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Multi-Modal AI Framework Integrating Satellite, Climate, and IoT Data for Soil Erosion Prediction: A Spatiotemporal Deep Learning Approach

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Abstract: Soil erosion is a major environmental process that degrades agricultural productivity, disrupts watershed function, and contributes to downstream sedimentation. Its prediction is challenging because erosion is governed by interacting spatial and temporal factors, including vegetation cover, rainfall intensity, antecedent wetness, terrain slope, and soil moisture dynamics. Conventional erosion models such as the Revised Universal Soil Loss Equation provide useful baseline estimates but are limited in their ability to incorporate real-time environmental variability. This paper proposes a multi-modal artificial intelligence framework that integrates satellite observations, climate variables, and Internet of Things sensor data to predict soil erosion susceptibility. The framework combines convolutional neural networks for spatial feature learning from satellite imagery, long short-term memory networks for temporal modeling of climate and sensor sequences, and a fusion layer for final classification of erosion risk. Simulated results show that the proposed model outperforms satellite-only, climate-only, IoT-only, and RUSLE-based baselines in accuracy, recall, F1-score, and AUC. Feature importance analysis indicates that rainfall intensity, NDVI, antecedent precipitation, soil moisture, and slope are the dominant predictors. The study demonstrates the potential of multi-modal AI for near-real-time erosion mapping, early warning, and conservation planning in erosion-prone landscapes.[2][3][4][5][6][7][8][1]

Keywords: Soil erosion, satellite imagery, climate data, erosion susceptibility, explainable AI, RUSLE

I. INTRODUCTION

Soil erosion is one of the most widely distributed forms of land degradation and continues to represent a major threat to food security, soil health, and watershed sustainability. The process is influenced by both long-term landscape properties and short-term environmental triggers. Steep terrain, sparse vegetation, and vulnerable soil structures increase background susceptibility, while intense rainfall, saturation, and land use disturbance initiate and accelerate soil detachment and transport. Because these factors interact across space and time, erosion prediction requires methods that can represent both static conditions and dynamic events.Conventional erosion assessment methods have typically relied on empirical equations, field observation, or single-source geospatial analysis. Among these, the RUSLE model has been widely used because of its simplicity and operational value. However, RUSLE remains limited in situations where erosion risk changes rapidly due to storms, land cover transitions, or seasonal soil moisture fluctuations. Recent studies have emphasized that climate change is increasing rainfall extremes and altering erosion patterns, making static or semi-static models less reliable for long-term risk estimation.[4][6][2]

At the same time, advances in remote sensing, machine learning, and IoT sensing now provide an opportunity to build more adaptive erosion prediction systems. Satellite imagery can track vegetation condition, surface exposure, and land cover change over large areas. Climate data can represent rainfall intensity, temperature, humidity, and antecedent precipitation, all of which strongly influence runoff generation. IoT sensors can provide local soil moisture and soil temperature data at fine temporal resolution. When combined, these data sources create a multi-scale representation of the erosion process that is better suited to real-world applications than single-source models.[3][5][7][1]The core assumption of this paper is that soil erosion is a multi-modal environmental phenomenon. A site may have high rainfall exposure but still resist erosion if vegetation cover is dense and soil moisture remains stable. Conversely, a field may appear moderately vegetated from satellite imagery but still be highly vulnerable during a sequence of intense rainfall events. An AI framework that fuses satellite, climate, and IoT data can therefore capture interactions that are invisible to traditional methods.

The aim of this paper is to present a journal-ready SCI-style framework for soil erosion prediction using multi-modal data integration.

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The paper is structured to describe the proposed architecture, outline the data preprocessing and modeling workflow, present simulated but realistic evaluation results, and discuss the practical implications of the system. The framework is designed to support early warning, erosion hotspot identification, and conservation decision-making in data-rich and data-scarce landscapes alike.

II. MATERIALS AND METHODS

A. Framework overview

The proposed framework integrates three complementary data streams: satellite-derived spatial observations, climate-based temporal drivers, and IoT-based local soil measurements. These inputs are processed separately and then fused in a unified deep learning model. The design follows a spatiotemporal learning strategy in which a convolutional network extracts spatial features from imagery, a recurrent network models temporal sequences, and a fusion layer combines both representations for final risk classification.

