Space-Ground Hybrid AI System for Flood and Landslide Monitoring Using Multi-Level Data Fusion

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***Abstract*— Floods and landslides represent critical hydro-meteorological hazards whose frequency and intensity are amplified by extreme precipitation, deforestation, unplanned urban expansion, and inadequate land-use management. Conventional Early Warning Systems (EWS) are typically constrained by reliance on single-source data streams such as satellite observations, IoT sensor networks, or community reports, resulting in fragmented situational awareness, elevated predictive uncertainty, and limited lead time. To address these limitations, this study proposes a Space-Ground Hybrid AI framework that integrates heterogeneous data sources through a hierarchical multi-level fusion architecture. The proposed system combines convolutional neural networks (CNNs) for spatial feature extraction, long short-term memory (LSTM) networks for temporal sequence modeling, and gradient-boosted ensembles for hazard-specific prediction, enabling comprehensive modeling of both large-scale environmental patterns and localized dynamic processes. These outputs are systematically fused at feature, decision, and risk levels to derive a Unified Hazard Risk Index (UHRI), which provides an interpretable and operationally actionable representation of multi-hazard risk. Experimental evaluation using multi-spectral satellite imagery, high-frequency IoT sensor measurements, and simulated community intelligence demonstrates that the proposed hybrid model achieves superior performance, with an accuracy of 91%, an F1-score of 0.89, and a substantial reduction in false alarm rates compared to single-source baselines. Furthermore, the framework improves warning lead time and maintains robust performance under partial data degradation scenarios, highlighting its resilience and suitability for real-world deployment. Overall, the results validate the effectiveness of multi-modal data fusion and hybrid AI modeling in enhancing predictive reliability, spatial coverage, and temporal responsiveness for disaster early warning systems, providing a scalable foundation for next-generation risk monitoring and management solutions.**

Keywords*— Multi-Hazard Early Warning, Data Fusion, Flood and Landslide Prediction, Hybrid Deep Learning Model, IoT and Remote Sensing Integration.

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I. Introduction

A. Background & Problem Statement

Among the most damaging hydro-meteorological and geoenvironmental hazards in the world are floods and landslides, which are made worse by excessive rainfall, deforestation, fast urbanization, and inadequate land-use planning. While landslides are mostly caused by slope instability influenced by human and environmental factors, floods are the result of intricate hydrological interactions. Despite their physical differences, these risks are closely related, especially in peri-urban and mountainous areas. Because of their nonlinear and multi-scale spatial-temporal characteristics, integrated monitoring systems are necessary.

However, single-source monitoring is the mainstay of current Early Warning Systems (EWS). IoT sensors provide real-time data but have limited coverage and technical vulnerabilities, while satellite systems offer wide coverage but have latency and atmospheric limitations. Although community observations offer quick situational insights, validation issues prevent them from being widely used. This fragmented approach increases uncertainty, false alarms, delayed responses, and inconsistent decision-making, highlighting the urgent need for a unified multi-source framework.

B. Research Gap

The majority of current research concentrates on discrete strategies, such as AI-based prediction, IoT monitoring, or satellite-based detection. Important gaps include: restricted frameworks for fusing data from multiple sources and a unified multi-hazard risk representation. Lack of strategies for hierarchical fusion, Inadequate operational scalability in real-time, and the interpretability of risk outputs is limited. These gaps highlight the necessity of an integrated, hierarchical, and operationally scalable framework.

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C. Research Questions

This research looks into:

How can community, IoT, and satellite data be methodically combined?

Can false alarms and uncertainty be decreased by hierarchical AI fusion?

How can the risks of landslides and floods be integrated into a single, easily interpreted index?

Which system architecture makes automated alerts and real-time monitoring possible?

II. Literature Review

Recent research shows a clear trend toward multi-source data integration for natural hazard early warning systems. Reviews of Flood Early Warning Systems highlight the technological, institutional,[1] and operational challenges in deploying reliable real-time systems and outline the growing importance of multi-platform data combinations (e.g., satellite, sensor, model outputs) in improving prediction accuracy and timeliness. For example, [2] flood EWS benefits and limitations, underscoring gaps related to data fusion and operational scalability. [3]

Several studies integrate ground and satellite data to enhance flood forecasting. [4] multi-platform rainfall and simulation data improve flood information in poorly gauged basins. Towards community integration, recent frameworks explore alignment between institutional and local warning initiatives, showing that combined community and institutional approaches can generate more equitable and accurate warnings.[5][6] [7]

In remote sensing research, advanced fusion techniques such as SAR and optical combinations have been used to refine flood detection, [7]and dedicated special issues exist that curate state-of-the-art multi-sensor fusion methods. Similarly, landslide EWS research emphasizes the synergy between IoT sensor networks and machine learning models for real-time detection and risk assessment.[8][9] [10]

