensing-Based Prioritization of Post-Fire Restoration Actions in Mediterranean Ecosystems: A Case Study in Cyprus. Remote Sensing, 17(7), 1269. https://doi.org/10.3390/rs17071269.
- Papachristoforou, A., Prodromou, M., Hadjimitsis, D., & Christoforou, M. (2023). Detecting and distinguishing between apicultural plants using UAV multispectral imaging. PeerJ, 11, e15065. https://doi.org/10.7717/peerj.15065.
- Prodromou, M.; Girtsou, S.; Leventis, G.; Charalampous, G.; Apostolakis, A.; Tzouvaras, M.; Mettas, C.; Giannopoulos, G.; Kontoes, C.; Hadjimitsis, D. Spatiotemporal Analysis of Forest Fires in Cyprus Using Earth Observation and Climate Data. Environ. Earth Sci. Proc. 2025, 35, 54. https://doi.org/10.3390/eesp2025035054.

ECoE - Habitat-Based Fuel Model Mapping Using Random Forest in Google Earth Engine: A Case Study of Cyprus

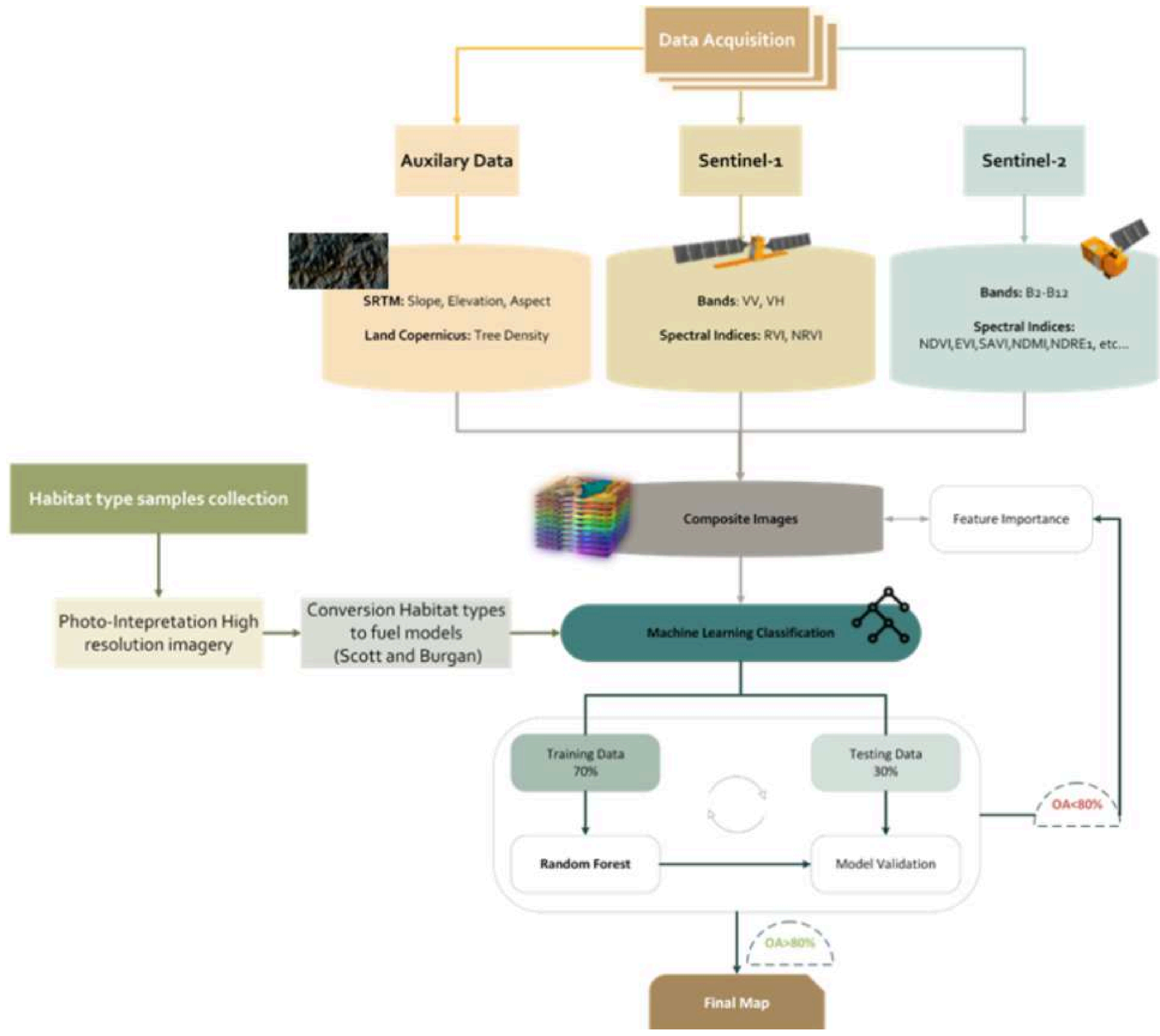


Figure 9: The Technical Framework Integrating Multi-Source EO Data and GeoAI Techniques for High-Resolution Fuel Model Mapping in Cyprus

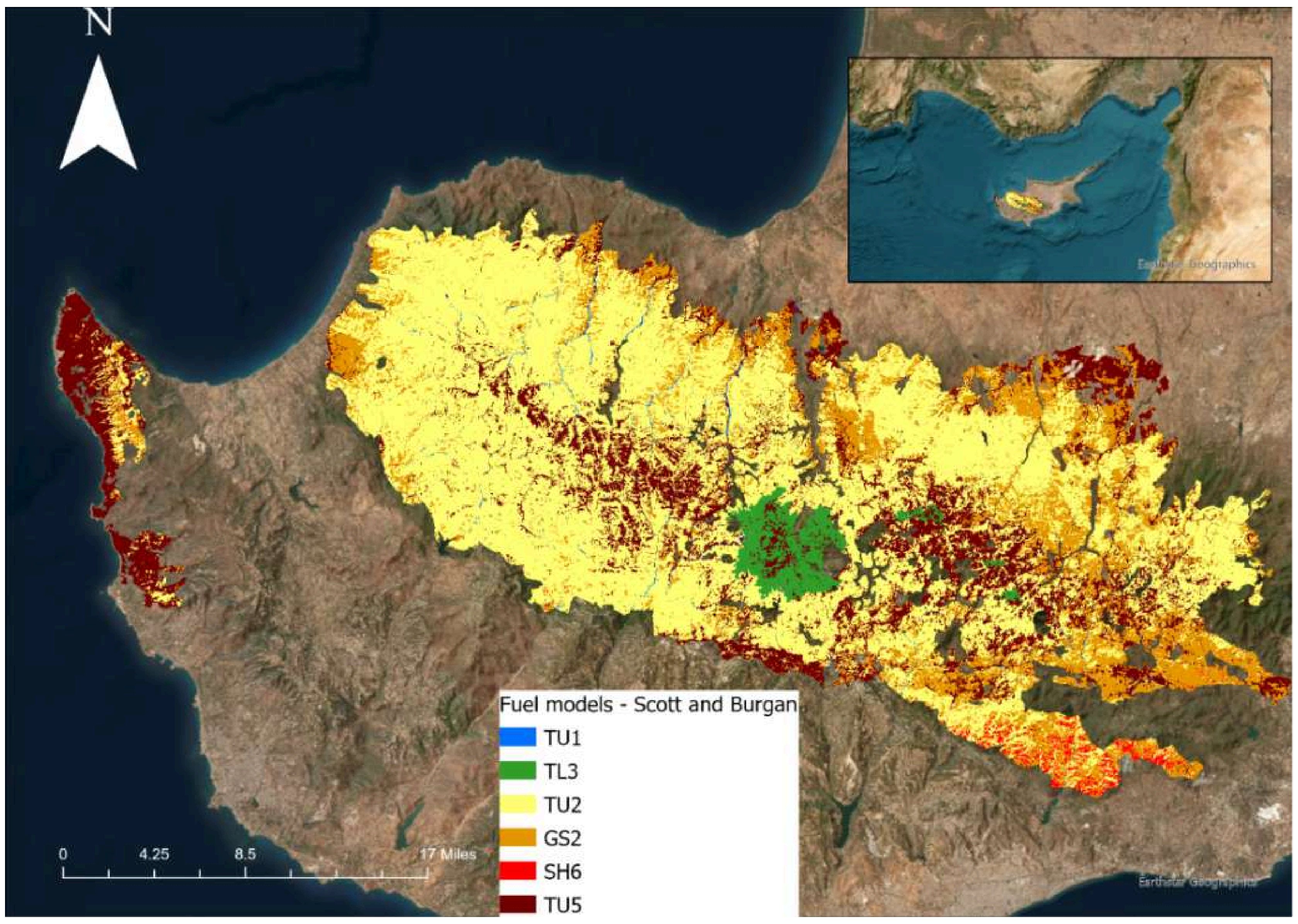


Figure 10: High-Resolution Map of Different Fuel Types Implemented From the Proposed Framework Based on *Scott and Burgan Fire Behavior Fuel Models*

ECoE - Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments

Title of GeoAI Practice

Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments

Brief Description

The island of Cyprus is dominated by small-scale watersheds that favor the occurrence of flash floods. The development of rapid flood screening tools is essential for better urban planning. This study uses four different machine learning algorithms, namely support vector machine (SVM), extreme gradient boosting (XGBoost), random forest (RF), and multilayer perceptron (MLP), to build models based on data collected from eight watersheds to enhance their within-region (Cyprus) generalization. Seven features were selected for tuning and testing the performance of these models. T-based confidence intervals were calculated to quantify uncertainty. All models achieved good agreement with the inventory database. Random Forest (RF) model was selected to build multi-level susceptibility maps. Half of the Georskipou watershed is classified as highly susceptible to flooding, mostly urban and semi-urban regions, whereas 38 % of the test watershed is not expected to experience severe flood events. Simplified RF models were developed by selecting different combinations of the most important features, revealing that land-use, terrain slope, terrain elevation, and flow accumulation are sufficient to achieve good accuracy (95 %) with flood inventory data. The results highlight the ability of simple, computationally efficient data-driven models to provide rapid predictions, thus avoiding the compilation of fully detailed physically based models.

BY **DEPLOYING** MULTI-BASIN MACHINE LEARNING ALGORITHMS, SUCH AS THE RANDOM FOREST MODEL, IT DISTILLS COMPLEX ENVIRONMENTAL VARIABLES DOWN TO JUST A FEW HIGHLY IMPACTFUL FEATURES LIKE LAND USE, TERRAIN SLOPE, AND FLOW ACCUMULATION. THIS COMPUTATIONALLY EFFICIENT APPROACH BYPASSES THE NEED FOR EXHAUSTIVELY DETAILED PHYSICAL MODELS OR EXTENSIVE SATELLITE REPOSITORIES. ULTIMATELY, IT **TRANSFORMS** THESE TARGETED DATASETS INTO RAPID, HIGHLY ACCURATE MULTI-LEVEL SUSCEPTIBILITY MAPS, EMPOWERING URBAN PLANNERS TO INTUITIVELY EXPLORE RISKS AND EXECUTE PROACTIVE, EVIDENCE-BASED DECISION-MAKING EVEN IN PREVIOUSLY **"UNSEEN" OR UNDER-MONITORED REGIONS**.

Challenge or Problem Addressed

Despite the existence of numerous studies reporting the successful application of MLMs to identify associations among flood parameters and processes, most of these studies have focused on developing site-specific models with unique characteristics. Consequently, the applicability of these models is expected to be limited to other, "unseen" regions that include different land contexts and physical characteristics. Moreover, most of these studies reported the collection of information from multiple databases, including satellite repositories, in situ monitoring systems, and detailed hydrogeological maps, which are not readily available for all regions. For example, flood events on the island of Cyprus are generated by short-duration precipitation events (flash floods), making it challenging to capture their dynamics using standard satellite missions (e.g., Sentinel, Landsat, Planet).

ECoE - Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments

Technical Approach and Methods

The implemented methodology comprised 3 distinct phases. Phase I focused on constructing the sampling dataset by collecting spatiotemporal information on flood-related factors (topographical properties, rainfall, soil properties, land use) and inventories from multiple sources (Coordination of Information on the Environment Land Cover, governmental geoportals). It also included the multicollinearity analysis, conducted to reduce data redundancy of the feature dataset. In Phase II, the sampling dataset was used to build the MLMs (random forest, extreme gradient boosting, support vector machine, multilayer perceptron) and included steps such as hyperparameter optimization and feature importance analysis. The last phase, Phase III, involved generating susceptibility maps using the best-performing machine learning algorithm, evaluating the performance of simplified models based on the most important features, and assessing the directionality of input variables using partial-dependence plots.

Implementation and Collaborations

Geospatial information was collected from the geoportal of the national water authorities, which represents the spatial extent of areas classified as high-risk for flood occurrence under the worst-case scenario that corresponds to a 500-year return period. This information was used as flood inventory database to validate the ML-derived flood susceptibility maps. For the same purpose, additional information was collected from alternative governmental reports of the national water authorities.

In addition, the preselection of the flood-related factors, used as input variables in the MLMs, was jointly discussed and approved by key representatives of the national water authorities, who are responsible for the effective implementation of the EU Flood directive in the Republic of Cyprus. Except from land use information, which was collected from CORINE Land Monitoring Service, all input data are collected from key governmental authorities, particularly Water Development Department (hydrological network, watershed borders), Department of Geological Survey (soil properties), Department of Land Surveys (topography), and Department of Meteorology (rainfall).

Impact and Outcomes

The main outcomes and expected impact of this study are summarized as follows:

- MLP neural network and SVM exhibited the highest performance among the MLMs, whereas RF achieved similar results across several classification performance metrics. RF was selected for compiling susceptibility maps because it enables the partitioning of predicted probabilities into multiple susceptibility classes, providing a fast-screening tool for policy-makers when prioritizing among different areas.
- Feature importance analysis revealed that LULC and TE are the most significant flood factors for all algorithms, supporting the fidelity of the resulting models.
- Half of the regions within the test watershed are highly prone to flood events, whereas the majority of the remaining regions are less likely to experience flooding. Particularly, the regions that are least prone to flooding are observed in the northern and eastcentral parts of the watershed. TE and TS exhibit their lowest median values in the high-risk zone, whereas the opposite is observed for LULC, providing valuable information to policy-makers for future planning.

ECoE - Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments

- The simplified RF models on the basis of the four most important features, particularly LULC, TS, TE, and FA, achieved very good agreement (BA=95 %) with the flood inventory data, whereas the mean squared error (Brier score) is 0.033. Consequently, these models can serve as computationally effective flood screening tools in data-scarce environments.
- The directionality assessment of the model predictions revealed threshold values for major flood indicators (LULC, TS, TE, FA) that are associated with large changes in the susceptibility levels. With respect to LULC, these values can be used by the authorities to design land use development policies that take into account flood mitigation planning.

Lessons Learned and Recommendations

This study demonstrates that shallow MLMs can be used instead of advanced, deep learning algorithms, as screening tools to classify susceptibility levels in terms of a limited number of major flood indicators. Particularly, simplified MLMs such as RF and SVM can assist policymakers as rapid flood screening tools, being also suitable for near-real time applications due to their computational efficiency, and ability to provide quick predictions. In contrast, fully detailed hydrodynamic models are associated with high computational burden and require vast amounts of information and time. This is particularly useful in data-scarce environments, which may not provide sufficient data to train a deep learning model. Moreover, these data-driven models can support more consistent and evidence-based decision-making processes.

Alignment with SDGs

In alignment with the mission of the United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER) to ensure that all countries have access to and develop the capacity to use space-based information for disaster management and emergency response, this work leverages flood mapping using machine-learning models to develop rapid screening tools, including simplified models based on a reduced subset of features, to support timely and effective decision-making.

In addition, the adverse consequences of flooding undermine global efforts to achieve the majority of sustainable development goals (SDGs). In particular, this phenomenon can limit the accessibility of financial resources which are needed to restore and develop business activities, including initiatives for alleviating poverty (SDGs 1, 8 and 11). These limitations can reduce citizens' capacity to cover their basic needs, such as access to clean water and safe food (SDG 2). Additional negative impacts that are directly linked to the SDGs include exacerbating imbalances among different groups of people (SDG 1,2,5, and 10); damaging infrastructure and delaying or postponing development initiatives (SDG 4 and 9); and worsening health quality (SDG 3). Therefore, effectively integrating the concept of disaster risk reduction into water and land development policies, including actions to support climate adaptation measures to reach sustainability goals, is essential.

ECoE - Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments

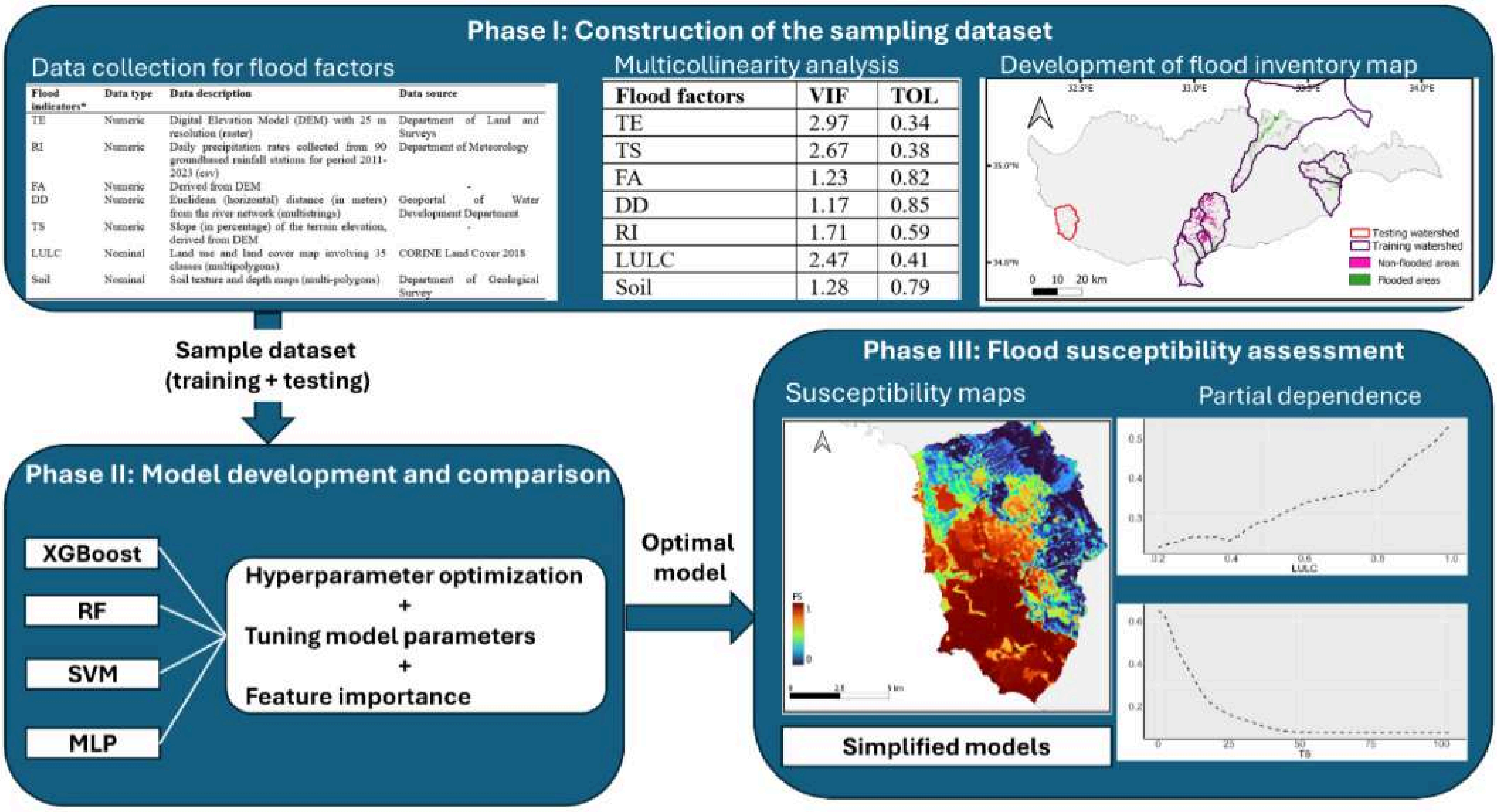
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

10 REDUCED INEQUALITIES

11 SUSTAINABLE CITIES AND COMMUNITIES

Additional References or Resources

- Panagiotou, C. F., Guerrisi, G., De Santis, D., Del Frate, F., & Tzouvaras, M. (2026). Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments in Cyprus. Journal of Hydrology: Regional Studies, 63, 103075. https://doi.org/10.1016/j.ejrh.2025.103075.
- Water Development Department Geoportal. https://geoportal-wdd.hub.arcgis.com/.
- CLMS (2018). Copernicus Land Monitoring Service. https://land.copernicus.eu/En/Products/Corine-Land-Cover.



Flood indicators*	Data type	Data description	Data source
TE	Numeric	Digital Elevation Model (DEM) with 25 m resolution (raster)	Department of Land and Surveys
RI	Numeric	Daily precipitation rates collected from 90 groundbased rainfall stations for period 2011-2023 (csv)	Department of Meteorology
FA	Numeric	Derived from DEM	-
DD	Numeric	Euclidean (horizontal) distance (in meters) from the river network (multistrings)	Geoportal of Water Development Department
TS	Numeric	Slope (in percentage) of the terrain elevation, derived from DEM	-
LULC	Nominal	Land use and land cover map involving 35 classes (multipolygons)	CORINE Land Cover 2018
Soil	Nominal	Soil texture and depth maps (multi-polygons)	Department of Geological Survey

Flood factors	VIF	TOL
TE	2.97	0.34
TS	2.67	0.38
FA	1.23	0.82
DD	1.17	0.85
RI	1.71	0.59
LULC	2.47	0.41
Soil	1.28	0.79

Figure 11: Overview of the Implemented Methodology, which includes the following acronyms: Flood-related factors: TE (terrain elevation), RI (rainfall intensity), FA (flow accumulation), DD (distance from drainage network), TS (terrain slope), LULC (land use and land cover); Machine learning models: XGBoost (extreme gradient boosting), RF (random forest), SVM (support vector machine), and MLP (multilayer perceptron neural network).

ECoE - Investigating the mechanisms of flood susceptibility with the use of multi-basin machine learning models in data-scarce environments

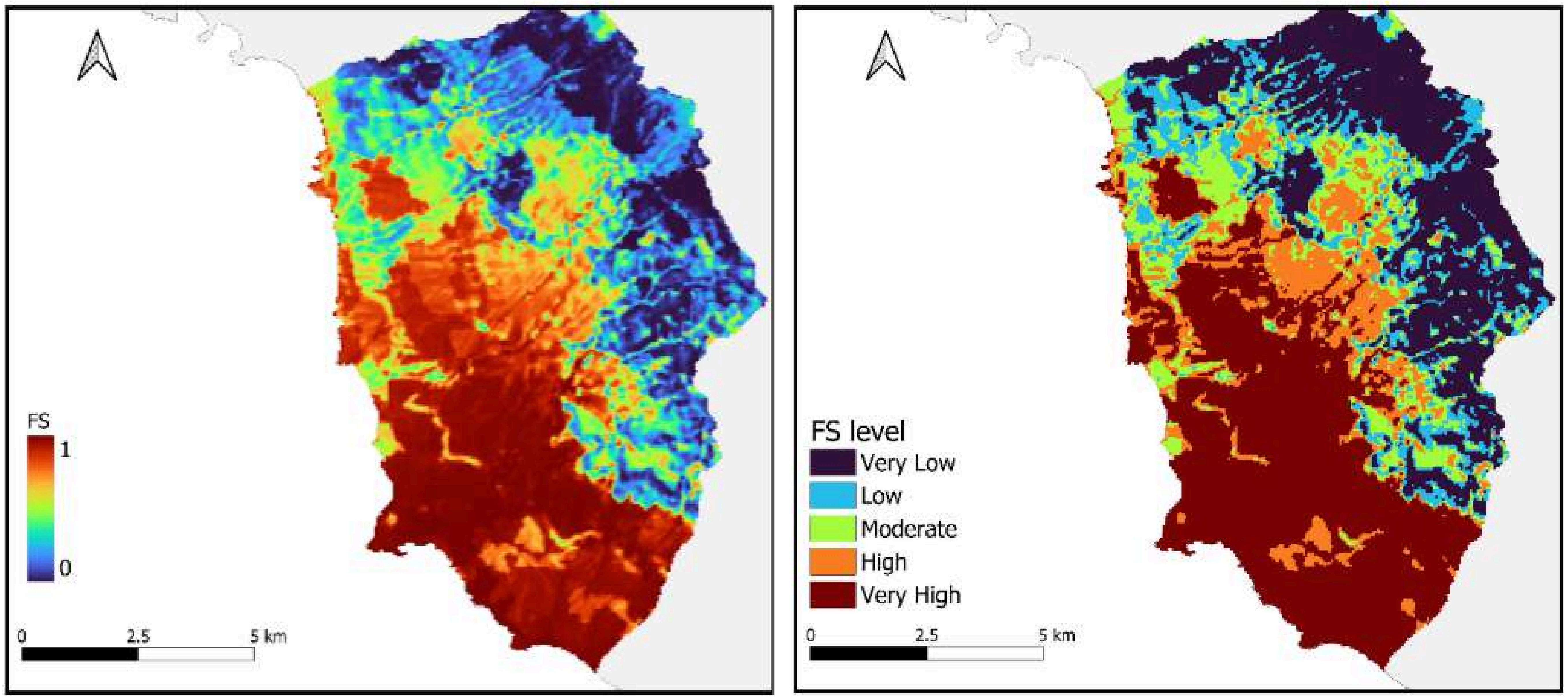


Figure 12: Geographical Distribution of Flood-Susceptibility (a) scores and (b) levels. FS denotes the flood susceptibility indicator. Risk levels are determined with respect to FS as: "Very Low" [0–0.2], "Low" [0.2–0.4], "Moderate" [0.4–0.6], 0.6–0.8 ["High"], and [0.8–1.0] ["High"].

ECoE - AI-Based Precipitation Fusion for Enhanced Landslide Susceptibility Mapping Using Multi-Criteria Analysis

Title of GeoAI Practice

AI-Based Precipitation Fusion for Enhanced Landslide Susceptibility Mapping Using Multi-Criteria Analysis

Brief Description

Precipitation is one of the most critical triggering factors of landslides in Cyprus; however, its accurate spatial representation remains a major challenge due to sparse in-situ observations and biases in satellite-derived datasets. This study presents a GeoAI-driven framework for improving precipitation representation through the development of an AI-enhanced precipitation layer. Satellite-derived precipitation data (CHIRPS) are fused with local rain gauge observations using a supervised machine learning model (Random Forest), resulting in a spatially continuous and locally calibrated precipitation dataset. The corrected precipitation layer is then integrated into a multi-criteria decision analysis (MCDA) framework alongside eight (8) other geomorphological and environmental factors, including slope, aspect, geology, land use/land cover, and distance to streams, roads, and faults, to generate high-resolution landslide susceptibility maps. The methodology was developed and applied in a pilot study area to evaluate its performance, with ongoing efforts to extend its implementation at a national scale.

BY DEPLOYING A RANDOM FOREST MACHINE LEARNING MODEL, IT SEAMLESSLY FUSES **LARGE-SCALE REMOTE SENSING PRECIPITATION DATASETS (CHIRPS)** WITH LOCALIZED, ON-SITE RAIN GAUGE MEASUREMENTS TO GENERATE A HIGHLY CALIBRATED, SPATIALLY CONTINUOUS PRECIPITATION LAYER. THIS MULTIDIMENSIONAL APPROACH INTEGRATES THE REFINED METEOROLOGICAL DATA WITH DIVERSE GEOMORPHOLOGICAL FACTORS INTO A **ROBUST MULTI-CRITERIA DECISION ANALYSIS (MCDA) FRAMEWORK**

Challenge or Problem Addressed

Landslide susceptibility depends on several factors, with precipitation acting as the most triggering mechanism in Cyprus. However, to accurately capture the spatial and temporal variability of precipitation remains challenging, especially in areas with complex terrain and localized rainfall patterns (e.g., mountains/ steep slopes, cities, etc.). Rain gauge networks are often sparse and unevenly distributed, as in the case of Cyprus island (Figure 13). The precipitation is a very dynamic and local phenomenon; thus, the rainfall observations may not fully represent the local conditions on a smooth spatial scale.

On the other hand, satellite-based datasets can provide high spatial coverage, while they may not fully represent the short-duration or high-intensity rainfall events. As a result, uncertainties are introduced in susceptibility assessments, reducing the reliability of hazard mapping, particularly at fine spatial scales.

Technical Approach and Methods

The methodology integrates EO data, machine learning, and GIS-based analysis to improve landslide susceptibility mapping. Daily satellite-derived precipitation data (CHIRPS) for the period 2019–2024 were combined with ground-based rain gauge observations using a supervised machine learning model (Random Forest) within a data fusion framework, producing a spatially continuous and locally calibrated precipitation layer across Cyprus. The model incorporates satellite estimates, temporal features (e.g., rainfall accumulations and seasonal patterns), and terrain-related variables to effectively capture precipitation variability.

ECoE - AI-Based Precipitation Fusion for Enhanced Landslide Susceptibility Mapping Using Multi-Criteria Analysis

Additional geospatial datasets, including a 10m Digital Terrain Model (DTM), geological maps, and land use/land cover data, were used to derive landslide conditioning factors such as slope, lithology, aspect, relative relief, and distance to streams, roads, and faults. The corrected precipitation data were aggregated into relevant indicators (e.g., Mean Annual Precipitation) and integrated into a MCDA framework. All factors were standardized to a common scale and weighted using the Analytic Hierarchy Process (AHP), while a Weighted Linear Combination (WLC) approach was applied to generate high-resolution landslide susceptibility maps (Figure 14).

Implementation and Collaborations

The methodology was developed and implemented within the Horizon Europe research project AI-OBSERVER (https://ai-observer.eu/) focused on the application of Artificial Intelligence and Earth Observation for environmental hazard assessment in Cyprus. The workflow was applied in a pilot study area in Trachypedoula that is landslide-prone area, to evaluate its performance, integrating satellite-derived precipitation data, in-situ observations, and geospatial datasets within a unified analytical framework. The implementation relied on the collaboration between academic and research institutions, combining expertise in geoinformatics, remote sensing, and machine learning. Ground-based precipitation data were provided by the Cyprus Department of Meteorology, while geospatial datasets, including terrain and geological information, were obtained from national mapping agencies, i.e., Cyprus Geological Survey Department, Department of Public Works, Department of Land and Surveys, etc.The integration of multi-source data and modelling approaches was supported by interdisciplinary collaboration among researchers and domain experts.

Last but not least, the workflow is reproducible end-to-end, enabling the extending of its application to larger geographical areas and supporting operational landslide risk assessment and decision-making processes.Outline how the initiative was implemented, including any partnerships or collaborations with local agencies, international organizations, private sector, academia, or other stakeholders.

Impact and Outcomes

The current approach significantly improves the representation of precipitation, a key triggering factor in landslide processes, leading to more reliable and spatially consistent susceptibility maps. The AI-based fusion of satellite and in-situ data reduces errors in precipitation estimates, achieving substantial improvements in accuracy, thus enhancing the quality of input data used in hazard modelling.

The integration of the corrected precipitation layer within a multi-criteria framework enables the generation of high-resolution (e.g., 10m) landslide susceptibility maps, supporting the identification of high-risk areas. Validation against landslide inventory data demonstrates the capability of the model to capture over 30% of known landslide occurrences within the highest susceptibility classes, increasing confidence in the results. The methodology enhances situational awareness and provides a robust basis for hazard assessment, spatial planning, and risk mitigation. Its scalable and transferable design allows for expansion to larger geographical areas, supporting national-level applications and facilitating evidence-based decision-making. The approach is particularly valuable in data-scarce environments, where improving the accuracy of key input variables can substantially enhance hazard modelling outcomes.

ECoE - AI-Based Precipitation Fusion for Enhanced Landslide Susceptibility Mapping Using Multi-Criteria Analysis

Lessons Learned and Recommendations

- Precipitation is critical: Improving precipitation data significantly increases the reliability of landslide susceptibility mapping.
- Data fusion improves accuracy: Combining satellite and ground data with machine learning reduces bias and enhances spatial consistency.
- Quality input data matters: Reliable terrain, geology, and land use data are essential for robust modelling results.
- Reproducibility is important: A well-structured and documented workflow ensures that the methodology can be replicated and applied in other regions.
- Validation is essential: The use of independent landslide inventory data is critical to assess model performance and build confidence in the results.

Alignment with SDGs

The methodology also supports the following Sustainable Development Goals (SDGs):

- SDG 11 – Sustainable Cities and Communities: by supporting safer spatial planning and reducing exposure to landslide hazards
- SDG 13 – Climate Action: by improving the understanding of climate-driven hazards such as extreme rainfall and slope instability
- SDG 15 – Life on Land: by contributing to the protection of ecosystems and land resources affected by geohazards

BY **SYNTHESIZING MULTIDIMENSIONAL** GEOSPATIAL DATASETS RANGING FROM REMOTE SENSING INPUTS TO TABULAR GROUND OBSERVATIONS. THIS **REPRODUCIBLE** GEOAI WORKFLOW DIRECTLY ADVANCES CORE GLOBAL SUSTAINABILITY TARGETS.

Additional References or Resources

- Kyriaki Fotiou, Giorgia Guerrisi, Fabio del Frate, Gerd Reis, Diofantos Hadjimitsis and Marios Tzouvaras, Advancing Rainfall-Driven Landslide Susceptibility Models: A Case Study from the Broader Trachypedoula Area, Cyprus. MedGU 2025 Conference, 11-13 November 2025, Athens, Greece. Oral Presentation.
- Alexakis, D.D.; Agapiou, A.; Tzouvaras, M.; Themistocleous, K.; Neocleous, K.; Michaelides, S.; Hadjimitsis, D.G. Integrated Use of GIS and Remote Sensing for Monitoring Landslides in Transportation Pavements: The Case Study of Paphos Area in Cyprus. Nat Hazards 2014, 72, 119–141, doi:10.1007/s11069-013-0770-3.
- Tzouvaras, M., Votsis, R., Fotiou, K., Prodromou, M., Panagiotou, C., Kalogirou, E., Christofi, D., Reis, G., Del Frate, F., Zacharatos, H., Hadjimitsis, D. G. Artificial intelligence and Earth Observation towards disaster risk reduction: the AI-OBSERVER's research exploratory project. Eleventh International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2025), Proc. SPIE 13816, 138161W, 19 September 2025. https://doi.org/10.1117/12.3075493.

ECoE - AI-Based Precipitation Fusion for Enhanced Landslide Susceptibility Mapping Using Multi-Criteria Analysis

Additional References or Resources

- Marios Tzouvaras, Kyriacos Themistocleous, Kyriakos Neocleous, Fabio Del Frate, Giovanni Schiavon, Haris Zacharatos, Eleftheria Kouppari, Diofantos G. Hadjimitsis "Enhancing Earth Observation Capabilities of the ERATOSTHENES Centre of Excellence on Disaster Risk Reduction through Artificial Intelligence: The AI-OBSERVER Horizon Europe Twinning Project" Proc. Ninth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2023), Poster presentation.
- M. Tzouvaras, G. Reis, F. Del Frate, H. Zacharatos and D. Hadjimitsis, "Enhancing Earth Observation Capabilities of the Eratosthenes Centre of Excellence on Disaster Risk Reduction Through Artificial Intelligence: Introducing the AI-OBSERVER Project," IGARSS 2024 – 2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 2024, pp. 2871-2874, https://doi.org/10.1109/IGARSS53475.2024.10640751.
- M. Tzouvaras, M. Mavrovouniotis, R. Votsis, K. Fotiou, E. Kalogirou, T. Polydorou, G. Reis, F.Del Frate, L. Giuliano Papale, G. Guerrisi, and D. G. Hadjimitsis "Enhancing disaster risk reduction through artificial intelligence: capitalizing on the capacity building activities of the AI-OBSERVER twinning project", Proc. SPIE 13212, Tenth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2024), 132120K (13 September 2024);
- Tzouvaras, M., Votsis, R., Fotiou, K., Prodromou, M., Panagiotou, C., Kalogirou, E., Christofi, D., Reis, G., Del Frate, F., Zacharatos, H., Hadjimitsis, D. G. Artificial intelligence and Earth Observation towards disaster risk reduction: the AI-OBSERVER's research exploratory project. Eleventh International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2025), Proc. SPIE 13816, 138161W, 19 September 2025. https://doi.org/10.1117/12.3075493.
- AI-OBSERVER: Enhancing Earth Observation capabilities of the Eratosthenes Centre of Excellence on Disaster Risk Reduction through Artificial Intelligence (https://ai-observer.eu/).

Figure 13: Local Rain Gauge Network in Cyprus

ECoE - AI-Based Precipitation Fusion for Enhanced Landslide Susceptibility Mapping Using Multi-Criteria Analysis

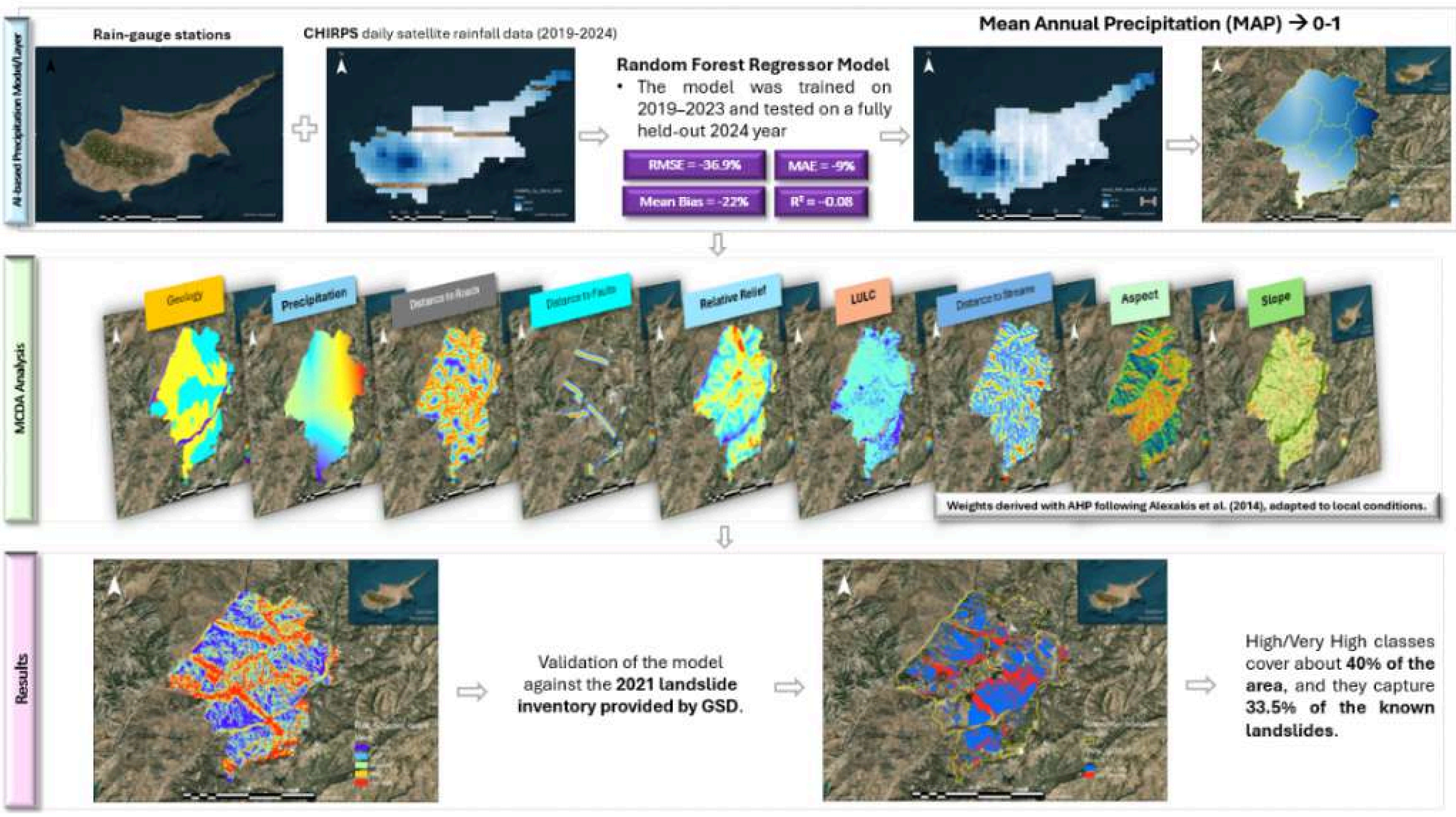


Figure 14: Workflow of the Proposed GeoAI Methodology, including AI-based precipitation fusion (CHIRPS and rain gauges), integration into a MCDA, and validation against landslide inventory data

ECoE -AI-Driven Satellite Shoreline Extraction and Change Analysis for Coastal Erosion Monitoring in Cyprus Using Pulse Coupled Neural Networks (PCNN) andDigital Shoreline Analysis System(DSAS)

Title of GeoAI Practice

AI-Driven Satellite Shoreline Extraction and Change Analysis for Coastal Erosion Monitoring in Cyprus Using Pulse Coupled Neural Networks (PCNN) and DSAS

Brief Description

Developed at the ERATOSTHENES Centre of Excellence, Cyprus, as part of the EU Horizon Europe AI-OBSERVER project (https://ai-observer.eu/), the practice involves developing an AI-based coastal erosion monitoring model. The technique consists of the shoreline extraction from Sentinel-2 NIR imagery (band 8 with 10m/p resolution) along the Chrysochou Bay, northwest Cyprus, using Pulse Coupled Neural Network (PCNN) image segmentation method, over the time period between 2017 and 2024. To validate the extracted data, the shoreline positions were compared with a shoreline derived from an orthophotography of the Cyprus Department of Land and Surveys (2019), giving an RMSE of 9.21 m regarding positional accuracy. After validation of the data, the (DSAS) (v6.0) in ArcGIS Pro was used to determine rates of change from the validated extracted multi-epoch shoreline positions in a spatially explicit manner along cross-shore transects. The technique was implemented to estimate the erosion and accretion rates of the Chrysochou Bay shoreline along the north-west coast of Cyprus before and after the construction of a breakwater in 2019 at the Latsi area. The results demonstrated that after the construction of the Latsi breakwater, shoreline variability along the Chrysochou bay almost doubled and the erosion rates at the southern end of the beach increased significantly. In addition, the results also showed an increased accretion rate on the northern end of the beach. The results were consistent and the model could be considered cost-effective and replicable for coastal hazard identification at large scales in any Island country and region.