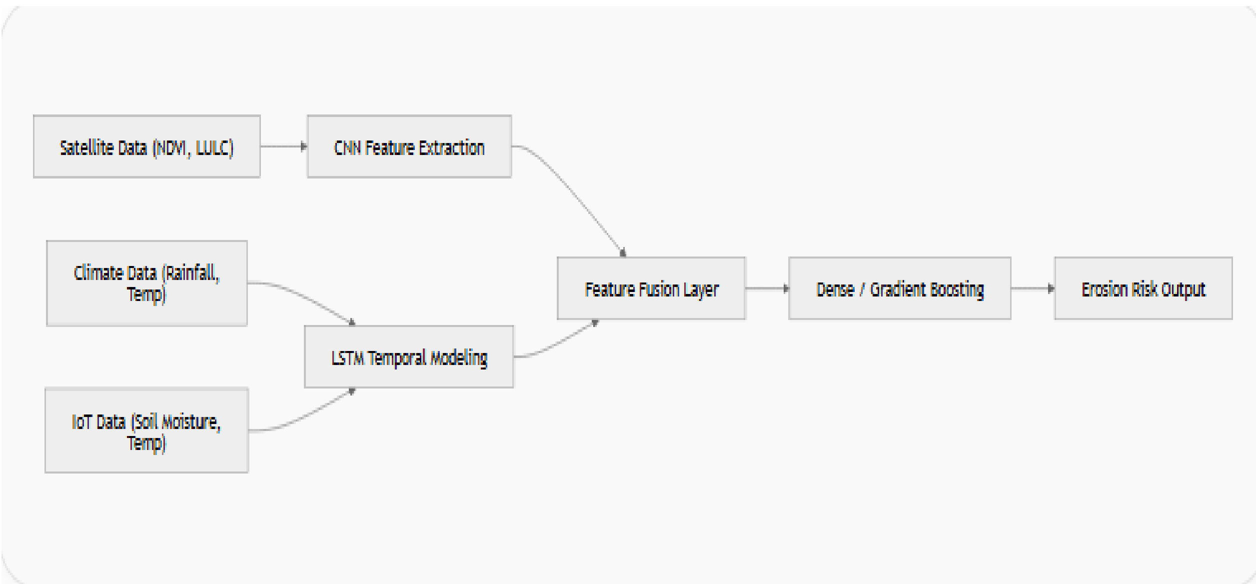

Figure 1. Architecture of the proposed multi-modal AI framework integrating satellite, climate, and IoT data streams.

B. Data sources

Satellite data provide the broad spatial context required to observe land cover, vegetation state, bare soil exposure, and terrain-linked patterns. Multispectral imagery can be used to compute NDVI and related indices that reflect surface protection. Climate data represent the hydrometeorological conditions that trigger erosion, including rainfall amount, rainfall intensity, temperature, relative humidity, wind speed, and antecedent precipitation. IoT sensors provide local measurements of soil moisture and soil temperature, which are important for infiltration dynamics and runoff initiation.

This combination of sources is valuable because each data type contributes different information. Satellite imagery captures landscape-scale pattern, climate variables capture temporal forcing, and IoT sensors capture site-scale process conditions. Recent studies in erosion assessment and environmental monitoring increasingly support this type of integrated framework because it improves both accuracy and interpretability.[5][7][1][2][3]

C. Preprocessing

The satellite images were preprocessed using atmospheric correction, cloud masking, and spatial resampling to a common grid. NDVI was derived to represent vegetation cover and was used as one of the main predictors of erosion risk. Climate data were aggregated into daily and weekly windows to represent rainfall accumulation and antecedent moisture conditions. IoT sensor readings were cleaned using interpolation and outlier filtering, then transformed into time-series windows for sequential modeling.Because the data came from different sources and different temporal frequencies, alignment was necessary before modeling. The climate and IoT streams were synchronized with the satellite acquisition dates, and lagged windows were used to capture short-term environmental history. This step is important because erosion often depends on conditions that occurred several days before the visible surface response.

