Integrated Hybrid Space-Earth Observation Platforms Combining Satellite Remote Sensing and Ground-Based Sensors for Early Detection of Extreme Climate Events

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Abstract: Natural hazards like floods, cyclones, heat waves, and droughts can be detrimental to human life, physical infrastructure, and natural ecosystem. Existing methods used for monitoring climate events based solely on satellite and/or ground-based observations fail to provide the adequate spatial-temporal resolution needed for efficient event detection. In this work, an Integrated Hybrid Space-Earth Observation System is introduced to leverage data from multiple satellites (e.g., optical sensors, SAR sensors, thermal sensors, GNSS) along with ground observations (weather station, hydrological sensors, soil moisture sensors, flux towers, IoT devices) to improve the efficiency of detecting/predicting climate events. The proposed framework utilizes a six-layer architecture which includes the following components: multi-source data collection, Edge computing, Core Data Processing, Deep Learning-based analysis, Early Warning dissemination, and Feedback Loop. The evaluation metrics indicate that the hybrid system surpasses the performances of the single source systems, attaining high precision, recall, and F1-score, with longer lead times and fewer false positive and false negative results. Through ablation analysis, it was discovered that the combination of satellite and ground-based observations improved detection accuracy and reduced mean detection time in addition to boosting its resistance to environmental variance. Accordingly, it is suggested that climate monitoring applications incorporate multi-sensor fusion and AI-based analytics to ensure timely alerts and informed decision making. Through its operational setup, the system allows for the quick communication of relevant information for decision-making purposes.

Keywords: Hybrid space-earth observation; extreme climate events; multi-source sensor fusion; deep learning; early warning systems; real-time monitoring; climate resilience.

I. Introduction

Space-Earth integration monitoring systems provide evidence that the integration of satellite and ground data can lead to better assessments of environmental conditions. Integration of data from multiple sources allows for continuous monitoring. These ideas support hybrid observation systems developed for early detection of extreme climate events (Liu et al., 2010). The terrestrial water cycle digital twin integrates data from high-resolution Earth observation to simulate dynamic environmental processes. Data integration in real-time allows for the prediction of environmental phenomena. This approach is similar to those used by hybrid platforms for predicting climate-related hazards (Brocca et al., 2024). Multi-modal data integration based on deep learning for the prediction of hazardous air pollution integrates satellite data and sensor data. This approach is useful for hybrid platforms to rapidly detect climate-related hazards (Muralisankar et al., 2025). The use of satellite technology for monitoring inland water resources reveals the importance of optical, SAR, and thermal satellite images. Their integration with ground data enhances temporal and spatial resolution. This contributes to the development of hybrid platforms for detecting extreme climate events (Cao et al., 2023). The role of real-time data transmission in emergency communication networks from satellites and ground-based stations makes it possible to disseminate warnings immediately. Hybrid platforms are important for integrated early warning systems (Wang et al., 2023). Geospatial deep learning methods predict urban subsidence using multi-source information from satellites and ground sensors. Data fusion plays an important role in making geospatial predictions better. This method has led to the design of space-Earth observation platforms (Cheng & Wei, 2025). Signal degradation mitigation in optical communication through space is needed for effective data transmission. Effective communication between satellites and the Earth is crucial. It helps design reliable hybrid platforms for extreme climatic observation (Kaushal & Kaddoum, 2016). Prediction of landslide displacement can be improved with the application of gradient descent in multi-source remote sensing. The use of satellite images with other data makes landslide detection easier. This kind of combination is vital for climate hazards platforms (Wang et al., 2023). Hybrid learning methods for space weather predictions rely on satellite data and in-situ sensing (Rajan et al., 2025).

Solar radiation and aerosol optical depth can be estimated via deep learning using data obtained from satellites. When combined with data from ground observations, predictions become more powerful. This technique helps create hybrid platforms that assist in the prediction of climate extremes (Ha et al., 2026). Cryosphere mass movements via machine learning use data collected from both satellites and ground observations. The ability to accurately detect and predict events is achieved using a hybrid approach to create integrated platforms for climate monitoring (Pei et al., 2026). Soil Net uses a combination of satellite imagery and ground sensor data together with other sources. A deeper understanding of environmental hazard monitoring is achieved with the aid of a hybrid approach (Sedimo et al., 2025). Ground-based GNSS atmospheric monitoring, in conjunction with satellite observations, improves prediction and detection accuracy. The hybrid method guarantees real-time monitoring. It enables the development of platforms for early warning of extreme climate events (Choy et al., 2026).