Challenge or Problem Addressed

Coastal erosion presents an ever-growing threat to coastal Mediterranean states. In Cyprus specifically, erosion affects coastal habitats that are highly valuable to the local communities and the tourism sector. Existing monitoring methods involving manual field surveys and manual photogrammetric interpretation of aerial and satellite images are expensive and labour-intensive, and do not provide the frequency needed to track significant short-term coastal changes. This project addresses this issue by providing:

THIS PRACTICE OVERCOMES THE LIMITATIONS OF **LABOR-INTENSIVE MANUAL SURVEYS** BY DEPLOYING A COST-EFFECTIVE, AUTOMATED GEOAI WORKFLOW CAPABLE OF **TRACKING DYNAMIC COASTAL CHANGES** ACROSS EXTENDED TIME PERIODS.THIS APPROACH EFFORTLESSLY TRANSFORMS COMPLEX SPATIOTEMPORAL DATA INTO SPATIALLY EXPLICIT INSIGHTS, SUCH AS EVALUATING THE EXACT SHORELINE VARIABILITY CAUSED BY NEW COASTAL INFRASTRUCTURE LIKE **BREAKWATERS**.

ECoE -AI-Driven Satellite Shoreline Extraction and Change Analysis for Coastal Erosion Monitoring in Cyprus Using Pulse Coupled Neural Networks (PCNN) and DSAS

- A framework for the monitoring of shorelines in Cyprus, and other small coastal states at a larger scale, using AI-enhanced methods of image processing applied on freely available satellite imagery, allowing for the identification of coastal areas with significant erosion problems.
- A methodology for quantifying the downstream impact of coastal works, such as breakwater construction, on coastal environments.
- Identification of erosion areas for targeted interventions by coastal managers, local governments and agencies for disaster risk reduction.

Technical Approach and Methods

To employ near-infrared imagery (NIR), 10 m resolution, corrected at the atmospheric level, we utilised the Sentinel-2 images (band 8) via Google Earth Engine. Obtained images between 2017 and 2024, specifically those covering the summer periods. Application of the PCNN algorithm to create a binary image depicting the edges of the land and water. PCNN is an AI-based unsupervisedimage segmentation method inspired by neural processing mechanismsbiologically inspired neural systems. No labelled information for learning is needed for PCNN to generate binary edge images of the boundaries of the water and the land. In order to generate binary edges, the algorithm is first applied only on the NIR bands of the images. After filtering the results for visually accurate images, a total of 19 shorelines remained out of initial 65 that were obtained. These 19 images were compared to the officially measured shorelines available at the Cyprus Department of Land and Surveys (1963, 1993, 2004, 2014, and 2019). For the purposes of this study, these official shorelines were used both for their historical value as well as for the purposes of comparison against the newly generated PCNN-generated shorelines. To do this, the generated binary edge images were first converted to polylines, then smoothed using the PAEK algorithm with a 50 m tolerance value and clipped to the Area of Interest.

For the purposes of validation, the 2019 orthophoto shorelines were compared using the Near tool. Once completed, using the tool, the DSAS (v6.0) was used to compute the rates of changes over the years, using cross shore transects. The DSAS tool computes a total of 5 rates:

- Shoreline Change Envelope (SCE)
- Net Shoreline Movement (NSM)
- End Point Rate (EPR)
- Linear Regression Rate (LRR)
- Weighted Linear Regression (WLR)

All the mentioned results were generated for the full 2017 to 2024 time period, a separate calculation for the pre-2019 period, and lastly a calculation for the post-2019 period.

Implementation and Collaborations

The ERATOSTHENES Centre of Excellence (ECoE) at the Cyprus University of Technology developed the coastal erosion model, in the framework of the Horizon Europe AI-OBSERVER project (https://ai-observer.eu/) and the INTERREG VI-A ECO-BEACHTECH project (https://www.ecobeachtech.gr/en). AI-OBSERVER is a EU Horizon Europe Twinning project (HORIZON-WIDERA-2021-ACCESS-03, grant agreement 101079468) provided advanced AI and machine learning expertise. DFKI (German Research Center for Artificial Intelligence) provides AI and machine learning.

ECoE -AI-Driven Satellite Shoreline Extraction and Change Analysis for Coastal Erosion Monitoring in Cyprus Using Pulse Coupled Neural Networks (PCNN) and DSAS

The University of Rome Tor Vergata (UNITOV) provides Earth Observation research and remote sensing collaboration. The EO Big Data AI management platform (for disseminating results) has been developed by CELLOCK Ltd. The ECO-BEACHTECH project is part of the INTERREG VI-A Cooperation Program "Greece-Cyprus 2021-2027" and is co-financed by the European Union (ERDF) and National Resources of Greece and Cyprus. The project consortium consists of the Special Account for Research Funds of the Aegean, the Regional Development Fund of the North Aegean, the ERATOSTHENES Centre of Excellence and the Municipality of Akamas. Official orthophoto shorelines were used as the validation data and came from the Cyprus Department of Land and Surveys. The case studies and hazard models were identified and prioritised through interaction with Cyprus' relevant stakeholders, such as the Department of Public Works and other coastal management agencies and local municipalities, which are the end users of the erosion monitoring.

Impact and Outcomes

The pre-2019 analysis (before breakwater construction) showed an average Shoreline Change Envelope of 11.8 m and Net Shoreline Movement of +5.75 m, with 79% of transects accretional and an End Point Rate of +2.85 m/yr, reflecting natural shoreline dynamics. The post-2019 period revealed a doubling of shoreline variability (SCE = 25.0 m), with 73% accretional transects but concentrated erosional hotspots reaching a maximum retreat of −14.3 m, demonstrating downdrift sediment starvation caused by the breakwater. Across the full 2017–2024 period, the average SCE was 25.8 m, NSM +7.68 m, and the weighted regression rate +0.95 m/yr, confirming prevailing accretion with masked local erosion. The PCNN-based workflow was validated with an RMSE of 9.21 m against official orthophoto data, demonstrating its applicability for regional-scale monitoring. The approach establishes a repeatable, low-cost, AI-driven coastal monitoring workflow transferable to other Mediterranean coasts and small Island Developing States and provides a satellite-based quantification of the Latsi breakwater's geomorphological impact. The project also significantly enhanced ECoE researchers' capacity in AI-EO methods through the Twinning knowledge transfer framework.

Lessons Learned and Recommendations

The PCNN algorithm is unsupervised which avoids the requirement for labelled training data; however, when ground truth is unavailable, parameter calibration is very important along with a visual inspection of the outcomes. For 10 m data, for example Sentinel-2 the smoothing of the PAEK method with a tolerance 40 to 50 m is required for the removal of artefacts of pixelation with the result of a trade-off between signal to noise and thus conditions should be reported.

The choice of separating the analysis into pre and post intervention enabled the identification of human impact from natural variation otherwise small erosion hotspots may have been masked by the overall accretion. The analysis would greatly benefit from the availability of high-resolution orthophoto data to enable extraction of shorelines from a national mapping agency with data sharing. Future studies could be encouraged to develop AI-based multi-temporal extraction of shorelines as a mainstream practice in coastal zone management; to invest in open source toolbox development to reduce technical barriers to government bodies; combine analysis of the satellite data and Unmanned Aerial Vehicle (UAV) and in-situ surveys at the identified hotspots; and explore new self-supervised vision foundation models for shoreline extraction.

ECoE -AI-Driven Satellite Shoreline Extraction and Change Analysis for Coastal Erosion Monitoring in Cyprus Using Pulse Coupled Neural Networks (PCNN) and DSAS

Alignment with SDGs

This practice advances UN-SPIDER's objective to enable all countries to access and develop the capacity to utilize space-based information for disaster management. As the workflow relies on Sentinel-2 data that is freely available and open-source GIS tools, this workflow allows lower costs for developing countries and SIDS to implement satellite-based coastal hazards monitoring. It also supports Sendai Framework Priority 1 (understanding disaster risk) by quantifying erosion in a systematic manner through AI, and Priority 4 (enhancing disaster preparedness) through the identification of hotspots with evidence. As this practice generates spatially explicit information about land erosion, this practice contributes to SDG 11 (Sustainable Cities and Communities) in terms of coastal land-use planning, to SDG 13 (Climate Action) in terms of supporting countries to increase their adaptive capacity with regard to coastal hazards related to climate change, to SDG 14 (Life Below Water) in terms of informing nearshore sediment monitoring and ecosystem monitoring, and to SDG 17 (Partnerships for the Goals) in terms of international collaboration in the Twinning project between Cyprus, Germany and Italy on capacity building for AI and EO with regard to disaster risk reduction

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

14 LIFE BELOW WATER

17 PARTNERSHIPS FOR THE GOALS

THIS WORKFLOW PROVIDES A **HIGHLY COST-EFFECTIVE MODEL** THAT EMPOWERS **DEVELOPING NATIONS AND SMALL ISLAND DEVELOPING STATES (SIDS)** TO IMPLEMENT ROBUST COASTAL HAZARD MONITORING.

Additional References or Resources

- AI-OBSERVER: Enhancing Earth Observation capabilities of the Eratosthenes Centre of Excellence on Disaster Risk Reduction through Artificial Intelligence (https://ai-observer.eu/, https://cordis.europa.eu/project/id/101079468).
- AI-OBSERVER platform: https://aiobserver.cellock.com/
- ECO-BEACHTECH project (https://www.ecobeachtech.gr/en).

ECoE -AI-Driven Satellite Shoreline Extraction and Change Analysis for Coastal Erosion Monitoring in Cyprus Using Pulse Coupled Neural Networks (PCNN) and DSAS

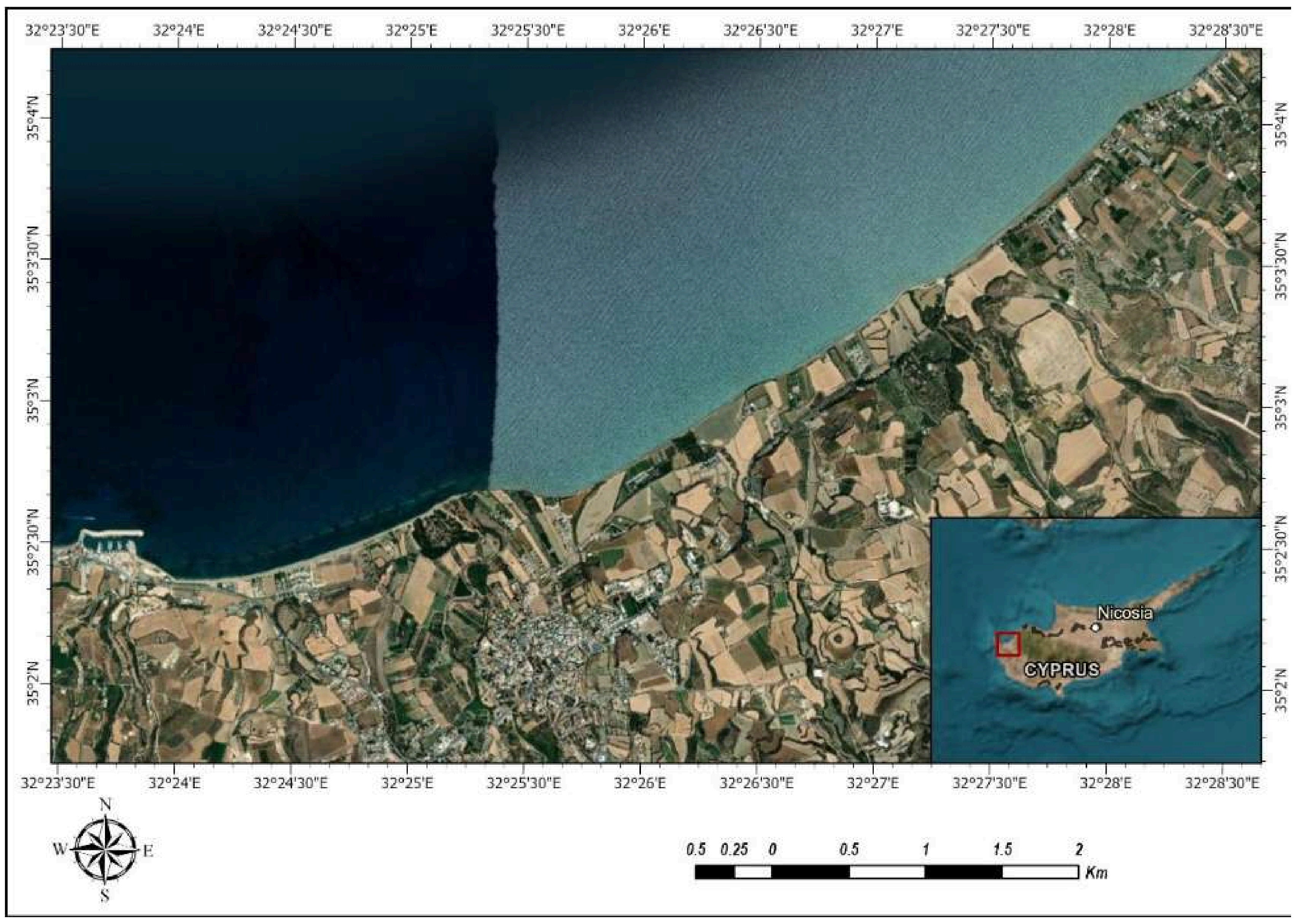


Figure 15: Study Area (Chrysochou bay,Cyprus)

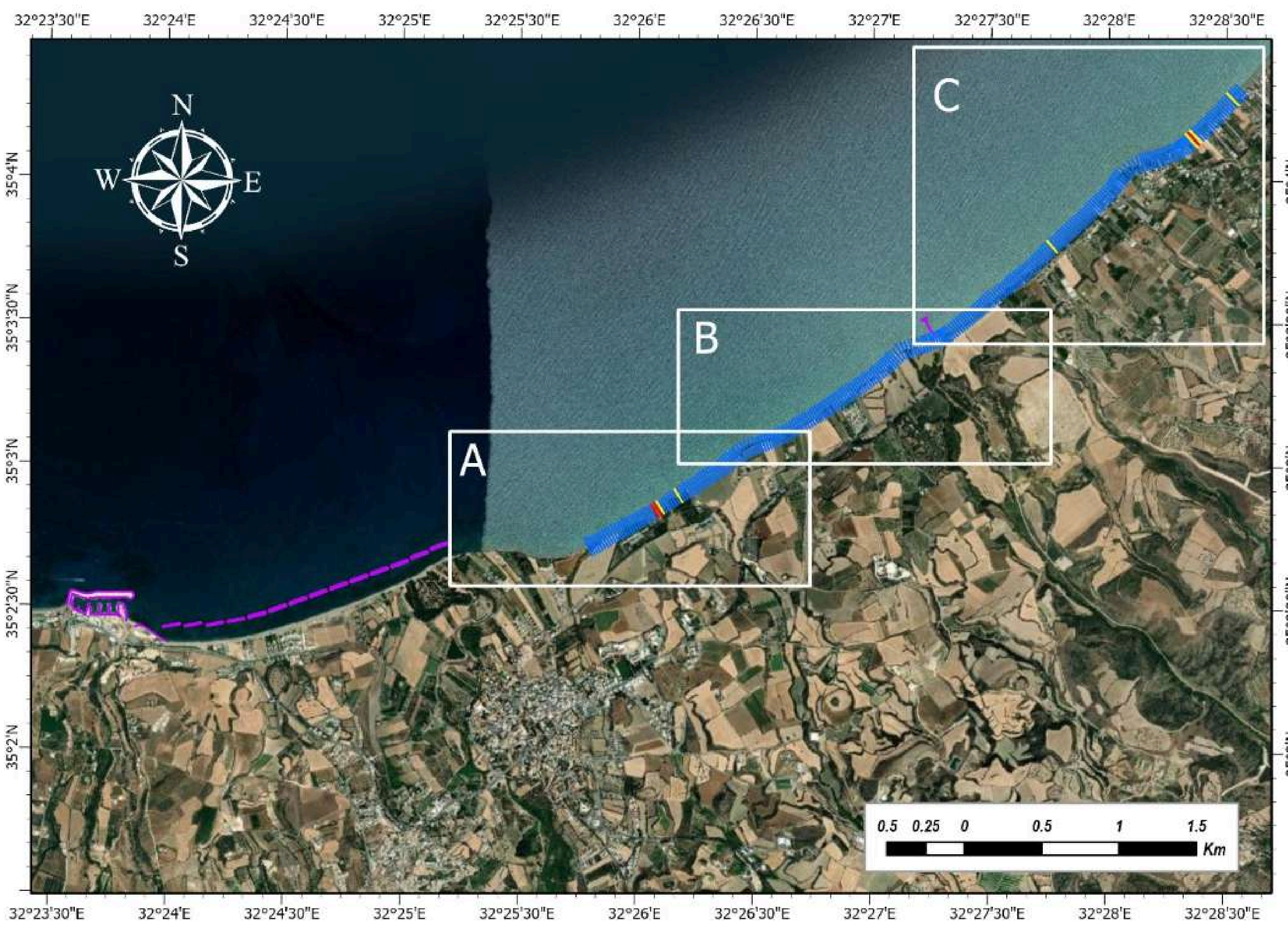


Figure 16: 2017-2024 Transects WLR Regarding the Coastline Behaviour

BGU - Flood Risk in India's Arid Ramsar Wetlands: Nonstationary Extreme Rainfall Analysis, Fuzzy Risk Assessment, and CMIP6 Projections

Title of GeoAI Practice

Flood Risk in India's Arid Ramsar Wetlands: Nonstationary Extreme Rainfall Analysis, Fuzzy Risk Assessment, and CMIP6 Projections

Brief Description

India's arid Ramsar wetlands are among the most ecologically valuable yet hydrologically fragile ecosystems in the world. This study presents the first integrated, multi-method flood risk assessment across 17 such wetlands using three complementary analytical frameworks. Using 72 years of daily gridded rainfall data at 0.5° × 0.5° spatial resolution from the India Meteorological Department (1951–2023), nonstationary Generalized Extreme Value (GEV) models were fitted with El Niño-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Atlantic Multidecadal Oscillation (AMO) as climate covariates across 56 configurations, with Bayesian inference providing return level estimates for four extreme precipitation indices. A fuzzy logic risk framework then integrated these hazard estimates with biodiversity and ecosystem exposure data from the India Biodiversity Portal and The Nature Conservancy geospatial archive to rank composite flood risk across all 17 sites. Future climate projections were derived from the NASA NEX-GDDP-CMIP6 satellite-downscaled dataset, and wetland boundaries were obtained from RSIS geospatial shapefiles. Modified Mann-Kendall trend analysis applied to 13 CMIP6 models under SSP245 and SSP585 quantified projected precipitation and temperature trends through 2100. Six wetlands are classified as very high risk, and all 17 face significantly rising temperatures.

BY DEPLOYING A FUZZY LOGIC RISK FRAMEWORK ALONGSIDE NONSTATIONARY STATISTICAL MODELING THAT ACCOUNTS FOR **LARGE-SCALE CLIMATE OSCILLATIONS**, IT TRANSFORMS COMPLEX DATASETS INTO A UNIFIED, HIGH-RESOLUTION RISK ASSESSMENT. THIS HOLISTIC APPROACH **EMPOWERS** WETLAND MANAGERS BY REPLACING GENERAL REGIONAL ESTIMATES WITH PRECISE, SITE-SPECIFIC HAZARD RANKINGS, PROVIDING A RELIABLE EVIDENCE BASE FOR PRIORITIZING TARGETED CONSERVATION INVESTMENTS AND MITIGATING THE COMPLEX IMPACTS OF **EXTREME RAINFALL.**

Challenge or Problem Addressed

India's arid wetlands are caught between two intensifying pressures: rising temperatures are driving increased evapotranspiration and longer dry spells, while climate change is simultaneously amplifying short-duration extreme rainfall events. When rare but intense rainfall strikes a wetland that has become structurally drier, the result is rapid inundation with little capacity for absorption or buffering.

Despite this, no comprehensive study had previously examined flood risk specifically for Ramsar-designated wetlands across India's arid zones. Risk management for these sites continued to rely on general regional estimates, which obscure site-level differences in hazard, vulnerability, and ecological exposure that are critical for targeted intervention. The absence of both a nonstationary statistical framework that accounts for large-scale climate oscillations and a multi-component risk assessment that integrates ecological exposure data left wetland managers without a reliable evidence base for prioritizing conservation investments. This study addresses these gaps directly. The risk model is validated by Sentinel-1 SAR-based flood observations generated in the below referenced practice on 'Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR' from BGU.

BGU - Flood Risk in India's Arid Ramsar Wetlands: Nonstationary Extreme Rainfall Analysis, Fuzzy Risk Assessment, and CMIP6 Projections

Technical Approach and Methods

The study used three integrated analytical layers. First, nonstationary GEV models were fitted to daily gridded rainfall data at 0.5° × 0.5° spatial resolution from the India Meteorological Department (1951–2023) using ENSO, IOD, and NAO as climate covariates across 56 model combinations. Bayesian Markov Chain Monte Carlo inference derived return levels for four extreme precipitation indices: Rx1, SDII, R10, and CWD. Wetland boundary geospatial shapefiles from the Ramsar Sites Information Service (RSIS) delineate the spatial extent of all 17 study sites, as shown in Figure 17. Second, a fuzzy logic risk framework using trapezoidal membership functions and Mamdani inference integrated hazard estimates with vulnerability data from the India Biodiversity Portal and exposure data from The Nature Conservancy geospatial data repository to produce composite risk scores for all 17 wetlands (Figure 18), with return level estimates. Third, future climate hazard was assessed using the NASA NEX-GDDP-CMIP6 satellite-downscaled climate projections dataset (13 models, SSP245 and SSP585, 2023–2100), with Modified Mann-Kendall trend analysis applied to each site. All statistical analysis was conducted in Python and R.

Implementation and Collaborations

This study was conducted as part of the FloodINT project, a research initiative focused on understanding flood dynamics in arid regions of India and Israel. This research was supported by a grant from the Ministry of Science and Technology of the State of Israel and the Ministry of Science and Technology, India, Division for International Scientific Relations, India-Israel Scientific Cooperation Unit. The work was carried out by a team of researchers from both countries in hydrology, climate science, and geospatial analysis. Rainfall data were sourced from the India Meteorological Department, and climate projections were drawn from the CMIP6 multi-model ensemble accessed via public repositories. Wetland boundary and land use data were obtained from the Ramsar Convention's Information Service and open satellite-derived datasets. The study was designed to be directly relevant to conservation managers, disaster risk authorities, and policy bodies responsible for Ramsar site protection and arid zone water management in India.

Impact and Outcomes

The study produced the first site-specific, quantitative flood risk rankings for all 17 arid Ramsar wetlands in India, integrating Earth Observation-derived exposure and vulnerability data into the risk framework. The use of Sentinel-2 land cover and surface water products to characterize each wetland's ecological exposure represents a replicable, scalable approach that other conservation bodies can apply with freely available satellite data. The finding that hazard rank and composite risk rank do not coincide at the same sites challenges the assumption that the wettest locations are automatically the most at risk, pointing conservation managers toward a more nuanced, multi-source understanding that combines climatic data with spatial EO evidence. Sentinel-1 SAR flood maps used as validation confirmed the spatial coherence of the risk rankings against real observed inundation. All 17 sites showed statistically significant warming trends under both SSP245 and SSP585, with risk levels projected to worsen without adaptive action. The integrated methodology is replicable and transferable to other wetland systems globally.

BGU - Flood Risk in India's Arid Ramsar Wetlands: Nonstationary Extreme Rainfall Analysis, Fuzzy Risk Assessment, and CMIP6 Projections

Lessons Learned and Recommendations

A key insight from this study is that rainfall extremes alone are insufficient to characterize flood risk in wetland ecosystems. Sites with moderate hazard but high ecological sensitivity and low adaptive capacity can face greater overall risk than locations with higher return levels. Practitioners attempting similar assessments should invest time in carefully defining locally meaningful indicators of vulnerability and exposure, as generic national-level proxies can mask site-specific differences. Selecting appropriate climate covariates for nonstationary GEV models requires testing multiple combinations and using information criteria rather than assuming a single covariate structure. For future work, integrating hydrological routing models with satellite-derived inundation observations would strengthen the link between statistical hazard estimates and on-the-ground flood dynamics. Collaboration with Ramsar site managers early in the process would also help ensure that risk rankings translate into actionable conservation strategies.

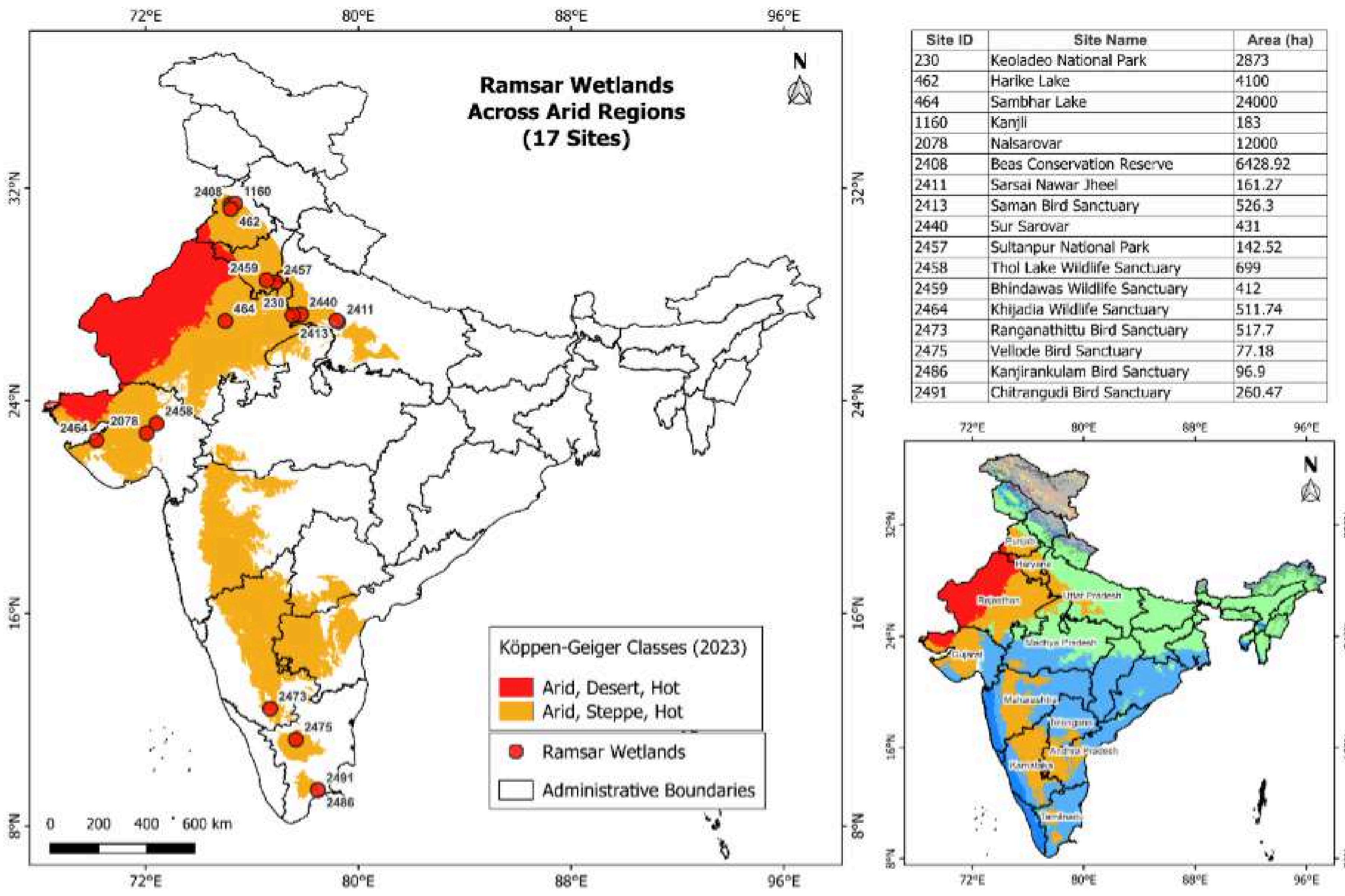
Alignment with SDGs

This practice directly supports UN-SPIDER's mandate to use space-based information for disaster risk reduction and emergency response. SAR-derived flood extent maps serve as spatial validation, making this a genuinely space-enabled risk assessment rather than a purely statistical one. The study contributes to the Sendai Framework for Disaster Risk Reduction (Priority 1: Understanding disaster risk). It aligns with SDG 13 (Climate Action) by quantifying future climate-driven flood hazard under CMIP6 scenarios; SDG 15 (Life on Land) by targeting Ramsar-designated ecosystems of international conservation significance; and SDG 6 (Clean Water and Sanitation) by addressing water availability and flood regulation in wetland systems. The integration of open-access satellite data processed through Google Earth Engine supports SDG 17 (Partnerships for the Goals) by ensuring the methodology is accessible and replicable across UN-SPIDER's Regional Support Office network without requiring expensive proprietary tools.

Additional References or Resources

Manuscript (under review): "Flood Risk in India's Arid Ramsar Wetlands: Integrating Extreme Rainfall Analysis, Fuzzy Risk Assessment, and CMIP6 Projections". Data sources: India Meteorological Department gridded daily rainfall dataset (1951–2022); CMIP6 multi-model ensemble (13 models, SSP245 and SSP585); Ramsar Sites Information Service (rsis.ramsar.org).

BGU - Flood Risk in India's Arid Ramsar Wetlands: Nonstationary Extreme Rainfall Analysis, Fuzzy Risk Assessment, and CMIP6 Projections



Site ID	Site Name	Area (ha)
230	Keoladeo National Park	2873
462	Harike Lake	4100
464	Sambhar Lake	24000
1160	Kanjli	183
2078	Nalsarovar	12000
2408	Beas Conservation Reserve	6428.92
2411	Sarsai Nawar Jheel	161.27
2413	Saman Bird Sanctuary	526.3
2440	Sur Sarovar	431
2457	Sultanpur National Park	142.52
2458	Thol Lake Wildlife Sanctuary	699
2459	Bhindawas Wildlife Sanctuary	412
2464	Khijadia Wildlife Sanctuary	511.74
2473	Ranganathittu Bird Sanctuary	517.7
2475	Vellode Bird Sanctuary	77.18
2486	Kanjirankulam Bird Sanctuary	96.9
2491	Chitrangudi Bird Sanctuary	260.47

Figure 17: Distribution of the 17 Arid Ramsar Wetlands Across India Overlaid on the Koppen-Geiger Climate Classification

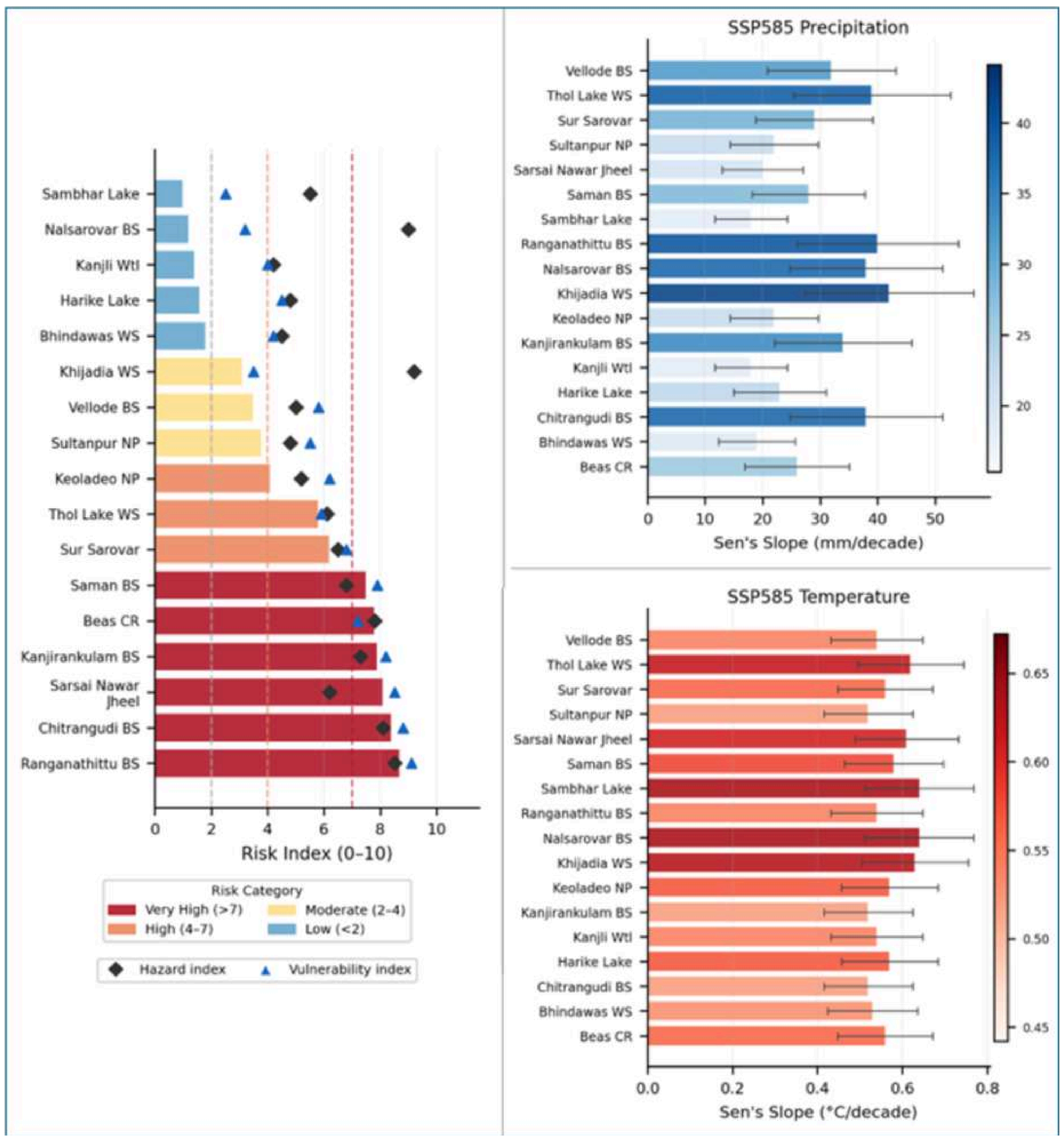


Figure 18: Fuzzy Logic Composite Risk Index for 17 Arid Ramsar Wetlands, ordered by descending composite risk score. Horizontal bars represent composite risk (color-coded by risk category: Very High >7, High 4–7, Moderate 2–4, Low <2). Diamond markers show individual hazard index values; triangle markers show vulnerability index values, illustrating how high-hazard but low-vulnerability sites (e.g., Khijadia) receive lower composite risk classifications than moderate-hazard, high-vulnerability sites. Also, the CMIP6-projected trends (2023–2100) across 17 arid Ramsar wetlands under SSP585 precipitation and SSP585 temperature, derived from the 13-model NEX-GDDP-CMIP6 ensemble using the Modified Mann-Kendall test. Bars show ensemble median Sen's slope; error bars represent the inter-model interquartile range across CMIP6 models. Color intensity reflects the magnitude of the ensemble median trend.

BGU - Long-Term Shifts in Climate Aridity Across India's Arid Ramsar Wetlands: An ERA5-Land Based Analysis (1960–2024)

Title of GeoAI Practice

Long-Term Shifts in Climate Aridity Across India's Arid Ramsar Wetlands: An ERA5-Land Based Analysis (1960–2024)

Brief Description

This study investigates how climate aridity has shifted over a 65-year period (1960–2024) across 17 arid Ramsar wetlands in India, drawing on the ERA5-Land monthly aggregated dataset from ECMWF accessed via Google Earth Engine (GEE). GEE's cloud-computing platform enabled efficient zonal extraction of monthly precipitation, potential evapotranspiration (PET, Penman-Monteith), and 2-meter air temperature across 10 km catchment buffers for all 17 sites, covering 1960–2024. The Aridity Index (AI = MAP/PET) was computed annually for each site and analyzed using the Modified Mann-Kendall trend test with Yue-Wang autocorrelation correction, and Sen's slope estimator quantified the rate of change per decade. The study identified two mechanistically distinct aridity regimes: a precipitation-driven wetting regime across Rajasthan and Gujarat (AI gains of +0.013 to +0.040 per decade), and a PET-driven drying regime in Punjab and southern India. Harike Lake showed the steepest drying rate of -0.050 AI units per decade ($p < 0.001$), with PET explaining 83% of AI variance. Wetland site boundaries were defined using RSIS geospatial shapefiles. The study provides the long-term aridity baseline essential for interpreting flood risk across all FloodINT project wetland sites.

> THE ANALYSIS REVEALS **TWO MECHANISTICALLY DISTINCT REGIMES**—PRECIPITATION-DRIVEN WETTING IN RAJASTHAN AND GUJARAT VERSUS PET-DRIVEN DRYING IN PUNJAB AND SOUTHERN INDIA.

Challenge or Problem Addressed

A persistent challenge in arid wetland science is that most flood risk frameworks treat aridity as a static background condition rather than a dynamic, evolving driver. In reality, a wetland that has been gradually drying over decades has reduced capacity to absorb sudden intense rainfall, making it structurally more vulnerable to flash flooding even as it receives less overall water. Conversely, wetlands undergoing a wetting trend face more frequent high-water events that can overwhelm surrounding land. Without long-term, site-specific aridity data, it is impossible to determine whether a flood event is an anomaly or part of a broader climatic shift. A further challenge is that conventional meteorological station networks are sparse across India's arid zones, making reanalysis data combined with satellite-derived land surface and water extent observations essential for filling observational gaps. This study addresses these challenges by integrating ERA5-Land reanalysis with Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature and JRC surface water products to produce the first systematic, 65-year characterization of aridity trends for all 17 arid Ramsar wetlands (Figure 19) , disentangling precipitation and evapotranspiration drivers at each site.