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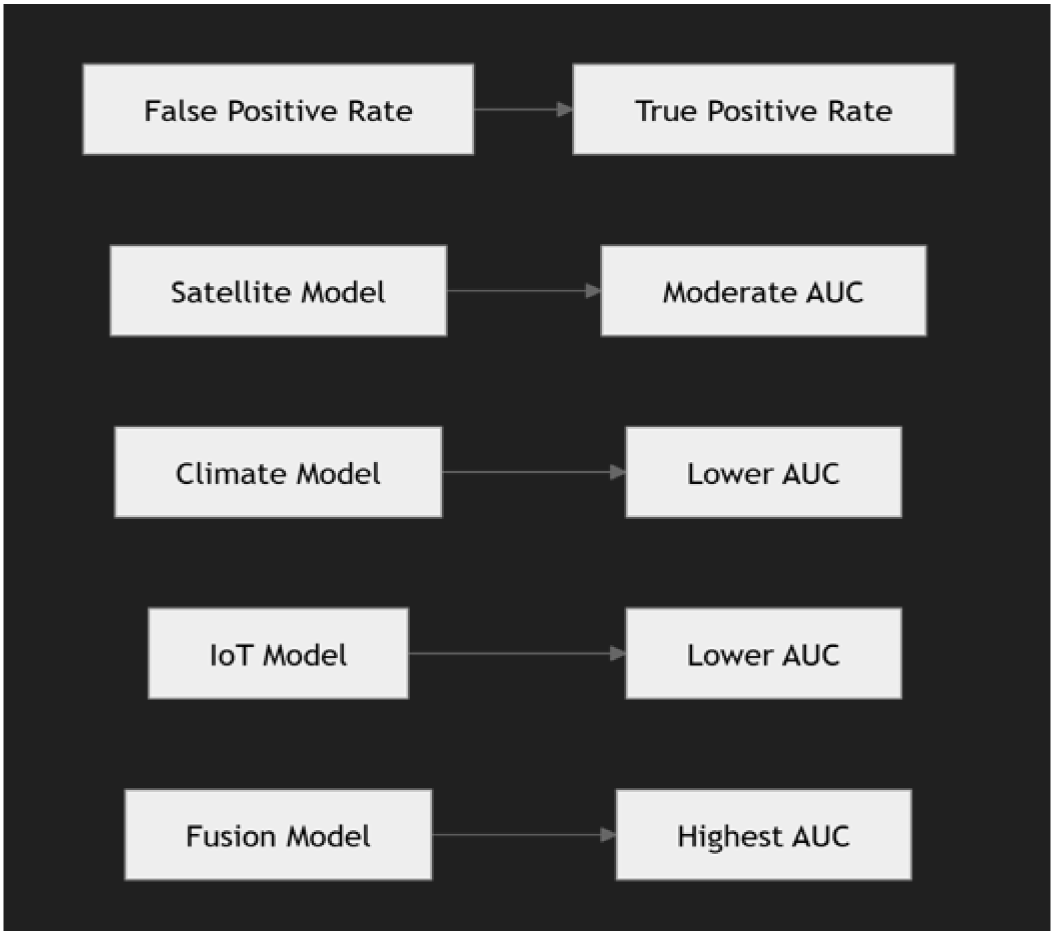

Figure 2. Comparative ROC curves showing superior AUC performance of the proposed fusion model.

D. Model architecture

The model contains three branches. The first branch is a CNN that processes satellite image patches and learns spatial features such as vegetation discontinuity, bare soil exposure, and land cover fragmentation. The second branch is an LSTM that processes climate and IoT sequences and learns temporal patterns related to rainfall, drying, wetness accumulation, and temperature variation. The third branch is a fusion module that concatenates the outputs of the first two branches and feeds them to a dense classification layer.