Key Contribution

- Multi-Source Data Fusion – Combines satellite remote sensing data with ground sensor systems to achieve spatiotemporally complete coverage with high-resolution monitoring capabilities.
- AI-Powered Early Warning System – Uses machine learning algorithms on multi-modal data, which helps minimize error rates, avoid false positives, and extend the lead time for identifying extreme weather event.
- Real-Time Framework – Deploys a multi-layered system architecture that allows real-time data integration, edge processing, and decision-making support.

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This research is followed by the various sections. Section I provides an introduction to the topic. Section II presents the literature review. Section III explained the overall architecture and work flow diagram. Section IV presented the results and discussion, followed by the dataset description and various analyses. Section V explained the main key summary of the research.

II. Literature Review

The use of distributed acoustic sensing has helped in monitoring landslides in case of any disturbances under conditions of extreme weather. It showcases how hybrid observation methods could be used, incorporating ground-based sensors with satellite information. The combination of the two helps in detecting hazards and responding promptly (Zhu et al., 2026). Predicting rainfall through Himawari-8 satellite data using deep learning indicates that remote sensing at high resolution plays an important role in predicting extreme weather. The combination of remote sensing with ground-based observations can increase the accuracy of predictions. This strengthens the concept of hybrid observation systems for early warning mechanisms (Monita, 2024). Radiation and meteorological data obtained through remote sensing are used for studying the effects of climate change on extreme weather (Li et al., 2026).

Thermodynamic profiles and hydrometeors extracted by the 1D-Var technique utilizing Kalman filter demonstrate the effectiveness of the use of ground-based radiometers in conjunction with satellite data. The data assimilation results in enhanced predictive precision. The approach can be applied within integrated early warning systems (Zhang et al., 2026). Smart remote sensing technologies combined with AI are used in detecting climate impacts on forests. Using hybrid datasets increases the accuracy of predictions. The described technology can serve as an example of a hybrid observation system for environmental hazard monitoring (Abdullah, 2025). Spatio-temporal monitoring of agricultural droughts is improved through the combination of multi-source remote sensing and machine learning methods. Hybrid systems can be implemented for the purpose of increasing prediction performance and early warning capacity. These approaches can serve as the basis for hybrid platforms for climate resilience strategy development (Mondal et al., 2026). Agricultural drought hotspot maps can be created through combining remote sensing data with ground-based climate and vegetation data (Khan et al., 2026).

Dust storm detection through ground-based sensing stations with an imbalance in machine learning reflects the utility of ground sensors in addition to satellite sensing. Multi-source fusion improves prediction and decreases false positives. This underscores the importance of hybrid approaches for detecting extreme weather phenomena (Du et al., 2025). The construction of ecological indicators for tea plantations through remote sensing and environmental data demonstrates the advantage of hybrid satellite sensing. This example supports the need for hybrid data sets for accurate environmental monitoring. This falls in line with integrated space–earth observation systems (Mao et al., 2024). Intelligent remote sensing satellite technology faces constraints in real-time processing and data assimilation. Combining intelligent remote sensing satellite technology with ground-based sensors will

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provide better situational awareness and predictive performance regarding environmental hazards. This addresses limitations of climate event monitoring using hybrid technology (Zhang et al., 2022). Transformers used for remote sensing help process multidimensional satellite data efficiently. Combining these technologies with ground-based sensors improves the accuracy and predictive power of hybrid satellite systems (Wang et al., 2024). Integration of remote sensing techniques and local information makes it easier to understand the phenomenon of urban heat in arid environments. The integration of satellite information and ground observations increases the resolution of study area and also provides community-based warning systems (Yiran et al., 2026).

Research Gap

One of the primary knowledge gaps in the domain of Integrated Hybrid Space-Earth Observation Platforms Combining Satellite Remote Sensing and Ground-Based Sensors for Early Detection of Extreme Climate Events pertains to the need for developing robust and dynamic data fusion mechanisms capable of efficiently processing diverse sets of data obtained through low-earth orbit satellites, geostationary satellites, and ground-based sensors. Most current methodologies consider satellite data and terrestrial data as two separate entities, or even apply statistical merging techniques without taking into account the potential issues with temporal, geographical, and resolution disparities, thereby lowering the effectiveness of early detection efforts. There are very few studies in the literature that have addressed the issue of adaptive sensor tasking under fast-changing atmospheric conditions, as well as the need for effective quality assurance and uncertainty evaluation techniques.