Open-access research further explores multi-sensor deep learning models for hazard mapping, such as Multinet for fused satellite imagery in flood building detection, and CNN-based evaluation of landslide risk from satellite data.[11] [12]Meanwhile, integrating social sensing (e.g., social media and crowdsourced reports) into operational systems has been shown to be feasible and beneficial for enhancing situational awareness and community engagement in early warning contexts. [13] [14]

III. Methodology

The proposed Space-Ground Hybrid AI framework employs a structured five-stage pipeline: multi-source data acquisition, data harmonization and feature engineering, hazard-specific predictive modeling, hierarchical multi-level fusion, and unified risk mapping. Figure 1 illustrates the overall system architecture.

A. Multi-Source Data Acquisition Strategy

Satellite-Derived Environmental Features Multi-spectral satellite imagery (Sentinel-1 SAR and Sentinel-2 optical) provides macro-scale environmental intelligence including rainfall distribution, normalized difference vegetation index (NDVI), soil moisture, terrain elevation (SRTM DEM at 30m resolution), and SAR-based flood extents. Each spatial grid cell encodes a feature vector of dimension $d = 12$, representing spectral bands and derived indices. Spatial convolution-based feature extraction is applied to preserve neighbourhood relationships and capture structured hydrological accumulation patterns.

Ground IoT Sensor Streams IoT sensors collect high-frequency time-series measurements at 15-minute intervals, including rainfall intensity (mm/hr), river water level (cm), volumetric soil moisture (%), and slope vibration (mm/s). These point-based measurements are represented as temporal sequences of length $T = 48$ timesteps (12-hour windows), enabling the model to learn cumulative threshold dynamics and delayed hydrological responses, which are critical given the memory effects inherent in hazard evolution.

Community Intelligence Integration Geotagged community observations and image-based confirmations are encoded as a reliability-weighted confidence score $C \in [0, 1]$, computed as:

$$C = \alpha \cdot S\_spatial + \beta \cdot S\_temporal + \gamma \cdot S\_credibility$$

where $S\_spatial$ reflects spatial clustering density, $S\_temporal$ measures report consistency within a defined time window, $S\_credibility$ is a user-history-based trust weight, and α, β, γ are learned fusion coefficients. This human-in-the-loop component reduces predictive uncertainty and improves calibration of automated hazard probabilities

B. Data Harmonization and Feature Engineering

Spatial Alignment: All data sources are reprojected onto a unified geographic grid at 100m resolution using nearest-neighbour interpolation for categorical layers and bilinear interpolation for continuous raster inputs. This prevents spatial mismatch between satellite raster grids and point-based IoT measurements.

Temporal Synchronization: A sliding window of length T with stride $s = 1$ is applied across all sensor streams, producing temporal feature matrices that preserve both short-term fluctuations and cumulative environmental stress leading up to each prediction timestep.

Feature Normalization: All input variables are standardized using z-score normalization ($\mu = 0, \sigma = 1$) computed over the training partition only, applied identically to validation and test partitions to prevent data leakage.

C. Hazard-Specific Predictive Modeling

Flood Prediction Module Flood prediction employs a two-branch architecture. The spatial branch applies a three-layer Convolutional Neural Network (CNN) with filter sizes [32, 64, 128] and ReLU activations to extract flood-prone terrain features such as low-elevation basins and upstream convergence zones. The temporal branch applies a two-layer Long Short-Term Memory (LSTM) network with hidden size $h = 128$ to model rainfall accumulation sequences and river level responses over the 48-timestep input window. Features from both branches are concatenated and passed through a fully connected layer with sigmoid activation to produce a flood probability estimate $P\_flood \in [0, 1]$.

Landslide Susceptibility Module Landslide susceptibility is modeled using a gradient-boosted ensemble (XGBoost) trained on slope gradient, rainfall intensity, soil moisture, NDVI, and slope vibration features. The ensemble approach reduces prediction variance across heterogeneous terrain types. An ensemble of $n = 100$ decision trees with maximum depth $d = 6$ and learning rate $\eta = 0.05$ outputs a localized slope instability probability $P\_landslide \in [0, 1]$.

D. Hierarchical Multi-Level Data Fusion

The core innovation of this framework is a three-stage hierarchical fusion strategy:

Stage 1 - Feature-Level Fusion: Spatial feature maps from the CNN and temporal embeddings from the LSTM are concatenated along the feature dimension before final classification. This preserves complementary multi-scale environmental signals within a unified latent representation.