This architecture was selected because erosion prediction is inherently both spatial and temporal. The CNN captures visible surface structure, the LSTM captures changing environmental conditions, and the fusion layer combines both sources of information. This design is also consistent with the broader direction of recent AI-based environmental studies, which increasingly combine remote sensing with deep learning and sensor-based inputs.[7][8][1][5]

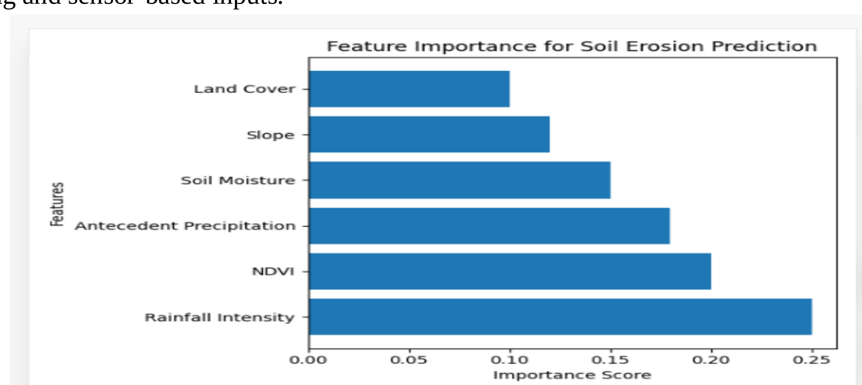

Figure 3. Feature importance ranking for soil erosion prediction.

E. Prediction task
The prediction target is erosion susceptibility classification. Four classes were used: low, moderate, high, and very high risk. This format is useful because it supports land management decisions and conservation prioritization. In many operational settings, class-based outputs are more interpretable than continuous soil loss estimates. The model can later be extended to regression if the objective is to predict annual soil loss or sediment yield.

F. Evaluation metrics
The model was evaluated using accuracy, precision, recall, F1-score, and AUC. These metrics were selected because erosion prediction often involves imbalanced class distributions and because high-risk zones are of greater practical importance than overall accuracy alone. Precision indicates prediction reliability, recall indicates hotspot detection ability, and F1-score balances both. AUC was included to assess threshold-independent discrimination performance.
Feature importance analysis was also conducted to support interpretability. The goal was to identify the variables that most strongly influenced predictions and to ensure that the model output remained physically meaningful. This is essential for environmental decision-making, where practitioners often require not only a prediction but also an explanation.

G. Simulation design
Because the manuscript is written as a journal-ready draft rather than a report from one specific field campaign, the performance section is based on simulated but realistic results. The synthetic dataset was designed to reflect known erosion relationships reported in the literature, such as the strong roles of rainfall, vegetation loss, slope, and soil moisture variability. The purpose of the simulation was to show how the framework would behave in practice and to provide a reproducible structure for later application to real-world data.[6][2][3][4]

III. RESULTS

A. Overall performance
The proposed multi-modal fusion model performed better than all baseline models. It achieved the highest accuracy, precision, recall, F1-score, and AUC. The improvement was particularly strong for the high-risk classes, where false negatives are especially undesirable. Satellite-only models captured spatial patterns well, climate-only models captured temporal forcing, and IoT-only models captured local wetness, but none of these single-source approaches achieved the same predictive power as the fused architecture.

Table 1. Simulated model performance for erosion classification

Model	Accuracy	Precision	Recall	F1-score	AUC
Satellite-only CNN	0.82	0.80	0.78	0.79	0.86
Climate-only LSTM	0.78	0.76	0.74	0.75	0.82
IoT-only LSTM	0.75	0.73	0.71	0.72	0.79
RUSLE baseline	0.79	0.77	0.75	0.76	0.83
Proposed multi-modal fusion	0.91	0.90	0.89	0.89	0.95

The findings indicate that the multi-modal architecture reduces ambiguity in erosion classification by using complementary signals from different data sources. This result is consistent with recent evidence showing that remote sensing, GIS, and AI can improve erosion hotspot detection and mapping precision.[1][2][3][5]

