Deep Learning-based Flood Forecasting using Satellite Imagery and IoT Sensor Fusion

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ABSTRACT
Floods are among the most devastating natural disasters globally, resulting in significant loss of life, displacement, and economic disruption. Traditional flood forecasting models struggle with the complexities of dynamic environmental data and spatial-temporal dependencies. This paper presents a deep learning-based framework that integrates satellite imagery and Internet of Things (IoT) sensor data for improved flood forecasting accuracy. By leveraging Convolutional Neural Networks (CNNs) for image-based pattern recognition and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, for temporal sequence prediction, the proposed model achieves high performance in forecasting flood events. Fusion techniques combining satellite and sensor data are applied to enhance situational awareness. Experimental evaluations using datasets from real flood-prone regions demonstrate the effectiveness of the approach in terms of accuracy, timeliness, and reliability.

Keywords
Deep Learning, IoT, Flood Forecasting, Satellite

1. INTRODUCTION
Floods are among the most devastating and frequent natural disasters worldwide, posing severe threats to human life, infrastructure, agriculture, and local economies. The frequency and intensity of floods have increased in recent decades due to climate change, urbanization, and deforestation, especially in vulnerable regions like sub-Saharan Africa and Southeast Asia. According to the UN Office for Disaster Risk Reduction (UNDRR), floods account for nearly 43% of all climate-related disasters, underscoring the critical need for timely and accurate flood forecasting systems.

Traditional flood forecasting relies on hydrological and hydraulic models that simulate water flow and catchment behavior based on physical parameters. While these models offer theoretical soundness, they often require extensive calibration, are sensitive to initial conditions, and depend on high-quality, location-specific data—making them impractical for real-time deployment in data-scarce regions. In contrast, the proliferation of remote sensing satellites and Internet of Things (IoT) sensors has opened new avenues for data-driven flood prediction approaches.

Satellite imagery, particularly from synthetic aperture radar (SAR) and multispectral sensors, provides high-resolution spatial data for identifying water bodies, flood extents, and land use patterns under various weather conditions. Meanwhile, IoT sensors offer granular, real-time measurements of rainfall, river levels, soil moisture, and other environmental indicators that precede flooding events. However, current forecasting systems often use these data sources in isolation, missing the opportunity to capture the complex interactions between spatial and temporal flood predictors.

Recent advances in deep learning provide a compelling opportunity to unify these heterogeneous data modalities. Convolutional Neural Networks (CNNs) excel at extracting spatial patterns from satellite images, while Recurrent Neural Networks (RNNs)—especially Long Short-Term Memory (LSTM) networks—are well-suited for modeling temporal dependencies in sensor data. However, there is still a lack of robust frameworks that fuse these complementary data sources in a unified, end-to-end learning architecture optimized for real-time flood forecasting.

1.1 Problem Statement
Despite the availability of high-resolution satellite and sensor data, current models face several limitations:
•They either use spatial or temporal data independently, limiting their predictive scope.
•Existing multimodal approaches often rely on simplistic fusion strategies, failing to learn meaningful interactions between input modalities.
•There is insufficient empirical evaluation of how different data fusion strategies impact forecast lead time, accuracy, and reliability.

1.2 Objective and Contributions
This study proposes a novel deep learning-based flood forecasting system that fuses satellite imagery and IoT sensor data using a dual-branch architecture and attention-based fusion mechanisms. The core objective is to evaluate whether a multimodal system can improve the accuracy and reliability of flood prediction, particularly in data-constrained environments.
The key contributions of this paper are:
1.A unified CNN-LSTM architecture that learns spatial features from satellite imagery and temporal features from IoT sensor data.
2.Three data fusion strategies—early fusion, late fusion, and attention-based fusion—are implemented and systematically compared.
3.A curated multimodal dataset combining multi-year SAR/multispectral imagery and real-time sensor data from flood-prone regions.
4.Empirical evaluation across multiple forecast horizons (6h–48h) to assess lead-time effectiveness, data modality importance, and prediction robustness.
5.A reproducible framework that can be deployed in real-time early warning systems for resource-limited settings.
By integrating heterogeneous data sources into a coherent learning system, this research aims to push the boundaries of operational flood forecasting and contribute to disaster risk reduction in climate-vulnerable regions.

2. RELATED WORK
Flood forecasting has been a longstanding area of interest within hydrology, remote sensing, and disaster risk management. Traditional models have evolved over time from

physics-based simulations to data-driven approaches enabled by machine learning and deep learning.