Stage 2 - Decision-Level Fusion: Flood and landslide probabilities are combined using a learnable weighted sum:

$$P\_combined = w_1 \cdot P\_flood + w_2 \cdot P\_landslide, \text{ where } w_1 + w_2 = 1$$

Weights are optimized during training to reflect the relative contribution and interdependence of each hazard mechanism, improving prediction stability when one subsystem experiences degraded input quality.

Stage 3 - Risk-Level Fusion (UHRI): The Unified Hazard Risk Index integrates combined hazard probability with community confidence:

$$UHRI = \lambda \cdot P\_combined + (1 - \lambda) \cdot C$$

where λ is a tunable weighting parameter set empirically to 0.75. The UHRI is mapped to four operational categories: Low (< 0.25), Moderate (0.25-0.50), High (0.50-0.75), and Critical (> 0.75), providing actionable and interpretable outputs for emergency decision-makers.

E. Model Training and Validation Strategy

The dataset is partitioned chronologically (70% training, 15% validation, 15% test) to preserve real-world forecasting integrity and prevent temporal data leakage. The model is trained using binary cross-entropy loss with L2 regularization ($\lambda\_reg = 1 \times 10^{-4}$), Adam optimizer ($lr = 0.001$), and early stopping with patience of 10 epochs on validation loss. Dropout ($p = 0.3$) is applied after dense layers to mitigate overfitting. Community data is treated as an auxiliary input during training and remains available at inference time through the UHRI computation stage, which does not require backpropagation.

F. Methodological Strengths

The proposed methodology demonstrates several key strengths:

- Integrates macro-scale and micro-scale environmental intelligence
- Reduces uncertainty through complementary evidence fusion
- Preserves interpretability via structured risk mapping
- Maintains robustness under partial data failure
- Supports scalable deployment

IV. Experimental Setup

A. Dataset

The experimental evaluation is conducted on a heterogeneous, multimodal dataset that integrates satellite observations, IoT sensor streams, and community-generated inputs. The dataset is structured to reflect real-world spatio-temporal dynamics of hydro-meteorological hazards.

Data sources include:

Multi-spectral satellite imagery
Acquired from Sentinel-1 (SAR) and Sentinel-2 (optical) platforms, including derived indices such as NDVI, soil moisture proxies, and flood extent masks. All raster layers are resampled to a uniform 100m spatial resolution grid, producing structured spatial tensors.

IoT-based environmental sensing streams
High-frequency time-series data sampled at 15-minute intervals, including:

- Rainfall intensity (mm/hr)
- River water level (cm)
- Volumetric soil moisture (%)
- Slope vibration (mm/s)
  Each sensor sequence is represented using fixed-length sliding windows (T = 48), capturing temporal dependencies and lag effects.

Simulated community intelligence inputs
Geotagged reports are encoded as probabilistic confidence scores derived from spatial clustering, temporal consistency, and user credibility. These inputs are spatially aligned to the grid representation and incorporated during the risk fusion stage.

Preprocessing pipeline:

- Spatial reprojection and interpolation (bilinear / nearest-neighbor)
- Temporal alignment via sliding window segmentation
- Feature standardization using **z-score normalization (μ=0, σ=1)** computed on training data only
- Missing data imputation using forward-fill and spatial averaging strategies

To preserve forecasting realism, the dataset is split using chronological partitioning (70% training, 15% validation, 15% testing), ensuring no temporal leakage between partitions.

B. Evaluation Metrics

Model performance is evaluated using both classification metrics and operational reliability indicators, reflecting real-world early warning requirements.

Primary Classification Metrics

$$\text{Accuracy} = TP + TN / \text{Total}$$
$$\text{Precision} = TP/TP+FP$$
$$\text{Recall} = TP/TP+FN$$
$$F1 = 2PR/P+R$$

Additional evaluation includes lead-time estimation and false alarm rate reduction.

V. Results & Analysis

A. Comparative Performance Evaluation

Table 1 presents the classification performance of the proposed Hybrid Model against three single-source baselines on the held-out test partition. The proposed model achieves 91% accuracy and an F1-score of 0.89, representing absolute improvements of 13 percentage points and 0.15 F1 points over the satellite-only baseline, and 8 percentage points and 0.09 F1 points over the IoT-only baseline.

Table 1: Comparative Model Performance

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**False Alarm Rate**	**AUC-ROC**
Satellite Only	78%	0.76	0.73	0.74	0.27	0.81
IoT Only	83%	0.81	0.79	0.80	0.19	0.86
Community Only	71%	0.68	0.70	0.69	0.33	0.74
Feature Fusion Only	87%	0.85	0.84	0.85	0.14	0.90
Proposed Hybrid	91%	0.90	0.88	0.89	0.09	0.94

B. Hazard-Specific Performance

Disaggregated analysis across hazard types reveals that the flood prediction module achieves an F1-score of 0.91, while the landslide susceptibility module yields an F1-score of 0.87. The performance gap is attributable to the greater spatial heterogeneity and limited sensor coverage in steep-terrain landslide-prone areas, where IoT deployment density is lower. This finding motivates future work on adaptive sensor placement and transfer learning for data-sparse terrain zones.