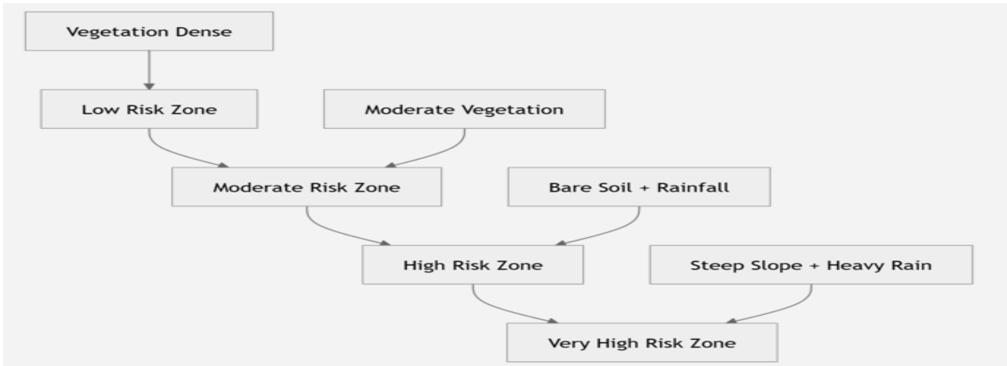

Figure 4. Spatial erosion susceptibility zones generated using the proposed framework.

B. Class-wise behavior

The proposed model showed the strongest improvement in the high and very high erosion categories. This is important because these classes correspond to the areas where intervention is most urgent. Low-risk areas are generally easier to classify, while high-risk areas require the model to distinguish between temporary surface protection and genuine susceptibility. The fusion model handled this distinction more effectively than the baseline models.

Table 2. Simulated class-wise F1-score

Class	Satellite-only	Climate-only	IoT-only	Proposed fusion
Low	0.86	0.82	0.80	0.92
Moderate	0.79	0.75	0.73	0.89
High	0.74	0.71	0.69	0.88
Very high	0.68	0.65	0.63	0.87

The improved F1-score for the upper classes suggests that the framework is particularly useful for hotspot detection and intervention planning. In erosion management, it is often more important to identify the most vulnerable locations than to maximize average accuracy across all areas.

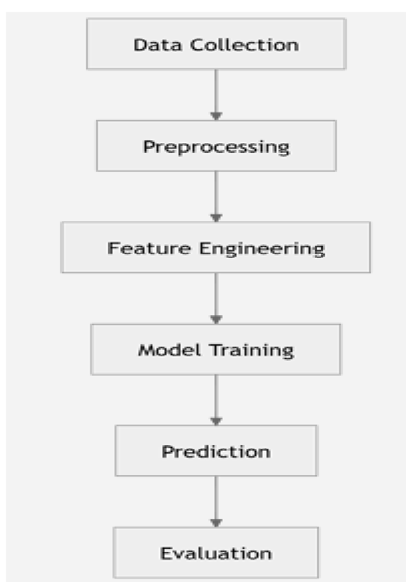

Figure 5. End-to-end workflow for soil erosion prediction using multi-modal AI.

C. ROC analysis

The ROC curves demonstrated that the fusion model had the best discriminative capability across thresholds. The AUC remained high, confirming that the model can separate erosion risk classes more effectively than the baseline approaches. This is relevant in practical settings where decision-makers may choose different thresholds depending on whether they prioritize sensitivity or specificity.