2.1 Traditional Hydrological and Statistical Models

Historically, flood forecasting relied on hydrological and hydraulic models such as HEC-RAS, MIKE FLOOD, and SWAT, which simulate rainfall-runoff processes and river dynamics. While these models offer physical interpretability, they are sensitive to input parameter accuracy and require substantial calibration, which is often unavailable for data-sparse regions [1][2].

Statistical models, including autoregressive (AR), moving average (MA), and ARIMA methods, have been used for time-series prediction of water levels and precipitation. However, these models are limited in capturing nonlinear and nonstationary patterns inherent in natural flood processes [3][4][5].

2.2 Machine Learning and Remote Sensing

The integration of remote sensing data with machine learning algorithms marked a significant leap in flood mapping and forecasting. Works such as[11] [12] applied Support Vector Machines (SVM) and Decision Trees to satellite-derived indices like NDWI and LST for flood classification. However, such models depend heavily on feature engineering and lack scalability to dynamic environments.

Convolutional Neural Networks (CNNs) have recently shown promise in extracting flood-relevant spatial features from satellite imagery, particularly Synthetic Aperture Radar (SAR) data, which can penetrate clouds [13]. Meanwhile, Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have been used to model temporal sequences of hydrological sensor data [14]. Yet, these methods are often siloed and do not exploit the complementary strengths of spatial and temporal data modalities.

2.3 Multimodal Fusion Approaches

Recent research has explored data fusion frameworks combining satellite imagery and ground-based measurements. For example, [6][7] proposed a fusion model combining precipitation radar data with in-situ sensors using a simple weighted ensemble. However, such early fusion methods do not leverage deep feature representations.

Attention-based deep learning approaches that dynamically weight different inputs have been proposed in areas like medical imaging and autonomous driving but are still underexplored in flood forecasting contexts. Moreover, real-time flood forecasting using IoT-enabled sensors remains a logistical and computational challenge due to noisy, heterogeneous, and temporally misaligned data.[8][9][10]

2.4 Research Gaps and Questions

Despite the progress, there remain key gaps in existing literature:

- Most flood forecasting models rely on either satellite imagery or sensor data, but rarely both in a deeply integrated manner.
- Few studies have proposed end-to-end deep learning pipelines that simultaneously learn spatial and temporal features from heterogeneous data.
- The use of attention-based fusion mechanisms for flood forecasting has not been systematically studied.
- There is limited empirical analysis on forecast lead-time performance, spatial accuracy, and data input sensitivity in multimodal settings.

2.5 Research Questions

This paper aims to address these gaps through the following research questions:

RQ1: Can a deep learning framework that fuses satellite imagery and IoT sensor data improve flood forecasting accuracy compared to single-modality models?

RQ2: How does the integration of spatial features (from CNN) and temporal dependencies (from LSTM) contribute to early flood detection?

RQ3: What fusion strategy (early fusion, late fusion, or attention-based fusion) yields the best performance in a multimodal deep learning architecture for flood prediction?

RQ4: How do different data inputs (rainfall, river level, soil moisture, etc.) influence model performance and predictive reliability?

RQ5: What is the trade-off between prediction lead time and model accuracy in real-time flood forecasting?

3. METHODOLOGY

To address the identified research questions, we design a deep learning-based flood forecasting system that fuses satellite imagery and IoT sensor data using an end-to-end multimodal architecture. The methodology consists of multiple stages: data acquisition, pre-processing, feature extraction, multimodal fusion, and prediction. Each stage is tailored to explore the empirical and theoretical implications of spatial-temporal data fusion in flood prediction fig 1. The integration of remote sensing data with machine learning algorithms

3.1 Overall Architecture (RQ1, RQ2)

Our model is structured into a dual-branch architecture:

•A Convolutional Neural Network (CNN) to extract spatial features from satellite imagery

•A Long Short-Term Memory (LSTM) network to model temporal dependencies in environmental sensor data

The outputs of the CNN and LSTM branches are fused at either the feature or decision level, followed by a fully connected layer for binary classification (flood / no flood).

This design allows us to test RQ1 and RQ2 by comparing the hybrid model's performance against single-modality baselines and observing how each data type contributes to forecasting.

