AI Data Augmentation for an Edge Satellite towards Low-latency Natural Disaster Alert and Monitoring

M.J. Martínez, R.A. Ramesh, F. Foroozan, M. Quintana, R. Ahmed[1]

1 Deimos, Tres Cantos, Spain.

The increasing severity of natural disasters (*e.g.*, 2.2 billion of population will be affected by floods by 2040), particularly floods, landslides, and wildfires, poses major challenges to disaster management, infrastructure resilience, and environmental sustainability. Advances in Space technologies and onboard satellite processing have enabled low-latency disaster detection and response. Satellite-based monitoring offers a critical advantage for detecting disasters in remote and inaccessible regions. Earth Observation (EO) intersects with Image Processing and Computer Vision, specifically applying deep learning techniques to analyze satellite imagery for disaster prediction or early-warning. These fields interact in processing large datasets, extracting meaningful patterns, and enabling automated recognition of disaster events in real time.

Our research focuses on the design, feasibility, and performance validation of a Disaster Potentiality and Early Warning System, leveraging deep neural networks and Remote Sensing technologies to provide real-time alerts and mapping, improving response strategies and decision-making. Our approach employes AI-driven on-board processing, allowing satellites to perform real-time data analysis, enhancing disaster identification and response times. The target users of this system are emergency responders, satellite data analysts, and policy makers. It also benefits organizations focused on environmental monitoring, infrastructure resilience, and sustainable development, providing them with timely, actionable insights for disaster prevention and mitigation.

In response to the increasing frequency and complexity of natural disasters, we addressed the initial stages of a multi-use-case, multi-modal EO whose output are alerts for emergency teams on the ground. By leveraging geological and environmental properties—such as soil composition, vegetation coverage, terrain elevation and weather patterns —our system improves predictive capabilities through spectral analysis, effectively distinguishing between rain-induced events (*e.g.*, floods, landslides) and human-initiated hazards (*e.g.*, wildfires). Prioritizing low-latency processing and direct communication channels, the system is optimized for instant disaster response, enabling timely and informed decision-making for ground-based emergency teams. Additionally, it aligns with international disaster management protocols by incorporating early warning systems, standardized intervention workflows and AI-driven risk evaluation strategies to support global hazard mitigation efforts.

To ensure the robustness of AI-driven disaster analysis, we developed a comprehensive data preprocessing pipeline capable of handling large-scale, heterogeneous EO datasets. This pipeline includes a spatial transformation targeting the alignment of image and WGS84 spaces. The pipeline is composed of Computer Vision primitives leveraging advanced features matching towards the augmentation and accuracy of the dataset composed. Through multi-modal data fusion, we enable cross-compatibility between EO platforms, including Sentinel-2 and highresolution commercial imagery, with tailored spectral band selection and computation of indices, such as NDVI[1], NDWI[2] and BAI[3], for early detection. Other relevant techniques explored are:

- Atmospheric corrections—including cloud masking and topographic adjustments—to further enhance data reliability.
- Context-aware change detection utilizing pre- and post-disaster data to refine event characterization
- Multi-temporal data handling to ensure temporal consistency by managing missing values and capturing evolving hazard patterns.

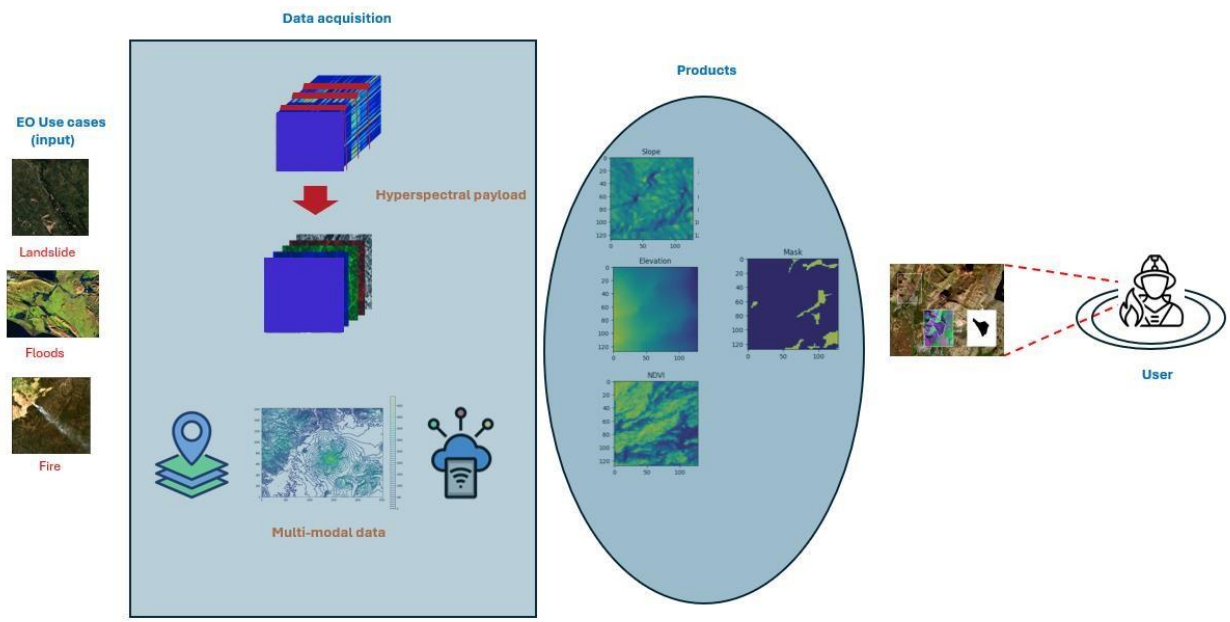

***Figure** 1. AI Data handling for EO.*

[1] Normalized Difference Vegetation Index
[2] Normalized Difference Water Index
[3] Burned Area Index