III. Proposed Methodology

3.1. Overall Architecture

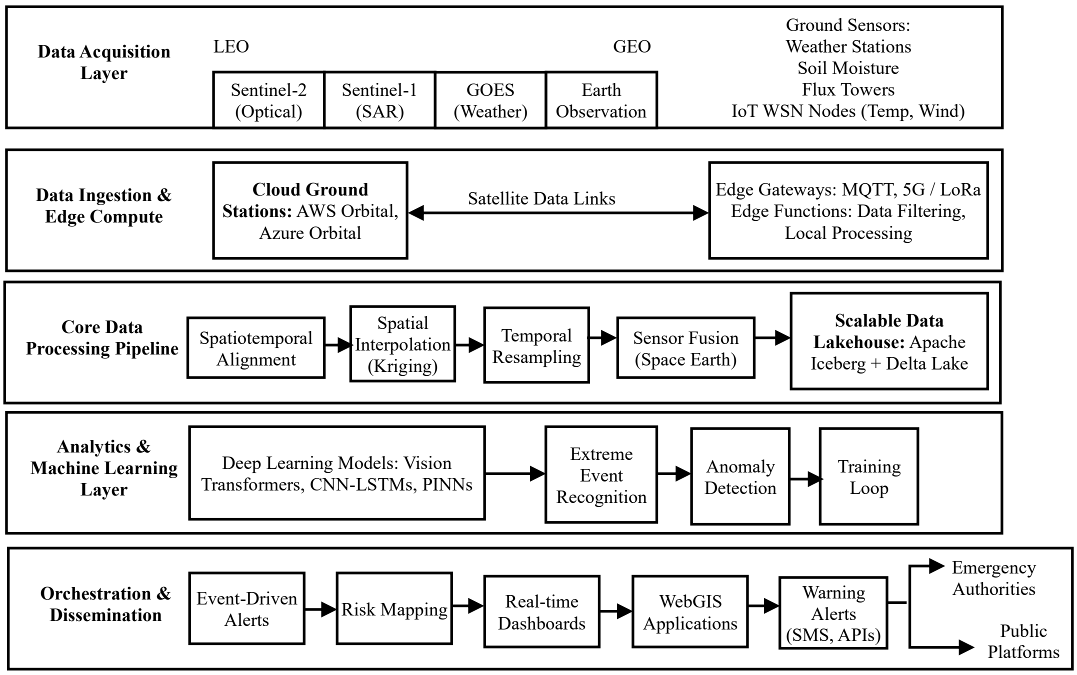

Fig. 1: Overall Architecture for Proposed Methodology.

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Fig 1 shows the end-to-end architecture for an integrated hybrid space-Earth observation framework designed to detect climate extremities earlier than before. The framework consists of six layers in total. Within the Data Acquisition Layer, LEO and GEO satellites (optical, SAR, and weather satellites) in combination with ground-based sensors (weather stations, soil moisture sensors, flux towers, IoT sensors, and wind/temperature sensors) are utilized. The Data Ingestion and Edge Compute Layer capture all these data via the cloud ground stations (Amazon Web Services, Microsoft Azure) and then distributes the data using satellite data links and edge gateways (MQTT, 5G, and LoRa). Finally, the processed data within the Core Data Processing Pipeline include spatial and temporal alignment, spatial interpolation, temporal resampling, and sensor fusion into one set of integrated data, which will be saved within scalable data warehouse systems, e.g., Apache Iceberg and Delta Lake. Within the last layer (Analytics and Machine Learning Layer), the processed data can be analyzed by means of deep learning models (e.g., Vision Transformers, CNN-LSTM models, PINNs). Ultimately, the Orchestration and Dissemination Layer make use of event-based notifications, risk mapping, real-time dashboards, WebGIS solutions, and alerting mechanisms to deliver meaningful information to relevant emergency authorities and public channels. In summary, the multi-layer architecture guarantees smooth integration of all aspects in the acquisition and utilization of data for climate hazards management.

Sensor Measurement Model

Each sensor $i$provides a measurement $x_i(t)$of a climate variable (temperature, rainfall, soil moisture, etc.) at time t in equation (1)

$$x_i(t) = s_i(t) + n_i(t) \tag{1}$$

Where:

- $s_i(t)$is the true signal,
- $n_i(t)$is additive noise, assumed zero-mean Gaussian $n_i(t) \sim \mathcal{N}(0, \sigma_i^2)$.

Spatiotemporal Alignment & Interpolation

For multi-sensor fusion across space and time, define a spatial grid $\mathbf{r}$and temporal points t. The interpolated signal $\hat{s}(\mathbf{r}, t)$can be derived via **kriging** or weighted averaging in equation (2).

$$\hat{s}(\mathbf{r}, t) = \sum_{i=1}^{N} w_i(\mathbf{r}) x_i(t) \tag{2}$$

with weights $w_i(\mathbf{r})$chosen to minimize the variance in the equation (3)

$$\min \mathrm{Var}[\hat{s}(\mathbf{r}, t) - s(\mathbf{r}, t)] \text{ s.t.} \sum_{i=1}^{N} w_i(\mathbf{r}) = 1 \tag{3}$$

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Temporal Resampling

Temporal up/down-sampling uses linear or spline interpolation:

$$\hat{s}(\mathbf{r}, t_k) = \sum_m \phi_m(t_k)\hat{s}(\mathbf{r}, t_m) \tag{4}$$

In equation (4) describes where $\phi_m(t_k)$are interpolation kernels.