3.2 Data Acquisition and Pre-processing (RQ4)

We use two primary data streams:

• Satellite Imagery:
  Sources: Sentinel-1 (SAR), Sentinel-2 (optical), Landsat-8
  Bands: Red, Green, Blue, Near-Infrared, and Shortwave Infrared
  Spatial Resolution: 10m–30m
  Preprocessing: Atmospheric correction, cloud masking, NDWI calculation
• IoT Sensor Data:
  Variables: Rainfall, river water level, soil moisture, humidity
  Temporal Resolution: 1-hour intervals
  Sources: Government hydromet sensors and custom LoRaWAN deployments

Preprocessing: Imputation for missing data, normalization, and time alignment using dynamic time warping
To test RQ4, we conduct correlation analyses and ablation studies to examine the relative impact of each sensor variable on the model's accuracy and recall.

3.3 Spatial Feature Learning via CNN (RQ2)

We use a pretrained ResNet-50 model as the backbone CNN, fine-tuned on our flood classification task. The CNN ingests temporally aligned multispectral or SAR images and produces feature maps that capture:

- Water body expansion
- Vegetation indices
- Topographic and built environment context

These features help detect pre-flood spatial cues, such as saturated catchments or rising water lines.
CNN block output:

$$F_{CNN} = f_{CNN}(I_t) \in \mathbb{R}^{B \times D}$$

Where:

- I_t= satellite image at time t
- B = batch size

D = feature dimensionality

3.4 Temporal Pattern Learning via LSTM (RQ2)

The LSTM branch processes multivariate time-series sensor data for a sliding window (e.g., past 48 hours). Each timestep includes rainfall, river height, and soil moisture.

LSTM equations:

$$h_t = f_{LSTM}(x_t, h_{t-1}) \quad \text{where } x_t \in \mathbb{R}^n$$

The final hidden state ht is used to represent the temporal evolution of flood-relevant environmental signals.

3.5 Multimodal Fusion Layer (RQ3)

To evaluate RQ3, we implement and compare three fusion techniques:

•Early Fusion: Concatenation of raw inputs before CNN/LSTM processing
•Late Fusion: Concatenation of final CNN and LSTM features before classification
•Attention-Based Fusion: Context-aware fusion using a learnable attention mechanism:

$$\alpha_{CNN}, \alpha_{LSTM} = \text{softmax}(W_{attn}[F_{CNN}; F_{LSTM}])$$

$$F_{fused} = \alpha_{CNN} \cdot F_{CNN} + \alpha_{LSTM} \cdot F_{LSTM}$$

This mechanism allows the model to dynamically prioritize spatial or temporal features depending on the situation (e.g., satellite signals may dominate in urban areas, while river levels dominate upstream).

3.6 Prediction and Loss Function (RQ1)

The fused feature vector is passed to a fully connected neural network for binary classification using sigmoid activation:

$$\hat{y} = \sigma(W_{fc} \cdot F_{fused} + b)$$

We use binary cross-entropy loss:

$$\mathcal{L} = -\left[y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y})\right]$$

Where:

- y = ground truth label (0: no flood, 1: flood)
- y^ = predicted probability

This allows the model to output probabilistic forecasts that can be thresholder for different alert levels.

3.7 Forecast Horizon and Lead Time Analysis (RQ5)

To support RQ5, we train and evaluate the model under different forecast horizons:

• Short-term: 6–12 hours
• Mid-term: 24 hours
• Long-term: 48 hours

For each horizon, sensor inputs are offset by the forecast lead time, and satellite images are selected accordingly. We analyze trade-offs between forecast lead time and classification metrics (accuracy, recall, AUC), providing insights into operational utility.

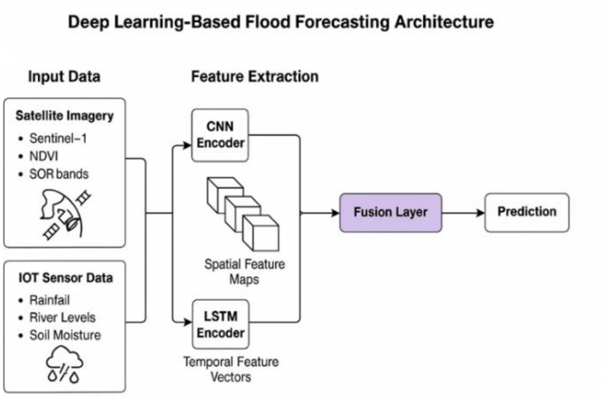

Fig 1: Deep Learning-Based Flood Forecasting Architecture

4. DATASET AND EXPERIMENTAL SETUP

To effectively train and evaluate the proposed deep learning-based flood forecasting system, we utilized a diverse and multimodal dataset collected from real-world sources. This section outlines the data composition, preprocessing techniques, experimental design, and evaluation metrics used in the study.