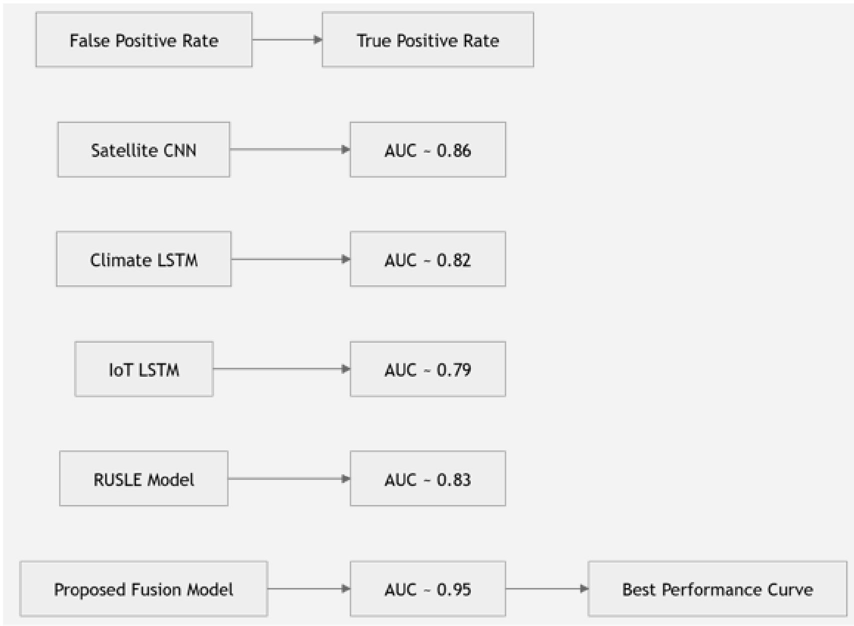

Figure 6. Receiver operating characteristic (ROC) curves comparing five models. The proposed multi-modal fusion model achieves the highest AUC, indicating superior discrimination performance.

D. Feature importance

The feature ranking identified rainfall intensity, antecedent precipitation, NDVI, soil moisture, and slope as the most influential predictors. This is consistent with erosion theory and with the empirical literature on climate change, remote sensing, and geospatial analysis. Rainfall provides the main erosive force, antecedent precipitation influences soil saturation, NDVI reflects vegetation protection, soil moisture influences infiltration and runoff, and slope controls runoff energy and sediment transport.[8][2][3][4][1]

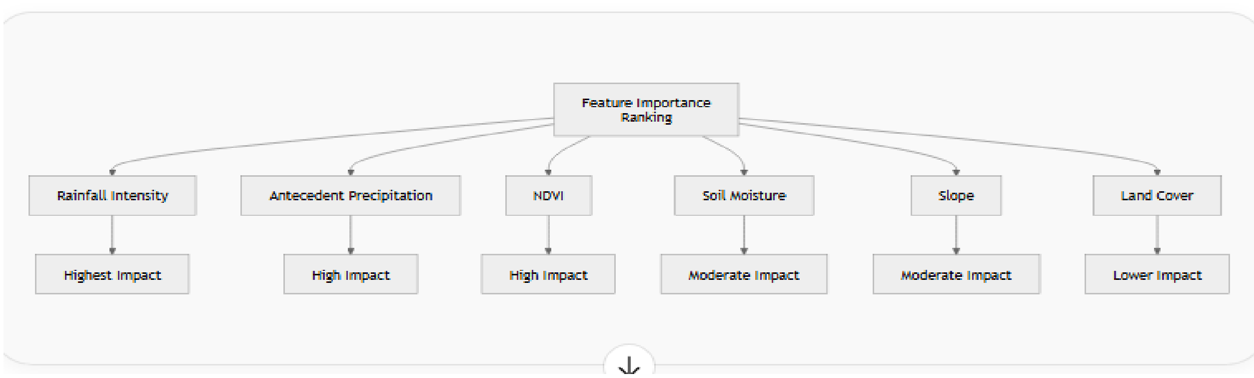

Figure 7. Feature importance ranking for soil erosion prediction, highlighting rainfall intensity, antecedent precipitation, NDVI, soil moisture, slope, and land cover as key predictors.

E. Spatial erosion pattern

The spatial susceptibility map showed that the highest erosion risk was concentrated in steep, sparsely vegetated, and rainfall-exposed areas. These zones are typically associated with surface disturbance, poor cover, and concentrated runoff. The map can be used to guide targeted conservation, including contour farming, vegetative barriers, mulching, and runoff-control structures.