BGU - Long-Term Shifts in Climate Aridity Across India's Arid Ramsar Wetlands: An ERA5-Land Based Analysis (1960–2024)

Technical Approach and Methods

Monthly mean annual precipitation and potential evapotranspiration (PET) were extracted from the ERA5-Land reanalysis dataset at 0.1-degree resolution for each of the 17 wetland sites covering the period 1960–2024. PET was estimated using the Penman-Monteith method. The Aridity Index (AI = MAP/PET) was computed annually for each site. To complement and validate the reanalysis-based aridity signals, two satellite-derived datasets were incorporated: MODIS MOD11A2 land surface temperature (LST) products were used as an independent proxy for evapotranspiration intensity, and the JRC Global Surface Water dataset was used to track long-term changes in permanent and seasonal water extent at each wetland, providing an observable, EO-based corroboration of the computed aridity trends. Temporal trend analysis was performed using the Modified Mann-Kendall test, and Sen's slope estimator quantified the rate of change per decade. Attribution of AI trends to precipitation versus PET drivers was assessed through decomposition analysis at each site. All processing was conducted in Python using the pyMannKendall library and ERA5-Land extraction scripts via the Copernicus Climate Data Store API, All ERA5-Land data were directly accessed and processed through Google Earth Engine, which provides native integration with the ERA5-Land dataset (ECMWF/ERA5/DAILY catalogue), eliminating the need for local downloads and enabling reproducible large-scale spatial analysis.

Implementation and Collaborations

This study was carried out as part of the FloodINT project by researchers specializing in climatology, hydrology, and remote sensing. This research was supported by a grant from the Ministry of Science and Technology of the State of Israel and the Ministry of Science and Technology, India, Division for International Scientific Relations, India-Israel Scientific Cooperation Unit. ERA5-Land monthly aggregated data were accessed through the ECMWF Copernicus Climate Data Store (cds.climate.copernicus.eu) and via the Google Earth Engine data catalogue (ECMWF/ERA5_LAND/MONTHLY_AGGR). All zonal extraction, processing, and trend computation for all 17 wetland buffer zones were conducted entirely within Google Earth Engine, a cloud-based geospatial remote sensing platform, enabling reproducible large-scale analysis without local computing infrastructure. Wetland site boundaries were defined using geospatial shapefiles from the Ramsar Sites Information Service (rsis.ramsar.org). No new primary data were collected; all data are publicly available through the repositories cited above. The study is designed to complement the broader FloodINT project framework, which includes parallel analyses of extreme rainfall return levels and Sentinel-1 SAR-based flood monitoring at the same wetlands. Results are intended to inform conservation bodies, the Ministry of Environment of India, and the Ramsar Convention Secretariat.

Impact and Outcomes

The study produced the first site-specific, RSIS-verified, network-wide aridity trend dataset for all 17 arid Ramsar wetlands in India. Twelve of 17 sites showed statistically significant trends: six recording AI gains driven by monsoon precipitation intensification in Rajasthan and Gujarat, and six recording significant AI declines driven by PET amplification in Punjab and southern India. The identification of two mechanistically distinct aridity regimes has direct practical value: wetting-trend sites require monitoring for invasive species and infrastructure impacts of hydrological expansion, while drying-trend sites require urgent intervention focused on evaporation reduction and water balance augmentation. The finding that Harike Lake is drying at -0.050 AI per decade, with PET explaining 83% of AI variance, provides a quantitative basis for urgently prioritizing adaptive water management at that site (Figure 20). The reproducible ERA5-Land and Google Earth Engine framework is directly applicable to Ramsar Convention ecological character assessments globally.

BGU - Long-Term Shifts in Climate Aridity Across India's Arid Ramsar Wetlands: An ERA5-Land Based Analysis (1960–2024)

Lessons Learned and Recommendations

A key lesson is that aridity trends across even a geographically defined arid zone are not uniform, and conflating sites under a single regional trend leads to incorrect conclusions. ERA5-Land proved a suitable data source at this scale, but its coarse resolution (~11.1 km) may not capture fine-scale topographic and land-use influences on local microclimate. At Harike Lake, the observed AI trend reflects a compound climate-human signal rather than a purely climatic one, as intensive agricultural water management in Punjab converges with climatic drying; practitioners should be aware that ERA5-Land AI trends at heavily managed sites may blend climate and anthropogenic drivers. The Modified Mann-Kendall test with the Yue-Wang autocorrelation correction is strongly recommended for hydroclimatic time series. Future research should integrate satellite-derived actual evapotranspiration datasets such as MODIS ET and GLEAM, process-based hydrological modeling of individual wetland water budgets, and extend this framework to India's full 98-site Ramsar inventory.

Alignment with SDGs

This practice supports UN-SPIDER's mission of using Earth Observation data for disaster risk reduction by characterizing the long-term climatic and hydrological conditions that govern flood vulnerability in protected wetlands. The combination of ERA5-Land reanalysis with MODIS land surface temperature and JRC Global Surface Water satellite products exemplifies the kind of multi-source, space-enabled analysis that UN-SPIDER promotes. The use of Google Earth Engine for satellite data processing aligns with UN-SPIDER's emphasis on open, accessible EO platforms. The study contributes to SDG 13 (Climate Action) by documenting observed climate change impacts on aridity over six decades; SDG 15 (Life on Land) by focusing on internationally protected wetland ecosystems; and SDG 6 (Clean Water and Sanitation) by quantifying long-term changes in the water balance governing wetland water availability. The diverging aridity trends documented here also provide a scientific basis for the early warning and monitoring frameworks that UN-SPIDER promotes across its Regional Support Office network.

6 CLEAN WATER AND SANITATION

13 CLIMATE ACTION

15 LIFE ON LAND

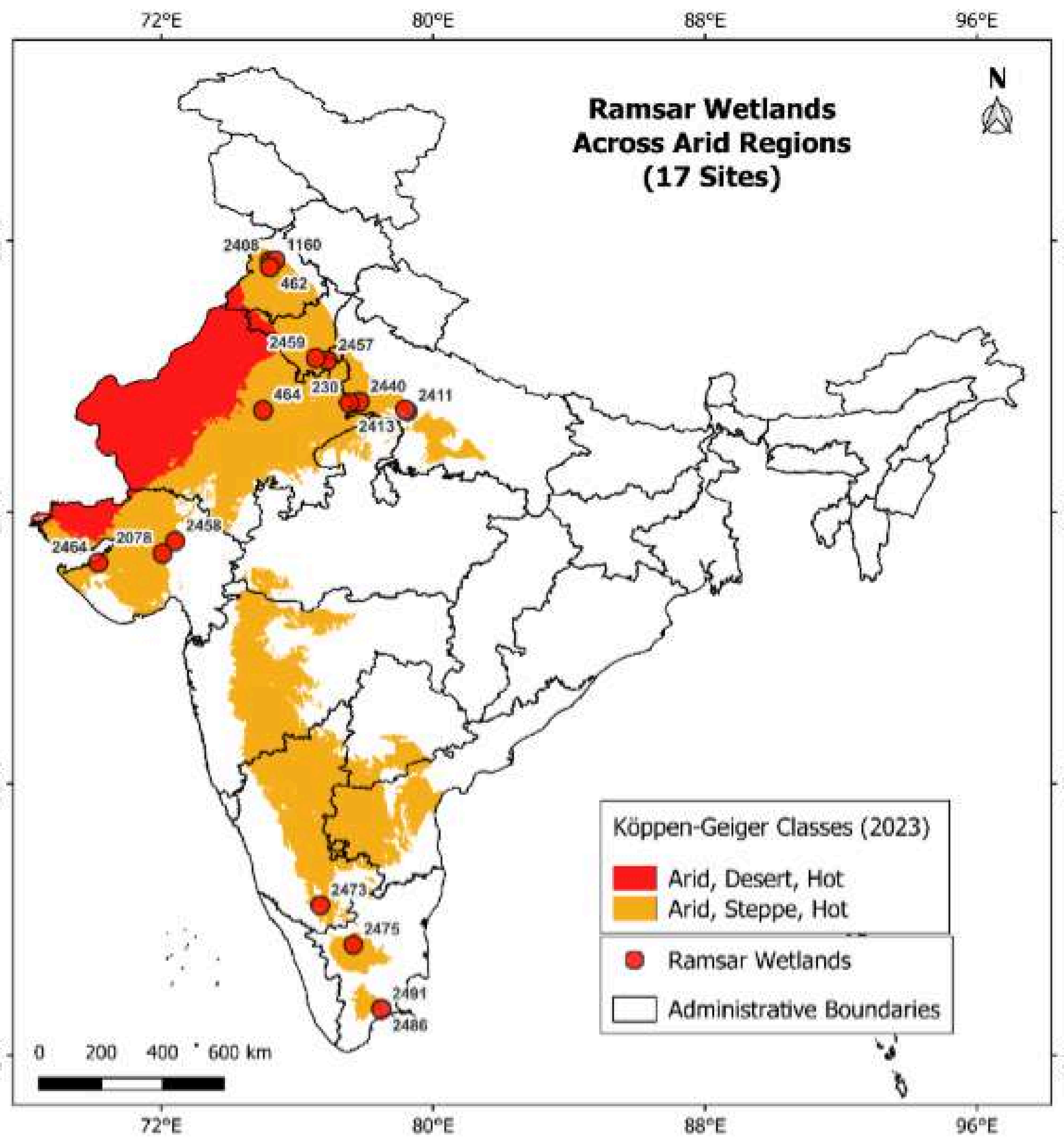
THIS STUDY SUPPORTS **SDG 13** (DOCUMENTING CLIMATE-DRIVEN ARIDITY TRENDS), **SDG 15** (FOCUSING ON RAMSAR WETLAND ECOSYSTEMS), AND **SDG 6** (QUANTIFYING LONG-TERM WATER-BALANCE CHANGES)

Additional References or Resources

Manuscript (under review): "Long-Term Shifts in Climate Aridity Across India's Arid Ramsar Wetlands: An ERA5-Land Based Analysis (1960–2024)". Data sources: ERA5-Land monthly reanalysis data (Copernicus Climate Data Store, cds.climate.copernicus.eu); Ramsar Sites Information Service (rsis.ramsar.org).

BGU - Long-Term Shifts in Climate Aridity Across India's Arid Ramsar Wetlands: An ERA5-Land Based Analysis (1960–2024)

Figure:



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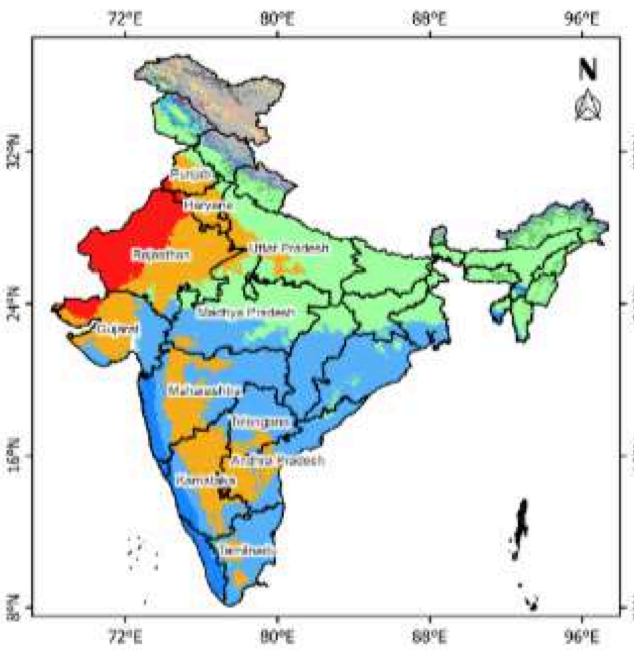


Figure 19: Distribution of the 17 Arid Ramsar Wetlands Across India Overlaid on the Koppen-Geiger Climate Classification

	1960–70	1971–80	1981–90	1991–00	2001–10	2011–20	2021–24
Keoladeo NP	-0.04	-0.00	-0.01	+0.02	+0.01	+0.03	+0.05
Sambhar Lake	-0.03	-0.02	-0.04	-0.00	+0.02	+0.02	+0.04
Nalsarovar BS	-0.03	-0.03	-0.00	-0.00	+0.01	+0.02	+0.02
Khijadia WLS	-0.02	-0.02	-0.01	-0.00	+0.00	+0.01	+0.02
Sur Sarovar	-0.01	-0.01	-0.01	+0.00	+0.01	+0.01	+0.01
Saman BS	-0.01	-0.01	-0.00	-0.01	+0.01	+0.01	+0.01
Sarsai Nawar	-0.00	-0.01	-0.01	+0.00	+0.00	+0.01	+0.01
Thol Lake WLS	-0.01	-0.01	-0.00	+0.00	+0.00	+0.01	+0.01
Sultanpur NP	+0.01	+0.01	+0.00	+0.00	-0.00	-0.01	-0.01
Bhindawas WLS	+0.01	+0.00	+0.01	-0.00	+0.00	-0.01	-0.01
Ranganathittu BS	+0.01	+0.01	-0.00	+0.00	-0.00	-0.00	-0.01
Vellode BS	+0.02	+0.00	+0.01	-0.00	-0.01	-0.00	-0.01
Kanjirankulam BS	+0.00	+0.01	+0.00	-0.00	-0.00	-0.01	-0.01
Chitrangudi BS	+0.02	+0.01	+0.00	+0.00	-0.00	-0.00	-0.02
Kanjli	+0.02	+0.02	+0.00	+0.01	-0.01	-0.00	-0.01
Beas Cons. Res.	+0.05	+0.04	+0.02	-0.01	-0.01	-0.01	-0.03
Harike Lake	+0.05	+0.04	+0.02	-0.02	-0.01	-0.03	-0.05

Figure 20: Decadal Aridity Index (AI) Anomalies Relative to the 1960–1970 Baseline Across 17 Arid Ramsar Wetlands in India. Positive values (red) indicate wetter conditions, while negative values (blue) indicate drying. Anomalies are computed as decadal mean AI minus the baseline mean; red bold labels denote sites with statistically significant drying trends ($p < 0.05$).

BGU - Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR: A Multi-Event Case Study Analysis (2019–2024)

Title of GeoAI Practice

Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR: A Multi-Event Case Study Analysis (2019–2024)

Brief Description

This study applies Sentinel-1 Synthetic Aperture Radar (SAR) imagery, processed via Google Earth Engine (GEE), to monitor and quantify flood dynamics across six documented flood events at arid Ramsar wetlands in India between 2019 and 2024. SAR's ability to penetrate cloud cover makes it particularly suited for flood mapping in monsoon-affected arid zones where optical imagery is frequently compromised. For each event, pre-flood and peak-flood SAR backscatter composites were compared using a change detection approach to delineate inundated areas. The study found extreme variability in flood response across sites, with the proportional increase in open water extent ranging from 1.4% to 107%. A strong inverse relationship (R^2 = 0.89) was identified between pre-flood baseline water extent and proportional flood response, suggesting that wetlands with smaller permanent water bodies experience the most dramatic relative flooding during extreme events. These satellite-derived flood maps serve as direct validation data for the risk models developed in parallel under the FloodINT project and provide a reproducible methodology for near-real-time flood monitoring at ecologically sensitive sites.

SYNTHETIC APERTURE RADAR (SAR) IS AN ACTIVE SYSTEM THAT PENETRATES **CLOUDS AND DARKNESS**, ENABLING **ALL-WEATHER FLOOD MAPPING**. SENTINEL-1 OFFERS FREE C-BAND SAR DATA WITH A 6-DAY REVISIT, CRUCIAL FOR TIMELY INUNDATION DETECTION IN MONSOON-AFFECTED REGIONS.

Challenge or Problem Addressed

Flood monitoring in arid wetlands presents a specific operational challenge: the events that matter most tend to be brief, intense, and occur during monsoon periods when cloud cover makes optical satellite imagery unreliable. Traditional flood-mapping approaches that rely on Landsat or Sentinel-2 imagery often fail precisely when they are needed. Without accurate, timely observations of the extent of actual inundation, it is impossible to validate statistical flood risk models, calibrate hydrological simulations, or assess the real-world impact on wetland ecology. This study addresses that challenge by applying Sentinel-1 C-band SAR, which acquires data regardless of weather or lighting conditions, to six confirmed flood events across India's arid Ramsar wetlands. A further challenge tackled in this work is understanding why two wetlands with similar rainfall inputs can exhibit fundamentally different flood responses, a phenomenon that cannot be explained by hazard alone and requires knowledge of the baseline hydrological state.

BGU - Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR: A Multi-Event Case Study Analysis (2019–2024)

Technical Approach and Methods

Sentinel-1 Ground Range Detected (GRD) imagery in VV and VH polarisations was accessed and processed through the Google Earth Engine cloud computing platform. Pre-processing steps included applying the border noise removal algorithm, thermal noise correction, radiometric calibration, and terrain correction using the SRTM digital elevation model. Flood detection was based on SAR backscatter thresholding combined with a change detection approach: pre-event and peak-event composites were differenced and classified to delineate inundated areas. Six flood events spanning 2019–2024 were analyzed at six wetland sites, selected based on confirmed flood records (Figure 21). Water extent was quantified for pre-flood and peak-flood conditions, and the proportional change was calculated. Statistical regression was used to investigate the relationship between baseline permanent water extent and proportional flood response. All image-processing and analysis scripts were developed using the GEE JavaScript API.

Implementation and Collaborations

This study was implemented as part of the FloodINT project using freely available Sentinel-1 data from the European Space Agency (ESA) Copernicus programme, accessed through Google Earth Engine. This research was supported by a grant from the Ministry of Science and Technology of the State of Israel and the Ministry of Science and Technology, India, Division for International Scientific Relations, India-Israel Scientific Cooperation Unit. Flood event dates were cross-referenced against disaster event records from the National Disaster Management Authority of India and news archives to ensure the six selected events represented genuine, documented inundation episodes. The GEE processing pipeline was developed in-house and is designed to be replicable for other users working on wetland flood monitoring. The methodology is directly aligned with UN-SPIDER's Recommended Practice for flood mapping using SAR data, and the study contributes an application-level validation of that framework for small, ecologically sensitive water bodies in arid regions where standard practices are less tested.

Impact and Outcomes

The study produced satellite-derived flood maps for six real flood events at arid Ramsar wetlands, providing the first empirical, SAR-based validation dataset for flood risk models developed in this research domain. The inverse relationship between baseline water extent and the proportional flood response ($R^2 = 0.89$) is a practically useful finding: it suggests that monitoring the permanent water body size of a wetland can serve as a proxy indicator of its flood amplification potential. This has direct applications for early warning system design and site prioritization under time pressure. The wide range of observed flood responses, from a 1.4% to a 107% increase in water extent, demonstrates that uniform flood-response assumptions used in some regional risk frameworks are inappropriate for arid wetlands (Figure 22). The open-access GEE methodology supports capacity-building for disaster management agencies seeking low-cost flood-monitoring tools.

Lessons Learned and Recommendations

The most important methodological lesson is that SAR-based flood mapping at small wetland water bodies requires careful calibration of backscatter thresholds. The standard thresholds developed for large river floodplains do not

BGU - Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR: A Multi-Event Case Study Analysis (2019–2024)

transfer directly to the confined, shallow water bodies typical of arid Ramsar wetlands, where the signal response can be influenced by emergent vegetation, wind roughening, and seasonal sediment conditions. Users should validate thresholds against independent data, such as high-resolution optical imagery from cloud-free windows, before relying on automated detection. The discovery of the inverse baseline-water-extent relationship was unexpected and emerged from comparing results across multiple sites rather than from a single case study, illustrating the value of multi-site, multi-event designs in SAR flood monitoring research. Future work should explore automated near-real-time monitoring pipelines and integrate SAR-derived flood extents with hydrological models to improve predictive capacity.

Alignment with SDGs

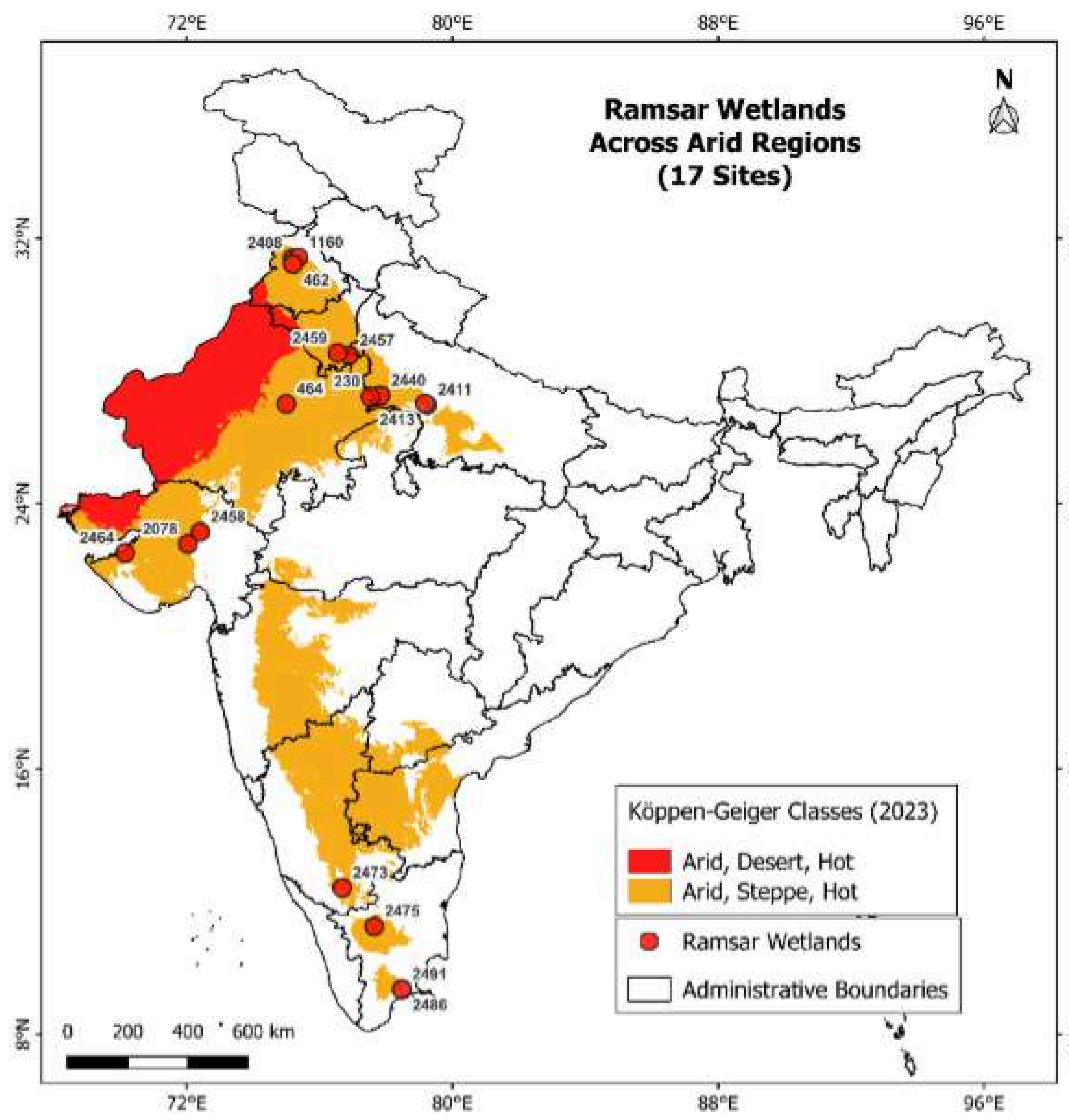
This practice is closely aligned with UN-SPIDER's core mandate: it directly applies space-based Earth Observation, specifically SAR satellite imagery, for disaster risk reduction and emergency response monitoring. The methodology follows and validates UN-SPIDER's Recommended Practice on flood assessment using Sentinel-1 data. It contributes to SDG 13 (Climate Action) by generating observational evidence of how climate-driven extreme rainfall manifests as flood inundation at ecologically sensitive sites; SDG 15 (Life on Land) by focusing on Ramsar-protected wetlands and understanding the physical stresses they face during extreme events; and SDG 11 (Sustainable Cities and Communities) by demonstrating satellite-based tools that can support local disaster management authorities in flood monitoring and response. The study also contributes to SDG 17 (Partnerships for the Goals) by using open platforms and freely available satellite data, thereby lowering barriers to replication in developing countries.

THE PRACTICE SUPPORTS **SDG 13** (CLIMATE-DRIVEN FLOOD EVIDENCE), **SDG 15** (RAMSAR WETLAND ECOSYSTEM STRESS), SDG 11 (DISASTER RESPONSE TOOLS FOR LOCAL AUTHORITIES), AND **SDG 17** (OPEN DATA AND PLATFORM PARTNERSHIPS).

Additional References or Resources

Manuscript (under review): "Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR: A Multi-Event Case Study Analysis (2019–2024)". Data sources: Sentinel-1 GRD imagery (ESA Copernicus, accessed via Google Earth Engine); SRTM DEM (NASA/USGS); National Disaster Management Authority India flood event records.

BGU - Monitoring Flood Dynamics in Arid Ramsar Wetlands Using Sentinel-1 SAR: A Multi-Event Case Study Analysis (2019–2024)



Site ID	Site Name	Area (ha)
230	Keoladeo National Park	2873
462	Harike Lake	4100
464	Sambhar Lake	24000
1160	Kanjli	183
2078	Nalsarovar	12000
2408	Beas Conservation Reserve	6428.92
2411	Sarsai Nawar Jheel	161.27
2413	Saman Bird Sanctuary	526.3
2440	Sur Sarovar	431
2457	Sultanpur National Park	142.52
2458	Thol Lake Wildlife Sanctuary	699
2459	Bhindawas Wildlife Sanctuary	412
2464	Khijadia Wildlife Sanctuary	511.74
2473	Ranganathittu Bird Sanctuary	517.7
2475	Vellode Bird Sanctuary	77.18
2486	Kanjirankulam Bird Sanctuary	96.9
2491	Chitrangudi Bird Sanctuary	260.47

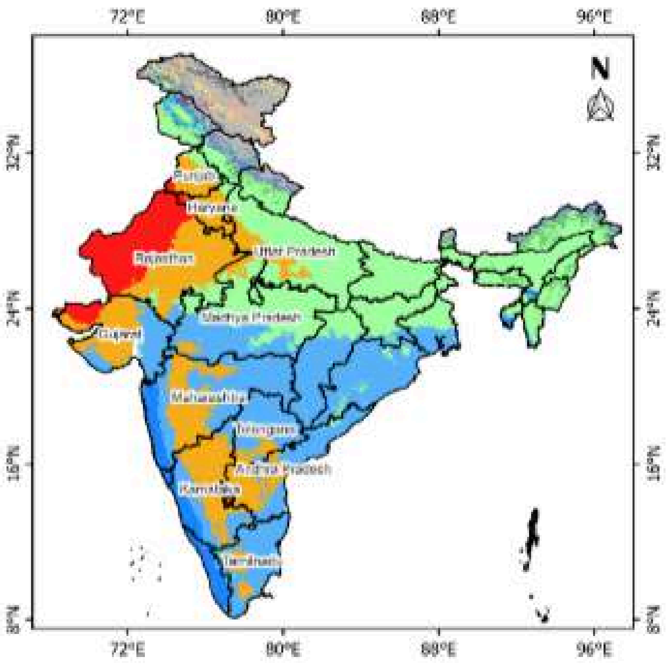


Figure 21: Distribution of the 17 Arid Ramsar Wetlands Across India Overlaid on the Koppen-Geiger Climate Classification

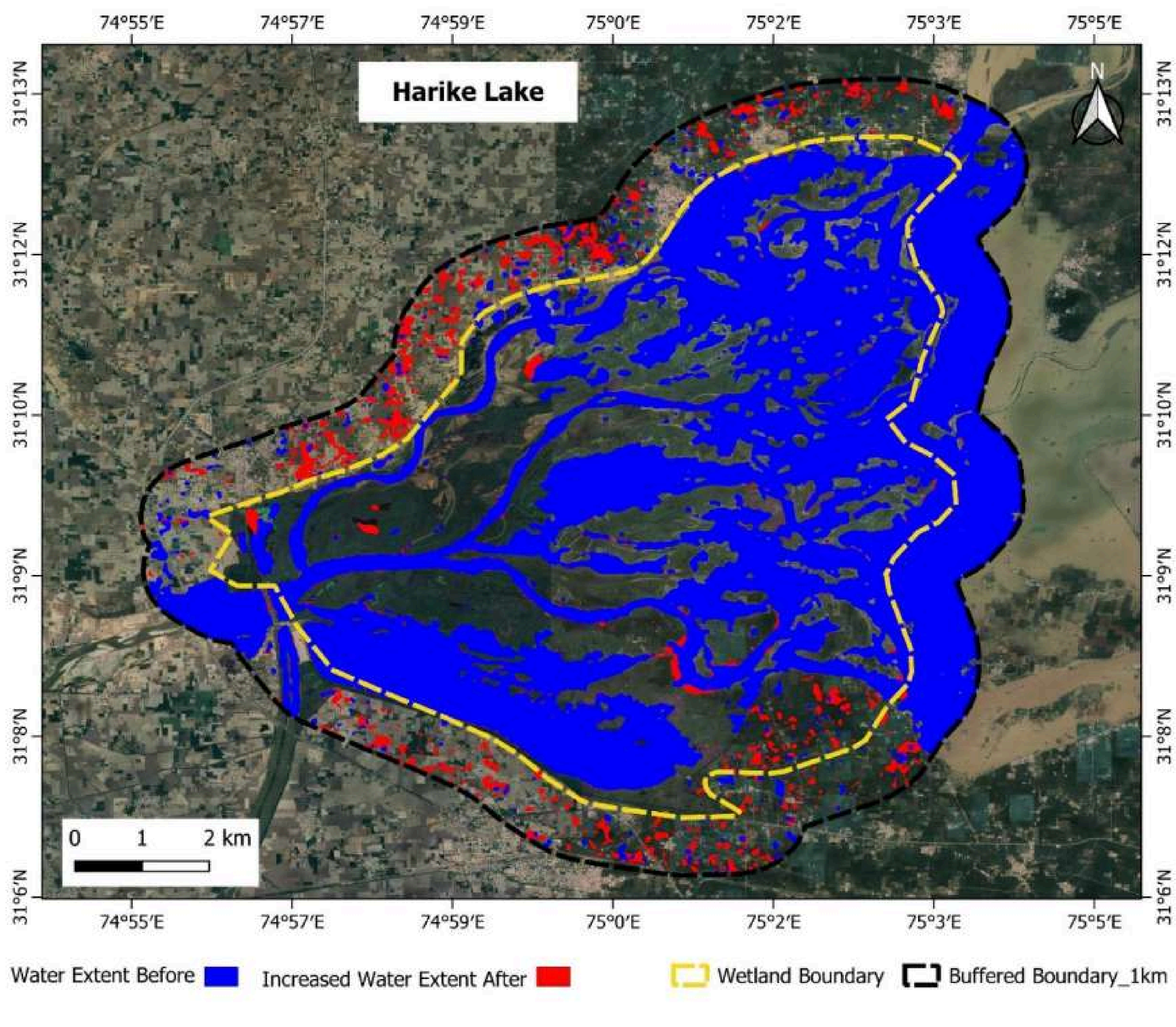


Figure 22: An Example of a Flood Extent Map of Harike Lake for September 1, 2023, flood event derived from Sentinel-1 SAR imagery. Blue areas represent water extent before the flood, red areas indicate newly flooded zones, the yellow dashed line shows the original wetland boundary, and the black dashed line represents the 1-km buffer boundary

Section B: Early Warning Systems and Preparedness

Overview

Forecasting, real-time analytics, and alert systems are key to effective early warning, enabling timely action to reduce disaster impacts. Satellite-based analytics help detect risks like drought and fire early, allowing governments, responders, and farmers to act proactively. AI-driven models enhance accuracy and localization of early warnings, supporting community-level preparedness. Tools like the AI-powered SADMS chatbot deliver tailored drought alerts, helping local users plan irrigation and protect crops. Overall, AI enables timely, location-specific responses, turning early warning into early action.

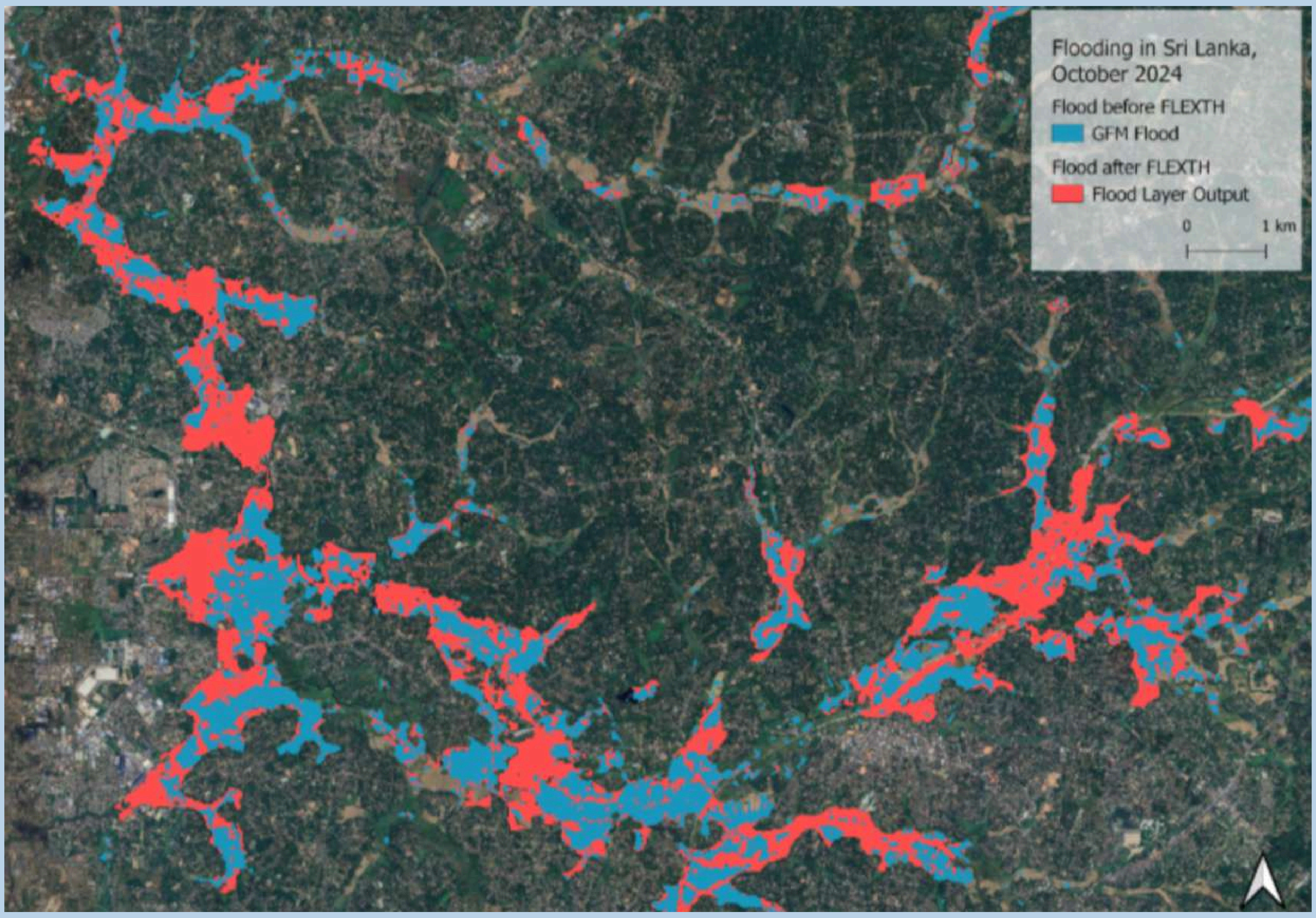


Figure 23 : October Floods 2024, Sri Lanka
(c) UN-SPIDER Knowledge Portal

NOA - Towards a Foundation Model for Earth Intelligence Using High-Frequency Earth Observation Data

Title of GeoAI Practice

Towards a Foundation Model for Earth Intelligence Using High-Frequency Earth Observation Data.

Brief Description

Advances in AI for Earth Observation methods create new opportunities for developing novel approaches to monitoring dynamic environmental phenomena. In this context, this practice presents HighFM, a first step towards a foundation model for Earth Intelligence applications, such as environmental monitoring and hazard detection, using high-frequency Earth Observation data. The approach makes use of multispectral imagery from the SEVIRI sensor onboard the Meteosat Second Generation platform, which provides observations every 15 minutes. It is designed to support continuous monitoring of dynamic environmental phenomena, particularly in regions such as the Mediterranean where hazards such as wildfires occur frequently. The model is developed as a general-purpose pretrained system that can be adapted to different downstream tasks. In this work, it is applied to cloud segmentation and active fire detection tasks, with evaluation results showing improved performance compared to baseline approaches. This methodology is intended to support a broader range of near-real-time Earth Observation applications, including environmental monitoring and hazard detection.

FOUNDATION MODELS ARE PRETRAINED ON MASSIVE UNLABELED DATA TO LEARN GENERALIZABLE REPRESENTATIONS, THEN FINE-TUNED FOR SPECIFIC TASKS. THIS APPROACH MAKES **EFFICIENT USE OF LIMITED LABELED DATA** — IDEAL FOR EARTH OBSERVATION APPLICATIONS LIKE CLOUD SEGMENTATION AND FIRE DETECTION FROM HIGH-FREQUENCY SATELLITE STREAMS.

Challenge or Problem Addressed

Climate-related hazards such as wildfires, floods, and rapidly changing atmospheric conditions require continuous monitoring and timely information to support early warning and response. However, many existing Earth Observation approaches, including AI-driven methods, rely on satellite data with limited temporal resolution, which constrains their ability to capture fast-evolving phenomena and provide near-real-time insights. While suitable for static or slowly evolving applications, these models are less effective in time-critical scenarios where frequent observations are needed. This creates a gap between the availability of high-frequency geostationary satellite data and the ability of existing models to make use of it. The practice addresses this challenge by focusing on methods that can learn from high-frequency data streams and support a range of near-real-time Earth Intelligence applications, including extreme event (wildfire, flood) detection and monitoring.

NOA - Towards a Foundation Model for Earth Intelligence Using High-Frequency Earth Observation Data

Technical Approach and Methods

The approach employs self-supervised pretraining using masked autoencoders applied to multispectral Earth Observation data. It uses imagery from the SEVIRI sensor onboard the Meteosat Second Generation (MSG) platform, which provides observations every 15 minutes across multiple spectral bands over Europe, Africa, and the Middle East. A large-scale dataset of satellite imagery (more than 2 TB) is used for pretraining. The model follows a self-supervised learning approach based on masked autoencoders, building on the SatMAE architecture. It is adapted to handle high-frequency geostationary data, including the use of fine-grained temporal information to capture short-term variability. The pretrained Vision Transformer encoders are then fine-tuned for downstream tasks using curated datasets with pixel-level annotations. In this work, these include cloud segmentation and pixel-level active fire detection, formulated as binary semantic segmentation tasks, where SEVIRI image patches are paired with corresponding cloud and fire masks derived from MODIS cloud products and collocated active fire detections. The approach is evaluated against baseline models, including convolutional networks, Vision Transformers trained from scratch or initialized on ImageNet, and existing Earth Observation foundation models, under different training objectives that emphasize either recall or spatial precision, demonstrating consistent performance improvements across evaluation metrics.

Implementation and Collaborations

This work has been carried out by NOA in collaboration with operational stakeholders involved in environmental monitoring and disaster response, including representatives of various departments of the Greek Fire Service, as well as the Civil Protection Ministry and the Region of Attica, Greece.

Impact and Outcomes

The pretrained models improved cloud segmentation and active fire detection performance compared to baseline approaches. Pretraining on high-frequency geostationary satellite data enabled the models to better capture temporally dynamic environmental phenomena and represent rapidly evolving conditions. This supports near-real-time Earth Observation applications by making more effective use of temporally dense data streams, particularly for monitoring events such as wildfires and atmospheric processes. The work also demonstrated the potential of reusable model architectures that can be adapted across multiple tasks, reducing the need for task-specific training and supporting more efficient use in Earth Observation workflows.