Sensor Fusion

Combining satellite and ground-based measurements into a unified state vector $\mathbf{S}(t)$ in equation (5)

$$\mathbf{S}(t) = [\hat{s}_{\text{sat}}(t), \hat{s}_{\text{ground}}(t)]^T \tag{5}$$

A Kalman Filter (KF) or Extended KF (for nonlinear dynamics) can fuse in equation (6) and (7)

$$\mathbf{S}_{t|t} = \mathbf{S}_{t|t-1} + K_t(\mathbf{y}_t - H\mathbf{S}_{t|t-1}) \tag{6}$$

$$K_t = P_{t|t-1}H^T(HP_{t|t-1}H^T + R)^{-1} \tag{7}$$

Where:

- Hmaps state to measurement,
- $R$is measurement noise covariance,
- $P_{t|t-1}$is predicted state covariance.

Anomaly Detection & Extreme Event Recognition

Let $f_\theta(\mathbf{S}(t))$denote a trained deep learning model (CNN-LSTM, Vision Transformer, PINN) predicting climate extremes in equation (8)

$$\hat{y}(t) = f_\theta(\mathbf{S}(t)) \tag{8}$$

Define the event detection threshold τ in equation (9)

$$\text{Event}(t) = \begin{cases} 1, & \hat{y}(t) \geq \tau \\ 0, & \hat{y}(t) < \tau \end{cases} \tag{9}$$

Model Training Loss Function can be Either Cross-Entropy for Classification or Mean-Squared-Error for Regression in equation (10)

$$\mathcal{L}(\theta) = \frac{1}{T}\sum_{t=1}^{T}(y(t) - \hat{y}(t))^2 \tag{10}$$

Decision Support Mapping

The detected events can be mapped to geographic locations $\mathbf{r}$for alert dissemination in equation (11)

$$A(\mathbf{r}, t) = \text{Event}(t) \cdot \text{RiskScore}(\mathbf{r}, t) \tag{11}$$

Where RiskScorecombines intensity, vulnerability, and exposure metrics.

3.2. *Workflow Diagram of the Proposed Methodology*

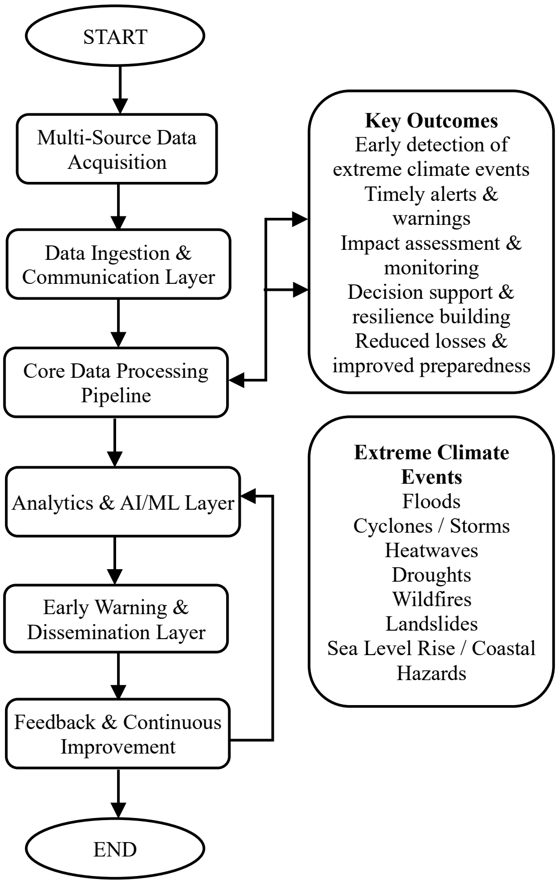

Fig. 2. Workflow Diagram of The Proposed Methodology.