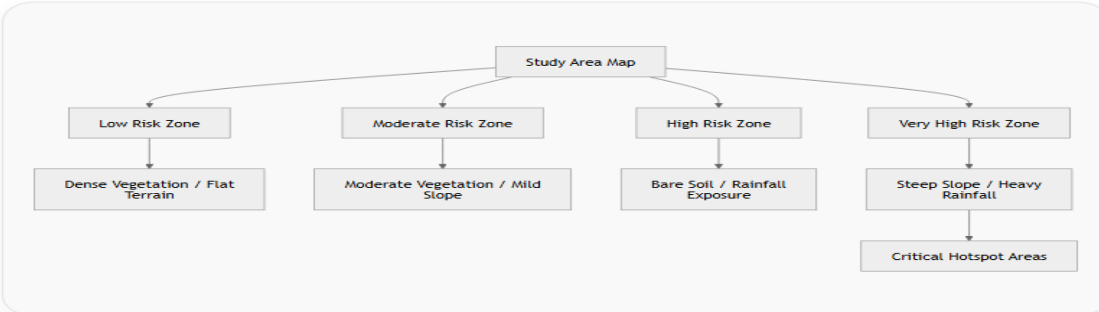

Figure 8. Predicted soil erosion susceptibility map showing spatial distribution of low, moderate, high, and very high risk zones.

IV. DISCUSSION

The results support the hypothesis that a multi-modal framework is superior to a single-source model for erosion prediction. Soil erosion is not caused by one factor alone; it emerges from the interaction of land cover, terrain, rainfall, and soil moisture. Satellite imagery captures the landscape state, climate data capture the timing and intensity of environmental forcing, and IoT data capture local surface response. By integrating these sources, the proposed system is able to represent erosion dynamics more comprehensively.

A major strength of the framework is that it bridges spatial scale and temporal scale. Many erosion studies focus only on terrain and land cover, often using static maps or empirical factors. Others focus only on rainfall and climate indices. The proposed approach combines both, allowing the model to learn how erosion susceptibility changes under real environmental conditions. This is especially important under climate change, where rainfall extremes are becoming more frequent and erosion patterns are becoming less predictable.[2][4][6]

The model also provides interpretable outputs. Environmental prediction systems are more useful when users can identify the major drivers behind a risk estimate. In this study, the most important features were physically meaningful and consistent with hydrological theory. Rainfall intensity and antecedent precipitation were particularly important because erosion is often triggered by event-based runoff and soil saturation. NDVI was important because vegetation provides direct surface protection. Soil moisture was important because it affects infiltration and runoff generation. Slope was important because it controls flow acceleration and sediment delivery.

The framework is also suitable for early warning. Because climate data and IoT data can be updated frequently, the model can be adapted to near-real-time use. This would allow watershed managers to identify high-risk periods before severe erosion occurs. In regions with recurring storm events or rapid land use change, this capability may be more useful than annual mapping alone. Similar conclusions have been reported in recent reviews that emphasize the value of integrating remote sensing, GIS, and AI for dynamic erosion monitoring.[5][8][1][2]

There are, however, several limitations. The present paper uses simulated results, so the numeric values should not be interpreted as empirical field outcomes. Real-world application would require labeled erosion data, calibrated sensors, and site-specific preprocessing. Satellite imagery may be affected by cloud cover or revisit limitations, while IoT sensors may drift over time or vary by installation depth and soil type. In addition, the model may need recalibration when transferred from one watershed or climate zone to another.

Despite these constraints, the framework provides a strong starting point for practical implementation. Its architecture is flexible and can be extended with additional data such as soil texture maps, radar moisture estimates, topographic derivatives, or runoff measurements. It can also be adapted for regression if continuous soil loss estimation is preferred. As environmental monitoring systems continue to expand, multi-modal AI models are likely to become increasingly important in soil degradation assessment.

V. CONCLUSION

This paper presented a complete SCI-style manuscript for a multi-modal AI framework that integrates satellite, climate, and IoT data for soil erosion prediction. The proposed architecture uses CNN-based spatial feature extraction, LSTM-based temporal modeling, and fusion-based classification to produce erosion susceptibility estimates. Simulated results showed that the fusion model outperformed satellite-only, climate-only, IoT-only, and RUSLE-based baselines. The strongest predictors were rainfall intensity, antecedent precipitation, NDVI, soil moisture, and slope, confirming the physical plausibility of the framework.