Lessons Learned and Recommendations

The work highlights the importance of adapting AI models to the specific characteristics of high-frequency geostationary satellite data, particularly in capturing short-term temporal variability that is often overlooked in existing Earth Observation approaches. It shows that large-scale self-supervised pretraining on unlabeled data can support the development of models that transfer effectively across different tasks, even when labeled datasets are limited. Future work focuses on extending the approach to additional regions and downstream applications, and on further integration into operational systems.

NOA - Towards a Foundation Model for Earth Intelligence Using High-Frequency Earth Observation Data

Alignment with SDGs

This practice supports the use of Earth Observation for disaster management and environmental monitoring, in line with the objectives of the UN-SPIDER Programme. It contributes to improving access to and use of satellite data through the development of reusable models. The work is relevant to SDG 13 (Climate Action) by supporting monitoring of climate-related hazards. It also contributes to SDG 11 (Sustainable Cities and Communities) by strengthening preparedness and risk reduction through improved information.

SUPPORTING **SDG 13 (CLIMATE ACTION)** AND **SDG 11 (SUSTAINABLE CITIES)**, THIS APPROACH USES **HIGH-FREQUENCY SATELLITE DATA AND AI TO IMPROVE WILDFIRE DETECTION**, STRENGTHENING EARLY WARNING SYSTEMS AND PROTECTING COMMUNITIES FROM CLIMATE-RELATED HAZARDS.

Additional References or Resources

S. Girtsou, K. Alexis, G. Giannopoulos, and C. Kontoes. HighFM: Towards a Foundation Model for Learning Representations from High-Frequency Earth Observation Data. arXiv preprint arXiv:2604.04306, 2026 (to appear in IJCAI-ECAI 2026).

IWMI - Digital Twin for Drought and Flood Monitoring in the Limpopo River Basin

Title of GeoAI Practice

Digital Twin for Drought and Flood Monitoring in the Limpopo River Basin

Brief Description

The Limpopo River Basin Digital Twin is an advanced GeoAI-driven platform developed by the International Water Management Institute (IWMI) under the Digital Innovations for Water Secure Africa (DIWASA) initiative supported by The Leona M. and Harry B. Helmsley Charitable Trust and Digital Transformation Accelerator of Consultative Group on International Agricultural Research (CGIAR). It creates a dynamic virtual replica of the Limpopo River Basin spanning approximately 400,000 km² across Botswana, Mozambique, South Africa, and Zimbabwe by integrating real-time IoT sensor data, satellite remote sensing, hydrological models, and AI-assisted river discharge measurement capability through citizen science and mobile technology, including computer vision algorithms for satellite image classification, CatBoost regression–based high resolution ET (20m) Downscaller, machine learning based irrigated area mapping and spatiotemporal pattern recognition for drought onset detection, forming the analytical backbone of the platform. The platform supports Disaster Risk Management by enabling near real time monitoring of river flows, reservoir levels, crop health and predictive simulations to forecast the impacts of extreme weather events such as floods and droughts on vulnerable communities and infrastructure. By bridging historical datasets with continuously updated observations and three month seasonal forecasts, the Digital Twin empowers transboundary water managers and decision-makers to test response scenarios before disasters strike, shifting disaster management from reactive response toward anticipatory, evidence-based resilience building. The developed prototype (2025) is in now production phase （from April 2026） and officially handed over to the Limpopo Watercourse Commission （LIMCOM） for operational trials across its four member states.

INTEGRATING IOT, SATELLITE EARTH OBSERVATION, AND AI FORECASTING, THE LIMPOPO DIGITAL TWIN DELIVERS TRANSBOUNDARY EARLY WARNING FOR FLOODS AND DROUGHTS — **ENABLING ANTICIPATORY ACTION THAT PROTECTS VULNERABLE COMMUNITIES ACROSS FOUR AFRICAN NATIONS.**

Challenge or Problem Addressed

The Limpopo River Basin is one of southern Africa's most climate-vulnerable transboundary watersheds, facing recurrent floods and prolonged droughts that threaten food security, livelihoods, and critical infrastructure across four nations. Key challenges include:

(1) Fragmented and sparse hydro-meteorological monitoring networks, with ground-based sensors unevenly distributed across the basin, creating significant data gaps that hinder timely early warning;
(2) Limited transboundary coordination, as water management decisions are often made in national silos without a shared operational picture of basin-wide conditions;
(3) Reactive disaster response paradigms, where authorities respond after extreme events have already caused damage rather than proactively preparing through scenario-based planning; and
(4) Lack of integrated decision-support tools that can

IMWI - Digital Twin for Drought and Flood Monitoring in the Limpopo River Basin

synthesize heterogeneous data streams from satellite imagery to in-situ sensors to community observations into actionable intelligence for drought and flood monitoring, environmental flow management, and water allocation under stress.

The Digital Twin directly addresses these challenges by providing a unified, continuously updated virtual environment for evidence-based, anticipatory water resource and disaster risk management.

Technical Approach and Methods

The Digital Twin is built on a SWAT (Soil and Water Assessment Tool) hydrological model running in near-real-time across 1,408 river channels calibrated against data from 305 discharge stations provided by South Africa's Department of Water and Sanitation. It integrates a high-resolution 3D topographical base map with multiple data layers including river discharge, rainfall, reservoir levels, and ecosystem health indicators. Satellite remote sensing from Digital Earth Africa and other data providers fills spatial gaps where ground-based sensors are sparse. Machine learning and neural network models are employed for reservoir volume estimation, flood prediction, drought index computation, and environmental flow assessment. The platform incorporates IoT sensor networks for real-time water level and quality monitoring, complemented by citizen science data collected through AI-powered digitization and validation tools co-developed with local partners, AWARD and GroundTruth. A three-month seasonal forecast module enables forward-looking scenario planning. The system is hosted on cloud infrastructure leveraging Microsoft Azure and Amazon Web Services, ensuring scalability and accessibility for transboundary stakeholders. Additionally, IWMI and Microsoft Research co-developed the Limpopo Water Copilot an AI-powered virtual assistant built on generative AI that interfaces directly with the Digital Twin to provide natural-language access to water availability data, environmental flow conditions, seasonal forecasts, and drought monitoring insights.

Specifically, the project is planning to employs Long Short-Term Memory (LSTM) networks trained on historical streamflow and satellite-derived precipitation data for multi-step-ahead forecasting, random forest and gradient boosting models for spatial downscaling of coarse-resolution climate inputs, and geospatial computer vision pipelines for automated land use and land cover change detection from high resolution remote sensing data like Sentinel-2.

Implementation and Collaborations

The Digital Twin was implemented through the DIWASA (Digital Innovations for Water Secure Africa) project, led by IWMI as a CGIAR Research Center, with funding and support from Enabel (Belgian Development Agency). The initiative brought together over 20 experts across a multi-stakeholder consortium. Key partnerships include: the Limpopo Watercourse Commission (LIMCOM), which serves as the primary end-user and transboundary governance body for the basin's four member states (Botswana, Mozambique, South Africa, and Zimbabwe); technology partners Microsoft Research (Farm Vibes project) and Amazon Web Services for cloud computing and AI capabilities; GroundTruth and AWARD (Association for Water and Rural Development) for citizen science data collection and validation tooling; Hidromod for hydrodynamic modeling expertise and YOMA-UNICEF digital marketplace for engaging youth citizen scientists. The hands-on training workshops were conducted for member-state representatives in Gaborone, Botswana, in June 2025.

IWMI - Digital Twin for Drought and Flood Monitoring in the Limpopo River Basin

Impact and Outcomes

The Digital Twin has delivered several tangible outcomes and anticipated benefits:

(1) Transboundary operational capability: The prototype was successfully handed over to LIMCOM, providing four nations with a shared, near-real-time decision-support platform for the first time, strengthening transboundary cooperation on flood preparedness, drought response, and water allocation;
(2) Enhanced monitoring coverage: By combining satellite remote sensing with ground-based sensors and citizen science, the platform dramatically expands observational coverage across the 400,000 km² basin, overcoming chronic data scarcity;
(3) Citizen science network: The initiative is establishing a transboundary network targeting at least 80 active citizen scientists contributing approximately 10,000 data points annually, embedding community participation in water governance;
(4) Anticipatory action: The three-month seasonal forecast capability enables proactive disaster preparedness rather than reactive response, potentially reducing flood and drought damages and enabling timelier humanitarian action;
(5) Capacity building: Training workshops for LIMCOM member-state representatives have built institutional capacity for sustained operation and further development of the platform;
(6) Replicability and scaling: Building on the Limpopo experience proves that digital twins are not just research prototypes but transferable, institution-ready tools, and we have developed another digital twin (prototype) to strengthen climate resilience in Dolo Ado, a highly fragile and climate-vulnerable district in Ethiopia's Somali Region.

Lessons Learned and Recommendations

Key lessons learned from implementing the Limpopo Digital Twin include:

(1) Co-design with end-users is essential: Early and sustained engagement with LIMCOM and national water agencies ensured the platform addressed real operational needs rather than purely academic objectives. The hands-on training workshops proved critical for building institutional ownership and sustainability.
(2) Citizen science bridges data gaps but requires sustained investment: While community-based monitoring dramatically expanded data coverage, maintaining an active network of citizen scientists across four countries requires ongoing coordination, training, and incentive structures such as the YOMA-UNICEF digital marketplace.
(3) Interoperability and open standards matter: Integrating heterogeneous data streams from national agencies, satellite providers, IoT sensors, and citizen observers demanded robust data standards and quality assurance protocols.
(4) Cloud-based architecture enables scalability: Leveraging Microsoft Azure and AWS provided the computational power needed for near-real-time hydrological modeling at basin scale, while ensuring accessibility for stakeholders across multiple countries.
(5) Transboundary governance adds complexity: Navigating data-sharing agreements and institutional arrangements across four sovereign nations required diplomatic sensitivity and the trusted convening role of LIMCOM.
(6) Recommendations for practitioners: invest heavily in stakeholder engagement from the outset, design for interoperability from day one, build local capacity for sustained operation, and plan for long-term institutional hosting beyond the project cycle.

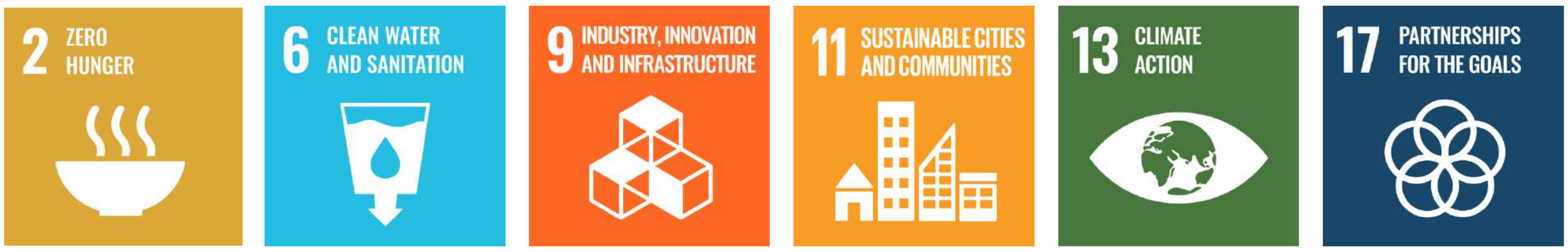
IWMI - Digital Twin for Drought and Flood Monitoring in the Limpopo River Basin

Alignment with SDGs

This practice directly supports UN-SPIDER's mission to ensure that all countries and international organizations have access to and develop the capacity to use space-based information for disaster management and emergency response. The Limpopo Digital Twin leverages satellite Earth Observation as a core data source to bridge monitoring gaps and deliver actionable early warning intelligence to disaster-vulnerable communities. Alignment with specific SDGs includes:

- SDG 2 (Zero Hunger) by improving drought monitoring and water allocation for agriculture, protecting food production in climate-stressed regions;
- SDG 6 (Clean Water and Sanitation) by providing near-real-time water quality monitoring and supporting equitable transboundary water resource management;
- SDG 9 (Industry, Innovation, and Infrastructure) through the innovative integration of IoT, AI, satellite remote sensing, and citizen science into a unified digital infrastructure;
- SDG 11 (Sustainable Cities and Communities) by enhancing flood early warning and resilience planning for vulnerable urban and rural communities;
- SDG 13 (Climate Action) by enabling anticipatory, evidence-based responses to climate-induced extreme weather events;
- SDG 17 (Partnerships for the Goals) through its multi-stakeholder, transboundary partnership model involving international organizations, national agencies, academia, private sector technology companies, and local communities.

The practice also aligns with the Sendai Framework for Disaster Risk Reduction by strengthening early warning systems and promoting the use of science, technology, and innovation for disaster resilience.



Additional References or Resources

- IWMI Digital Twins Portal: https://digitaltwins.iwmi.org/
- Limpopo River Basin Programme: https://digitaltwins.iwmi.org/programmes/limpopo-river-basin/
- Somalia Programme: https://digitaltwins.iwmi.org/programmes/somali-region-of-ethiopia/
- CGIAR News: "Digital twin for water management handed over for trial in the Limpopo River Basin," https://www.cgiar.org/news-events/news/digital-twin-handover-limpopo/
- DIWASA Project Page: https://www.iwmi.org/projects/diwasa/
- Ghosh, S., Kayathri, V., Dickens, C. et al. Recent Drought Prevalence in the Limpopo River Basin: Insights from the Digital Twin Platform. J Indian Soc Remote Sens (2025). https://doi.org/10.1007/s12524-025-02133-y

IWMI - Digital Twin for Drought and Flood Monitoring in the Limpopo River Basin

- Afham, A.; Kiala, Z.; Ghosh, S.; Garcia Andarcia, M. 2025. Evolving the Limpopo Digital Twin Open Data Cube: from legacy catalogs to spatiotemporal asset catalog-native, user managed and containerized workflows. Colombo, Sri Lanka: International Water Management Institute (IWMI). CGIAR Accelerator for Digital Transformation. 31p. https://hdl.handle.net/10568/181458
- Retief, H.; Vigneswaran, K.; Ghosh, S.; Garcia Andarcia, M.; Dickens, C. (2025). Satellite-surface-area machine-learning models for reservoir storage estimation: regime-sensitive evaluation and operational deployment at Loskop Dam, South Africa. arXiv, 20p. https://doi.org/10.48550/arXiv.2502.19989
- Kiala, Z.; Matheswaran, K.; Dickens, C.; Andarcia, M.G.; Ludwig, F.; Ghosh, S. (2026). Operational Sentinel-2 Based System for Near Real-Time Irrigated Area Monitoring in the Limpopo River Basin. Discover Water. https://doi.org/10.1007/s43832-026-00360-z
- Vigneswaran, K.; Retief, H.; Clifford-Holmes, J.; Garcia Andarcia, M.; Tennakoon, H. (2025). AI-assisted river discharge measurement through citizen science and mobile technology. Colombo, Sri Lanka: IWMI. CGIAR Accelerator for Digital Transformation. 53p. https://hdl.handle.net/10568/181393
- Afham, A.; Kiala, Z.; Ghosh, S.; Garcia Andarcia, M. (2025). Evolving the Limpopo Digital Twin Open Data Cube: from legacy catalogs to spatiotemporal asset catalog-native, user managed and containerized workflows. Colombo, Sri Lanka: IWMI. CGIAR Accelerator for Digital Transformation. 31p. https://hdl.handle.net/10568/181458
- Jolaiya, E. A.; Retief, H.; Silva, P.; Afham, A.; Vickneswaran, K.; Garcia Andarcia, M. 2025. Limpopo Digital Twin architecture report. Colombo, Sri Lanka: International Water Management Institute (IWMI). CGIAR Accelerator for Digital Transformation. 18p. https://hdl.handle.net/10568/180960
- Tlhomole, J.; Borgomeo, E.; Matheswaran, K.; Garcia Andarcia, M. 2026. Towards operational streamflow forecasting in the Limpopo River Basin using long short-term memory networks. arXiv, 14p. doi: https://doi.org/10.48550/arXiv.2601.06941

IWMI - WaterCopilot: An AI-Driven Virtual Assistant for Flood and Drought Decision Intelligence in the Limpopo River Basin

Title of GeoAI Practice

WaterCopilot: An AI-Driven Virtual Assistant for Flood and Drought Decision Intelligence in the Limpopo River Basin

Brief Description

WaterCopilot is an AI-driven virtual assistant developed jointly by the International Water Management Institute (IWMI) and Microsoft Research to democratize access to flood and drought decision intelligence across the Limpopo River Basin. Built on Retrieval-Augmented Generation (RAG) and tool-calling architectures, WaterCopilot interfaces directly with the Limpopo Digital Twin to empower decision-makers with daily, actionable situational awareness without requiring technical expertise in hydrology or data science. At its core, WaterCopilot exemplifies the GeoAI paradigm by fusing geospatial data layers, including satellite-derived flood extent maps from Sentinel-1 SAR imagery, spatially distributed hydrological models, and georeferenced IoT sensor readings with large language model reasoning to enable location-aware, context-sensitive decision support. Through a natural-language chatbot interface, users can query real-time and historical hydrological conditions, receive automated alerts when monitoring stations breach critical discharge thresholds, identify dams with critically low storage levels, and access visual hydrographs and animated flood-extent maps. The system supports guided multilingual interactions in English and Portuguese, reflecting the transboundary nature of the basin spanning Botswana, Mozambique, South Africa, and Zimbabwe. By enabling a decision-maker to move from a high-level basin overview to granular, station-specific risk assessment in seconds, WaterCopilot transforms complex hydrological data into a reliable, up-to-date situational picture that guides policy actions, cross-border coordination, early warning issuance, and community preparedness efforts, shifting disaster management from reactive crisis response to proactive risk mitigation.

WATERCOPILOT TRANSLATES COMPLEX **SATELLITE-DERIVED FLOOD MAPS AND HYDROLOGICAL FORECASTS INTO INTUITIVE NATURAL-LANGUAGE ANSWERS AND VISUAL ALERTS** — ENABLING NON-TECHNICAL DECISION-MAKERS TO ACT ON REAL-TIME DROUGHT AND FLOOD RISKS ACROSS THE LIMPOPO RIVER BASIN.

Challenge or Problem Addressed

Water managers and disaster risk officials across the Limpopo River Basin face a critical bottleneck: while the Digital Twin generates vast quantities of hydrological data river discharge, reservoir levels, rainfall patterns, environmental flow conditions, and seasonal forecasts translating this information into timely, actionable decisions remains a formidable challenge. Key problems include:

(1) Data accessibility gap: Decision-makers often lack the technical expertise in GIS, hydrology, or data science needed to query, interpret, and act upon complex model outputs, creating a disconnect between available intelligence and operational decision-making;

(2) Time-critical response requirements: During flood events, authorities need to identify which stations are breaching dangerous discharge thresholds and which communities are at risk within minutes, not hours of manual analysis;

(3) Drought creep and dam storage depletion: Slow-onset droughts require continuous monitoring of storage levels and environmental flow conditions across

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Slow-onset droughts require continuous monitoring of storage levels and environmental flow conditions across dozens of dams and hundreds of stations, a task beyond manual capacity;
(4) Transboundary language and coordination barriers: With four countries and multiple official languages, information must be accessible in English and Portuguese to support cross-border coordination;
(5) Lack of intuitive visualization: Raw data tables and model outputs are difficult for non-technical stakeholders to interpret without visual aids such as hydrographs and animated flood-extent maps that convey risk at a glance.

Technical Approach and Methods

WaterCopilot is architected on two foundational AI paradigms: Retrieval-Augmented Generation (RAG) for document-grounded question answering, and agentic tool-calling for real-time data retrieval and computation. The system comprises two custom plugins:

(1) The iwmi-doc-plugin, which enables semantic search over an indexed corpus of basin policy documents, water management reports, and environmental guidelines using Azure AI Search with vector embeddings; and
(2) the iwmi-api-plugin, which queries live hydrological databases from the Limpopo Digital Twin to deliver dynamic, real-time insights including environmental-flow alerts, rainfall trend analysis, reservoir storage levels, water accounting metrics, and irrigation demand data.
(3) The AI orchestration layer powered by large language models via Azure OpenAI Service interprets user queries in natural language, selects the appropriate plugin and data source, performs automated calculations, and generates contextual responses accompanied by visual outputs including interactive hydrographs, time-series charts, and animated flood-extent maps derived from satellite imagery and hydrological model outputs. Data sources include the SWAT hydrological model running in near-real-time across 1,408 channels, 305 discharge monitoring stations, satellite remote sensing from Digital Earth Africa, IoT sensor networks, and citizen science observations.
(4) The system is deployed via Docker containers on AWS infrastructure for scalability and reliability and supports guided multilingual interactions in English and Portuguese. Evaluation using the Retrieval-Augmented Generation Assessment (RAGAS) framework, a standard framework for assessing retrieval-augmented AI systems, demonstrates strong performance with an overall score of 0.80, including high answer relevancy (0.86) and context precision (0.80), confirming the reliability of its AI-generated responses for operational decision-making.
(5) The GeoAI dimension is central to the system's architecture: geospatial machine learning models process multi-temporal satellite imagery to generate flood inundation maps, while spatial indexing enables the AI agent to reason over geographic proximity, upstream-downstream connectivity, and basin topology when answering user queries. This tight coupling of geospatial reasoning with generative AI distinguishes WaterCopilot from conventional chatbot systems that lack spatial awareness.

Implementation and Collaborations

WaterCopilot was developed through a strategic partnership between the International Water Management Institute (IWMI), a CGIAR Research Center, and Microsoft Research, combining IWMI's deep domain expertise in water resource management with Microsoft's advanced AI and cloud computing capabilities. The initiative was implemented as a complementary interface layer to the Limpopo River Basin Digital Twin, itself developed under the DIWASA (Digital Innovations for Water Secure Africa) project with funding from Enabel (Belgian Development Agency). Implementation followed a co-design approach with the Limpopo Watercourse Commission (LIMCOM) and its four member-state water

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agencies in Botswana, Mozambique, South Africa, and Zimbabwe, ensuring the system addressed real operational workflows and decision-making needs. Microsoft Research contributed the Farm Vibes AI framework and Azure OpenAI Service capabilities, while Amazon Web Services provided the scalable Docker-based deployment infrastructure. The semantic search component leverages Azure AI Search for document indexing, and the live data pipeline connects to the Digital Twin's hydrological databases maintained by IWMI. User testing and iterative refinement were conducted with LIMCOM officials and national water managers during hands-on training workshops, including sessions in Gaborone, Botswana (June 2025). The WaterCopilot was presented at the UAE AI Ecosystem for Global Agricultural Development through CGIAR, and a peer-reviewed technical paper was published on arXiv, demonstrating the scientific rigour of the approach. Plans are underway to upgrade WaterCopilot to a mobile application with enhanced real-time push-notification features for field-level use.

Impact and Outcomes

WaterCopilot has delivered and is anticipated to deliver the following measurable outputs and outcomes:

(1) Usage: Water Copilot has demonstrated strong global adoption, with 190 registered users across 20+ countries, generating over 85,000 API requests and engaging 42+ organisations. Notably, 37% of the usage is research-driven, with peak activity reaching over 4000+ requests on 2 April 2026. South Africa emerged as the leading user base, contributing 31,000+ API requests.
(2) Dramatically reduced time-to-insight: Decision-makers can move from a high-level basin overview to a granular, station-specific flood or drought risk assessment in seconds through natural-language queries, compared to hours or days of manual data analysis previously required;
(3) Automated threshold-based early warning: The system continuously flags stations breaching high-flow warning and extreme-flow alert discharge percentiles and identifies dams with critically low storage, enabling leaders to prioritize emergency resource allocation and issue early warnings before conditions deteriorate;
(4) Validated AI reliability: RAGAS framework evaluation yielded an overall performance score of 0.80, with answer relevancy of 0.86 and context precision of 0.80, providing confidence in the accuracy of AI-generated responses for operational use;
(5) Multilingual accessibility: Support for English and Portuguese removes language barriers to transboundary information sharing across the four LIMCOM member states;
(6) Non-technical user empowerment: The natural-language interface with visual hydrographs and animated flood-extent maps eliminates the need for GIS or hydrological modeling expertise, broadening the user base to include policy-makers, emergency managers, and community leaders;
(7) Enhanced cross-border coordination: A shared, AI-mediated situational picture supports coordinated flood preparedness and drought response across national boundaries;
(8) Transparency and traceability: Every response includes source referencing, allowing users to verify the underlying data and documents, building trust in AI-driven decision support; and
(9) Scalable architecture: The Docker-on-AWS deployment pipeline is designed for replication across other river basins and water management contexts globally.
(10) GeoAI-powered spatial risk profiling: By combining satellite-derived land cover, elevation models, and real-time hydrological outputs through geospatial AI pipelines, WaterCopilot can automatically identify spatially vulnerable communities and infrastructure within flood-prone zones, enabling targeted rather than blanket early warning dissemination.

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Lessons Learned and Recommendations

Key lessons from developing and deploying WaterCopilot include:

(1) Domain grounding is non-negotiable for trust: The RAG architecture's ability to cite specific source documents and data provenance proved essential for building confidence among government officials. Decision-makers need to verify AI outputs against authoritative sources, and transparent referencing dramatically increases adoption willingness;
(2) User-centric design trumps technical sophistication: The most impactful design decisions were not algorithmic but experiential guided conversation flows, multilingual support, and visual outputs (hydrographs, animated flood maps) that matched how water managers actually think and communicate about risk. Co-design workshops with LIMCOM officials were indispensable;
(3) Threshold-based alerting bridges the awareness-action gap: Automated exceedance alerts and critical dam storage warnings convert passive data streams into proactive decision triggers, directly enabling the shift from reactive to anticipatory management;
(4) Evaluation must be rigorous and domain-specific: The RAGAS framework evaluation provided quantitative confidence in system reliability, but domain-specific validation with hydrologists was equally important to ensure outputs were not just linguistically fluent but hydrologically sound;
(5) Multilingual AI remains challenging: While English and Portuguese are supported, achieving consistently high-quality responses across all three languages, particularly for technical hydrological terminology, required extensive prompt engineering and evaluation.
(6) Infrastructure simplicity enables sustainability: The Docker-on-AWS deployment model allows LIMCOM to maintain the system with minimal DevOps expertise. Thus, prioritize transparent AI with source attribution, invest deeply in co-design with end-users, build evaluation frameworks early, design for multilingual contexts from the start, and ensure the deployment architecture matches the institutional capacity of the host organization.
(7) GeoAI requires robust geospatial data pipelines: The effectiveness of AI-driven water management tools depends critically on the quality, timeliness, and spatial resolution of underlying geospatial datasets. Ensuring continuous ingestion of satellite imagery, maintaining georeferenced sensor networks, and validating spatial model outputs are prerequisites that demand sustained investment and institutional commitment beyond the AI layer itself.

Alignment with SDGs

WaterCopilot directly advances UN-SPIDER's core mission of ensuring universal access to space-based information for disaster management by translating complex satellite-derived and model-generated hydrological intelligence into plain-language, actionable guidance that any decision-maker can use regardless of technical background. It embodies UN-SPIDER's emphasis on bridging the gap between data availability and decision-making capacity, particularly in developing countries. Alignment with specific SDGs includes:

- SDG 1 (No Poverty) by enabling anticipatory action and early warning that protects vulnerable livelihoods from flood and drought shocks;
- SDG 2 (Zero Hunger) by providing real-time drought monitoring and dam storage intelligence that safeguards agricultural water supplies;

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- SDG 6 (Clean Water and Sanitation) by supporting equitable transboundary water allocation through transparent, data-driven environmental flow monitoring;
- SDG 9 (Industry, Innovation, and Infrastructure) as a pioneering application of RAG-based generative AI and agentic tool-calling architectures for operational water management;
- SDG 11 (Sustainable Cities and Communities) by providing flood-extent visualization and threshold alerts that enable urban and rural disaster preparedness;
- SDG 13 (Climate Action) by empowering climate adaptation through seasonal forecasting and trend analysis accessible via natural language;
- SDG 16 (Peace, Justice, and Strong Institutions) by strengthening transboundary institutional cooperation through a shared, trusted, AI-mediated information commons;
- SDG 17 (Partnerships for the Goals) through the IWMI-Microsoft Research-LIMCOM partnership model combining public research, private technology, and intergovernmental governance.

The practice further aligns with the Sendai Framework's Priority 1 (Understanding Disaster Risk) by making risk information accessible and actionable at all levels.

Additional References or Resources

- WaterCopilot Platform: https://water-copilot.digitaltwins.iwmi.org/
- Vickneswaran, et al. (2026), "WaterCopilot: An AI-Driven Virtual Assistant for Water Management," arXiv preprint, https://arxiv.org/abs/2601.08559
- WaterCopilot Technical Guide: https://cgspace.cgiar.org/items/09223b77-1725-41d4-9a5c-84cac812a5a2
- WaterCopilot User Guide V0: https://cgspace.cgiar.org/items/39a21bcd-6303-49cb-b730-fd6b8185e515
- IWMI Water Copilot Project Page: https://www.iwmi.org/projects/water-copilot/
- IWMI News: "AI agent by IWMI and Microsoft to drive new thinking in water management," https://www.iwmi.org/news/ai-agent-by-iwmi-and-microsoft-to-drive-new-thinking-in-water-management/
- PreventionWeb: "AI agent by IWMI and Microsoft to drive new ideas in water management," https://www.preventionweb.net/news/ai-agent-iwmi-and-microsoft-drive-new-thinking-water-management
- IWMI Digital Twins Portal: https://digitaltwins.iwmi.org/
- Limpopo River Basin Programme: https://digitaltwins.iwmi.org/programmes/limpopo-river-basin/

IWMI - SukhaRakshak AI: India's First AI-Powered Drought Advisory and Anticipatory Action System

Title of GeoAI Practice

SukhaRakshak AI: India's First AI-Powered Drought Advisory and Anticipatory Action System

Brief Description

SukhaRakshak AI ("Drought Protector") is India's first integrated, AI-powered drought advisory system, designed to bridge the gap between early warning and early action. Developed by the International Water Management Institute (IWMI) with Indian Council of Agricultural Research (ICAR) partners under the CGIAR Climate Action Program, the platform fuses satellite Earth Observation, artificial intelligence, and weather/climate forecasts with India's district-level agriculture contingency plans. It builds on IWMI's South Asia Drought Monitoring System (SADMS) and adds a Retrieval-Augmented Generation (RAG) chatbot powered by Google Gemini and a Qdrant vector database to generate hyper-local, anticipatory advisories at village and district scales. Localized outputs are delivered in 22+ Indian languages through AI4Bharat and Sarvam AI, reaching smallholder farmers, extension officers, and drought managers via SMS, IVR, WhatsApp, mobile apps, and community radio. By shifting India's drought management from reactive relief to anticipatory risk reduction, SukhaRakshak AI protects livelihoods, stabilizes farmer incomes, and strengthens water and food security across 158 priority drought districts.

BY FUSING SATELLITE EARTH OBSERVATION, **AI-DRIVEN PROBABILISTIC FORECASTING**, AND A RAG-BASED CHATBOT GROUNDED IN DISTRICT CONTINGENCY PLANS, SUKHARAKSHAK AI DELIVERS HYPER-LOCAL, MULTILINGUAL DROUGHT ADVISORIES IN **22+ LANGUAGES** — EMPOWERING **120 MILLION** SMALLHOLDER FARMERS AND DISTRICT AUTHORITIES TO TAKE ANTICIPATORY ACTION WEEKS BEFORE DROUGHT STRIKES.

Challenge or Problem Addressed

Approximately 68% of India's cultivated area is drought-prone, exposing over 120 million smallholder farmers to recurring crop failure, livestock loss, and rural distress. Historical droughts (1965–67, 1987, 2002, 2015–16) cut national food-grain production by up to 29 million tons per event, and climate change is intensifying rainfall variability and agricultural drought frequency across South Asia. India's institutional response has traditionally been reactive — centered on compensation and emergency water supply — with fragmented data systems, limited real-time information flow, and coordination gaps between IMD, CWC, NDMA, NRAA, and state agriculture departments delaying action. Critical last-mile advisories have often been absent, overly generic, or delivered too late, or communicated in languages and formats that smallholders — especially women and marginalized groups — cannot easily use. This fragmentation prevents timely conversion of early warning into early action at farm and district scales.

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Technical Approach and Methods

SukhaRakshak AI is a cloud-native, AI-driven geospatial platform that converts multi-source Earth Observation, climate, and agronomic data into actionable, location-specific drought advisories. Its architecture rests on four pillars.

1. Multi-Source Data Integration: The system ingests satellite-derived indices (NDVI, VCI, Integrated Drought Severity Index, rainfall deficit, soil moisture), together with short-term (1–10 day) and sub-seasonal-to-seasonal (S2S) forecasts from IMD, NOAA's Global Ensemble Forecast System and Climate Forecast System, and IRI probabilistic precipitation outlooks. IWMI's South Asia Drought Monitoring System (SADMS) provides near-real-time regional assessments using SPI and vegetation-health indices. Digitized District Agriculture Contingency Plans developed by ICAR-CRIDA for 600+ districts supply region-specific crop, water, and livestock recommendations.
2. AI-Driven Analytics: A hybrid AI architecture combines (i) machine-learning models — transformer networks and time-series LSTMs trained on 20+ years of historical climate and drought-impact data — producing probabilistic drought forecasts at district and sub-district scales up to four weeks ahead; and (ii) a Retrieval-Augmented Generation (RAG) chatbot powered by Google Gemini 2.0 Flash, with an open-source Qdrant vector database that stores contingency-plan knowledge and retrieves context for user queries in natural language.
3. Localized Multilingual Delivery: AI4Bharat and Sarvam AI language models translate advisories into 22+ Indian languages and dialects, delivered as voice (IVR) and text through SMS, WhatsApp, mobile apps, and community radio. User-type adaptation tailors the message: farmers receive concise action-oriented alerts; extension officers receive technically detailed guidance; and government managers access dashboards with hotspot maps and resource-allocation summaries.
4. Cloud and Geospatial Infrastructure: The platform runs on AWS with Docker containerization for scalability and uses Google Earth Engine for rapid satellite-data processing. A FastAPI backend exposes APIs so that government portals (e.g., Krishi DSS, Meghdoot, Kisan Suvidha) and agri-tech platforms can integrate SukhaRakshak alerts seamlessly. Near-real-time ingestion pipelines convert new satellite observations of vegetation and moisture stress into updated advisories with minimal latency.
5. Data Flow and Outputs: Raw Earth Observation and forecast data → drought indices and AI-derived probabilistic forecasts → district/village-level risk classification → matched with contingency-plan actions → multilingual advisories pushed to end users and dashboards. Outputs include four-week drought-probability maps, village-level hotspot layers, crop and water-management recommendations, insurance-trigger signals, and monitoring indicators for government drought managers. The system is designed to interoperate with the Government of India's Krishi DSS and the Digital Agriculture Ecosystem (IDEA), ensuring that AI-driven anticipatory action complements existing digital public infrastructure rather than operating in isolation.

Implementation and Collaborations

SukhaRakshak AI is led by the International Water Management Institute (IWMI) with ICAR–Central Research Institute for Dryland Agriculture (CRIDA), the National Rainfed Area Authority (NRAA), and India's Ministry of Agriculture and Farmers' Welfare. The platform was presented at the UN AI for Good Global Summit (Geneva, July 2025) and is being piloted in Odisha and Tamil Nadu, with planned scale-up to 158 priority drought districts through state agriculture departments, KVKs, and ATMA networks. It is supported by the CGIAR Climate Action, Sustainable Farming, and Digital Transformation programs.

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Impact and Outcomes

SukhaRakshak AI is shifting Indian drought governance from reactive relief to anticipatory action. Initial pilots in Odisha and Tamil Nadu demonstrate that hyper-local, multilingual advisories enable smallholders to adjust sowing dates, switch to drought-tolerant varieties, and activate water-saving practices weeks ahead of onset. Extension officers and KVKs report stronger credibility and consistency in farmer outreach through standardized, evidence-based advisories. District administrators use geo-referenced hotspot dashboards to pre-position fodder, water tankers, and MGNREGA works. The platform creates objective triggers for faster PMFBY insurance payouts and data-driven drought declarations under NDMA and NRAA protocols. Expected benefits — tracked through structured M&E — include reduced crop losses, stabilized smallholder incomes, faster insurance disbursement, and better-targeted relief. By institutionalizing AI-driven drought services, SukhaRakshak AI helps safeguard livelihoods, water, and food security for millions of rural households.

Lessons Learned and Recommendations

First, technology alone is insufficient — AI outputs must be embedded in existing policy instruments (PMFBY, PMKSY, NDMA drought guidelines, state contingency plans) to scale. Second, last-mile delivery must be designed deliberately: 22+ languages, IVR for low-literacy users, WhatsApp/SMS for connected users, and community radio for remote areas all matter. Third, user-type adaptation matters — farmers, extension officers, and drought managers each need different levels of technical detail and visualization. Fourth, open data sharing from IMD, ISRO, and ICAR dramatically improves forecast accuracy; policy support for open APIs is critical. Fifth, RAG-based chatbots add value only when grounded in authoritative local sources — district contingency plans — rather than generic web knowledge.

We recommend: (i) institutionalize AI drought services within official drought protocols; (ii) link early warnings to financing (SDRF/NDRF, parametric insurance, MGNREGA); (iii) invest in ground data infrastructure; (iv) build capacity across extension networks; and (v) ensure inclusive, gender-responsive last-mile access led by NRAA

Alignment with SDGs

SukhaRakshak AI directly advances UN-SPIDER's mandate of using space-based information for disaster risk reduction and emergency response by operationalizing satellite Earth Observation and AI for anticipatory drought action. It contributes to the Sendai Framework for Disaster Risk Reduction (Priorities 1–4: risk understanding, governance, investment, and preparedness) and to the WMO-led Early Warnings for All (EW4All) initiative by strengthening end-to-end early-warning-to-early-action value chains for slow-onset hazards.

The platform supports multiple Sustainable Development Goals:

- SDG 2 (Zero Hunger) by protecting food production in rainfed areas;
- SDG 6 (Clean Water and Sanitation) through improved water-resource planning and efficiency;
- SDG 13 (Climate Action) by enabling adaptive, climate-informed agriculture; SDG 1 (No Poverty) by stabilizing smallholder incomes;
- SDG 5 (Gender Equality) through inclusive vernacular advisories that reach women farmers;

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- SDG 17 (Partnerships for the Goals) via multi-stakeholder collaboration across CGIAR, ICAR, NRAA, NDMA, and the UN system.

It is also aligned with India's National Action Plan on Climate Change and the National Mission for Sustainable Agriculture.

Additional References or Resources

- Amarnath, G.; Schmitter, P.; Sikka, A.; Rao, K. V.; Sudhishri, S.; Singh, V. K. 2025. SukhaRakshak AI – transforming drought preparedness in India. IWMI Policy Brief. Colombo, Sri Lanka: International Water Management Institute (IWMI). 16p. https://hdl.handle.net/10568/180380
- IWMI (2025). India to get its first AI-based chatbot to tackle drought. IWMI Blog, 8 July 2025. https://www.iwmi.org/blogs/india-to-get-its-first-ai-based-chatbot-to-tackle-drought/
- South Asia Drought Monitoring System (SADMS): https://dms.iwmi.org
- Drought Action Catalyst (IWMI / CGIAR): https://www.iwmi.org/projects/droughtaction/
- CGIAR Climate Action Program: https://www.cgiar.org/cgiar-research-portfolio-2025-2030/climate-action/

Section C: Emergency Response and Rapid Damage Assessment

Overview

GeoAI enables rapid damage mapping and relief coordination by analyzing satellite imagery in near real time. It can automatically detect impacts such as building collapse or flooding, improving response speed and accuracy in major disasters. Quick-turnaround analytics provide responders and planners with real-time insights, allowing fast decision-making and resource allocation. Tools like nighttime satellite imagery and AI models enhance situational awareness, supporting both immediate relief and long-term recovery planning.