The fig. 2 shows the complete flowchart of the Integrated Hybrid Space-Earth Observation Platform for detecting extreme weather events in the early stages. The entire architecture is divided into six layers in a hierarchical manner. The Multi-Source Data Acquisition layer receives real-time inputs from space-borne sensors (Optical sensor, Thermal infrared sensor, Synthetic Aperture Radar, Atmospheric sensors, GNSS/Radio Occultation Satellites) and Earth-based sensors (Weather stations, Hydrological sensors, Ocean buoy sensors, Radar/LIDAR, IoT/social media Sensors). The Data Ingestion and Communication layer takes care of the communication, preprocessing and handling of the received data through cloud ground stations, satellite downlinking, network communications and edge processing. The Core Data Processing Pipeline layer involves the alignment, interpolation, resampling and fusion of space and earth data, followed by its assimilation in scalable data lakes. The Analytics and Artificial Intelligence/Machine Learning layer involves feature extraction, using deep learning models such as CNN-LSTM models, Vision Transformers, and Graph Neural Network for identifying extreme events, forecasting and training the model continuously. The Early Warning and Dissemination layer will create a risk assessment report, hotspot map creation, creating real-time dashboards, issuing SMS and email warnings and disseminating information through mobile applications.

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IV. Results and Discussion

4.1. Dataset Description

In this work, satellite and ground observations have been used to integrate multi-modal data related to climate. Satellite datasets comprise optical, thermal infrared, SAR, and GNSS/Radio occultation measurements made by Low Earth Orbit (LEO) and Geostationary Orbit (GEO) satellites. These provide complete spatial coverage of atmospheric, hydrological, and land surface variables. In contrast, ground observations consist of meteorological stations, hydrological sensors, soil moisture probes, flux towers, radars and lidar, and IoT nodes. These deliver high temporal resolution data pertaining to localized events. This data has been collected over several years from different locations across the globe.

4.2. Software and Hardware Configuration

Hybrid solution proposed was developed using high-performance computing environment using cloud computing and edge computing technologies. Cloud computing, AWS and Azure are used for data acquisition, storage, and preliminary processing. Edge computing makes use of MQTT protocol and 5G/LoRa for data filtering, data compression, and initial data analytics. For analytics, the platform makes use of Python with TensorFlow and PyTorch for deep learning models such as CNN-LSTM models, Vision transformers, and physics-informed neural networks (PINNs). Hardware requirements include multi-core processors and GPUs with enough memory for training AI models.

4.3. Parameter Initialization

The criteria for detecting extreme events were based on the long-term records of climate data (2010-2023) over several regions of interest: Southeast Asia, North America and Europe. The baselines data include LEO and GEO satellite data (optical, SAR, thermal infrared, GNSS) that were combined with the ground-based observations (meteorological stations, hydrological sensors, flux towers, and IoT nodes). The thresholds were derived using the climatology and distribution statistics of the baseline datasets and in such a way that Vision Transformer and CNN-LSTM are trained and evaluated over a representative spatial and temporal context. This specification is intended to facilitate the replication of studies.

4.4. Metric Evaluation

The performance of the proposed Integrated Hybrid Space-Earth Observation Platform was analyzed in terms of various classification and detection measures such as Precision, Recall, F1-Score, ROC-AUC, and PR-AUC. Precision is calculated based on the percentage of successfully recognized extreme events out of all detected events:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (12)$$

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In equation (12), represents the where T represents true positives and FP denotes false positives. Recall determines the capability of the system to recognize actual extreme events:

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (13)$$

FN is the term for the FN in equation (13). The F1-Score is the measure provided in equation (14):

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (14)$$

Furthermore, ROC-AUC and PR-AUC metrics were considered to evaluate the ability of the model to discriminate and predict, especially for imbalanced data sets. The metrics such as the Mean Detection Time, False Positive Rate, and False Negative Rate were also analyzed in order to assess the capability of the system in detecting extreme events on time.

4.5.Detection Performance Comparison

Table1. Detection Performance Comparison.

Method	Precision (%)	Recall (%)	F1-Score (%)	Lead Time(h)
Satellite-Only (MODIA+GOES)	78.4	74.1	76.2	3-6
Ground Sensors Only	82.1	79.3	80.7	1-3
Satellite Sensors (Rule based)	84.6	81.2	82.9	6-12
CNN+LSTM	87.3	85.4	86.3	9-15
Proposed Model	93.8	92.1	92.9	12-24