C. Ablation Study

To quantify the contribution of each fusion stage, an ablation study was conducted by sequentially removing hierarchical components. Table 2 summarizes the results.

Table 1:Ablation Study - Fusion Stage Contribution

Configuration	**Accuracy**	**F1-Score**
Feature Fusion Only	87%	0.85
Feature and Decision Fusion	89%	0.87
Feature and Decision and Risk (Full UHRI)	91%	0.89

Each successive fusion stage provides incremental improvement, confirming that the multi-level hierarchical design contributes substantively rather than marginally to overall performance. The integration of community confidence at the risk level accounts for an additional 2% accuracy improvement, validating the utility of the human-in-the-loop component even when community inputs are partially simulated.

D. ROC-AUC and False Alarm Analysis

The proposed model achieves an AUC-ROC of 0.94, compared to 0.81 for the satellite-only baseline and 0.86 for the IoT-only baseline. The reduction in false alarm rate from 0.27 (satellite-only) to 0.09 (proposed hybrid) represents a 67% relative reduction, directly addressing a primary operational concern in early warning systems where unnecessary evacuations erode public trust and compliance.

E. Warning Lead Time

The hierarchical fusion framework increases average warning led time to approximately 3.2 hours prior to hazard onset, compared to 1.8 hours for the single IoT baseline and 2.1 hours for the satellite-only system. This improvement arises from the LSTM module's ability to detect cumulative rainfall thresholds and early soil saturation trends before observable surface indicators emerge.

F. Robustness Under Data Degradation

To assess real-world operational reliability, experiments were conducted under simulated data degradation scenarios where satellite inputs were withheld (e.g., cloud cover obstruction) or IoT streams were interrupted (e.g., sensor failure). Under satellite dropout, the model retains an accuracy of 85%, relying on the IoT temporal module and community inputs. Under IoT failure, accuracy decreases to 82%, with the spatial satellite module compensating. These results confirm the system's designed redundancy, where no single source creates a critical point of failure.

G. Computational Complexity

The convolutional layers contribute an approximate computational cost of $O(nk^2)$ per spatial feature map, where n is the number of filters and k is the kernel size. The LSTM temporal modeling scales linearly with sequence length T. Total inference time averages 340ms per prediction cycle on a standard CPU environment, which is operationally acceptable for the 15-minute sensor update interval used in deployment.

VI. Discussion

The proposed hybrid framework demonstrates that integrating satellite observations, ground-based IoT measurements, and community inputs can significantly improve the reliability of flood and landslide early warning. The multi-level data fusion approach reduces the limitations of individual data sources by combining large-scale environmental context with localized real-time measurements. This integration improves prediction stability, reduces false alarms, and increases warning lead time, which are critical for timely disaster response.

From a technical perspective, the hierarchical fusion strategy enhances system robustness by allowing the model to maintain operational performance even when one data source becomes unavailable or delayed. The Unified Hazard Risk Index also provides an interpretable risk representation that supports decision-making by authorities and emergency managers. Additionally, the cloud-based and modular architecture enables scalability and supports deployment across different geographic regions.

However, practical deployment challenges remain. These include the cost and maintenance of IoT sensor networks, communication reliability in remote areas, data quality variations from community reports, and privacy and security considerations. Despite these limitations, the proposed architecture provides a feasible foundation for real-world disaster monitoring systems.

VII. Conclusion

This study presented a hybrid space-ground-community AI framework for integrated flood and landslide monitoring using multi-level data fusion. By combining satellite observations, real-time IoT sensor measurements, and community-reported information, the proposed system improves spatial coverage, temporal responsiveness, and prediction reliability compared to conventional single-source approaches. The integration of CNN-based spatial analysis, temporal sequence modeling, and hierarchical fusion enables the computation of a Unified Hazard Risk Index that supports interpretable and operational early warning. Experimental evaluation indicates improved accuracy, reduced false alarms, and increased warning lead time, demonstrating the effectiveness of multi-source fusion for disaster risk intelligence.

VIII. Future Work

Future research will focus on real-time field deployment and validation using live multi-source data streams. Edge computing techniques can be incorporated to reduce latency and support operation in low-connectivity environments. The system can also be extended to include additional hazard types such as urban flash floods, droughts, and wildfires. Further improvements may include adaptive model updating, uncertainty quantification for risk estimation, and enhanced decision-support interfaces for emergency management agencies.

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