Figure 24: Earth Observation of Night-Time Lights for Flood Risk Management
(c) UN-SPIDER Knowledge Portal

SUPARCO - Deep Learning Based Framework for Automated Damage Detection from Satellite Imagery using YOLOv11 and SAMGeo

Title of GeoAI Practice

Deep Learning Based Framework for Automated Damage Detection from Satellite Imagery using YOLOv11 and SAMGeo

Brief Description

Disasters such as earthquakes, floods, and hurricanes cause widespread destruction to buildings and infrastructure, making rapid and reliable damage assessment critical for effective disaster response. This GeoAI practice presents a deep learning–based framework for automated post-disaster damage detection from satellite imagery by integrating YOLOv11 for object detection and SAMGeo for geospatial segmentation. Using the xView open-source satellite dataset, the workflow detects built structures in pre- and post-disaster imagery, generates precise pixel-level segmentation masks, and performs change detection to identify damaged or missing buildings. The system produces interpretable damage maps and building-loss statistics that visually highlight affected areas.

Challenge or Problem Addressed

Post-disaster damage assessment traditionally relies on manual inspection of satellite imagery, which is time-consuming, labour-intensive, and prone to human error, particularly when analysing large geographic regions under emergency conditions. Delays in assessment directly hinder rescue operations, resource allocation, and recovery planning, potentially costing lives. Additionally, many disaster-affected regions in developing countries lack the technical infrastructure and trained personnel to rapidly process high-resolution satellite imagery at scale. This practice addresses these challenges by automating the entire damage detection pipeline from building detection and segmentation to change analysis and damage mapping using deep learning and geospatial AI tools. It also addresses the gap between the availability of remote sensing data and its practical use in governance and decision-making, ensuring that AI-generated outputs are directly usable by disaster management authorities for prioritizing interventions and planning post-disaster reconstruction.

Technical Approach and Methods

The framework employs a two-stage deep learning pipeline (Figure 25). First, YOLOv11 (You Only Look Once, v11), a single-stage object detection model, is fine-tuned on the xView satellite dataset, an open-source dataset containing over one million annotated objects across diverse urban and rural environments. The model was trained for 500 epochs using 640×640 pixel input resolution, an SGD optimizer with cosine learning rate scheduling, and a 70:20:10 train/validation/test split. YOLOv11 detects and localizes buildings and infrastructure in both pre- and post-disaster high-resolution satellite images, producing bounding boxes with confidence scores.

Second, the bounding boxes are passed as prompts to SAMGeo (Segment Anything Model for Geospatial Data), which extends Meta AI's foundational SAMGeo generates pixel-accurate segmentation masks that precisely delineate building footprints and infrastructure boundaries.

SUPARCO - Deep Learning Based Framework for Automated Damage Detection from Satellite Imagery using YOLOv11 and SAMGeo

Change detection is then performed by comparing pre- and post-disaster segmentation masks to produce binary change maps that highlight missing or damaged structures. Outputs are visualized using geemap and matplotlib, overlaid on satellite basemaps for easy interpretation. All pre-processing steps include image tiling, normalization, annotation formatting to YOLO-compatible formats, geospatial alignment of temporal image pairs, and GeoTIFF conversion for SAMGeo compatibility. The entire pipeline was implemented using the Ultralytics YOLO framework and Python-based geospatial libraries on GPU-enabled environments.

Implementation and Collaborations

This project was undertaken to strengthen existing capabilities in space-based disaster management by introducing an AI-enabled framework for rapid and automated damage assessment from satellite imagery. The work demonstrates how deep learning and geospatial analysis can enhance current disaster response workflows through faster and more consistent infrastructure damage mapping. Building on the success of this implementation for structural damage detection, the work is now being extended to address flood damage assessment, with the aim of broadening its applicability across multiple disaster types and further supporting operational decision-making.

Impact and Outcomes

The framework produced several measurable and impactful outcomes:

- Automated building detection: YOLOv11 achieved a mean Average Precision at IoU 0.5 (mAP@50) of approximately 0.9, demonstrating strong localization accuracy for building detection from satellite imagery.
- Quantified structural loss: Change detection analysis on Gaza imagery revealed a 58% building loss (300 pre-disaster buildings reduced to 126 post-disaster), while the Myanmar earthquake case showed a 13.62% building loss (279 to 241 buildings), providing concrete damage statistics for decision-makers.
- Rapid damage mapping: The automated pipeline significantly reduces the time required for post-disaster assessment compared to manual interpretation, enabling near-real-time situational awareness.
- Interpretable visual outputs: Damage maps, segmentation overlays, and building-loss comparison charts were generated in formats directly usable by disaster management authorities and policymakers, enhancing transparency and evidence-based governance.
- Capacity building: The project demonstrated that open-source deep learning and geospatial tools can be effectively combined for disaster damage detection, providing a replicable model for institutions in developing countries with limited computational and financial resources.
- Governance relevance: The outputs were designed to inform emergency resource allocation, recovery prioritization, and infrastructure rebuilding decisions, bridging the gap between technical AI research and practical disaster governance.

Lessons Learned and Recommendations

Key Insights:

SUPARCO - Deep Learning Based Framework for Automated Damage Detection from Satellite Imagery using YOLOv11 and SAMGeo

- Combining object detection (YOLOv11) with foundation-model segmentation (SAMGeo) provides a powerful and flexible pipeline for damage detection that leverages the strengths of both approaches—fast localization and precise boundary delineation.
- Open-source datasets such as xView and freely available AI frameworks make it feasible for institutions in resource-constrained settings to develop effective GeoAI solutions for disaster management.
- Integrating a governance perspective into technical AI projects ensures that outputs are designed for actionable use by decision-makers, not just academic evaluation.

Challenges Encountered:

- Small object detection in dense urban areas: Densely packed structures and overlapping bounding boxes in urban regions posed challenges for accurate detection and segmentation.

Alignment with SDGs

The practice contributes to the following Sustainable Development Goals (SDGs):

- SDG 11 (Sustainable Cities and Communities): By identifying damaged infrastructure and supporting resilient urban recovery planning.
- SDG 13 (Combat Climate Change and its Impacts): By providing tools to rapidly assess the impact of climate-related disasters such as floods and extreme weather events on built environments.
- SDG 9 (Resilient Infrastructure): By employing cutting-edge deep learning (YOLOv11) and foundation models (SAMGeo) to innovate infrastructure damage assessment workflows.

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

Future Work

UN-SPIDER regional support office in Pakistan, i.e., SUPARCO, is currently implementing this approach for the 2025 flood. Outcomes of this study will be provided to UN-SPIDER at the time of final review.

Additional References or Resources

- D. Lam et al., "xView: Objects in Context in Overhead Imagery," arXiv:1802.07856, 2018.

SUPARCO - Deep Learning Based Framework for Automated Damage Detection from Satellite Imagery using YOLOv11 and SAMGeo

- A. Kirillov et al., "Segment Anything," arXiv:2304.02643, 2023.
- Q. Wu and L. P. Osco, "samgeo: A Python package for segmenting geospatial data with the Segment Anything Model (SAM)," Journal of Open Source Software (JOSS), vol. 8, no. 89, 2023.
- Ultralytics, "YOLOv11 documentation," 2025. Available: https://docs.ultralytics.com/models/yolo11/
- xView Dataset: http://xviewdataset.org/
- SAMGeo GitHub Repository: https://github.com/opengeos/segment-geospatial
- Xu, Y., Tu, Z., & Li, H. (2020). Building damage detection in satellite imagery using deep learning. Remote Sensing, 12(23), 4055.
- Rahman, M. S., Kervyn, M., & Kervyn, F. (2021). Remote sensing and geospatial technologies for rapid damage assessment and post-disaster governance. Natural Hazards, 107(1), 143–162.

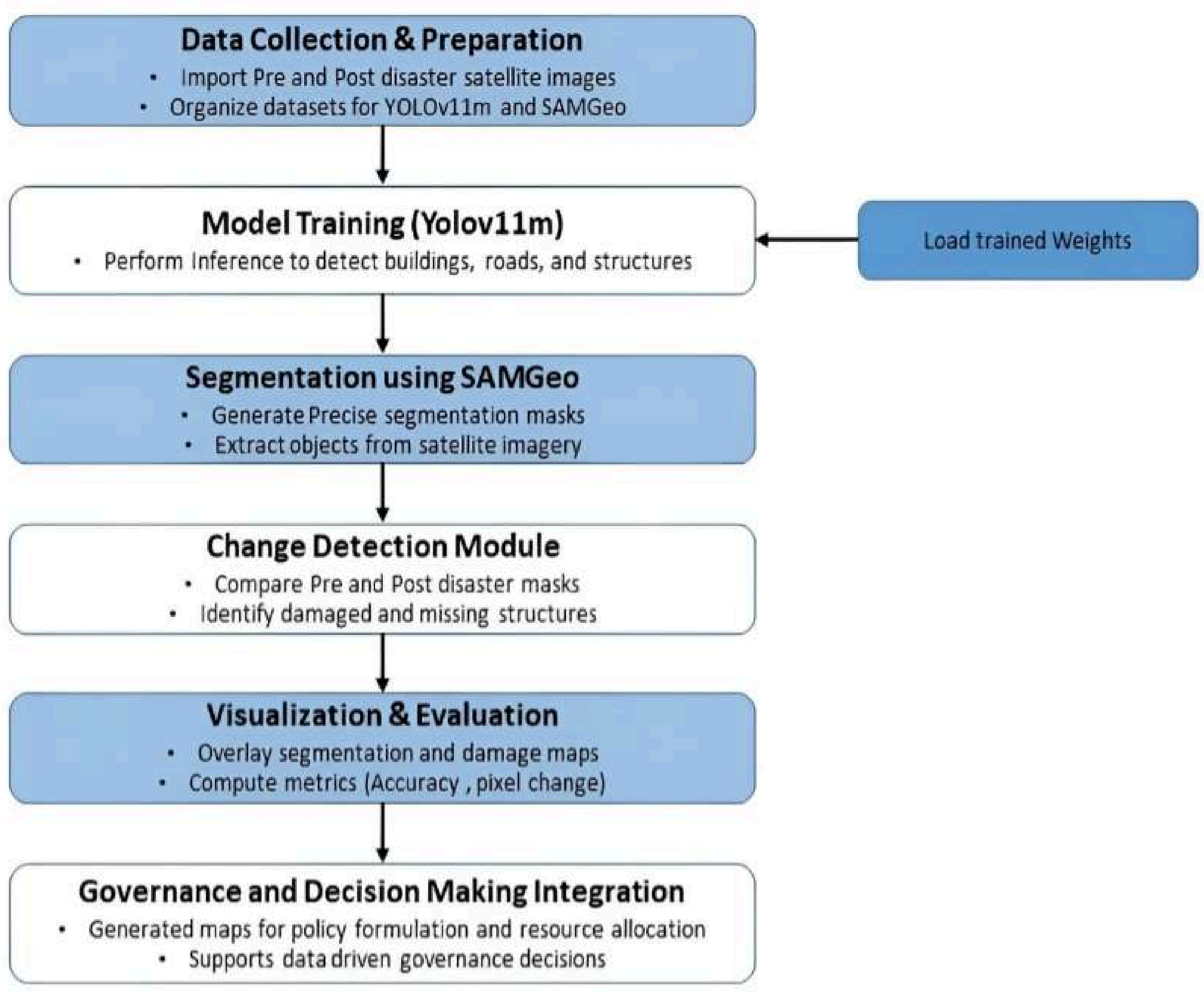

Figure 25: Deep Learning Based Detection & Segmentation Workflow (YOLOv11 + SAMGeo)

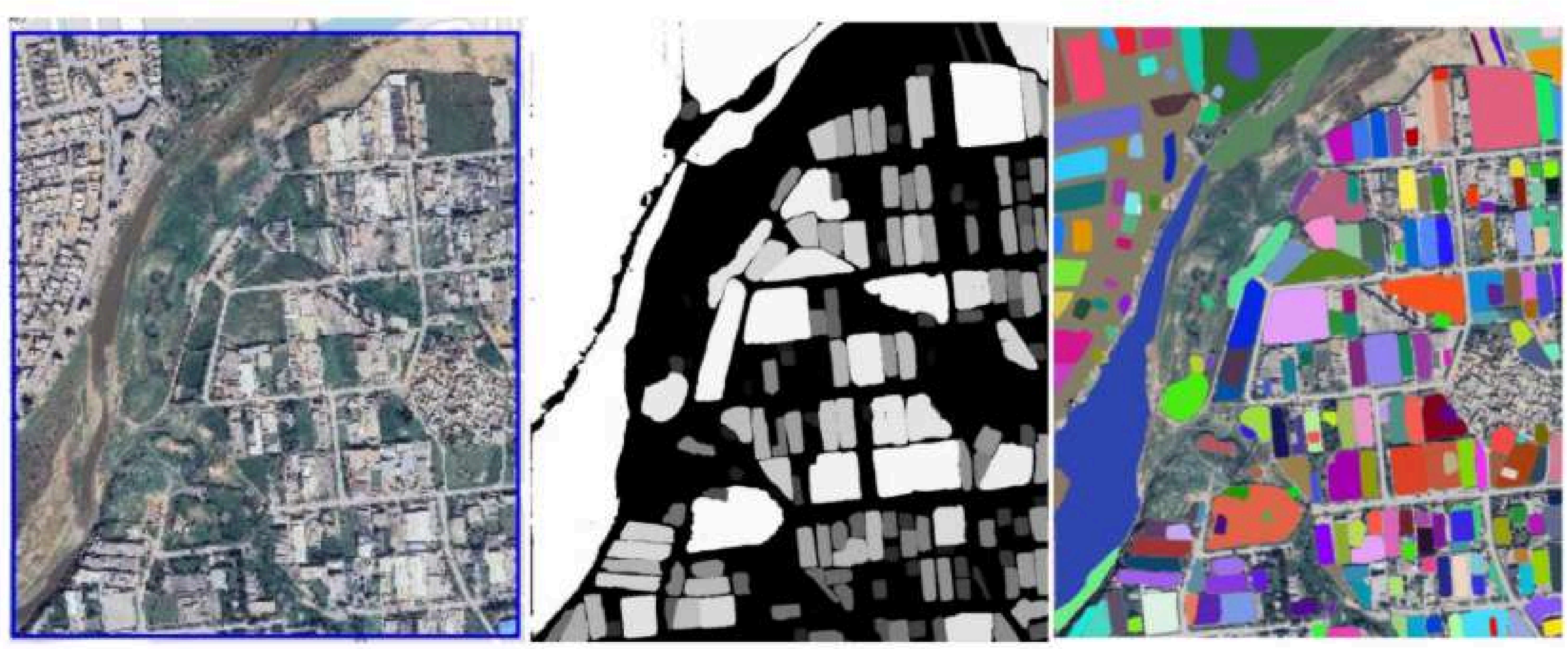

Figure 26: Segmentation Input and Output

SUPARCO - Deep Learning Based Framework for Automated Damage Detection from Satellite Imagery using YOLOv11 and SAMGeo

Figure 27: Segmentation Output on Input Image

Figure 28: Myanmar Earthquake 2025

Figure 29: Inference Prediction Results of Gaza, Palestine (2022 and 2024)

Section D: Recovery, Reconstruction, and Resilience Building

Overview

Post-disaster recovery must address both immediate humanitarian needs and long-term rebuilding to avoid recurring vulnerabilities. Integrating disaster risk reduction and climate resilience—such as improved building codes and early warning systems—helps ensure safer, more sustainable recovery. Geospatial and AI technologies support this by providing damage maps, risk assessments, and satellite imagery that guide reconstruction. These tools help prioritize interventions, inform land-use planning, and ensure resources reach the most affected areas, accelerating recovery and building lasting resilience.

Figure 30: Satellite Imagery Used for Assessment and Aid Relief Efforts After Earthquake Hit Port-Au-Prince
(c) UN Earth Observation and Imagery

Delta State University - GeoAI for Institutional Dependency and Automation Bias Awareness

Title of GeoAI Practice

GeoAI for Institutional Dependency and Automation Bias Awareness

Brief Description

This GeoAI practice examines how organizations can become operationally dependent on AI-driven spatial decision systems. Developed through Delta State University's GeoAI Risks curriculum, the initiative explores institutional dependency, automation bias, and overreliance on GeoAI-generated outputs within emergency management and disaster-response environments. Through applied exercises and simulation-based learning, participants evaluate how human operators respond to conflicting spatial information and how institutional structures influence trust in automated systems.

> THROUGH **SCENARIO-DRIVEN SIMULATIONS**, THIS PRACTICE EXPOSES **HOW AUTOMATION BIAS AND INSTITUTIONAL DEPENDENCY CAN UNDERMINE DISASTER DECISIONS**—AND EQUIPS OPERATORS WITH THE CRITICAL OVERSIGHT NEEDED TO KEEP GEOAI A TRUSTED TOOL, NOT A DEFAULT AUTHORITY

Challenge or Problem Addressed

As GeoAI systems become increasingly integrated into disaster-response operations, organizations may begin treating AI outputs as unquestioned authorities. This creates risks associated with automation bias, institutional fragility, and reduced human oversight. The practice addresses the need for governance-aware GeoAI education that reinforces human judgment, operational skepticism, and resilient decision-making.

Implementation and Collaborations

The initiative was implemented through Delta State University's GeoAI Risks educational framework using interdisciplinary instruction combining GIS, AI ethics, emergency management, and spatial decision support. Laboratory exercises and facilitated discussions were used to encourage critical evaluation of AI-generated outputs.

Technical Approach and Methods

The practice combines geospatial analysis, operational simulations, scenario-based decision exercises, and governance-focused AI evaluation. Participants use ArcGIS Pro, spatial dashboards, Earth Observation products, and simulated emergency management scenarios to evaluate how decision systems behave under uncertainty and conflicting information conditions.

Delta State University - GeoAI for Institutional Dependency and Automation Bias Awareness

Impact and Outcomes

Participants gained a deeper understanding of automation bias, institutional dependency, and the importance of maintaining human oversight within GeoAI-enabled systems. The initiative strengthened awareness of trustworthy AI principles and helped reinforce resilient operational decision-making practices.

Lessons Learned and Recommendations

- Effective GeoAI systems require governance-aware implementation strategies that maintain human accountability and operational transparency. Future programs should integrate ethics, uncertainty analysis, and human-machine interaction into disaster management education and training.
- Applied simulations required participants to evaluate conflicting Earth Observation products, including discrepancies between satellite-derived flood extents and locally reported ground conditions, in order to examine human reliance on GeoAI outputs during operational decision-making.
- The framework emphasizes scalable and transferable governance-aware GeoAI education that can support disaster management training programs internationally.

Alignment with SDGs

This practice aligns with UN-SPIDER goals by promoting responsible and resilient use of geospatial technologies for disaster management. It supports SDG 16 (Peace, Justice, and Strong Institutions), SDG 11 (Sustainable Cities and Communities), and SDG 9 (Industry, Innovation, and Infrastructure).

Delta State University - GeoAI for Institutional Dependency and Automation Bias Awareness

Additional References or Resources

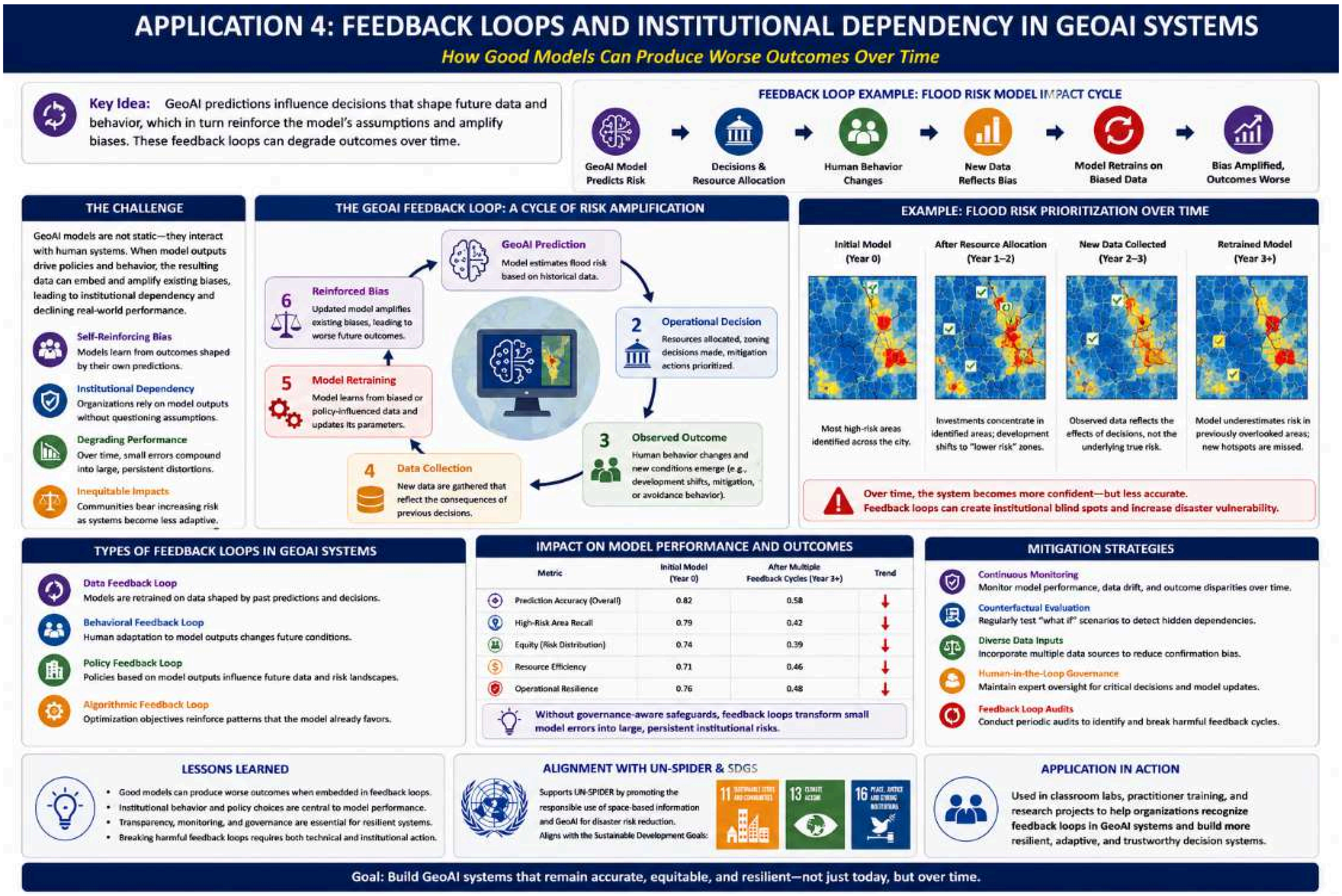

Figure 31: Feedback Loops and Institutional Dependency in GeoAI Systems

Delta State University - GeoAI Educational Framework for Disaster Risk Reduction Capacity Building

Title of GeoAI Practice

GeoAI Educational Framework for Disaster Risk Reduction Capacity Building

Brief Description

This GeoAI practice represents an interdisciplinary educational framework designed to build disaster risk reduction capacity through applied GeoAI instruction. Developed within the Delta State University GIT program, the initiative integrates Earth Observation, spatial analytics, machine learning, emergency management, and governance-aware AI into a cohesive instructional ecosystem. The curriculum combines classroom instruction with hands-on laboratories using ArcGIS Pro, Python, Google Earth Engine, and open-source geospatial tools. Students engage with real-world disaster management scenarios involving flood risk, wildfire exposure, spatial bias, adversarial geography, and GeoAI ethics.

Challenge or Problem Addressed

Many GeoAI educational programs emphasize technical AI development without adequately addressing governance, operational decision-making, spatial uncertainty, or disaster risk reduction. This practice addresses the need for interdisciplinary GeoAI education capable of supporting resilient and responsible use of geospatial technologies.

Technical Approach and Methods

The educational framework incorporates Earth Observation analysis, machine learning workflows, geospatial simulation, spatial statistics, multiscale analysis, and operational decision-support exercises. Instruction is delivered through modular lectures, applied laboratories, reproducible workflows, and interdisciplinary discussions focused on resilient GeoAI implementation.

GEOAI EDUCATION THAT UNITES **TECHNOLOGY, GOVERNANCE, AND HUMAN JUDGMENT** FOR STRONGER DISASTER PREPAREDNESS.

Implementation and Collaborations

The framework was implemented through Delta State University's GIT curriculum and GeoAI Risks instructional ecosystem. The initiative integrates classroom instruction, laboratory exercises, open-source workflows, and operational case studies to support scalable capacity-building in GeoAI and disaster management.

Impact and Outcomes

The initiative strengthened student understanding of GeoAI applications, disaster risk reduction, and governance-aware spatial analytics. Participants developed practical skills in geospatial AI workflows while also gaining awareness of uncertainty, ethics, resilience, and operational decision quality.

Lessons Learned and Recommendations

Delta State University - GeoAI Educational Framework for Disaster Risk Reduction Capacity Building

- GeoAI education is most effective when technical instruction is combined with governance awareness, operational realism, and interdisciplinary problem-solving. Future educational initiatives should prioritize scalable and reproducible learning environments capable of supporting international collaboration.
- Students completed operational exercises using Sentinel-1, Sentinel-2, Landsat, OpenStreetMap, NASA Earth Observation products, and digital elevation datasets to support flood-risk mapping, wildfire analysis, and vulnerability assessment.
- The framework was intentionally developed around reproducible and scalable workflows using both commercial and open-source geospatial technologies to maximize international accessibility and institutional adoption.

Alignment with SDGs

This practice directly supports UN-SPIDER's mission to improve capacity-building and access to geospatial technologies for disaster management. It aligns with SDG 4 (Quality Education), SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 9 (Industry, Innovation, and Infrastructure).

4 QUALITY EDUCATION

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

Delta State University - GeoAI Educational Framework for Disaster Risk Reduction Capacity Building

Additional References or Resources

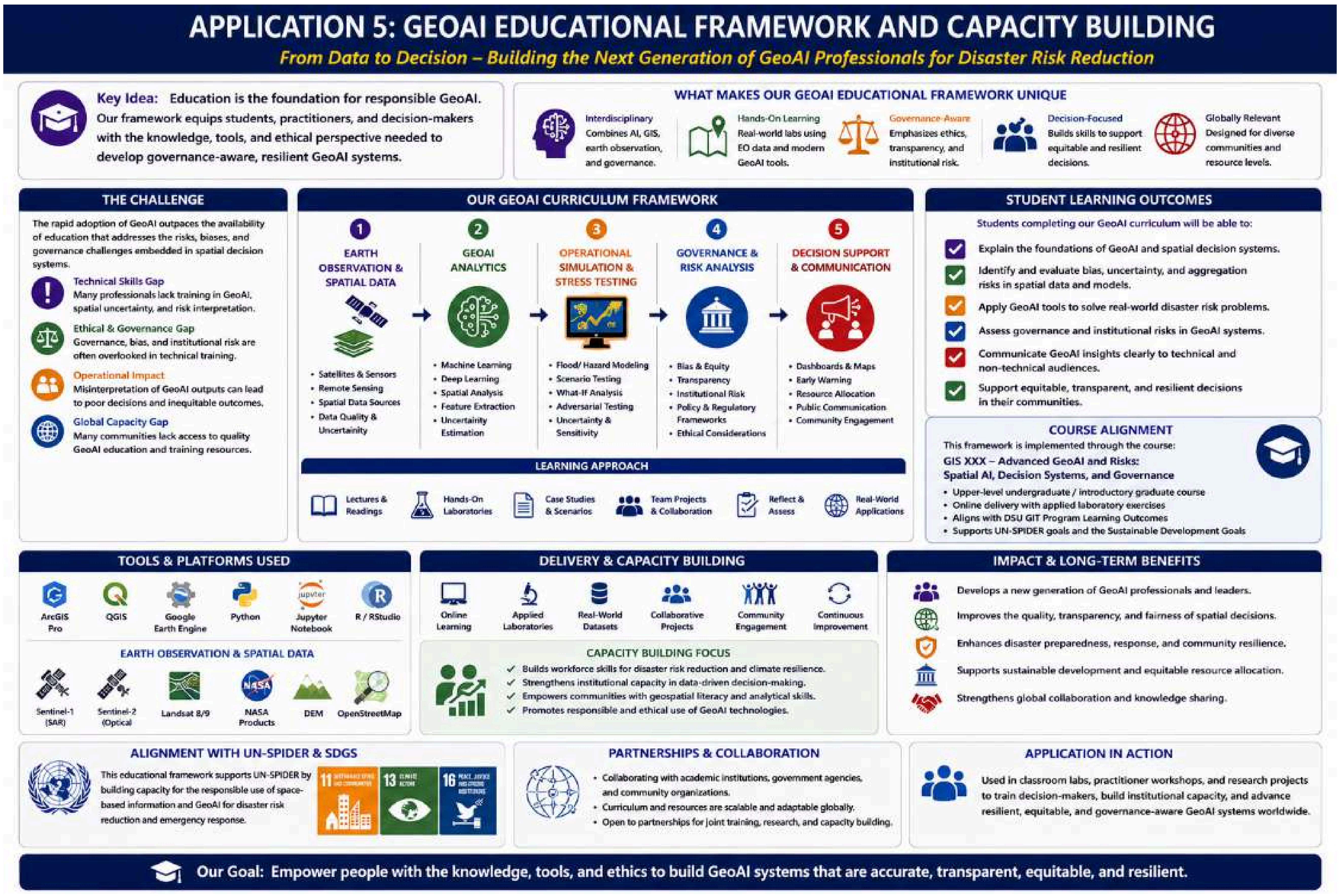

Figure 32: GeoAI Educational Framework and Capacity Building

IWMI- A Water-REPEAT framework for enhancing water reuse to increase climate resilience in the MENA region

Title of GeoAI Practice

A Water-REPEAT framework for enhancing water reuse to increase climate resilience in the MENA region

Brief Description

Water scarcity is one of the most pressing challenges of our time, and nowhere is this more acute than in the Middle East and North Africa (MENA) region. The e-ReWater project — Enhancing Water Reuse in the MENA Region using AI-Based Technologies — was developed by the International Water Management Institute (IWMI) to address this critical gap. By combining artificial intelligence, Earth Observation, and advanced data analytics, e-ReWater delivers a scalable, evidence-based framework to help governments plan and prioritize wastewater reuse across multiple sectors. IWMI implemented the e-ReWater project, developing and deploying Water-REPEAT (Water Reuse Plan using Earth-Observation and AI-based Technologies), an AI-enabled digital framework designed to help governments systematically assess, prioritize, and plan for wastewater reuse at scale.

ABOUT **82% OF WASTEWATER** IN THE MENA REGION IS NEITHER USED NOR TREATED, CREATING A NEED FOR IMPROVEMENT. IF **WASTEWATER USAGE** IS ENHANCED, THE GAP BETWEEN WATER SUPPLY AND DEMAND COULD BE CLOSED.

Challenge or Problem Addressed

Despite hosting nearly six percent of the global population, the MENA region has access to only one percent of the world's freshwater resources. More than 60 percent of people living in the MENA region are exposed to high to very high water stress, placing enormous pressure on agriculture, economies, and ecosystems. Climate change is intensifying this crisis by reducing rainfall, accelerating evaporation, and increasing the frequency of droughts.

Treated wastewater represents one of the most reliable and climate-resilient alternative water sources available to the region. Yet its potential remains largely untapped due to fragmented data, limited planning tools, and weak institutional capacity. National governments lack the digital infrastructure needed to systematically assess where wastewater is generated, where treatment capacity exists, and how reclaimed water can be matched to agricultural, industrial, and environmental demand. e-ReWater was designed to precisely fill this gap — transforming raw data into actionable reuse planning at scale.

Technical Approach and Methods

IWMI- A Water-REPEAT framework for enhancing water reuse to increase climate resilience in the MENA region

At the heart of e-ReWater is Water-REPEAT — an integrated, data-driven framework that combines Earth Observation (EO) data, AI/ML models, and multi-sectoral information. The framework was applied across Saudi Arabia, Egypt, and the United Arab Emirates, encompassing 13 administrative regions, 27 governorates, and 7 emirates, respectively. It is structured around four sequential steps:

Step 1 — Wastewater Treatment Plant (WWTP) Inventory Development

The first step establishes a comprehensive, structured database of wastewater treatment plants across the target countries. Primary and secondary data sources are compiled to capture the name, location, operational status, startup dates, and reuse project status of each facility. This inventory forms the foundational layer of the entire planning framework, enabling analysts to understand the current treatment landscape, identify operational facilities, and flag where reuse programs are already active. Systematic validation procedures are applied to the database to ensure accuracy and consistency before analysis proceeds.

Step 2 — AI-Based Detection and Gap Filling

Building on the Step 1 inventory, Step 2 employs high-resolution satellite imagery, computer vision models, large language models, and AI/ML models to automatically detect wastewater treatment facilities that are absent from official records or secondary data sources. For example, in Egypt alone, the AI-based detection model identified approximately 164 new WWTPs beyond the 552 already documented from secondary sources — a 30 percent increase in known infrastructure. The model also characterizes treatment capacity and identifies newly constructed plants not yet captured in national databases.

Step 3 — Multi-Sectoral Water Demand Modeling

Step 3 quantifies water demand across three key sectors — agriculture, industry, and the environment — using a combination of EO-based models and AI-driven data collection. Agricultural and environmental demands are estimated through Earth Observation-based analytical frameworks, while industrial demand is assessed using AI combined with EO data, cross-referenced against Places API data (6,131 records), web scraping (3,819 records), and OpenStreetMap API data (12,385 records). This multi-source approach ensures comprehensive coverage of demand points across diverse geographies. Demand estimates are then modeled against supply data from Steps 1 and 2 to identify where wastewater supply and sectoral water needs align most effectively.

Step 4 — Potential, Prioritization, and Planning

The final step integrates all preceding outputs into an optimised prioritization framework that ranks wastewater treatment plants by their reuse potential across agriculture, industry, and environmental sectors. By matching supply and demand spatially, the framework identifies priority investment zones and generates evidence-based reuse plans tailored to national and regional policy goals. The result is an actionable planning tool that governments can use to guide infrastructure investment, water allocation decisions, and regulatory strategy.

Implementation and Collaborations

IWMI- A Water-REPEAT framework for enhancing water reuse to increase climate resilience in the MENA region

The project was implemented in three countries – Egypt, Saudi Arabia, and the United Arab Emirates. In Egypt, we partnered with the Arab Water Council. In Saudi Arabia, we closely worked with the national water holding company and the National Irrigation Authority. In the UAE, we partnered with the water holding company in Abu Dhabi (TAQA). Funding for this study was provided by Google.org.

Impact and Outcomes

The e-ReWater project delivered measurable outcomes across three dimensions:

Project-Level Outcomes

- Development of Water-REPEAT, an integrated AI and EO-based digital planning framework applicable across the MENA region and beyond.
- Mapping of wastewater treatment infrastructure using AI detection techniques, significantly expanding known plant inventories.
- Generation of spatial wastewater supply and multi-sectoral demand datasets, providing an evidence base previously unavailable to national planners.
- Identification of high-impact reuse opportunities and priority investment zones across agriculture, industry, and the environment.

Strategic Impact Pathways

- Climate Resilience: Wastewater reuse is promoted as a reliable, drought-resilient water supply alternative, reducing dependence on increasingly stressed freshwater systems.
- Water Security: Improved understanding of alternative water supplies reduces pressure on conventional freshwater resources across the region.
- Institutional Capacity: Government agencies are better equipped to use digital tools for strategic, evidence-based water planning and investment decisions.

Lessons Learned and Recommendations

Water scarcity is one of the most acute development challenges in the MENA region, yet the vast majority of wastewater generated across the region remains untreated or unused—a significant, recoverable resource that is routinely lost. While governments increasingly recognize that wastewater reuse can meaningfully alleviate freshwater stress, policy decisions have often been slow and reactive rather than timely and data-driven. A central barrier has been the fragmented, incomplete, or entirely absent data on wastewater generation, treatment capacity, and both direct and indirect reuse, leaving planners without the evidence base needed to act decisively. The e-ReWater project demonstrated that satellite imagery and artificial intelligence can effectively bridge this data gap, and the Water-REPEAT framework developed through this work offers a practical, scalable tool that equips policymakers and decision-makers with reliable data to prioritize and plan wastewater reuse. Critically, Water-REPEAT is not country-specific: it is a transferable modeling framework that can be deployed across any national context to unlock reuse potential in agriculture, industry, and the environment, making it an asset for the broader MENA region and beyond.

IWMI- A Water-REPEAT framework for enhancing water reuse to increase climate resilience in the MENA region

Alignment with SDGs

The e-ReWater project directly advances SDG 6 (Clean Water and Sanitation) by improving the sustainable management of water resources and expanding safe wastewater reuse across the MENA region and contributes to SDG 13 (Climate Action) by promoting climate-resilient water supply alternatives that reduce dependence on increasingly stressed freshwater systems. Its support for agricultural productivity through reclaimed water also aligns with SDG 2 (Zero Hunger) and SDG 15 (Life on Land), where environmental water demand modeling supports ecosystem sustainability. The project's use of Earth Observation and AI-based spatial analysis resonates strongly with the mandate of UN-SPIDER (UN Platform for Space-based Information for Disaster Management and Emergency Response), which promotes the application of space-based technologies to support sustainable development and disaster risk reduction — particularly in water-stressed and climate-vulnerable regions. By demonstrating how satellite imagery and AI can be operationalized within national planning systems, e-ReWater serves as a replicable model for the kind of space-enabled, evidence-based governance that both the SDG framework and UN-SPIDER seek to advance.

Additional References or Resources

- Project Overview (https://www.iwmi.org/projects/erewater-mena/)
- Blog: https://rewater-mena.iwmi.org/projects/erewater/
- Media report: https://reliefweb.int/report/egypt/iwmi-announces-development-new-google-supported-tool-will-harness-ai-and-satellite-data-water-reuse-middle-east-and-north-africa
- Project Brief: Velpuri, N., Mateo-Sagasta, J., and Brouziyne, Y., (2025) e-ReWater: A revolutionary tool to boost water reuse in the MENA region, International Water Management Institute.

BGU - TerraX -A Satellite-Based Multi-Expert Decision Support System for Precision Agriculture

Title of GeoAI Practice

TerraX - A Satellite-Based Multi-Expert Decision Support System for Precision Agriculture

Brief Description

TerraX (https://terraxsite.com/) a satellite-based decision support system designed to help smallholder farmers and agricultural planners make data-driven crop selection and risk management decisions. By integrating multi-source geospatial data, including Sentinel-2 multispectral imagery (vegetation health), ISRIC soil data, NASA POWER climate records, and terrain elevation models, TerraX aims to deliver field-level crop recommendations tailored to the specific agronomic, financial, and environmental conditions of a user-defined land polygon.

The system operates at a 10-meter spatial resolution and uses a large language model as a dynamic fusion engine to synthesize expert-level agronomic, financial, and vegetation intelligence into actionable crop rankings. Beyond crop selection, TerraX integrates near real-time disaster risk monitoring module that continuously assesses field-level exposure to drought, flood, severe storms, and wildfire using live meteorological data from Open-Meteo and satellite-derived fire detection from NASA FIRMS. When elevated risk is detected, the system automatically triggers crop-specific water management advisories and delivers proactive email alerts directly to the farmer - enabling early warning response and climate-adaptive decision-making at the field scale.

CROP RANKING IS A METHOD TO **EVALUATE AND ORDER DIFFERENT CROPS** IN A REGION BASED ON **VARIOUS PARAMETERS TO DETERMINE THEIR SUITABILITY**.
FOR EXAMPLE, IN THE TERRAX PROJECT, FIELD-SPECIFIC CROP RECOMMENDATIONS ARE MADE BY EVALUATING **SOIL CONDITIONS, CLIMATE PATTERNS, TERRAIN, AND MARKET ECONOMICS**, AS WELL AS BY ACCOUNTING FOR DISASTER RISK.

Challenge or Problem Addressed

TerraX aims to fill the gap between space-based science, technology, and farmers. The app addresses the challenge of uninformed crop selection and climate vulnerability in precision agriculture. Smallholder farmers in data-scarce and climate-vulnerable regions often rely on tradition or intuition when deciding what to grow, leading to yield losses, financial risk, and soil degradation. TerraX aims to resolve this by delivering satellite-grounded, field-specific crop recommendations that account for soil conditions, climate patterns, terrain, and market economics - and by alerting farmers to emerging disaster risks before they impact their fields - transforming complex geospatial data into a free, end-user, actionable farming decision.