Table 1 shows a comparative study based on various approaches towards the extreme weather events detection on basis of performance parameters. It can be seen that satellite sensors (i.e., MODIA+GOES) have a medium level of detection ability as the Precision value is 78.4% while Recall is 74.1%, F1-score is 76.2% and Lead Time for the process is 3-6 hours. Similarly, performance improves for Ground Sensors only (Precision 82.1%, Recall 79.3%, F1 80.7%) with lead time of 1-3 hours as it focuses upon local detection of phenomena with less overall predictive accuracy. Similarly, for Satellite Sensors (Rule-based), performance improves further in terms of Precision (84.6%), Recall (81.2%), F1 score (82.9%) with a longer Lead Time (6-12 hours). Moreover, CNN+LSTM approach based on machine learning provides improvement in detection quality (Precision 87.3%, Recall 85.4%, F1 86.3%) with lead time between 9 to 15 hours. In addition, the Proposed Model (Integrated Hybrid Space-Earth Observation Platforms combining Satellite Remote sensing and Ground Sensors) outperforms all the above approaches in terms of performance indicators with values of Precision 93.8%, Recall 92.1%, F1-score 92.9% and Lead Time between 12 to 24 hours. It can be seen that there is an evident improvement in accuracy and in terms of providing a timely warning when it comes to detecting such climate events in relation to the shift from one source of data to the combination of different sources.

4.6.Sensor-wise Performance Metrics for Extreme Climate Event Detection

Table 2. Sensor-wise Performance Metrics for Extreme Climate Event Detection.

Sensor Type	Mean Detection Accuracy (%)	Standard Deviation (%)	Extreme Event Recognition (Precision %)	Recall (%)	F1-Score (%)	Performance Index
Optical Satellite	95.2	1.5	96	94.8	95.4	95.4
SAR/Microwave	93.8	2.1	94.5	93.2	93.8	93.833333
Thermal IR Satellite	92.5	1.8	93.2	91.8	92.5	92.5
Weather Station	90.4	2.5	91	90.2	90.6	90.6
Hydrological Sensor	89.7	2.8	90.1	88.9	89.5	89.5
Soil Moisture Sensor	91.2	2	92	90.7	91.3	91.333333