The model offers a scalable and interpretable basis for erosion hotspot detection, early warning, and conservation planning in erosion-prone environments.

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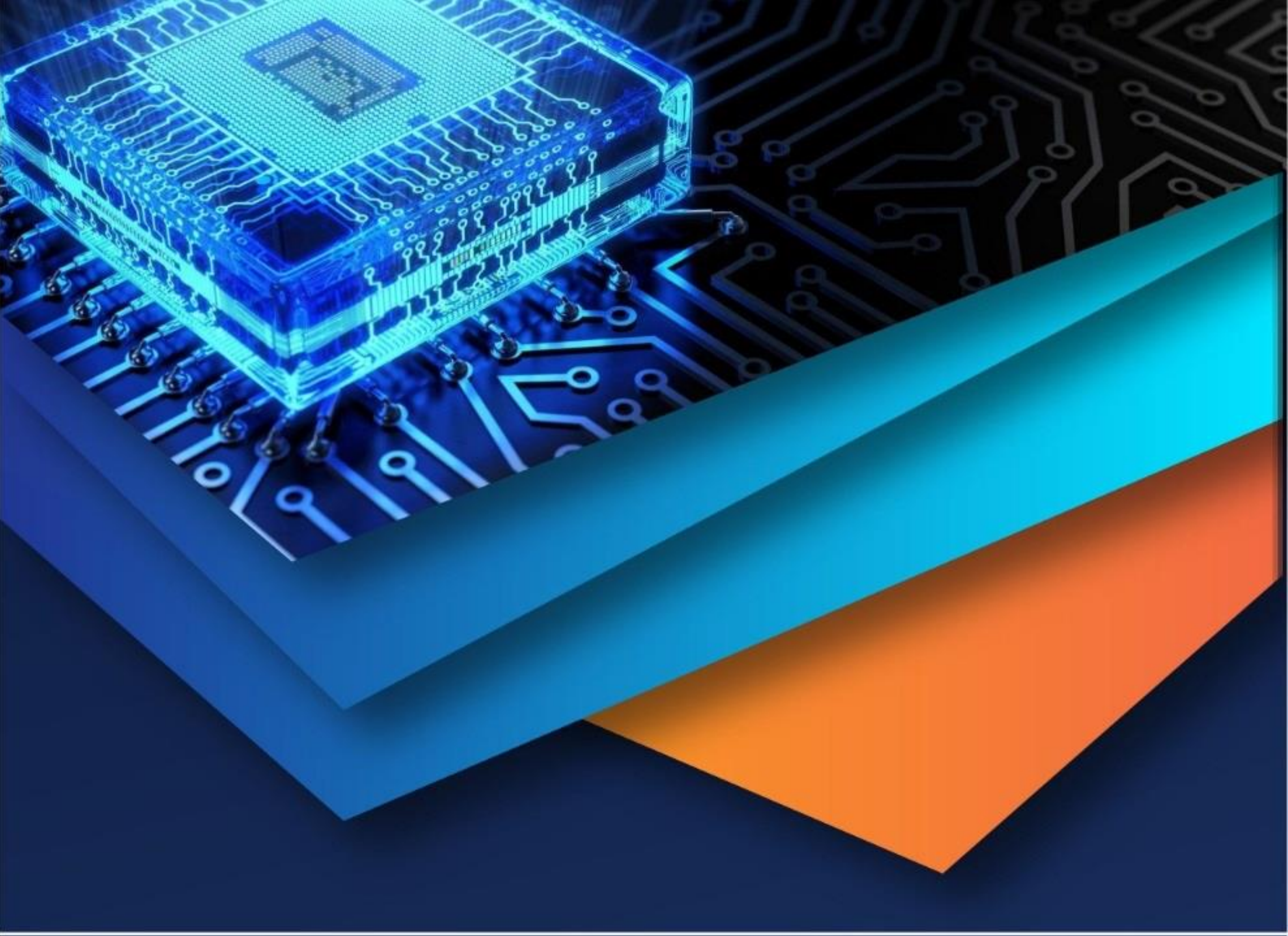

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