BGU - TerraX -A Satellite-Based Multi-Expert Decision Support System for Precision Agriculture

Technical Approach and Methods

TerraX integrates four parallel geospatial data streams, each sourced from established international platforms:

Satellite Imagery: Sentinel-2 (ESA/Copernicus) multispectral imagery at 10m spatial resolution with a 5-day revisit cycle, used to compute NDVI-based vegetation health indices. Terrain data is derived from the Copernicus DEM GLO-30 at 30m resolution, providing elevation, slope, and aspect parameters.

Geospatial Databases: ISRIC SoilGrids250m for soil properties (pH, texture, organic carbon) and NASA POWER Agroclimatology for monthly climate variables (temperature, rainfall, wind speed, soil moisture).

AI & Machine Learning Methodology: A three-module multi-expert architecture combining a deterministic NDVI scoring algorithm with two LLM-based reasoning agents (Agronomic and Financial Experts). A large language model serves as the fusion engine, performing implicit multi-criteria reasoning across all data streams without hardcoded weights.

Platform: Web-based application with near-real-time API integration and interactive polygon field mapping.

Implementation and Collaborations

TerraX was designed and developed by Assaf Shaked as an M.Sc. thesis project at the International Space University (ISU), Strasbourg, under joint academic supervision from ISU and Ben-Gurion University of the Negev (BGU), Israel. Academic Partnerships: ISU - primary thesis institution, providing space engineering and systems methodology framework. BGU / Prof. Shimrit Maman (UN-SPIDER RSO REP) - thesis co-supervisor, contributing domain expertise in remote sensing, hyperspectral imagery, arid-environment geospatial analysis, and validation of the method.

International Organizations & Data Providers:

- ESA/Copernicus - Sentinel-2 satellite imagery (open access) and Copernicus DEM GLO-30 terrain elevation model
- NASA POWER - Agroclimatology dataset (open access)
- ISRIC - SoilGrids250m global soil database (open access)
- FAO - land evaluation framework (methodological reference)
- Open-Meteo - real-time meteorological API providing daily precipitation, temperature, and wind forecasts for field-level drought, flood, and severe storm risk assessment (open access)
- NASA FIRMS - Fire Information for Resource Management System - satellite-derived global wildfire and thermal hotspot detection (open access)
- Technology Stack: Built on open-access APIs and cloud-based geospatial platforms, ensuring reproducibility and scalability without proprietary data dependencies.
- Target Beneficiaries: Farmers (especially of emerging and developing countries), agricultural planners, and agri-tech organizations.

BGU - TerraX -A Satellite-Based Multi-Expert Decision Support System for Precision Agriculture

Impact and Outcomes

This initiative is developing an accessible, AI-powered decision-support platform designed to bridge the long-standing gap between scientific knowledge, advanced technologies, and real-world farming practices. By translating complex environmental, agronomic, and market intelligence into actionable recommendations, the tool aims to promote precision agriculture and make data-driven farming accessible to all.

Expected impacts include: 1) reducing agricultural uncertainty and risk through integrated analysis of agronomic conditions, financial viability, vegetation dynamics, and environmental factors

Increasing farmer resilience and economic sustainability by optimizing crop selection and improving alignment between production strategies and market opportunities. Furthermore, 2) this study aims to enable climate-smart and adaptive agriculture, particularly in vulnerable arid and semi-arid regions facing increasing environmental pressures. 3) Expand equitable access to AI-driven agricultural intelligence, allowing underserved communities to benefit from advanced decision-making tools without requiring specialized expertise.

TerraX requires no field-level training datasets, enabling rapid deployment across diverse geographic and socio-economic contexts.

By lowering barriers to adoption and providing farmers with actionable intelligence, this work has the potential to transform agricultural decision-making from reactive and intuition-based practices into proactive, evidence-driven systems capable of strengthening food security, livelihoods, and long-term resilience at scale.

Lessons Learned and Recommendations

While this study highlights both the potential and current limitations of integrating large language models (LLMs) with Earth Observation systems for agricultural decision support, the findings at this stage should be considered preliminary. However, several important observations emerged during the development process. First, the use of LLM-based expert fusion reduces the dependence on labelled training datasets, which may be a significant advantage for agricultural regions where field data are limited or unavailable. Second, the integration of open-access data sources and APIs, including Sentinel-2, NASA POWER, and ISRIC SoilGrids, suggests that global deployment could be feasible at very low data cost while supporting near real-time analysis capabilities.

At the same time, several challenges were identified. LLM reasoning is inherently non-deterministic, meaning that outputs may vary between runs and cannot always be reproduced or fully audited in the same manner as traditional rule-based or machine learning systems. In addition, the integration of datasets with different spatial resolutions (e.g., 10 m Sentinel imagery and 250 m SoilGrids data) introduces uncertainty at the field scale and may affect the precision of agronomic recommendations.

Based on these observations, future work should include ground-truth validation of the system recommendations through comparison with agronomist expert assessments and field observations before operational implementation. Furthermore, future system development may benefit from integrating deterministic analytical components together with LLM-based reasoning modules, allowing a balance between reproducibility and the flexibility offered by expert-like reasoning capabilities.

BGU - TerraX -A Satellite-Based Multi-Expert Decision Support System for Precision Agriculture

Alignment with SDGs

UN SDGs Addressed:

SDG 2 - Zero Hunger: Improving food security through precision agriculture and optimized crop yields. SDG 9 – Industry & Innovation: Advancing GeoAI as accessible agricultural infrastructure for developing economies. SDG 13 - Climate Action: Enabling climate-adaptive farming decisions using real-time and historical climate data. SDG 15 - Life on Land: Promoting sustainable land use and reducing soil degradation through data-informed decisions. TerraX bridges the gap between satellite remote sensing capabilities and practical on-ground agricultural planning, particularly in data-scarce or arid environments.

2 ZERO HUNGER

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

13 CLIMATE ACTION

15 LIFE ON LAND

Additional References or Resources

- [1] Segarra, J., Buchaillot, M.L., Araus, J.L., & Kefauver, S.C. (2020). Remote Sensing for Precision Agriculture: Sentinel-2 Improved Features and Applications. Agronomy, 10(5), 641. https://doi.org/10.3390/agronomy10050641
- [2] Skakun, S., Franch, B., Vermote, E., Roger, J.C., Becker-Reshef, I., Justice, C., & Kussul, N. (2019). Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. Remote Sensing of Environment, 195, 244-258. https://doi.org/10.1016/j.rse.2017.04.026
- [3] Hengl, T., de Jesus, J.M., Heuvelink, G.B.M., et al. (2017). SoilGrids250m: Global gridded soil information based on machine learning. PLOS ONE, 12(2), e0169748. https://doi.org/10.1371/journal.pone.0169748
- [4] Bai, J., Chen, X., & Li, J. (2022). Advanced Farming Strategies Using NASA POWER Data: A Comparison with Surface Station Data for Agricultural Applications. MDPIAgriculture, 6(1), 27. https://doi.org/10.3390/agri6010027
- [5] Sys, C., Van Ranst, E., & Debaveye, J. (1993). Land Evaluation: Principles in Land Evaluation and Crop Production Calculations. Agricultural Publications, Brussels. (Standard AHP/multi-criteria reference for crop suitability)
- [6] Ronay, I., Ephrath, J.E., Eizenberg, H., Blumberg, D.G., & Maman, S. (2021). Hyperspectral Reflectance and Indices for Characterizing the Dynamics of Crop-Weed Competition for Water. Remote Sensing, 13(3), 513. https://doi.org/10.3390/rs13030513
- [7] LikangWu,Zhi Zheng., Li, J., et al. (2023). A Survey on Large Language Models for Recommendation. arXiv:2305.19860. https://arxiv.org/abs/2305.19860
- [8] Manvi, R., Khanna, S., Burke, M., Lobell, D., & Ermon, S. (2024). Geollm: Extracting geospatial knowledge from large language models. International Conference on Learning Representations (ICLR 2024).
- [9] AgroLLMTeam (2024). AgroLLM: Connecting Farmers and Agricultural Practices through a Domain-Governed Large Language Model. MDPI AI, 8(1):38. https://doi.org/10.3390/ai8010038
- [10] Liakos, K.G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine Learning in Agriculture: A Review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674
- [11] Jonsson, P., & Eklundh, L. (2004). TIMESAT —A program for analyzing time-series of satellite sensor data. Computers & Electronics in Agriculture, 42(1–2), 31–51. https://doi.org/10.1016/j.compag.2003.10.006

Section E: Cross-Cutting Applications Supporting UN-SPIDER Mandate

Overview

GeoAI enables climate adaptation, environmental management, and disaster prevention by integrating satellite data, AI, and socioeconomic indicators. It supports monitoring of sea-level rise, greenhouse gas emissions, and ecosystem health, as well as agricultural conditions affecting food security. Vulnerability mapping helps identify at-risk populations for targeted support. These applications enhance multi-hazard preparedness and contribute to sustainable and inclusive development.

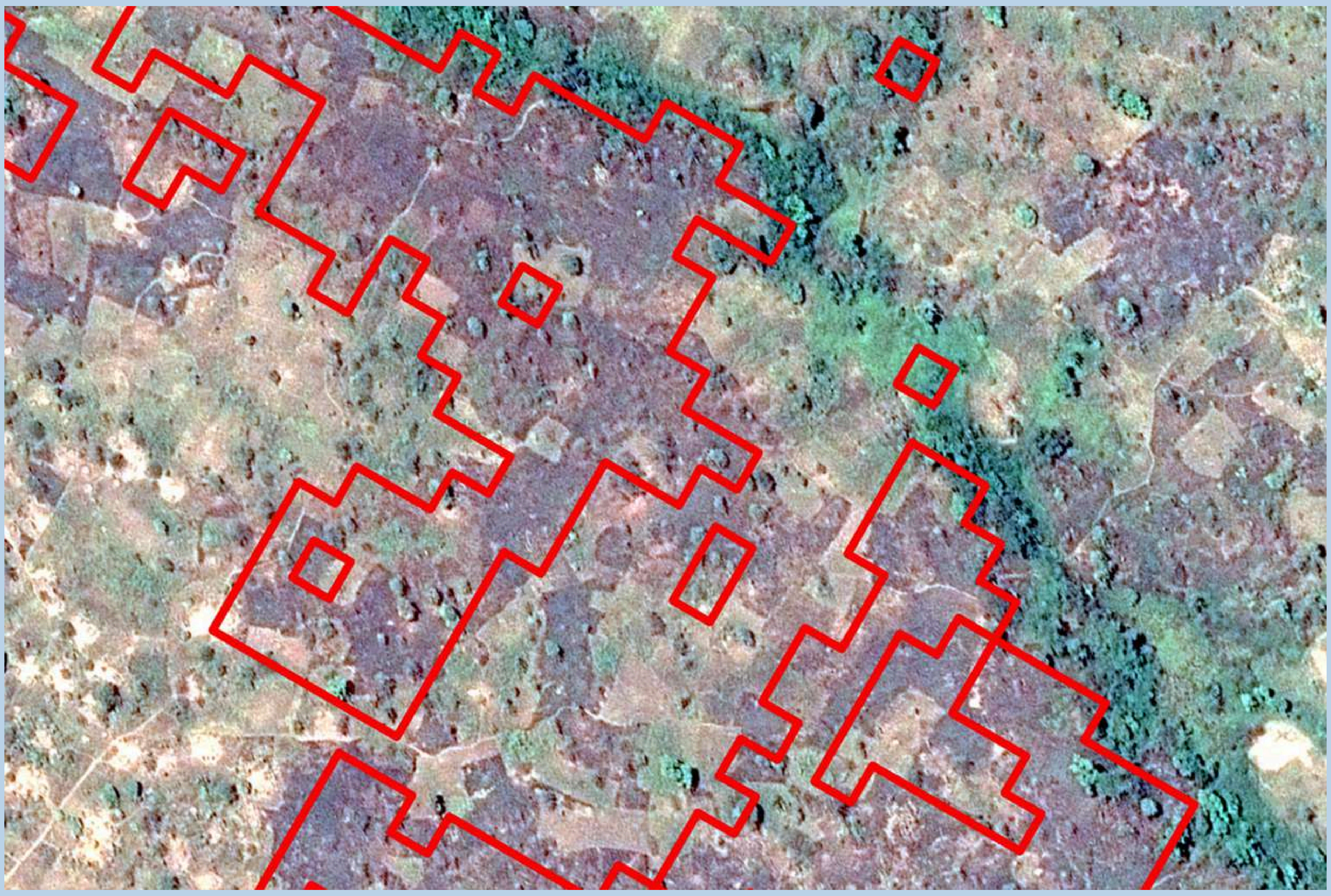

Figure 33: Analyses of Imagery Shows Alleged Intentional Burnt Field in Yambio Province
(c) UN Earth Observation and imagery

SRI Ukraine - DT4LC: A Cognitive Digital Twin Framework for Land Cover Change Detection

Title of GeoAI Practice

DT4LC: A Cognitive Digital Twin Framework for Land Cover Change Detection

Brief Description

DT4LC (Digital Twin for Land Cover) is an extensible Python framework for land cover change detection that combines geospatial analysis methods, machine learning models and large language model (LLM) orchestration into a cognitive Digital Twin (Figure 34). The framework includes built-in algorithms and models including spectral indices (NDVI, EVI, NDWI, NDSI), multi-index change detection, land cover classification and the NASA/IBM Prithvi foundation model which is designed to be extended with additional methods, third-party models and custom analysis pipelines through a declarative component registry. Users interact with the system through natural language via the cognitive interface, while developers can access the execution engine directly through the REST API.

The core of the software is based on an agent-based approach (Figure 36) and has a four-stage cognitive orchestration engine that translates user intent into executable analysis pipelines: (1) an intent classifier distinguishes analysis requests from conversational queries, (2) a context agent extracts structured goals from natural language, (3) a hybrid planner selects between template-based and LLM-powered pipeline generation and (4) a plan validator checks type compatibility and resource constraints before execution. The declarative registry allows researchers to integrate new algorithms or external models by implementing a Python function and adding a YAML configuration entry, making the framework adaptable to diverse research workflows.

> LARGE LANGUAGE MODELS (LLM) ENABLE THE **TRANSLATION OF NATURAL LANGUAGE QUERIES** INTO AUTOMATED GEOSPATIAL ANALYSIS WORKFLOWS

Challenge or Problem Addressed

The modern world is facing a profound environmental crisis driven predominantly by anthropogenic activities. Industrialization, increasing greenhouse gas emissions, and intensive land use practices are causing irreversible changes in natural ecosystems. While the impacts of these processes manifest differently across regions, they share a common origin — long-term and largely uncontrolled human influence on the environment [25].

For instance, in Switzerland, global industrial activity and atmospheric emissions contribute to climate change and accelerate the melting of Alpine glaciers [1–3]. In Ukraine, by contrast, significant changes in land cover and land use are primarily driven by armed conflict [4–6], resulting in widespread damage to forest ecosystems [7–9], agricultural lands [10–13], and protected natural areas [14].

SRI Ukraine - DT4LC: A Cognitive Digital Twin Framework for Land Cover Change Detection

Addressing such processes requires timely detection of environmental changes and support for informed decision-making. To this end, international organizations are actively advancing environmental monitoring approaches based on Earth Observation technologies and satellite data. A central role in this effort is played by Digital Twins of natural systems, which integrate observation, modeling, and prediction capabilities. Notably, the European Union's Destination Earth (DestinE) initiative, jointly implemented by ESA, ECMWF, and EUMETSAT, processes more than 800 million observations daily to support climate adaptation and extreme weather analysis [15]. The Digital Twin Ocean (EDITO), developed by Mercator Ocean International, enables scenario-based simulations for marine environmental assessment [16, 17]. Similarly, NASA's Earth System Digital Twin program encompasses domain-specific digital twins for hydrology, air quality, and wildfire monitoring [18].

Despite their significant potential, most existing Digital Twin systems remain difficult to use in practice due to their reliance on specialized interfaces and the high level of technical expertise required from users. Recent advances in Large Language Models (LLMs) and multi-agent systems offer promising opportunities to overcome these limitations by enabling intuitive natural language interaction with the analytical capabilities of Digital Twins [19, 20]. Early examples of such approaches include the ECMWF Climate and Weather Chatbot [21] and the experimental NASA Earth Copilot project [22]. However, direct integration of natural language interfaces with the analytical core of Digital Twin systems remains limited.

One of the most important developed parts is a cognitive user interface for a Digital Twin system designed for land cover change detection, developed within the Ukrainian–Swiss DT4LC project [23–25].

Technical Approach and Methods

The DT4LC framework integrates multi-source Earth Observation data, machine learning, and AI-driven orchestration into a GeoAI digital twin for land cover and land use monitoring. The main data sources include Sentinel-2 (optical) and Sentinel-1 (SAR) imagery, complemented by climate data and user-provided geospatial inputs. The methodology combines traditional remote sensing techniques with advanced AI models. Spectral indices (NDVI, NDWI, EVI, NDSI), multi-temporal change detection, and land cover classification are used together with deep learning and foundation models (e.g., Prithvi) for feature extraction and segmentation.

A key component is a cognitive GeoAI layer based on a multi-agent architecture, where large language models enable translation of natural language queries into automated geospatial analysis workflows. These workflows integrate preprocessing, modelling, and visualization steps.

The system is implemented as a modular, extensible framework with a registry-based architecture, supporting integration of third-party models and deployment in both cloud and local environments, with interactive interfaces and API access for scalable analysis and decision support.

Implementation and Collaborations

SRI Ukraine - DT4LC: A Cognitive Digital Twin Framework for Land Cover Change Detection

The DT4LC project is being implemented as a collaborative effort within the Ukrainian–Swiss Joint Research Programme (USJRP), funded by the Swiss National Science Foundation, bringing together academic and research institutions from Ukraine and Switzerland. The core development integrates expertise in Earth Observation, machine learning, and environmental modelling to build a scalable digital twin framework for land cover and land use monitoring based on the agent concept and a cognitive user interface (Figure 34).

The system is developing as a modular, extensible architecture combining multi-source satellite data (e.g., Sentinel-1/2), climate datasets, and AI-driven analytical pipelines. A key implementation feature is the cognitive layer based on a multi-agent orchestration approach, which translates natural language queries into executable geospatial workflows, enabling automated analysis and significantly lowering the barrier for non-expert users. The framework supports integration of both classical algorithms and advanced models, including foundation models, through a registry-based design that allows seamless extension with third-party components.

The initiative is aligned with and builds upon major international efforts in Earth System Digital Twins, including Destination Earth (DestinE) and NASA ESDT, and is connected to Horizon Europe projects such as SWIFTT and FUTUREFOR, ensuring methodological interoperability and knowledge exchange.

The system is designed for practical use by a wide range of stakeholders, including researchers, policymakers, and practitioners in environmental monitoring and disaster management. Through its interactive dashboard, API-based access, and scenario analysis capabilities, the platform supports cross-sector collaboration, capacity building, and the operational use of GeoAI technologies for decision-making in both research and real-world contexts.

Impact and Outcomes

The DT4LC current results demonstrate measurable improvements in environmental monitoring and decision support through the integration of GeoAI and digital twin technologies. The system enables efficient rapid detection and quantification of land cover changes across different temporal scales, as illustrated by pilot use cases, including the identification of approximately 12% average vegetation loss in war-affected forest areas in Ukraine and over 26% glacier area reduction in Alpine regions between 2021–2025. These results highlight the capability of the platform to provide quantitative, spatially explicit indicators for both rapid anthropogenic impacts and long-term climate-driven processes.

The usage of a cognitive user interface significantly enhances situational awareness and accessibility, allowing non-expert users to perform complex geospatial analyses through natural language interaction and obtain actionable insights without requiring advanced technical skills. Automated pipeline generation reduces analysis time and supports more timely decision-making in disaster response and environmental management contexts.

Additional benefits include improved capacity building through user-oriented tools and training potential, enhanced interoperability and data standardization via modular architecture, and strengthened policy support by enabling scenario-based analysis and evidence-driven planning. The framework also contributes to the development of new harmonized datasets and advances in machine learning methodologies for land cover change detection, supporting both scientific research and operational applications.

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Lessons Learned and Recommendations

Our current results and development of Earth System Digital Twins (ESDTs) demonstrate strong potential for environmental monitoring, climate adaptation, and disaster response. A key lesson learned is that integrating multi-source EO data with AI-driven analytics and continuous data assimilation significantly improves the timeliness and reliability of monitoring and forecasting systems.

At the same time, during the research, several limitations were identified. Current ESDTs provide limited support for fine-grained land use monitoring, particularly for human-driven changes such as agricultural dynamics or post-conflict land restoration. High-resolution, near-real-time analysis remains computationally demanding and requires scalable cloud infrastructures. In addition, the lack of standardized and interoperable data pipelines continues to hinder the integration of heterogeneous datasets.

Another important lesson concerns the use of foundation models. While they offer flexibility, their performance in domain-specific tasks is still limited without substantial adaptation. In practice, task-specific machine learning and deep learning approaches remain more reliable for operational applications.

Finally, insufficient user interaction and feedback mechanisms reduce transparency and trust in digital twin systems. Experiments with large language models highlight their potential for improving interpretability, but also reveal risks related to accuracy and data quality. That is why we have been addressing all these challenges.

Recommendations:

- Ensure scalable cloud-based processing for continuous EO data streams.
- Develop standardized and interoperable data pipelines.
- Prioritize task-specific models while complementing them with foundation models where appropriate.
- Implement human-in-the-loop validation for critical applications.
- Enhance user interaction and feedback mechanisms to improve usability and trust.

Alignment with SDGs

The practice from the implementation of GeoAI-based DT4LC for land cover monitoring demonstrates strong alignment with both the Sustainable Development Goals (SDGs) and the mission of the United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER).

The project DT4LC (Digital Twin for Land Cover) and its cognitive interface as a core element for interaction with stakeholders could contribute to the following SDGs:

- SDG 2 – Zero Hunger: improving agricultural monitoring, yield-related tasks' solving, and damage assessment.
- SDG 6 – Clean Water and Sanitation: supporting analysis of water-related processes such as droughts and floods.
- SDG 11 – Sustainable Cities and Communities: providing tools for urban monitoring and evidence-based planning, including recovery processes, particularly in Ukraine.
- SDG 13 – Climate Action: enabling near real-time monitoring of climate-induced land cover changes and improved environmental forecasting.

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- SDG 15 – Life on Land: supporting detection of land degradation, ecosystem disturbances, and post-conflict land restoration.
- SDG 17 – Partnerships for the Goals: fostering international collaboration and knowledge exchange.

In addition, the project closely aligns with the UN-SPIDER mission, which aims to ensure universal access to and effective use of space-based information for disaster risk reduction and emergency response. The developed GeoAI digital twin framework supports this mission by:

- Integrating satellite Earth Observation data into actionable, near real-time monitoring systems.
- Supporting early detection of disasters such as floods, wildfires, and conflict-related land degradation.
- Enabling informed decision-making for disaster preparedness, response, and recovery.
- Promoting capacity building through user-oriented tools, interactive dashboards, and knowledge transfer.
- Facilitating the use of advanced AI technologies by stakeholders, including policymakers and practitioners.
- Overall, the project and its results contribute to bridging the gap between space-based data and practical decision-making, strengthening resilience and supporting sustainable development in line with both SDGs and UN-SPIDER objectives.

2 ZERO HUNGER | 6 CLEAN WATER AND SANITATION | 11 SUSTAINABLE CITIES AND COMMUNITIES | 13 CLIMATE ACTION | 15 LIFE ON LAND | 17 PARTNERSHIPS FOR THE GOALS

Additional References or Resources

1. C. Poussin, P. Peduzzi, and G. Giuliani, "Snow observation from space: An approach to improving snow cover detection using four decades of Landsat and Sentinel-2 imageries across Switzerland," Science of Remote Sensing, vol. 11, p. 100182, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S266601722400066X.
2. C. Poussin, P. Peduzzi, B. Chatenoux, and G. Giuliani, "A 37 years [1984–2021] Landsat/Sentinel-2 Derived Snow Cover Time-Series for Switzerland," Scientific Data, vol. 12, no. 1, p. 632, Apr. 2025. [Online]. Available: https://www.nature.com/articles/s41597-025-04961-6#citeas.
3. C. J. Huber, A. Eichler, E. Mattea, S. Bru¨tsch, T. M. Jenk, J. Gabrieli, C. Barbante, and M. Schwikowski, "High-altitude Glacier Archives Lost due to Climate Change-Related Melting," Nature Geoscience, vol. 17, no. 2, p. 110–113, Jan. 2024. [Online]. Available: https://www.nature.com/articles/ s41561-023-01366-1#citeas.
4. K. Deininger, D. A. Ali, N. Kussul, A. Shelestov, G. Lemoine, and H. Yailimova, "Quantifying War-Induced Crop Losses in Ukraine in Near Real Time to Strengthen Local and Global Food Security," Food Policy, vol. 115, p. 102418, 2023. [Online]. Available: https://www.sciencedirect. com/science/article/pii/S0306919223000167.
5. N. Kussul, A. Shelestov, B. Yailymov, H. Yailymova, G. Lemoine, and K. Deininger, "Assessment of War-Induced Agricultural Land Use Changes in Ukraine Using Machine Learning Applied to Sentinel Satellite Data," International Journal Of Applied Earth Observation And Geoinformation, vol. 140, p. 104551, 2025. [Online]. Available: https://www.sciencedirect. com/science/article/pii/S1569843225001980.

SRI Ukraine - DT4LC: A Cognitive Digital Twin Framework for Land Cover Change Detection

6. W. L. Filho, M. Fedoruk, J. H. Paulino Pires Eustachio, A. Splodytel, A. Smaliychuk, and M. I. Szynkowska-Jo´z´wik, “The Environment as the First Victim: The Impacts of the War on the Preservation Areas in Ukraine,” Journal of Environmental Management, vol. 364, p. 121399, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301479724013859.
7. B. Yailymov, A. Shelestov, H. Yailymova, and L. Shumilo, “Google Earth Engine Framework for Satellite Data-Driven Wildfire Monitoring in Ukraine,” Fire, vol. 6, no. 11, 2023. [Online]. Available: https://www.mdpi.com/2571-6255/6/11/411.
8. Y. Salii, V. Kuzin, N. Kussul, and A. Lavreniuk, “Forest Stress Detection Using Feature Engineering and Selection Approach Optimized for Satellite Imagery,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 19, pp. 2461–2473, 2026.
9. C. Belis, A. Petrosian, O. Turos, et al. “Status of Environment and Climate in Ukraine,” JRC Publications Repository, 2025. [Online]. Available: https://doi.org/10.2760/6292177.
10. N. Kussul, S. Drozd, H. Yailymova, A. Shelestov, G. Lemoine, and K. Deininger, “Assessing Damage to Agricultural Fields from Military Actions in Ukraine: An Integrated Approach Using Statistical Indicators and Machine Learning,” International Journal of Applied Earth Observation and Geoinformation, vol. 125, p. 103562, 2023. [Online]. Available: https://www. sciencedirect.com/science/article/pii/S1569843223003862.
11. E. C. Duncan, S. Skakun, A. Kariryaa, and A. V. Prishchepov, “Detection and Mapping of Artillery Craters with Very High Spatial Resolution Satellite Imagery and Deep Learning,” Science of Remote Sensing, vol. 7, p. 100092, May 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666017223000172?via%3Dihub.
12. O. Parkhomchuk, S. Drozd, A. Shelestov, and P. Mikava, “Symbiotic Artificial Intelligence and Satellite Imagery for Rapid Assessment of War-Induced Agricultural Damage in Ukraine,” Advances in Geodesy and Geoinformation, vol. vol.74, no. No. 1, p. e59, 2025. [Online]. Available: http://journals.pan.pl/Content/135396/PDF/e59 3k.pdf.
13. L. Shumilo, S. Drozd, and N. Kussul, “Satellite Data Aids the Study of the War’s Environmental and Economic Consequences for Ukraine’s Agriculture Sector,” 2025. [Online]. Available: https://uwecworkgroup.us9.list-manage.com/track/ click?u=528f414adac434c7d7ea5dde0&id=cb0186d7b7&e= 687698d482.
14. S. Drozd, N. Kussul, and A. Shelestov, “Satellite-Based Analysis of Forest Damage in Ukraine’s Protected Areas,” In Proceedings Of The 13th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology And Applications (IDAACS), Gliwice, Poland, Sep. 2025, 4–6 September 2025.
15. J. Doblas-Reyes, J. Kontkanen, I. Sandu et al., “The Destination Earth Digital Twin for Climate Change Adaptation,” EGUsphere, vol. 2025, pp. 1–41, 2025. [Online]. Available: https://egusphere.copernicus.org/preprints/2025/egusphere-2025-2198/
16. K. von Schuckmann, A. Godoy-Faundez, V. Garc¸on, et al, “Global Ocean Indicators: Marking Pathways at the Science-Policy NEXUS,” Marine Policy, vol. 184, p. 106922, 2026. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0308597X25003380.
17. B. Mart´ın M´ıguez, A. Novellino, M. Vinci, et al. “The European Marine Observation and Data Network (Emodnet): Visions and Roles of the Gateway To Marine Data in Europe,” Frontiers in Marine Science, vol. Volume 6 - 2019, 2019. [Online]. Available: https://www.frontiersin.org/ journals/marine-science/articles/10.3389/fmars.2019.00313.
18. “NASA Earth System Digital Twins (ESDT) For a Sustainable Future - NASA Technical Reports Server (NTRS) — ntrs.nasa.gov,” https://ntrs.nasa.gov/citations/20250000171, [Accessed 10-01-2026].
19. T. Guo, X. Chen, Y. Wang, R. Chang, et al. “Large Language Model Based Multi-Agents: A Survey of Progress and Challenges,” in Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI-24, K. Larson, Ed. International Joint Conferences on Artificial Intelligence Organization, 8 2024, pp. 8048–8057, survey Track. [Online]. Available: https://doi.org/10.24963/ijcai.2024/890.

SRI Ukraine - DT4LC: A Cognitive Digital Twin Framework for Land Cover Change Detection

20. X. Li, S. Wang, S. Zeng, Y. Wu, and Y. Yang, "A survey on LLM-based Multi-Agent Systems: Workflow, Infrastructure, and Challenges," Vicinagearth, vol. 1, no. 1, Oct. 2024.
21. "Development Seed to Create a Climate and Weather Chatbot in DestinE — destine.ecmwf.int," [Accessed 10- 01-2026]. [Online]. Available: https://destine.ecmwf.int/news/development-seed-to-create-a-climate-and-weather-chatbot-in-destine.
22. T. Akinboyewa, Z. Li, H. Ning, and M. Lessani, "Gis Copilot: Towards an Autonomous GIS Agent for Spatial Analysis," 11 2024.
23. N. Kussul, G. Giuliani, A. Shelestov et al. "AI-Powered Digital Twin Framework for Land Use Change in Disaster Affected Regions," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 18, pp. 27 473–27 492, 2025.
24. N. Kussul, G. Giuliani, A. Shelestov, S. Drozd, A. Kolotii, Y. Salii, A. Cherniatevych, O. Yavorskyi, V. Malyniak, and C. Poussin, "Digital Twins for Land Use Change". Cham: Springer Nature Switzerland, 2026, pp. 371–389. [Online]. Available: https://doi.org/10.1007/978-3-031-97529-5 22.
25. A. Cherniatevych, S. Drozd, N. Kussul, A. Shelestov. LLM-Driven Multi-Agent Cognitive User Interface for Land Cover Change Digital Twin System, IGARSS 2026 (accepted).

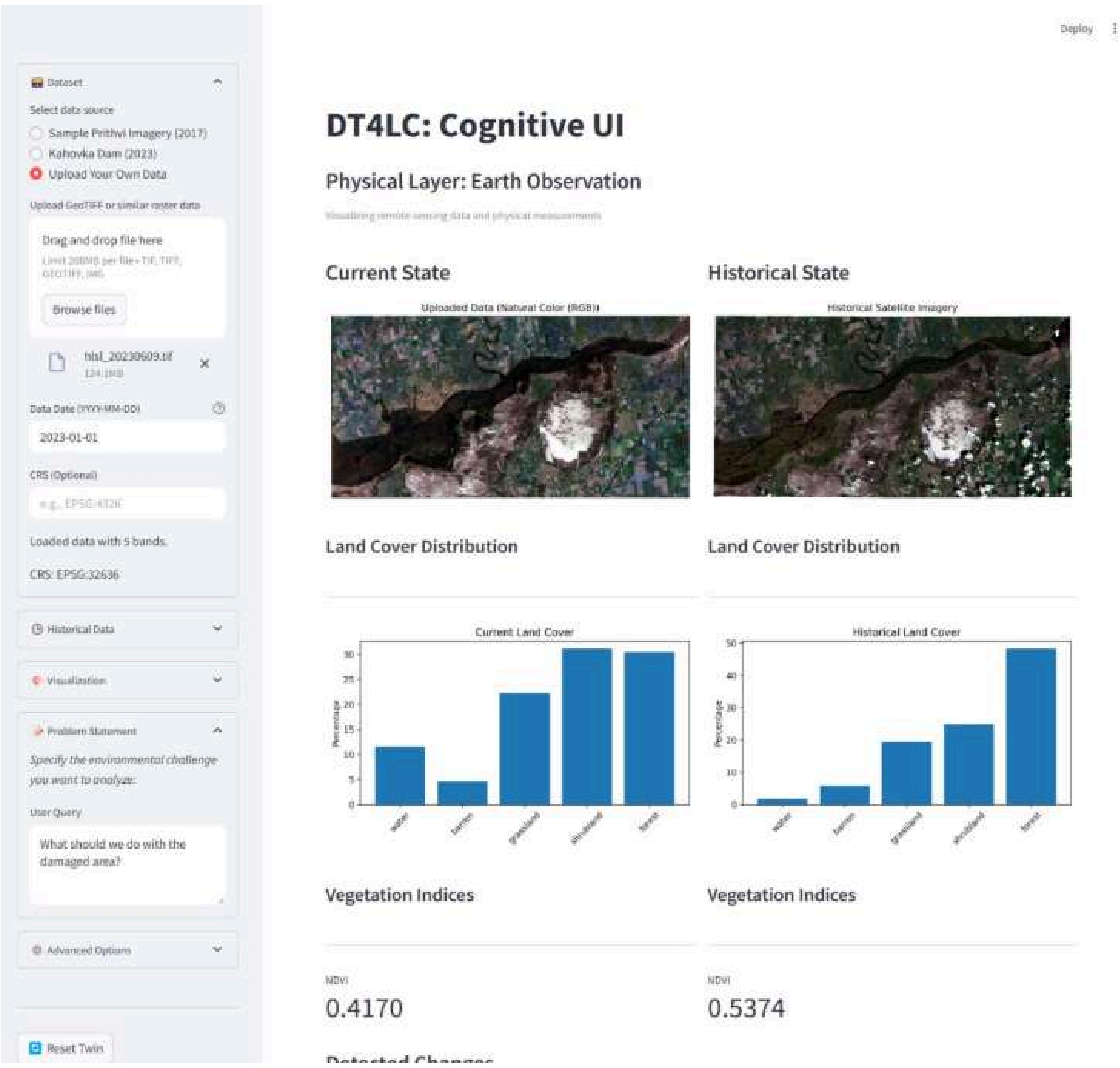

Figure 34: DT4LC Cognitive UI Page

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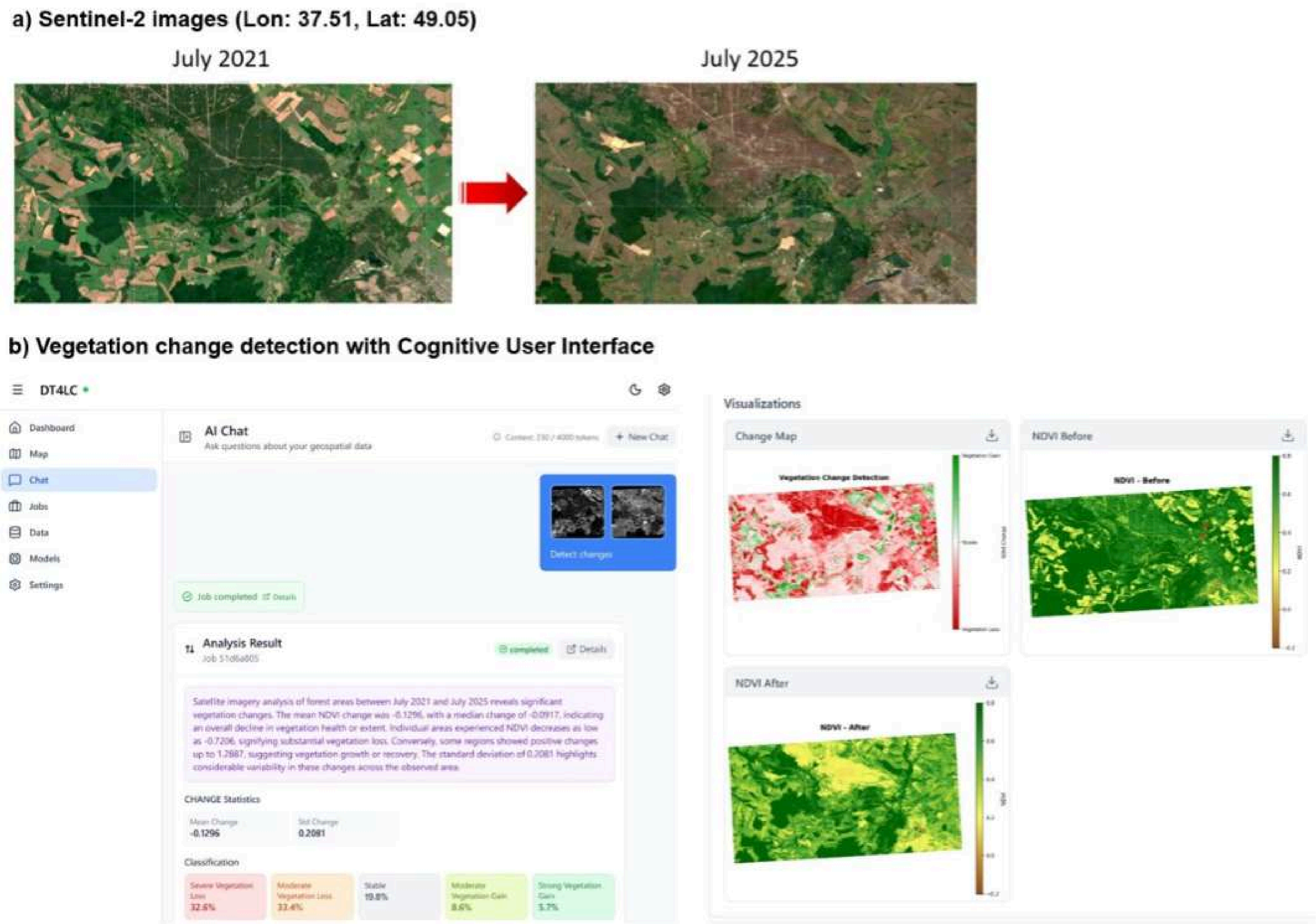