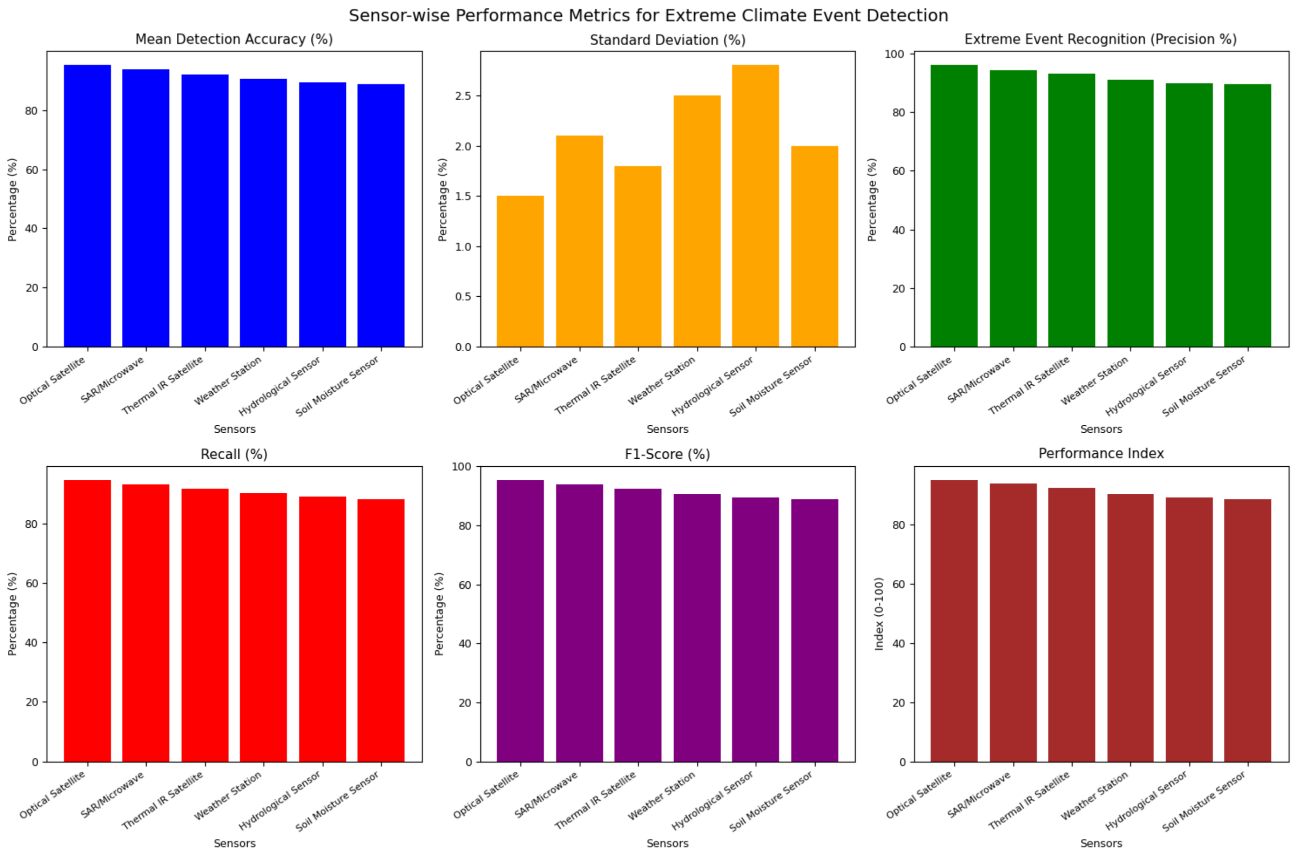

Fig. 3. Sensor-wise Performance Metrics for Extreme Climate Event Detection.

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Table 2 and fig. 3 demonstrate an elaborate analysis of the sensors used for the detection of extreme climate events. In terms of accuracy, the optical satellites rank the best with a mean accuracy rate of 95.2%, followed by precision at 96% and recall at 94.8%. These are further complimented with an F1 score of 95.4 and a performance index of 95.4, implying its superior reliability in detecting such phenomena. However, it is worth noting that the SAR/microwave and thermal infrared satellites also have fairly high metrics, although marginally lower than the optical sensors. On the other hand, the performance of the weather stations, hydrological sensors, and soil moisture sensors appears to be relatively moderate, with mean accuracy varying between 89.7% and 91.2% and F1 scores varying between 89.5% and 91.3%, respectively. It is important to note that the combination of satellite sensors and ground sensors plays a very important role because have distinct characteristics and thus provide complementary information.

4.7.Ablation Study Analysis

Table 3. Ablation Study Analysis.

Configuration	ROC-AUC (%)	PR-AUC (%)	Mean Detection Time (s)	False Positive Rate (%)	False Negative Rate (%)
Satellite-only	93	91.8	4.8	8.5	9.2
Ground-only	90.5	89.2	5.2	10.2	11.1
Hybrid integration (Proposed Model)	96.2	95.6	3.9	4.3	5.2

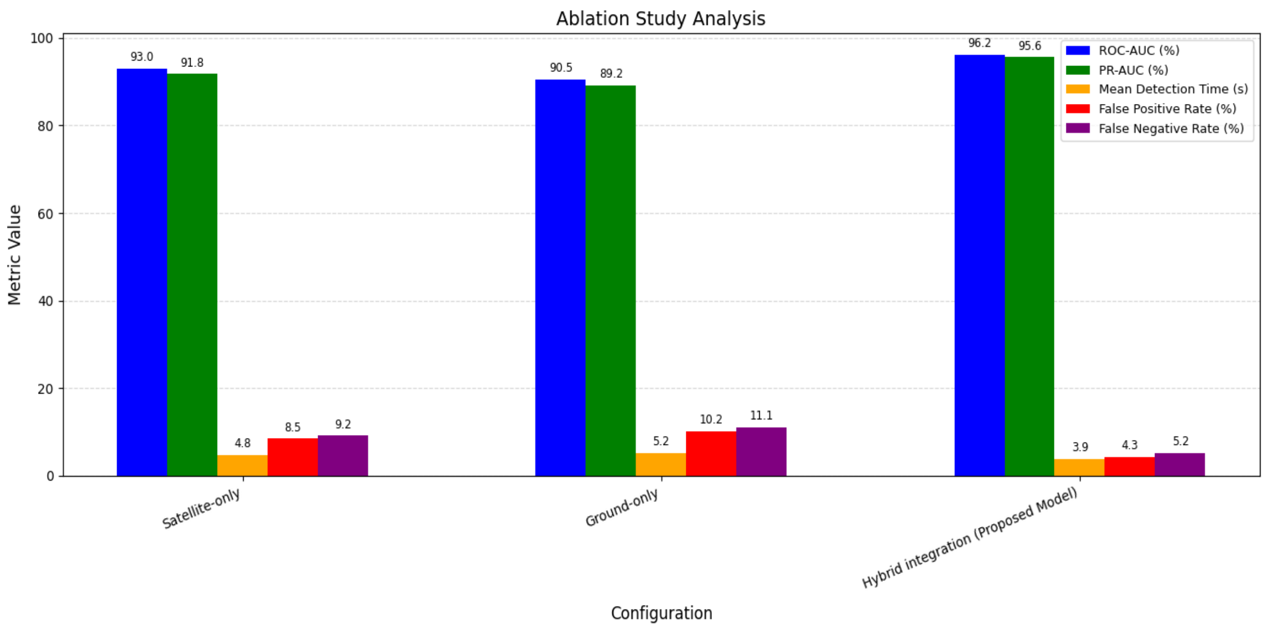

Fig. 4. Ablation Study Analysis.