Figure 35: DT4LC Cognitive Interface

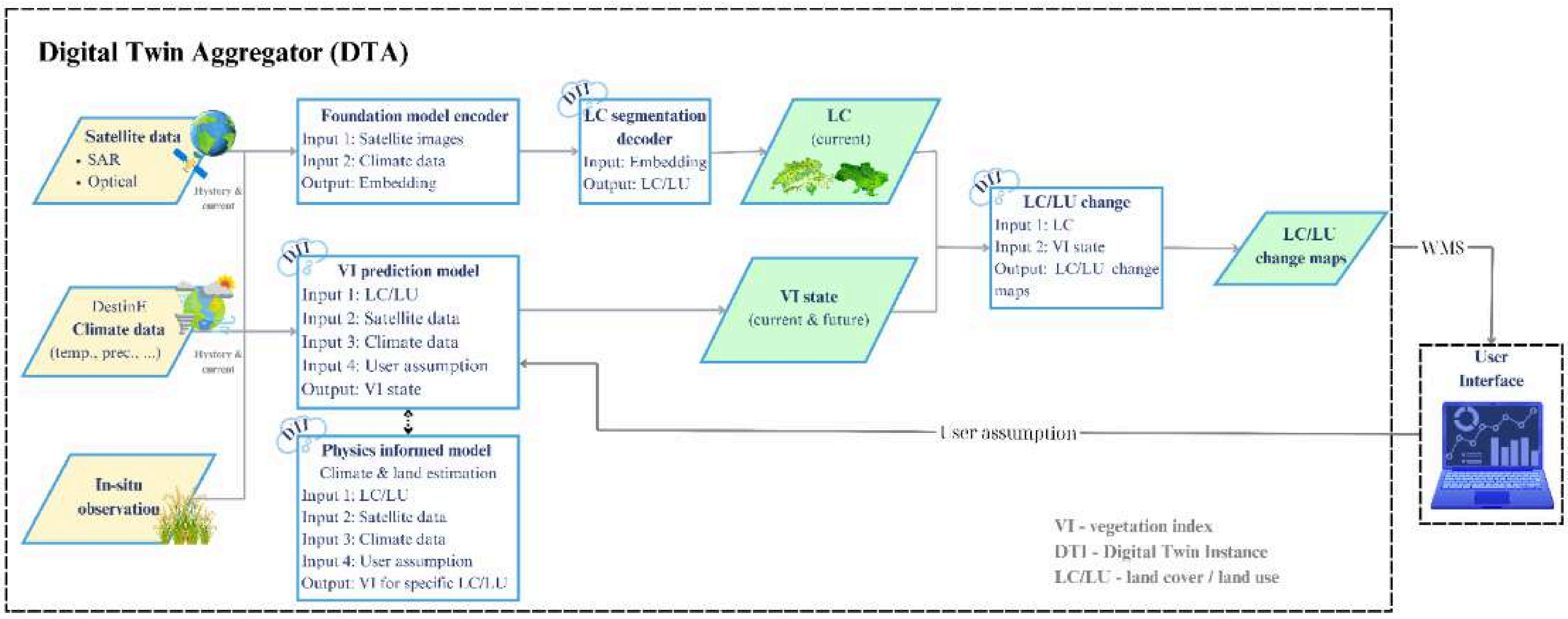

Figure 36: High-Level Dt4LC Architecture

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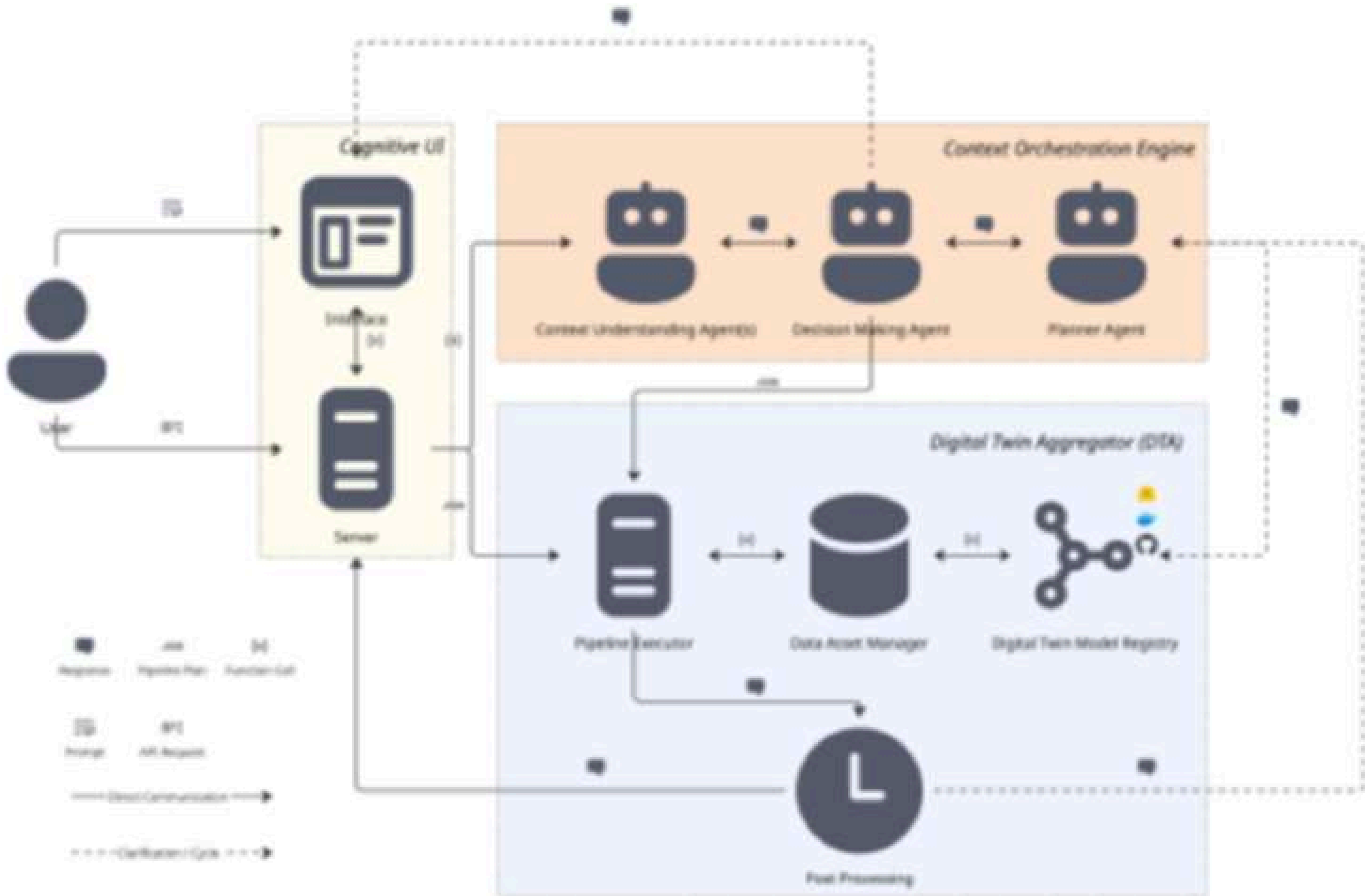

Figure 37: DT4LC Agent-Based Architecture: user requests flow through the Context Orchestration Engine (COE) which routes between conversational responses and pipeline execution via the Digital Twin Instance (DTI)

IWMI - Climate Smart Governance (CSG) Dashboard and AI Agent – Operationalizing Climate Adaptation Finance for Disaster Resilience Infrastructure through Geospatial AI-Driven Prioritization

Title of GeoAI Practice

Climate Smart Governance (CSG) Dashboard and AI Agent – Operationalizing Climate Adaptation Finance for Disaster Resilience Infrastructure through Geospatial AI-Driven Prioritization

Brief Description

The Climate Smart Governance (CSG) Dashboard, developed by the International Water Management Institute (IWMI) under the CGIAR Climate Action Program, is a first-of-its-kind geospatial intelligence platform that integrates Earth Observation, climate analytics, and finance data to support climate adaptation planning in vulnerable countries. In November 2025, IWMI launched the CSG AI Agent — a "Climate Risk Intelligence Assistant" — that transforms complex geospatial, climate, and investment datasets into decision-ready intelligence through conversational AI. Using a Retrieval-Augmented Generation (RAG) architecture powered by a hybrid ensemble of large language models (GPT-Omni and LLAMA), the AI Agent allows national planners to query nine integrated dashboard modules in plain language, run scenario simulations, and generate evidence-based investment recommendations. The platform combines validated national datasets with models from the Coalition for Disaster Resilient Infrastructure (CDRI), World Bank climate scenarios, and UN SDG indicators. Currently deployed in Sri Lanka, Kenya, Senegal, and Zambia, the CSG Dashboard and AI Agent provide governments with a unified tool to prioritize climate investments and track progress toward Nationally Determined Contributions (NDCs).

THE CGIAR CLIMATE ACTION PROGRAM AIMS TO DRIVE SCIENCE, INNOVATION, AND COLLABORATION TO **TRANSFORM FOOD, LAND, AND WATER SYSTEMS** FOR A **CLIMATE-RESILIENT, NET-ZERO, AND EQUITABLE FUTURE**. THE PROGRAM WORKS IN THE FOLLOWING COUNTRIES: BANGLADESH, CAMBODIA, CÔTE D'IVOIRE, ETHIOPIA, HONDURAS, INDIA, KENYA, NEPAL, NIGERIA, PAKISTAN, PHILIPPINES, SENEGAL, SUDAN, TANZANIA, ZAMBIA, AND ZIMBABWE.

Challenge or Problem Addressed

Developing countries face a severe adaptation finance gap — requiring US$310–365 billion annually by 2035 while receiving only US$26 billion in adaptation finance in 2023. This scarcity is compounded by fragmented data ecosystems, institutional silos, and weak analytical capacity, which often result in misallocation of scarce funds. In Sri Lanka, climate-related losses exceed US$300 million annually, yet NDC implementation requires US$10.85 billion by 2030. Planners lack a consolidated, geospatially referenced view of climate risks, ongoing projects, and investment gaps. Traditional dashboards generate high-value data, but senior policymakers without technical expertise cannot easily navigate multi-layered geospatial outputs — creating a critical "last-mile gap" between Earth Observation science and actionable investment decisions.

IWMI - Climate Smart Governance (CSG) Dashboard and AI Agent – Operationalizing Climate Adaptation Finance for Disaster Resilience Infrastructure through Geospatial AI-Driven Prioritization

The CSG Dashboard and AI Agent directly address these data fragmentation, cognitive load, and governance coherence challenges by creating a single, AI-enabled evidence base for prioritizing adaptation investments.

Technical Approach and Methods

The CSG Dashboard is built as a modular geospatial analytics platform integrating nine thematic modules: (1) Country Overview, (2) Climate Outlook, (3) Project Tracker, (4) Geospatial Tools, (5) Monitoring & Evaluation, (6) Development Indicators, (7) Adaptation Catalogue, (8) Investment Portfolio Planning, and (9) How-to Guide. The platform fuses satellite Earth Observation data, climate reanalysis and projection datasets (CMIP6 Shared Socioeconomic Pathways), hazard models from the Coalition for Disaster Resilient Infrastructure (CDRI), World Bank Climate Knowledge Portal data, UN SDG indicators, and validated national statistics.

The Geospatial Tools module enables policymakers to overlay infrastructure, hazard exposure (floods, droughts, cyclones, landslides, tsunamis), and socio-economic indicators (literacy, sanitation access, poverty) at sub-national scales, identifying zones where unmet need and climate exposure converge.

In November 2025, the platform was enhanced with an AI Agent — the Climate Risk Intelligence Assistant — operating on a layered architecture that combines four large language models in a hybrid ensemble. GPT-Omni handles complex multi-step reasoning while LLAMA supports data sovereignty and operational efficiency. Crucially, the system employs a Retrieval-Augmented Generation (RAG) mechanism that grounds every response in verified CSG data, ensuring traceability and preventing hallucinations common to pure generative models.

The AI Agent provides three tiers of decision support: (i) a Data Concierge that retrieves summary statistics and generates geospatial visualizations; (ii) a Scenario Modeler that runs “what-if” simulations (e.g., modelling the impact of a 20% increase in flood risk combined with a 10% rise in cyclone risk); and (iii) a Strategic Advisor that synthesizes hazard, vulnerability, and finance data to recommend investment allocations.

To operationalize the analytics, IWMI developed two proprietary composite indices: the Water Adaptation Finance Index (WAFI) and the Agriculture Adaptation Finance Index (AAFI). WAFI integrates three pillars — (a) climate and hydrological risk (Annual Expected Water Criticality Index; Average Annual Loss from floods and droughts), (b) socio-economic vulnerability, and (c) adaptation gap (inverse of active project density; funding deficit relative to actual losses). AAFI compares Pillar A (Demand: agricultural dependency, smallholder prevalence, food insecurity, multi-hazard exposure, adaptation cost) against Pillar B (Response: total adaptation finance, insurance penetration, smallholder finance access). District-level gap scores are visualized on interactive maps, enabling tiered investment allocation. Applied to Sri Lanka’s 25 districts, this framework identified Mullaitivu, Kilinochchi, and Mannar in the Northern Dry Zone as highest-priority areas, while also flagging Ratnapura as a flood and landslide hotspot with critically low financial response despite moderate demand.

IWMI - Climate Smart Governance (CSG) Dashboard and AI Agent – Operationalizing Climate Adaptation Finance for Disaster Resilience Infrastructure through Geospatial AI-Driven Prioritization

Implementation and Collaborations

The CSG Dashboard is implemented by IWMI under the CGIAR Climate Action Program, in partnership with Sri Lanka's Department of National Planning, Ministry of Environment (Climate Change Secretariat), and Ministry of Finance. It is operationally deployed in Sri Lanka, Kenya, Senegal, and Zambia, with planned rollouts in Morocco, Guatemala, and the Philippines. Key technical and data partners include the Coalition for Disaster Resilient Infrastructure (CDRI), the World Bank Group, and the UN Statistics Division. Funding is provided by the CGIAR Trust Fund and Japan's Ministry of Agriculture, Forestry and Fisheries (MAFF). The AI Agent was launched at COP30 in Belém, Brazil (November 2025).

Impact and Outcomes

Since its launch, the CSG Dashboard is actively used by Sri Lanka's National Planning Department to prioritize sub-national climate adaptation investments and tracks adaptation projects valued at US$4.27 billion across the water and agriculture sectors. The platform has identified that the water supply and sanitation sector alone faces a 526% financing gap, with Northern Dry Zone districts (Mullaitivu, Kilinochchi, Mannar) requiring 50–60% of new national adaptation budgets. The WAFI and AAFI indices provide the first objective, data-backed prioritization framework linking Sri Lanka's US$10.85 billion NDC financial requirement to district-level allocation. The AI Agent has dramatically reduced the time required to generate investment-ready briefings — from weeks of manual analysis to minutes of conversational querying. The platform is actively supporting Sri Lanka's National Climate Finance Strategy (2025–2030), which mobilizes approximately US$500 million annually for climate-resilient infrastructure.

Lessons Learned and Recommendations

Four lessons emerge from the CSG experience. First, geospatial AI tools must be co-designed with national partners (planning commissions, finance ministries) from day one — institutional ownership is as important as technical quality. Second, RAG-based grounding is essential: pure generative AI produces hallucinations unacceptable in governance contexts, but retrieval against verified geospatial datasets preserves accuracy and traceability. Third, decision-makers demand plain-language interfaces; the cognitive cost of traditional dashboards excludes non-technical leadership from the analytical pipeline. Fourth, composite indices (WAFI, AAFI) that combine Earth Observation risk metrics with finance data convert abstract climate science into budget-relevant decisions.

Recommendations: (i) integrate GeoAI platforms directly into NDC and National Adaptation Plan processes rather than treating them as parallel tools; (ii) invest in data sovereignty through open-source LLM components (e.g., LLAMA); (iii) prioritize capacity building so national analysts can interrogate and extend the AI Agent; and (iv) establish continuous feedback loops between ground truth and AI-generated recommendations.

IWMI - Climate Smart Governance (CSG) Dashboard and AI Agent – Operationalizing Climate Adaptation Finance for Disaster Resilience Infrastructure through Geospatial AI-Driven Prioritization

Alignment with SDGs

The CSG Dashboard and AI Agent directly advance UN-SPIDER's mandate to ensure that all countries and international and regional organizations have access to and develop the capacity to use all types of space-based information to support the full disaster management cycle. By operationalizing Earth Observation, geospatial AI, and disaster risk data into national policy workflows, the platform enables evidence-based decision-making across preparedness, response, recovery, and long-term adaptation. The initiative contributes to multiple Sustainable Development Goals:

- SDG 1 (No Poverty) and SDG 2 (Zero Hunger) through targeted support for climate-vulnerable smallholder farmers;
- SDG 6 (Clean Water and Sanitation) via the WAFI water prioritization framework;
- SDG 9 (Industry, Innovation and Infrastructure) through resilience ratings aligned with the World Bank Resilience Rating System;
- SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action) by mainstreaming climate intelligence into fiscal planning;
- SDG 17 (Partnerships for the Goals) through multi-stakeholder coordination across ministries, development partners, and the CGIAR system.

Additional References or Resources

- CSG Dashboard (platform): https://csg.iwmi.org/
- Climate Risk Intelligence Assistant (AI Agent): https://csg.iwmi.org/aiagent/
- IWMI Introduces AI Tool for Climate-Smart Planning and Investments. IWMI News, 14 November 2025. https://www.iwmi.org/news/iwmi-introduces-ai-tool-for-climate-smart-planning-and-investments/
- IWMI Launches the Climate Smart Governance Dashboard in Sri Lanka. IWMI News, 26 April 2024. https://www.iwmi.org/news/iwmi-launches-the-climate-smart-governance-dashboard-in-sri-lanka/
- Amarnath, G.; Alahacoon, N.; Randeni, L.; Jayarathna, K.N.P.; Amarasinghe, U.; Sikka, A. (2025). The Climate-Smart Governance Dashboard and AI Agent: Operationalizing Adaptation Finance through Data-Driven Prioritization. Colombo, Sri Lanka: IWMI / CGIAR Climate Action Program. 15p. https://hdl.handle.net/10568/181625
- Amarnath, G. et al. (2023). The Climate Smart Governance Dashboard: Supporting Nations to Prepare for and Adapt to Climate Hazards. Colombo: IWMI. https://cgspace.cgiar.org/bitstreams/6cf4c96d-f9ce-40ef-90cb-1492454b3160/download
- CGIAR Climate Action Program: https://www.cgiar.org/cgiar-research-portfolio-2025-2030/climate-action/

ECoE - GeoAI-Based Coastal Water Quality Assessment in Cyprus Using Sentinel-2 and Machine Learning

Title of GeoAI Practice

GeoAI-Based Coastal Water Quality Assessment in Cyprus Using Sentinel-2 and Machine Learning.

Brief Description

This GeoAI practice focuses on assessing coastal water quality in Cyprus using satellite remote sensing and machine learning techniques[1]. Sentinel-2 multispectral imagery is processed within a cloud-based geospatial environment, namely, Google Earth Engine (GEE) to detect differences in water turbidity, which is a key indicator of water quality[2].

The analysis specifically focuses on a rainfall period (or urban flooding), during which surface runoff, sediment transport, and land-sea interactions significantly influence coastal waters. Since Cyprus' coastal economic activities are relying on marine and coastal resources, such monitoring and early identification are important for coastal authorities.

A set of spectral indices, including Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI), and Normalized Difference Turbidity Index (NDTI), along with proxy indicators for chlorophyll-a and total suspended matter (TSM), are used to characterize water properties[3]. A Random Forest (RF) model is trained using labeled samples of clean and turbid water, producing a continuous turbidity probability map. The results provide spatial insight into water quality dynamics along the Cypriot coastline, supporting environmental monitoring and coastal management applications.

Challenge or Problem Addressed

Coastal water quality in Cyprus is highly variable and particularly sensitive to rainfall-driven processes, such as increased sediment loads and runoff from terrestrial sources. These processes can lead to rapid and localized degradation of water quality, especially in nearshore environments.

Traditional monitoring methods rely on in-situ measurements, which are often limited in spatial and temporal coverage. This practice addresses the challenge of large-scale, near-real-time monitoring of water quality, enabling the detection of turbidity patterns and water quality changes during critical environmental conditions.

Technical Approach and Methods

The methodology integrates Earth Observation data, namely Sentinel-2 multispectral [4] and undergoes machine learning within the Google Earth Engine platform. Key elements include:

- Study Area: Coastal regions of Cyprus
- Data Source: Sentinel-2 Surface Reflectance (COPERNICUS/S2_SR_HARMONIZED)
- Temporal Focus: Selection of a rainfall period to capture runoff-related turbidity
- Preprocessing: Cloud masking using the Scene Classification Layer (SCL)
- Spectral Features:
- NDWI (Normalized Difference Water Index)
- MNDWI (Modified NDWI)
- NDTI (Normalized Difference Turbidity Index)
- Chlorophyll proxy (B5/B4)
- TSM proxy (B4/B3)
- Water Masking: Extraction of water pixels using NDWI and MNDWI thresholds
- Machine Learning: Random Forest classifier
- Output: Continuous turbidity probability (values between 0 and 1)
- Post-processing: Spatial smoothing and classification into turbidity levels

To better represent actual environmental conditions

ECoE - GeoAI-Based Coastal Water Quality Assessment in Cyprus Using Sentinel-2 and Machine Learning

during rainfall events, short temporal windows were used to generate Sentinel-2 composites that minimize cloud contamination while preserving short-term turbidity signals. As shown in Figure 38 a Sentinel-2 Surface Reflectance dataset was utilized for analysis-ready composite image in the GEE environment. The dataset was filtered spatially and temporally for the target area and timeframe, with cloud and shadow contamination minimized using the Scene Classification Layer. The imagery was radiometrically scaled to surface reflectance values. A compositing method was applied to reduce atmospheric noise and temporal variability by computing the median or mean of the filtered collection. The final composite, clipped to the study area, included relevant spectral bands for further analysis, yielding a consistent, cloud-free, and noise-reduced dataset ideal for water quality assessment and machine learning applications in GEE.

Implementation and Collaborations

The workflow is implemented in the Google Earth Engine platform, allowing efficient processing of large-scale satellite datasets. The approach can be applied in collaboration with:

- Environmental authorities in Cyprus
- Coastal and marine monitoring agencies
- Academic and research institutions
- International organizations involved in Earth Observation

Such collaborations can support the integration of GeoAI methods into operational environmental monitoring systems.

Impact and Outcomes

The application provides:

- Spatially explicit maps of water turbidity along the Cyprus coastline
- Improved detection of water quality changes following rainfall events
- Enhanced understanding of sediment transport and coastal dynamics
- Identification of areas affected by increased turbidity

These outputs support:

- Environmental monitoring
- Coastal zone management
- Evidence-based decision-making

Alignment with SDGs

This practice contributes to the UN-SPIDER mission by promoting the use of space-based information for environmental monitoring and risk-informed decision-making. It aligns with the following Sustainable Development Goals:

- SDG 6 – Clean Water and Sanitation
- SDG 13 – Climate Action
- SDG 14 – Life Below Water

MACHINE LEARNING IS A "FIELD OF STUDY THAT GIVES COMPUTERS THE ABILITY TO LEARN WITHOUT EXPLICITLY BEING PROGRAMMED".

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Lessons Learned and Recommendations

Key lessons include:

- Coastal environments are highly dynamic, particularly during rainfall periods
- Multi-temporal compositing may introduce artifacts and non-realistic patterns
- Single-date or short temporal analysis provides more reliable results
- Residual atmospheric effects can influence classification outcomes

Recommendations:

- Use imagery acquired immediately after rainfall events
- Apply robust cloud and water masking techniques
- Improve training data quality and representativeness
- Validate outputs using field measurements where possible

Conclusions:

- Positive outcomes for advancing water quality monitoring
- ML algorithms give promising results for water parameter retrieval
- Multispectral Sentinel-2 is more sensitive to concentrations variability
- Complementarity with in-situ sampling
- Involvement of stakeholders has proven to be a useful practice

Additional References or Resources

- Ambika, K., Shanmugapriya, P., Alghamdi, A.G. et al. Monitoring Coastal Water Quality Using Remote Sensing and Machine Learning. Ocean Sci. J. 61, 22 (2026). https://doi.org/10.1007/s12601-026-00274-w.
- Sent, G., Biguino, B., Favareto, L., Cruz, J., Sá, C., Dogliotti, A. I., Palma, C., Brotas, V., & Brito, A. C. (2021). Deriving Water Quality Parameters Using Sentinel-2 Imagery: A Case Study in the Sado Estuary, Portugal. Remote Sensing, 13(5), 1043. https://doi.org/10.3390/rs13051043.
- Lock, M., Saintilan, N., van Duren, I., & Skidmore, A. (2023). Monitoring Coastal Water Body Health with Sentinel-2 MSI Imagery. Remote Sensing, 15(7), 1734. https://doi.org/10.3390/rs15071734.
- Sobel, R.S., Kiaghadi, A. & Rifai, H.S. Modeling water quality impacts from hurricanes and extreme weather events in urban coastal systems using Sentinel-2 spectral data. Environ Monit Assess 192, 307 (2020). https://doi.org/10.1007/s10661-020-08291-5.

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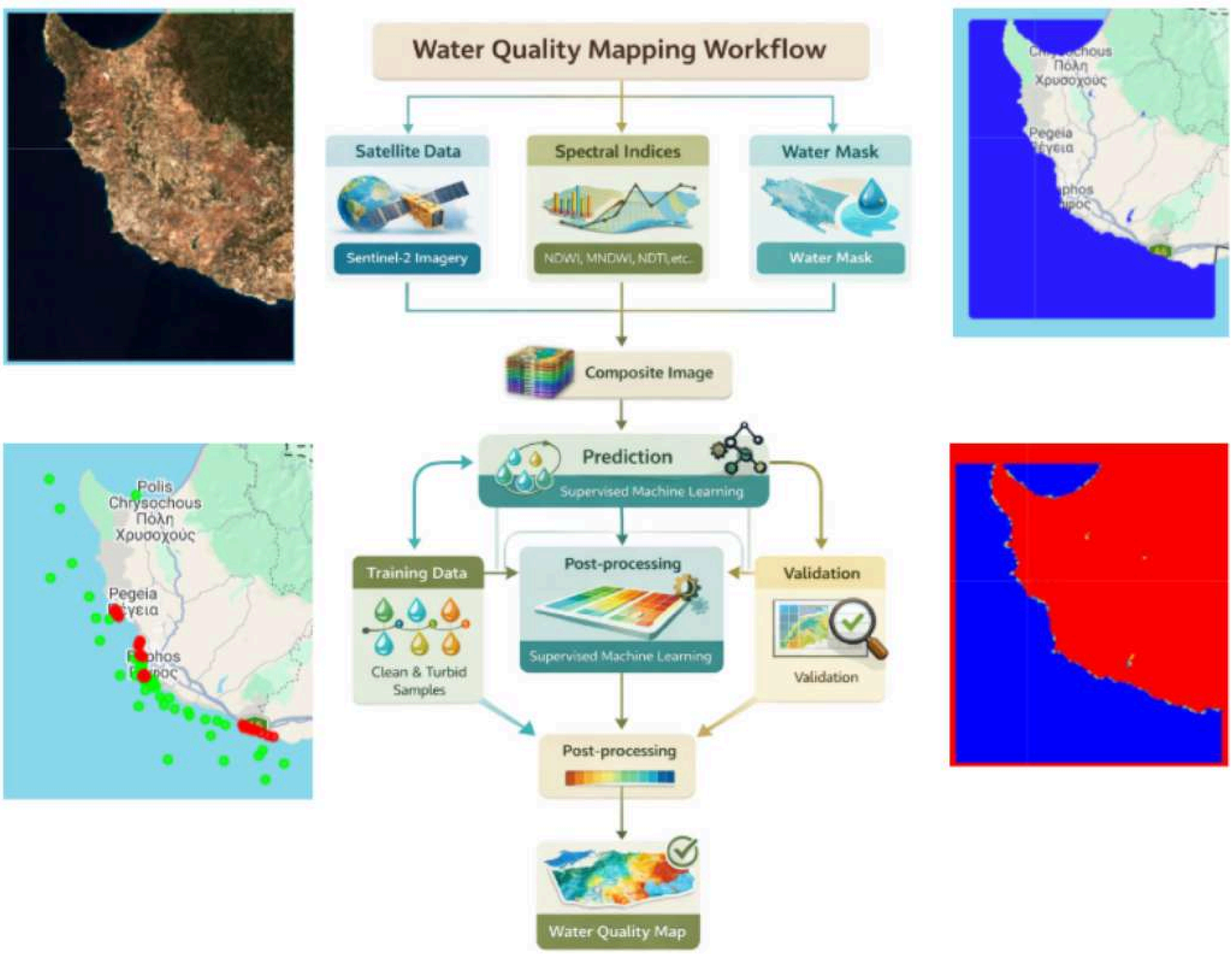

Figure 38: Methodology Workflow Using Multispectral Imagery in GEE to Monitor Water Quality

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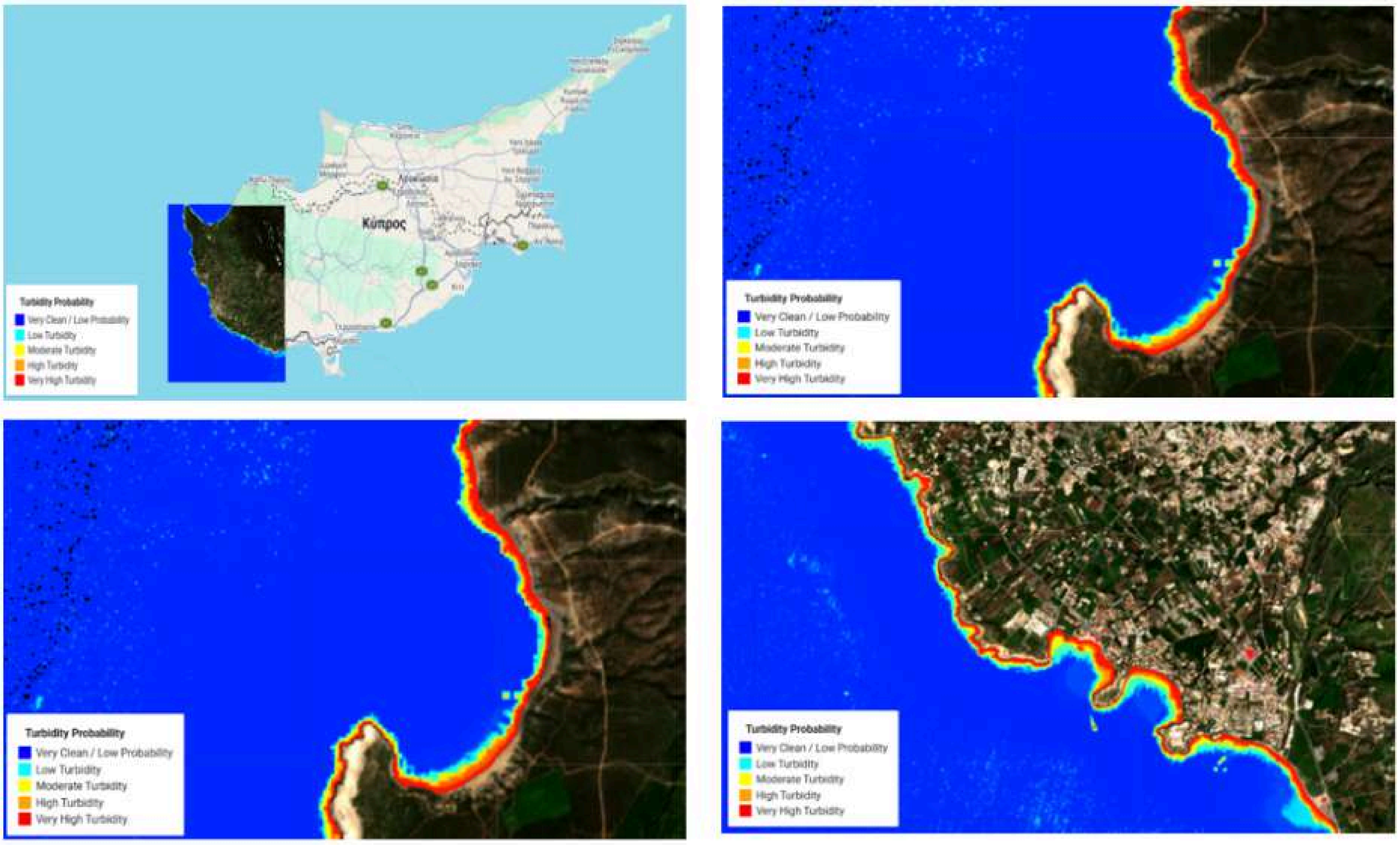


Figure 39: Spatial Analysis of Coastal Water Quality in Cyprus Based on Turbidity Probability

University of Lancashire - AI-Powered Soil Temperature Modeling for Sustainable Agriculture in Arid Regions: A Case Study of Bustan, Uzbekistan

Title of GeoAI Practice

AI-Powered Soil Temperature Modeling for Sustainable Agriculture in Arid Regions: A Case Study of Bustan, Uzbekistan

Brief Description

This study evaluates machine learning methods for predicting soil temperature in Bustan, Uzbekistan, a region facing climate stress. Sixteen years of weather data, including air temperature, humidity, and wind speed, were used to test eight models. The Bi-LSTM model achieved the highest accuracy, with R^2> 0.94 for temperatures at 10 cm depth. A two-step approach used surface temperature predictions to estimate subsurface temperature. This method supports improved irrigation planning, higher crop yields, and sustainable land management. It provides a practical, scalable solution for agriculture in arid and data-limited regions.

Challenge or Problem Addressed

This practice aims to improve soil temperature prediction in arid and climate-sensitive regions such as Bustan. It addresses the lack of accurate, continuous, and depth-specific soil temperature data, which is essential for effective agricultural decision-making.

In many dry regions, monitoring soil temperature changes is challenging due to limited data, high climate variability, and scarce resources. This impacts irrigation planning, crop yield prediction, soil health management, and climate adaptation. Traditional methods depend on direct measurements, which are often costly and unavailable.

This study uses AI and machine learning, particularly Bi-LSTM, to predict surface and subsurface soil temperatures from readily available weather data. This enables farmers and policymakers to make informed, data-driven decisions for sustainable agriculture, even in data-scarce environments.

ARID REGIONS ARE CHARACTERIZED BY NEGATIVE MOISTURE BALANCES, I.E., POTENTIAL EVAPOTRANSPIRATION RATES PERMANENTLY EXCEED PRECIPITATION RATES.

Technical Approach and Methods

This study applies GeoAI (Geospatial Artificial Intelligence) and machine learning techniques to predict soil temperature in Bustan using long-term environmental data.

Data Sources:
The model uses 16 years (2008–2023) of meteorological data, including atmospheric temperature (min, max, mean), relative humidity, and wind speed. Soil temperature data at the surface and 10 cm depth were obtained from the regional meteorological centre. Due to very low rainfall, precipitation was excluded.

Machine Learning Methods:
Eight models were tested: XGBoost (Extreme Gradient Boosting), CatBoost (Categorical Boosting), LSTM (Long Short-Term Memory), Bi-LSTM (Bidirectional Long Short-Term Memory), ANN (Artificial Neural Network), Ridge (Ridge Regression), Lasso (Least Absolute Shrinkage and Selection Operator), and ElasticNet (a regularised regression method). The Bi-LSTM model performed best because it captures both past and future patterns in time-series data.

University of Lancashire - AI-Powered Soil Temperature Modeling for Sustainable Agriculture in Arid Regions: A Case Study of Bustan, Uzbekistan

Modelling Approach:
A two-step modelling framework was used:
1. Predict surface soil temperature from climate variables.
2. In the next step, the predicted surface temperature, combined with climate data, was used to estimate subsurface temperature (10 cm). This sequential approach underpins the structure of the modelling framework.

Techniques and Tools:
Data preprocessing included noise removal, handling of missing values, and statistical filtering (z-scores, standard deviation). Model optimisation used grid search and k-fold cross-validation.

In summary, this approach provides a robust, scalable GeoAI framework for soil temperature prediction in data-scarce, arid environments, demonstrating how the methodological steps integrate to address regional challenges.

Implementation and Collaborations

The initiative was implemented as an academic-led, data-driven research project that combined expertise from multiple international institutions. The study was conducted in Bustan using a structured workflow encompassing data collection, model development, validation, and application.

Implementation Approach:
The project used historical meteorological and soil data (2008–2023) obtained from the regional Meteorological Centre. After data cleaning and preprocessing, multiple machine learning models were developed and tested. The Bi-LSTM model was selected and applied in a two-step framework to predict both surface and subsurface soil temperatures. The results were validated against real-world observations to ensure reliability for practical use in agriculture.

Collaborations and Partnerships:
This initiative reflects a strong multi-institutional collaboration involving:

- Leading academic institutions from Sri Lanka, Uzbekistan, the UK, Ireland, Japan, and Russia deliver top-tier expertise in engineering, environmental science, and AI.
- Local agencies in Uzbekistan, particularly the meteorological authority, provided essential long-term climate and soil datasets.
- International research collaboration facilitated dynamic knowledge exchange in machine learning, climate science, and sustainable agriculture.

Overall, while the study is primarily academic, it lays the foundation for future collaboration with government bodies, agricultural stakeholders, and technology developers to implement real-time decision-support systems for farmers and policymakers.

Impact and Outcomes

This project has made a real difference for sustainable farming and climate resilience in Bustan and other dry areas.

University of Lancashire - AI-Powered Soil Temperature Modeling for Sustainable Agriculture in Arid Regions: A Case Study of Bustan, Uzbekistan

Key Outcomes:
- The study predicted soil temperatures very accurately. The Bi-LSTM model reached R^2 values above 0.94 for temperatures 10 cm below the surface. It also tracked seasonal and climate changes well, showing it works reliably in real situations.

Practical Impact:
- Better irrigation planning: Farmers can manage water use more effectively by using predicted soil conditions.
- Improved crop yield forecasts: Accurate soil temperature data helps farmers make better choices about when to plant and harvest.
- Sustainable land management: This approach helps track soil health and lowers the risk of soil damage.
- Cost-effective solution: Farmers no longer need to constantly measure soil temperature in the field.

Broader Outcomes:
This method uses AI and can be used in other places with little data or tough climates. It helps improve food security and supports sustainable farming over time. It also gives policymakers solid information for planning and adapting to changes.

Lessons Learned and Recommendations

Summary of Key Insights:

- Advanced artificial intelligence models, particularly Bi-LSTM, demonstrate high effectiveness in time-series environmental prediction by capturing complex climate–soil interactions.
- A two-step modeling approach, which predicts surface temperature followed by subsurface temperature, enhances prediction accuracy and more accurately represents actual soil processes.
- Reliable predictions are attainable using commonly available meteorological data, thereby reducing reliance on costly field sensors.
- This approach exhibits significant potential for scalable GeoAI applications in arid and data-limited regions such as Bustan.

Identified Challenges:

- Limited data availability and the absence of detailed soil properties, such as soil type and moisture content, constrained the range of model inputs.
- Data quality issues, including the presence of noise and missing values, necessitated extensive preprocessing.
- The exclusion of precipitation data, resulting from low rainfall in the study area, may restrict the model's applicability to other climatic regions.
- A gap persists in translating research outputs into operational tools accessible to farmers and policymakers.

Recommendations:

- Prioritize long-term, high-quality environmental data collection efforts, encompassing both soil and climate variables.
- Integrate remote sensing and satellite data sources to enhance spatial coverage and increase model robustness.
- Employ hybrid modelling approaches that combine artificial intelligence with physical models to improve interpretability.

University of Lancashire - AI-Powered Soil Temperature Modeling for Sustainable Agriculture in Arid Regions: A Case Study of Bustan, Uzbekistan

- Develop user-friendly platforms, such as web or mobile applications, to deliver predictive outputs to end users.
- Promote collaboration among multiple stakeholders, including government, academia, and technology providers, to facilitate real-world implementation and scalability.

Alignment with SDGs

This practice advances the mission of the United Nations Office for Outer Space Affairs' UN-SPIDER by promoting data, advanced analytics, and environmental intelligence to improve decision-making in climate-sensitive regions.

Support to UN-SPIDER Mission:
This study supports UN-SPIDER's goal of improving access to geospatial and environmental information for risk reduction. Applying AI to long-term climate datasets enhances understanding of environmental variability, which is essential for drought risk management, early warning systems, and climate adaptation planning in arid regions.

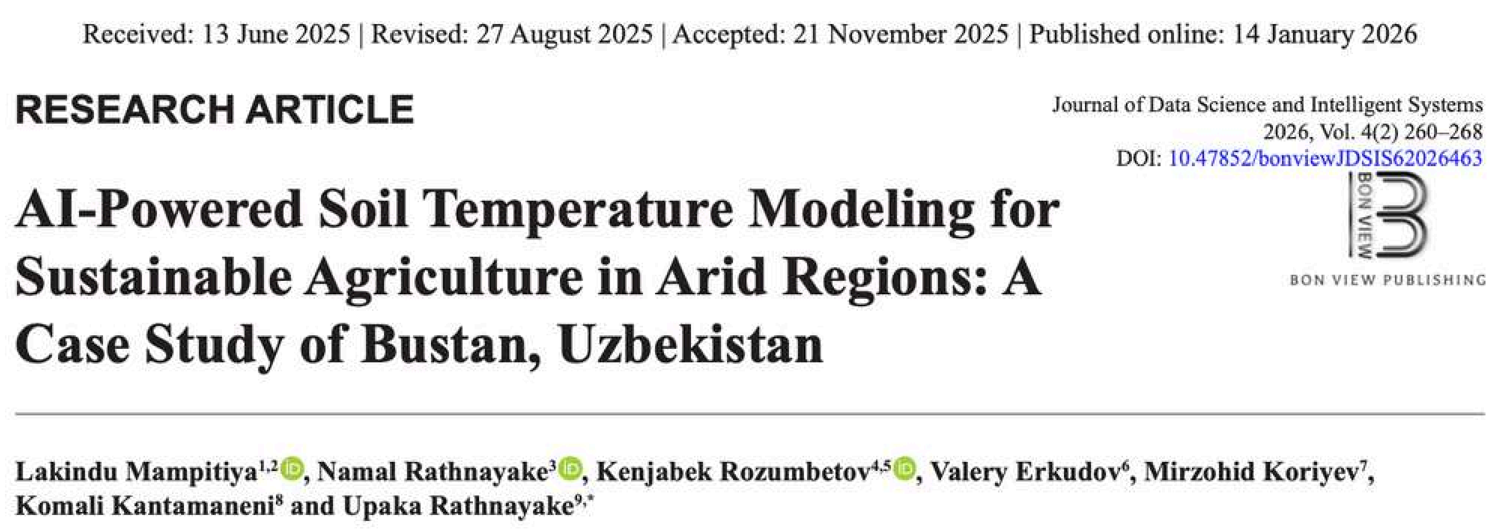
Alignment with Sustainable Development Goals (SDGs):

- SDG 2: Zero Hunger – Improves agricultural productivity through better soil and irrigation management.
- SDG 13: Climate Action – Supports adaptation to climate variability by predicting soil temperature changes.
- SDG 15: Life on Land – Promotes sustainable soil management and ecosystem health.
- SDG 6: Clean Water and Sanitation – Enhances efficient water use in agriculture through improved irrigation planning.

Overall, this AI-driven approach strengthens resilient, data-informed agricultural systems and directly supports global sustainability and disaster risk reduction efforts.

Additional References or Resources

This is a collaborative article published in the Journal of Data Science and Intelligent Systems. Dr. Komali Kantamaneni (UN-SPIDER UK RSO) is one of the co-authors. Weblink:https://ojs.bonviewpress.com/index.php/jdsis/article/view/6463


Received: 13 June 2025 | Revised: 27 August 2025 | Accepted: 21 November 2025 | Published online: 14 January 2026

RESEARCH ARTICLE

Journal of Data Science and Intelligent Systems
2026, Vol. 4(2) 260–268
DOI: 10.47852/bonviewJDSIS62026463

BON VIEW PUBLISHING

AI-Powered Soil Temperature Modeling for Sustainable Agriculture in Arid Regions: A Case Study of Bustan, Uzbekistan

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UN-SPIDER in collaboration with ZFL - UN-SPIDER's practice to Developing a Digital Twin for Trinidad and Tobago and the Greater Accra region

Title of GeoAI Practice

UN-SPIDER's practice to Developing a Digital Twin for Trinidad and Tobago and the Greater Accra region.

Brief Description

In 2024, a high-resolution digital twin for the island of Tonga was created. After that, in line with the Space2030 Agenda and the EW4All (Early Warning for All) Initiative introduced at COP27, the project expanded its focus to developing AI-based digital twins for disaster-prone regions in Trinidad and Tobago and Ghana between January and March 2025. These digital twins are used to model flooding and sea-level rise scenarios, providing actionable insights and gathering ideas to support emergency preparedness and response planning.

The initiative was carried out jointly by the United Nations Office for Outer Space Affairs and SpaceData Inc., with technical support provided by the Center for Remote Sensing of Land Surfaces (ZFL) at the University of Bonn and Maxar Technologies. The RSO ZFL was mainly a supporter in the modelling of the sea level rise and storm surge rise extent for both regions.

In 2024, a high-resolution digital twin for the island of Tonga was developed. Building on this work, and in line with the Space2030 Agenda and the EW4All (Early Warning for All) Initiative introduced at COP27, the project expanded between January and March 2025 to develop AI-based digital twins for disaster-prone regions in Trinidad and Tobago and Ghana. These digital twins are used to simulate flooding and sea-level rise scenarios, providing actionable insights to support emergency preparedness, response planning, and risk communication.

The initiative was implemented jointly by the United Nations Office for Outer Space Affairs (UNOOSA) and SpaceData Inc., with technical support provided by the Center for Remote Sensing of Land Surfaces (ZFL) at the University of Bonn and Maxar Technologies. The

THE DIGITAL TWINS FOR COMMONWEALTH NATIONS PROJECT AIMS TO **ENHANCE DISASTER RISK MANAGEMENT & RESILIENCE** USING CUTTING-EDGE SATELLITE DATA & DIGITAL TWIN TECHNOLOGY.

UN-SPIDER Regional Support Office ZFL primarily contributed to the modelling of sea-level rise and storm surge extents for both regions.

Challenge or Problem Addressed

Ghana and Trinidad and Tobago are increasingly exposed to coastal flooding and storm-related hazards in the context of climate change. Meanwhile, opportunities remain to further strengthen integrated early warning systems and risk-informed planning tools. The practice addresses gaps in the availability of high-resolution spatial data and advanced analytical capacities for coastal risk simulation, particularly with regard to detailed 3D representations of the built environment. It responds to the need for accessible, scalable solutions that enable the simulation and visualisation of future flood scenarios, supporting improved preparedness, response planning, and risk communication for vulnerable communities and critical infrastructure. Through the CommonSpace Initiative - Digital Twins for Commonwealth Nations Project, two pilot regions (Trinidad island and Greater Accra region) were chosen to address the stated challenges and problems.

UN-SPIDER in collaboration with ZFL - UN-SPIDER's practice to Developing a Digital Twin for Trinidad and Tobago and the Greater Accra region

Technical Approach and Methods

For both regions, Trinidad and Tobago (Tobago Island) and Ghana (Greater Accra region), very high-resolution (30-50 cm) optical satellite imagery was procured through Maxar Technologies. AI models were then used by SpaceData Inc. to generate LOD1 (Level of Detail 1) 3D models of the environment for large-scale analysis and LOD3 models for select high-priority areas such as ports and informal settlements. Using deep learning and 3D reconstruction techniques such as NeRF and Gaussian Splatting, realistic urban models were produced. Blender and Cesium ion platforms were utilized to simulate dynamic scenarios like flash floods and storm surges. In parallel, storm surge simulations were conducted with technical guidance and model outputs from the University of Bonn, based on the UN-SPIDER Recommended Practices: Use of Digital Elevation Data for Storm Surge Coastal Flood Modelling.

Implementation and Collaborations

This initiative was implemented by UNOOSA/UN-SPIDER in partnership with multiple stakeholders, including the National Disaster Management Organisation Ghana (NADMO), University of Trinidad and Tobago, Space Data Inc., University of Tokyo, Maxar Technologies, and Center for Remote Sensing of Land Surfaces (ZFL) from the University of Bonn.

Impact and Outcomes

The Commonwealth Digital Twin Project enhanced disaster preparedness in Trinidad and Tobago and the Greater Accra Region in Ghana through the development of AI-driven digital twin models. These models provide visualisations of realistic flood and sea-level rise scenarios, aiming to support risk assessment and early warning planning. Furthermore, the project strengthened local technical capacities through the use of advanced tools such as Cesium ion, ArcGIS Pro, and QGIS applications. It also fostered multi-stakeholder collaboration and contributed to the disaster risk management cycle, the EW4All Initiative, and the Space2030 Agenda.

Project outputs included the exchange of high-resolution optical satellite imagery (30-50 cm), digital twin datasets in GIS-ready formats at LOD 1, and simulation and promotional videos visualising potential flooding and sea-level rise impacts. The products were made accessible via platforms such as Cesium ion and ArcGIS Online Scene Viewer. Further details and links to the products are provided in the additional references and resources section.

Lessons Learned and Recommendations

A lack of training data and limited information on building heights necessitate the estimation of building dimensions based on classification results, which introduces uncertainties into the dataset. In addition, an evaluation of 3D modelling software is needed to identify the most appropriate tool for this application. The generation of high levels of detail for building footprints is also time-intensive, typically requiring approximately two to three months of processing.

To further improve the practice (in a second project phase), the integration of water level sensors and rain gauges within river systems could be considered. Such sensors, together with the 3D twin, could support more adaptive evacuation planning by enabling, e.g., evacuation route optimisation based on real-time flood depth conditions. In addition, the development of a 3D digital platform for disaster risk management would enhance accessibility to data and facilitate the practical use of the generated products in a 3D environment.

UN-SPIDER in collaboration with ZFL - UN-SPIDER's practice to Developing a Digital Twin for Trinidad and Tobago and the Greater Accra region

Alignment with SDGs

This initiative contributes to enhanced disaster risk reduction, the strengthening of technical capacities, improved access to datasets, and increased stakeholder collaboration. It further aligns with the Sendai Framework for Disaster Risk Reduction, Sustainable Development Goal 13 (Climate Action), Sustainable Development Goal 11 (Sustainable Cities and Communities), and Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure). By employing advanced digital solutions, the initiative also supports the objectives of the Space2030 Agenda.

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
11 SUSTAINABLE CITIES AND COMMUNITIES
13 CLIMATE ACTION

FIND OUT MORE ABOUT HOW **EARTH OBSERVATION DATA** CAN BE USED FOR THE SDGS IN UN-SPIDERS RECENT PUBLICATION: **EO4SDG BOOK**

Additional References or Resources

1. Simulation and Promotion Videos

A Digital Twin - Accra, Ghana: https://youtu.be/q-1KDfeM3WA?si=QoqbhYz083aqDBk2
Flooding video in Ghana: https://youtu.be/nf0BqoPCye4
Flooding video in Trinidad and Tobago: https://youtu.be/TyB-8ENlukA

2. Cesium ion Platform

Ghana James Town Fishing Harbour: https://ion.cesium.com/stories/viewer/?id=b354cdfd-d00f-4ec2-9a08-548f4b28f869#slide-id-303516
Trinidad and Tobago Airport: https://ion.cesium.com/stories/viewer/?id=e995969b-8576-4393-b62a-1ada81d5d05b#slide-id-306935

3. ArcGIS Online Scene Viewer

https://www.arcgis.com/home/webscene/viewer.html?webscene=990ff45d1fca47199d18acba800f9da6

4. Media

https://www.un-spider.org/projects/CommonSpaceInitiative
https://www.zfl.uni-bonn.de/research/projects/digital-twin-for-improved-visualization-of-coastal-flood-risks
https://en.spacedata.jp/news/202505_dx_disasterresponse

Section F: Common Elements of Success and Lessons Learned

Overview

GeoAI adoption is strengthened by common success factors across RSOs, including strong data governance, integrated technical workflows, and institutional collaboration. Validated ground truth and open data standards are essential for model reliability. Capacity-building efforts and localized training support long-term sustainability. Policy alignment and user engagement ensure that tools are actionable and context-specific. These elements help scale effective GeoAI practices across regions.

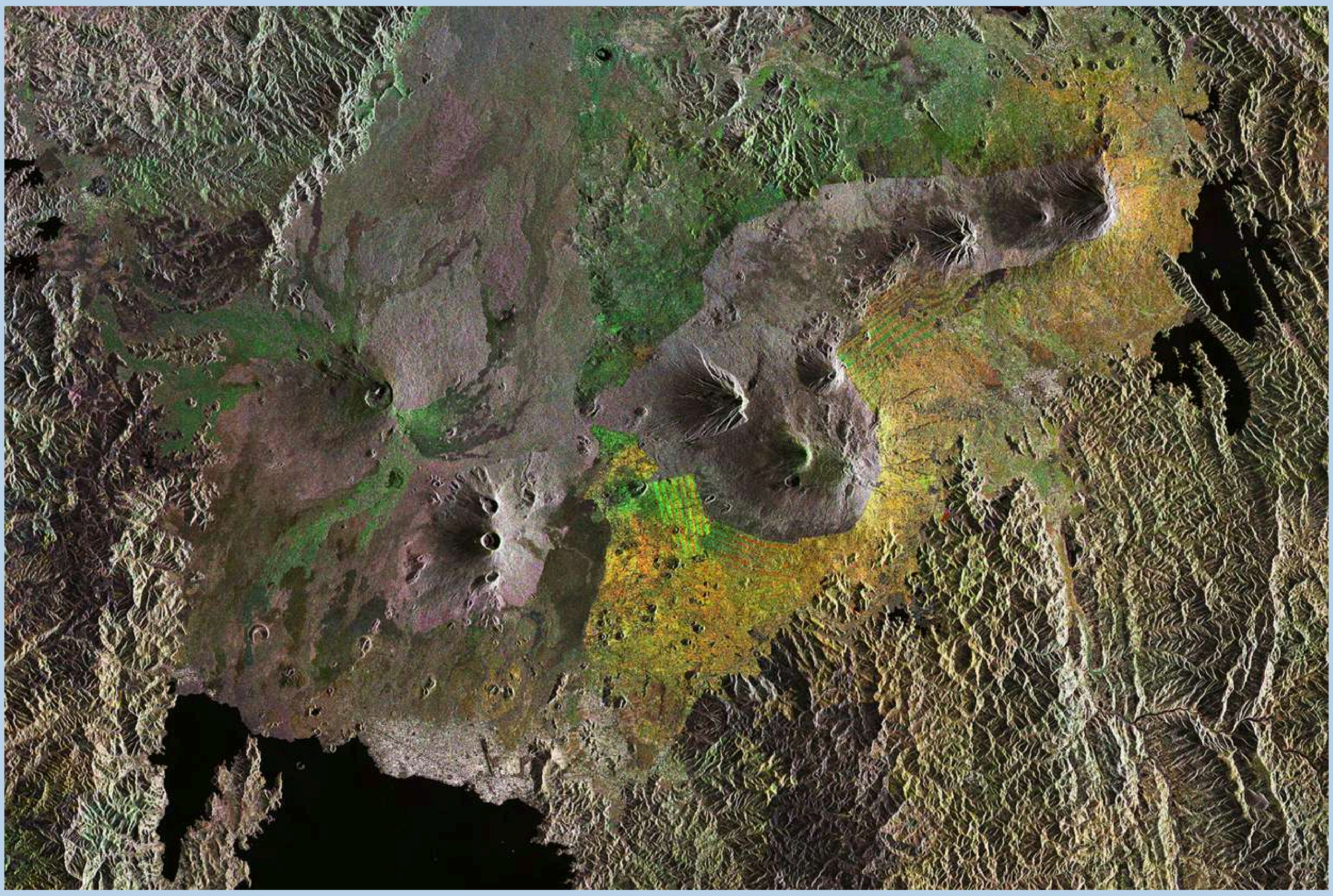


Figure 40: Earth Observation to Evaluate Natural Risk to Human Settlements and Agriculture in the East of the Democratic Republic of the Congo
(c) UN Earth Observation and imagery

The practices gathered in this chapter span different hazards, regions and methods, from wildfire fuel mapping and flood susceptibility modelling to landslide assessment, coastal-erosion monitoring, water-quality classification and regional water-reuse planning. Despite that variety, a consistent set of patterns distinguishes the work that reached operational use from the work that remained experimental. This section draws those threads together, identifying the elements that recurred wherever GeoAI delivered value and the gaps that recurred wherever it stalled. Together they form the bridge between the evidence presented above and the recommendations that follow.

Data Governance and Integration

The single most consistent enabler across these practices was the use of open, freely available Earth-observation data, principally the Sentinel-1 and Sentinel-2 archives, complemented by open precipitation products such as CHIRPS and by open-source geospatial tooling. This foundation kept costs low and made the workflows reproducible by others, a precondition for transfer across the network. Equally consistent was the reliance on data integration rather than any single sensor: the strongest results came from fusing optical and radar imagery with terrain, vegetation, hydrological and meteorological layers, and, critically, with whatever local ground truth was available.

That last point reflects the defining constraint these practices faced, which was data scarcity. The landslide and flood work succeeded precisely because they integrated sparse in-situ observations, such as a handful of rain gauges or an incomplete hazard inventory, with satellite data to compensate for thin local records. The regional water-reuse work confronted a related problem of fragmented or absent official data, and used AI-based detection to recover infrastructure that national records had missed, identifying a substantial body of previously undocumented treatment plants. The governance lesson is twofold. First, integration is what turns scarce and uneven data into usable intelligence. Second, the data-sharing and residency restrictions noted in the methodology remain a real limit on what can be pooled across borders, and addressing them through model-sharing rather than data-sharing is an unfinished task for the network.

Technological Approaches and Capacity Gaps

A clear technological preference runs through these cases: computationally efficient and interpretable models, deployed on cloud-native platforms, in preference to the heaviest available architectures. Random Forest recurs across the majority of the practices, and in the flood study, a deliberately simplified model using only a few widely available variables matched the performance of more complex alternatives. Cloud platforms such as Google Earth Engine lowered the infrastructure barrier by removing the need to download and store large archives locally. Where labelled data were scarce, unsupervised approaches such as the Pulse Coupled Neural Network used for shoreline extraction proved their worth, and the water-reuse work points toward an emerging frontier in which computer vision and large language models are combined to interpret unstructured information at scale.

The recurring gap is human rather than technical. Several practices depended on a small number of skilled analysts and on external capacity-building mechanisms, notably the twinning arrangements that transferred AI and Earth-observation expertise into the host institution. This dependence is a strength while it lasts and a vulnerability when it ends. Without recurring investment in skills, defined technical roles and the means to sustain workflows beyond the life of a single project, capability built during a pilot can dissipate once the funding or the partnership concludes. Closing that gap is as important as any algorithmic advance.

Policy and Institutional Coordination

In every case, the analytical output was designed with a decision in mind rather than as an end in itself. Fuel-type maps were framed to help authorities prioritise prevention and allocate suppression resources; flood screening tools were positioned to inform water and land-development policy; landslide and coastal outputs were built to support spatial planning and hazard mitigation; and the water-reuse framework was structured explicitly around multi-sectoral planning and investment decisions. Each practice also mapped its contribution to the Sendai Framework priorities and to specific Sustainable Development Goals, which strengthens the case for institutional adoption and for finance.

These outcomes were possible because of coordination across institutions, including national mapping and meteorological agencies, government ministries, universities and international research consortia. The persistent gap lies in the step from producing decision-ready outputs to embedding them in routine institutional workflows. Multi-sectoral applications such as water reuse depend on coordination across ministries that do not always share data or mandates, and even strong technical results can stall without a clear institutional owner responsible for running, updating and acting upon them. Sustained policy impact therefore depends as much on governance arrangements as on model accuracy.

Validation, Transparency and Trust

A feature common to all of these practices, and central to their credibility, was independent validation. Results were tested against external reference data rather than asserted, whether against flood and landslide inventories, official orthophotography for shoreline accuracy, or documented infrastructure records. Reporting accuracy in transparent terms, including error magnitudes and the share of known events correctly captured, gives decision-makers a basis for judging when an output can be trusted and when it cannot. The preference for interpretable models and openly documented, reproducible workflows reinforced that trust, since a result that can be explained and repeated is one that authorities are more willing to act upon. Carrying this discipline forward, through clear documentation of data, methods, and limitations, is what separates analytics that inform policy from analytics that are merely produced.

Transferability and Scalability

Finally, the practices that promise the greatest network-wide value were those designed from the outset to travel. The coastal-monitoring workflow was built to be low-cost and transferable to other Mediterranean coasts and small island developing States; the susceptibility methods were structured to scale from local studies toward national application; and the water-reuse framework was deliberately country-agnostic, intended for deployment in any national context rather than tied to the geography in which it was first developed. The common ingredients were reliance on globally available open data, modular and well-documented methods, and an explicit intention to lower the barriers facing less-resourced institutions. Transferability of this kind is what allows a practice pioneered in one office to become a shared asset for the whole UN-SPIDER community, and it is the quality the next edition of this Compendium will seek to amplify.

Highlights of RSO Contributions

The case studies in this edition illustrate the breadth of operational GeoAI now in use across the network:

- **Wildfire fuel mapping (Cyprus):** A Random Forest framework in Google Earth Engine fused Sentinel-1 and Sentinel-2 data with terrain and vegetation variables to produce fuel-model maps at 10 to 30 metre resolution, a substantial improvement over the coarser regional datasets previously available for local fire-behaviour planning.
- **Flood susceptibility in data-scarce basins (Cyprus):** Comparing four machine-learning models across eight watersheds, the work showed that a simplified Random Forest model using only land use, slope, elevation and flow accumulation achieved around 95 per cent agreement with flood-inventory data, offering authorities a rapid, low-cost screening tool in place of fully detailed hydrodynamic models.
- **AI-enhanced landslide susceptibility (Cyprus):** Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) were fused with sparse rain-gauge observations using machine learning, then combined with geomorphological factors in a multi-criteria framework, producing high-resolution susceptibility maps that captured more than 30 per cent of known landslide occurrences within the highest-risk classes.
- **Coastal erosion monitoring (Cyprus):** An unsupervised Pulse Coupled Neural Network extracted shorelines from Sentinel-2 imagery (validated to an RMSE of 9.21 metres) and quantified the downdrift impact of a coastal breakwater, establishing a repeatable, low-cost workflow transferable to other Mediterranean coasts and small island developing States.
- **Water reuse planning across the Middle East and North Africa (MENA) region:** The Water-REPEAT framework combined Earth Observation, computer vision and large language models to map wastewater infrastructure and demand across Egypt, Saudi Arabia and the United Arab Emirates. In Egypt alone, AI-based detection identified approximately 164 treatment plants beyond the 552 already documented, a thirty per cent increase in known infrastructure, supporting evidence-based, climate-resilient water planning.
- **Coastal water-quality assessment (Cyprus):** A Random Forest classifier applied to Sentinel-2 imagery in Google Earth Engine generated turbidity-probability maps along the coastline, enabling near-real-time detection of rainfall-driven water-quality changes for environmental monitoring and coastal management.

VI. RECOMMENDATIONS AND WAY FORWARD

Across the Regional Support Office network, GeoAI has moved from proof of concept to operational reality. The practices gathered in this Compendium show models running in production, feeding susceptibility maps, damage assessments, and reuse plans into the hands of national authorities. Yet the same evidence base reveals uneven access to compute resources, skills and sustained financing, and a set of technical and institutional barriers that no single office can resolve alone. The recommendations below translate those lessons into an actionable roadmap for the next triennium, covering 2026 to 2029, organised around the partnerships, scaling pathways and research directions that will determine whether GeoAI becomes durable infrastructure rather than a series of isolated pilots.

STRENGTHENING MULTI-STAKEHOLDER COLLABORATION

The practices that achieved the fastest operational uptake were those that coupled RSO geospatial expertise with local domain knowledge and, where appropriate, private-sector technology stacks. Several of the case studies in this edition were delivered through exactly this model, combining national mapping agencies, meteorological services, universities and EU research consortia around a single workflow. Institutionalising that pattern should be a priority for UN-SPIDER and its partners.

First, UN-SPIDER should establish a GeoAI Partnership Portal hosted on the UN-SPIDER Knowledge Portal, maintaining a living inventory of open models, available cloud credits, reference workflows and focal-point contacts so that an office beginning a new project can find proven assets and willing collaborators in one place. Second, RSOs should align their pilots with global accelerator programmes and open-data initiatives, such as Digital Earth Africa, the CEOS Open Data Cube and the disaster-response licensing schemes offered by commercial imagery providers, so that archive and processing costs are absorbed by the provider rather than the host agency. Third, the network should formalise collaboration that already extends beyond the UN system: imagery providers that waive fees during emergencies, academic laboratories that release foundation-model checkpoints, and philanthropic funders that finance training and open-source development. These alliances reflect a core premise of the Sendai Framework, namely that risk reduction is a shared responsibility, and they allow a multilateral body to amplify its impact by coordinating rather than owning every link in the value chain.

SCALING GEOAI SOLUTIONS

The step from a successful pilot to national roll-out depends on replicable workflows, permissive licensing, cloud-native architecture and, above all, the means for less-resourced offices to participate on equal terms. The following actions would help close the gap between offices that already operate production pipelines and those still constrained by data, compute, or skills.

UN-SPIDER and contributing RSOs should publish containerised reference pipelines for common tasks, including flood mapping, landslide and wildfire susceptibility, and damage assessment, tested across major cloud platforms so that any office can deploy a proven workflow with minimal configuration. Each pipeline should ship with a standardised model card and data sheet that documents training data, performance bounds and known limitations, allowing emergency-operations centres and regulators to judge when a model is fit for a given purpose. To bridge the digital divide directly, the network should negotiate a pooled compute facility, in effect a shared pool of GPU hours accessible through federated identity, so that the least-connected offices can queue inference jobs without provisioning hardware of their own.

Scaling across borders also requires a response to data-sovereignty constraints. Because raw imagery often cannot leave national clouds, privacy-preserving federated learning offers a compliance-ready alternative in which model weights, rather than raw pixels, move between jurisdictions and improve with each iteration. In parallel, global models must be localised to perform reliably: every operational deployment should reserve a local hold-out set for validation and include at least one round of transfer learning using indigenous samples or crowd-sourced labels.

Investment in multilingual data pipelines and in community labelling campaigns that pair education programmes with small grants would steadily expand the pool of locally relevant training data. Finally, none of this endures without sustainable financing. Offices and governments should embed recurring line items for GeoAI analytics within disaster management and climate-adaptation budgets, rather than relying on ad hoc project grants, and explore blended finance in which insurers or catastrophe-bond issuers co-fund model maintenance once accuracy benchmarks reduce underwriting uncertainty.

ADVANCING INNOVATION AND RESEARCH

Next-generation sensors and algorithms are poised to lift both the spatial and the semantic resolution of disaster analytics, and UN-SPIDER, together with its academic partners, should prioritise the research directions most likely to translate into operational gain.

Three directions stand out. Constellation fusion with on-board inference would allow first-look hazard masks to be generated aboard low-orbit satellites and delivered within a single downlink pass, compressing the sensor-to-action timeline still further. Time-aware foundation models, trained to treat space-time data cubes as native input, would strengthen forecasting of slow-onset processes such as drought, coastal change and urban growth. Self-supervised vision models, which learn from unlabelled imagery, are especially promising for data-scarce settings where labelled examples are the binding constraint, as the unsupervised shoreline-extraction work in this edition illustrates. Alongside these, the network should continue to favour explainable and, where feasible, physics-informed approaches, since interpretability is what allows decision-makers to trust and act upon model outputs. More exploratory avenues, including quantum-assisted optimisation for problems such as large-scale evacuation routing, merit monitoring and selective experimentation as the underlying hardware matures, without diverting resources from methods that are operational today.

Innovation must be matched by governance. Bias audits, privacy-impact assessments and cryptographically verifiable model provenance should be embedded from the first commit rather than retrofitted after deployment, and compliance with these practices should become a condition of hosting a workflow on the UN-SPIDER Knowledge Portal. Ethics and transparency are not constraints on innovation; they are what make innovation usable in a public-safety context.

FUTURE OUTLOOK

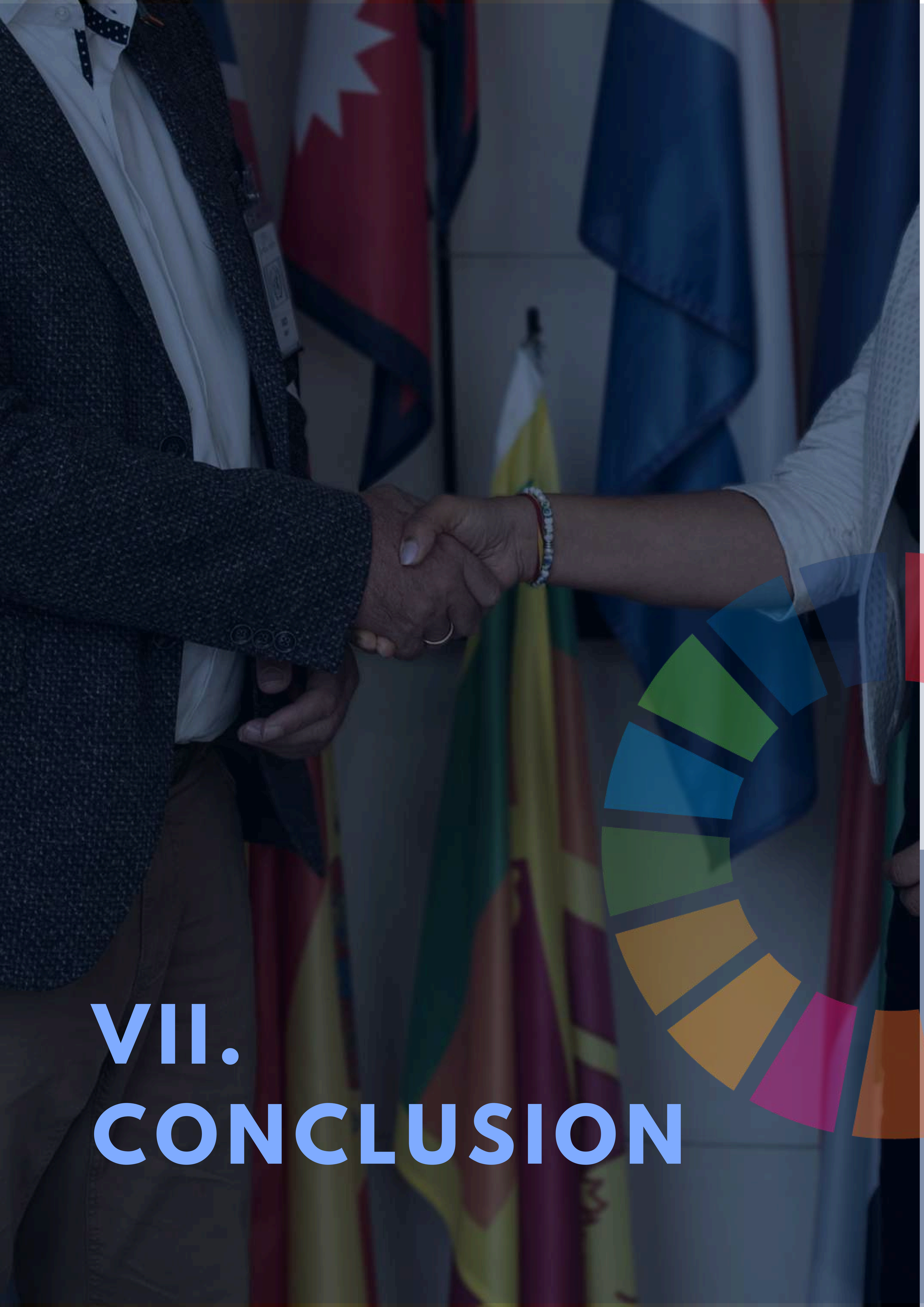
The next policy window will determine whether GeoAI matures from an early-adopter toolset into standard operating infrastructure for disaster-risk governance. That window is densely populated with milestones. COP 31 will be held in Antalya, Türkiye, from 9 to 20 November 2026, followed by COP 32 in Addis Ababa, Ethiopia, in 2027, the mid-point SDG review of 2027, the 2027 target of the Early Warnings for All initiative, and the 2030 stock-take of the Sendai Framework. With the Loss and Damage Fund now operationalised and adaptation finance set on a path to triple by 2035, the demand for defensible, satellite-derived evidence will only intensify. Against that backdrop, three mutually reinforcing trajectories are already visible.

The first is the shift from mapping to probabilistic foresight. GeoAI workflows are moving from retrospective damage delineation toward sub-seasonal impact forecasting, as ensemble pipelines that fuse numerical weather prediction, Earth-observation time series and socio-economic exposure layers begin to deliver probabilistic scenarios weeks ahead of a hazard window. This gives governments the lead time to pre-position relief goods, adjust cropping calendars and plan resilient infrastructure rather than respond after the fact.

The second is the movement from pixels to policy dashboards. Real-time GeoAI outputs are climbing the value chain, from GIS desktops to cloud dashboards wired into budgeting, insurance and loss-and-damage accounting. For UN-SPIDER, this implies packaging reference pipelines not only as geospatial layers but as application-ready services that ministries of finance and planning can consume without specialist geospatial expertise.

The third is the spread of privacy-preserving federated learning, which will allow models to improve across borders without raw data ever leaving sovereign clouds, a capability that is becoming essential for states with strict data-residency laws and a precondition for tackling transboundary hazards collectively.

Realising these trajectories will require sustained investment in people, platforms and governance. RSOs must cultivate talent that combines geospatial expertise with machine-learning fluency; UN-SPIDER must broker long-term compute agreements that insulate critical operations from volatility in cloud pricing; and the whole network must hold to the principle that analytics intended to protect lives are validated, transparent and equitably accessible. If the actions set out in this chapter are institutionalised over the coming triennium, GeoAI will take its place not as a boutique research interest but as a dependable backbone for disaster resilience and sustainable development, at the moment the planet's risk landscape demands it most.



VII. CONCLUSION

Concluding Remarks

The practices assembled in this Compendium make one conclusion difficult to avoid: GeoAI now sits at the centre of UN-SPIDER's mandate to make space-based information accessible, actionable and equitable. What began as a promise to widen access to satellite data has, over the course of a few years, become something more consequential. The case studies presented here show models that detect hazards as they unfold, forecast their impacts in advance, and turn raw imagery into the kind of defensible evidence that disaster managers, planners and finance ministries can act upon. The shift is not merely one of speed or accuracy. It is a change in who can do this work, and at what cost.

That is the transformation worth emphasising. A decade ago, the analytic capacity on display in these pages was the preserve of the world's largest space agencies. Today, an office with modest resources, a few skilled analysts and access to open data and sponsored cloud credits can produce high-resolution susceptibility maps, near-real-time damage assessments and basin-scale planning tools. Open-weight models, cloud-native platforms and computationally efficient methods have lowered the barriers to entry to the point where capability is no longer determined by budget alone. The practices in this edition, from wildfire fuel mapping and flood susceptibility modelling to coastal-erosion monitoring and water-reuse planning, demonstrate that rigorous, decision-ready GeoAI is now within reach of the institutions that need it most.

The evidence also carries a sober reminder. Automation is necessary but not sufficient; high-throughput inference earns the trust of decision-makers only when it is paired with careful validation and honestly communicated uncertainty. Global models must be adapted to local conditions, since even strong performers degrade in landscapes and climates unlike those they were trained on. Transparency, provenance and ethical safeguards cannot be added after the fact; they have to be built in from the outset. And capability outlives hardware only when it is anchored in institutions, through budget lines, defined roles and career pathways, rather than in the presence of a single grant or individual. These are not reasons for caution so much as the conditions under which GeoAI delivers on its promise.

None of this is the achievement of any one organisation. The strength of the UN-SPIDER approach lies in its distributed character, in which sovereign data is held locally, shared algorithms circulate globally, and validation is applied regionally with the ground truth and contextual knowledge that only national institutions possess. The Regional Support Offices are the heart of this model. Their analysts contribute the case studies, the field expertise, and the peer review that give this publication its authority, and their partnerships with national space agencies, disaster management authorities, universities, the private sector, and other UN bodies show how a multilateral platform can amplify its impact by coordinating expertise rather than concentrating it. Collaboration of this kind reflects a founding principle of the Sendai Framework, that the reduction of disaster risk is a shared responsibility, and it is the surest guarantee that the methods catalogued here will travel beyond the offices that pioneered them.

The task now is institutionalisation. The technology has proven itself; what remains is to embed it, to sustain the skills, platforms and governance that keep it running, and to ensure that the least-resourced and most hazard-exposed States can join on their own terms. If the network holds to that course over the coming years, GeoAI will become not a boutique research interest but a dependable backbone for disaster resilience and sustainable development, helping to turn the steady stream of satellite observations into earlier warnings, faster responses and safer lives and livelihoods for the communities that depend on them.

VIII. ANNEXES

VIII. ANNEXES

This publication aims to assess the current state of Geospatial Artificial Intelligence (GeoAI) applications in disaster risk reduction and to identify operational challenges and best practices from across the UN-SPIDER Regional Support Offices network. To complement background research and internal analysis, a structured questionnaire was circulated to all RSOs within the UN-SPIDER Programme. This process aimed to document field-tested applications of GeoAI, spanning various hazard types and use cases across the disaster management cycle.

Best Practice Submission Template
(as used by all RSOs)

Each GeoAI practice in this compendium was submitted using the standardized form below. It ensures clarity, consistency, and comparability across all Regional Support Offices.

Section	Details Required
Title of the GeoAI Practice	A clear, descriptive title that reflects the essence of the project.
Brief Description	100–200 word summary including purpose and context.
Challenge or Problem Addressed	The specific problem this practice aims to resolve (e.g., early warning, hazard mapping).
Technical Approach and Methods	Summarize the key GeoAI tools, methodologies, and data sources utilized (e.g., type of satellite imagery, machine learning techniques, platforms or frameworks).
Implementation and Collaborations	Partnerships with agencies, academia, or private sector.
Impact and Outcomes	Measurable benefits (e.g., faster response, better planning, policy use).
Alignment with UN-SPIDER Goals or SDGs	How it supports UN-SPIDER's mandate or aligns with SDG targets. 8. Lessons Learned and Recommendations
Lessons Learned and Recommendations	Key insights, implementation tips, and challenges encountered.
Additional References or Resources	Links to publications, data, visuals, or external tools.

LIST OF ABBREVIATIONS

Abbreviation	Definition
AI	Artificial Intelligence
AMO	Atlantic Multidecadal Oscillation
API	Application Programming Interface
BGU	Ben-Gurion University of the Negev
CGIAR	Consultative Group on International Agricultural Research
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
COP	Conference of the Parties
CORINE	Coordination of Information on the Environment
CRIDA	Central Research Institute for Dryland Agriculture
DEM	Digital Elevation Model
DRR	Disaster Risk Reduction
DSAS	Digital Shoreline Analysis System
ECoE	ERATOSTHENES Centre of Excellence

LIST OF ABBREVIATIONS

Abbreviation	Definition
EFFIS	European Forest Fire Information System
ENSO	El Niño-Southern Oscillation
EO	Earth Observation
ESA	European Space Agency
EW4All	Early Warnings for All
GEE	Google Earth Engine
GeoAI	Geospatial Artificial Intelligence
GEV	Generalized Extreme Value
GIS	Geographic Information System
GPU	Graphics Processing Unit
GIC	Geoinformatics Center
GIT	Center for Interdisciplinary Geospatial Information Technologies
IAASARS/NOA	Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing

LIST OF ABBREVIATIONS

Abbreviation	Definition
ICAR	Indian Council of Agricultural Research
IOD	Indian Ocean Dipole
IWMI	International Water Management Institute
LULC	Land Use and Land Cover
LIMCOM	Limpopo Watercourse Commission
LSTM	Long Short-Term Memor
MAUP	Modifiable Areal Unit Problem
MCDA	Multi-Criteria Decision Analysis
MENA	Middle East and North Africa
ML	Machine Learning
MLMs	Masked Language Models
MLP	Multilayer Perceptron
MODIS	Moderate Resolution Imaging Spectroradiometer

LIST OF ABBREVIATIONS

Abbreviation	Definition
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio
NDMA	National Disaster Management Authority
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NRAA	National Rainfed Area Authority
PCNN	Pulse Coupled Neural Networks
RAG	Retrieval-Augmented Generation
RAGAS	Retrieval-Augmented Generation Assessment
RF	Random Forest
RSME	Root Mean Square Error
RSO	Regional Support Office
SAMGeo	Segment Anything Model for Geospatial Data

LIST OF ABBREVIATIONS

Abbreviation	Definition
SAR	Synthetic Aperture Radar
SDG	Sustainable Development Goal
SRI NASU-SSAU	Space Research Institute of the National Academy of Sciences of Ukraine and the State Space Agency of Ukraine
SRTM	Shuttle Radar Topography Mission
SUPARCO	Space and Upper Atmosphere Research Commission
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
UN-SPIDER	United Nations Platform for Space-based Information for Disaster Management and Emergency Response
UNOOSA	United Nations Office for Outer Space Affairs
XGBoost	Extreme Gradient Boosting
YOLO	You Only Look Once
ZFL	Center for Remote Sensing of Land Surfaces (University of Bonn)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