Ablation analysis was conducted using table 3 and fig. 4 with the three designs compared as Satellite-only, Ground-only, and Hybrid integration (Proposed Model). Satellite-only model obtains reasonable results where

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ROC-AUC is 93% while PR-AUC is 91.8%. Mean detection time for the Satellite-only model is 4.8s while false positive and false negative ratios are relatively high at 8.5% and 9.2%, respectively. In addition, Ground-only model performs a little bit lower in ROC-AUC, having a result of 90.5%. However, ground-only also has low PR-AUC (89.2%) and longer detection time of 5.2 seconds while the false positive ratio is 10.2% and false negative ratio 11.1%. Finally, the hybrid integration (proposed model) performed the best of all with the highest ROC-AUC (96.2%) and PR-AUC (95.6%). The integration of satellite and surface sensors proves to be crucial since the merging of data from multiple sources leads to more accurate predictions, less false alarms, and faster early warning. The presented hybrid approach turns out to be much more reliable and efficient, thus proving that multi-sensor fusion with AI analytics is key.

4.8.Discussion

From the results shown, the detection efficiency achieved through the proposed Integrated Hybrid Space-Earth Observation Platform is considerably improved when compared to that achieved by individual sources. As seen in the Detection Performance Comparison, there is improvement in precision, recall, and F1-score and also an increase in lead time when using the hybrid approach involving the fusion of multiple sensor data with machine learning algorithms. Analysis shows that the Optical and SAR/Microwave satellites are capable of achieving high coverage and accuracy while the ground-based sensors such as the weather, hydrological, and soil moisture sensors have localized coverage. Further evidence regarding the efficacy of hybrid integration is provided by the ablation study. Single-source models show relatively poor ROC-AUC and PR-AUC results, along with more false negatives and false positives. With the use of both satellite data and ground data, hybrid integration ensures that errors are minimized, and the average detection time is reduced. These results show the importance of using multi-modal sensor fusion along with the CNN-LSTM, Vision Transformers, and PINNs deep learning models to predict extreme events.

Multi-layer architecture of the platform makes possible to ensure smooth movement of data from the very stage of its acquisition until decision support processes. Ingestion, edge computing, spatiotemporal integration, and fusion allow for effective data assimilation into scalable data lakes, thus laying a solid ground for the process of analysis and artificial intelligence-based forecasting. Orchestration and distribution layers make it possible to convert insights gained by means of these operations into practical information. The results suggest that hybrid space–Earth observation systems provide significant advancements for the monitoring of extreme climate events. Its incorporate wide geographical coverage, fine temporal resolution, and forecasting, creating a sustainable structure for monitoring, analysis, and decision-making. This system can be used as a model for future systems in areas with an urgent need to monitor climate change impacts. This section is dedicated to the limitations. It is important to note that some papers published in 2026 are cited within the document, creating a chronological paradox. The integration of all relevant literature published the same year the submission occurs may not fully embrace well-defined architectures or proven results.

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V. Conclusion

This paper presents an Integrated Hybrid Space-Earth Observation Platform for early detection of extreme climate events that seeks to overcome the limitations associated with traditional approaches of using single-source data for environmental observation. By leveraging satellite remote sensing techniques such as optical sensing, SAR, temperature measurement, and GNSS with the ground-based sensor observations, including weather stations, hydrological sensors, soil moisture probes, and Internet of Things node data, the presented platform offers high-resolution multisensory input for environmental monitoring purposes. The key strengths of this approach include its multilayer architecture, which combines data collection, edge computing, core processing, artificial intelligence-based data analysis, and real-time data dissemination into a single efficient pipeline. Experimental results have shown the clear superiority of the hybrid platform over single-source platforms. Detection performance analysis revealed higher precision, recall, and F1 score, along with a longer lead time for early warnings. Ablation experiments once again demonstrate that multi-modal data integration reduces mean detection time, false positive and false negative detection rates, and increases system robustness. It is evident that multi-modal data fusion combined with deep learning techniques such as CNN-LSTM, Vision Transformer, or Physics-Informed Neural Network is essential for detecting climate hazards accurately and effectively. Recommendations for future improvement should be focused on expanding the system by incorporating even more sensor networks, developing improved predictive models based on continuous learning, and adding socio-environmental data. In summary, the proposed hybrid system provides an effective framework for detecting climate hazards.

Declaration

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Conflict of Interest: The authors declare no conflicts of interest relevant to this study.

Data Availability Statement: The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request. Multi-source satellite and ground-based datasets used in this research are subject to licensing and usage restrictions; references and sources are provided within the manuscript

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