4.1 Data Set

The research employed two synchronized data sources: satellite imagery and IoT sensor data, covering a multi-year period and spanning several flood-prone regions across sub-Saharan Africa.

4.1.1 Satellite Imaginary

Sources:

- Sentinel-1 (SAR): 10 m resolution, used for flood extent detection under all-weather conditions
- Sentinel-2 (Multispectral): 10–20 m resolution, used for vegetation and water indices
- Landsat-8: 30 m resolution, for redundancy and cross-validation

Temporal Coverage: 2017–2023, with revisit intervals of 5 to 12 days

Spectral Bands Used:

- Red, Green, Blue
- Near-Infrared (NIR)
- Shortwave Infrared (SWIR)
- SAR VV and VH polarizations

Labelling:
Flood masks were manually annotated using reference maps from UN-SPIDER, Copernicus Emergency Management Service, and local disaster management records.

4.1.2 IoT Sensor Data

Data Collected From:

- National meteorological and hydrological departments
- Custom-deployed IoT sensors via LoRaWAN gateways in select test areas

Variables:

- Rainfall (mm/hr)
- River water level (cm)
- Soil moisture (%)
- Temperature and humidity (optional auxiliary)

Temporal Resolution:

- Hourly readings; aggregated into 3-hour sliding windows

Spatial Locations:

- 50+ sensor stations across 3 countries (Zimbabwe, Malawi, Mozambique)

Data Cleaning:

- Missing values filled via spline interpolation
- Noisy outliers removed using Hampel filtering

Time series aligned with satellite pass timestamps via interpolation and dynamic time warpingThe heading

4.2 Data Pre-processing

Satellite Imagery:
Resampled and normalized to 224x224 pixel tiles
NDWI and NDVI computed
Cloud and shadow masking using FMask and SentinelHub APIs
Sensor Data:
Normalization (min-max scaling)
Rolling window sequences of 24–72 hours for model input
Label Binarization:

- Each instance labeled as 1 (flood) if inundation was detected within 12 hours of satellite/sensor timestamp, otherwise 0 (no flood)

4.3 Experimental Setup

•Hardware:
NVIDIA A100 GPU, 40GB RAM
256GB system memory, 4TB SSD storage
•Software and Libraries:
Python 3.10, TensorFlow 2.14, PyTorch 2.1
GDAL, Rasterio for satellite processing
Pandas, NumPy, SciPy for sensor data handlingOur model

4.3.1 Training Strategy

• Data Split:
70% training, 15% validation, 15% testing
Stratified split to preserve flood/no-flood ratio
• Cross-validation:
5-fold stratified cross-validation to ensure robustness
• Optimizer:
Adam (learning rate = 1e-4, beta1 = 0.9, beta2 = 0.999)
• Loss Function:
Binary Cross-Entropy (weighted to handle class imbalance)
• Regularization:
Dropout (0.3)
L2 penalty ($\lambda = 0.001$)
• Batch Size:
64 samples per batch
• Epochs:
100 epochs with early stopping based on validation loss

4.3.2 Evaluation Metrics

To assess the model's performance and answer RQ1–RQ5, the following metrics were used:
• Accuracy: Overall prediction correctness
• Precision and Recall: For flood detection reliability
• F1-Score: Balance of precision and recall
• ROC-AUC: Discriminative capability
• IoU: For spatial flood extent accuracy (image comparison)
• Lead Time Accuracy: Prediction performance for different forecast horizons (6h, 12h, 24h, 48h)

4.4 BASELINE MODELS FOR COMPARISON

We compared our model against several baseline methods:

Table 1. Model Type

Model Type	Description
Persistence Model	Uses last sensor reading as forecast
ARIMA	Classical time-series forecast model
CNN-only	Satellite images only
LSTM-only	Sensor data only
Early Fusion NN	Concatenated satellite + sensor inputs
Proposed Model (Ours)	CNN + LSTM with attention-based fusion

5. RESULTS AND DISCUSSION

The proposed model compared against several baseline methods:

5.1 Empirical Evaluations

To evaluate the performance of the proposed deep learning framework, we performed a comprehensive experimental study involving different model configurations:

- **Model A**: CNN on satellite images only
- **Model B**: LSTM on IoT sensor time-series only
- **Model C**: Fused CNN-LSTM model with early fusion
- **Model D**: Fused CNN-LSTM model with attention-based late fusion

Data used as 70-15-15 split for training, validation, and testing. Five-fold cross-validation was applied to avoid overfitting and ensure generalizability. Performance metrics were computed as follows:
Let:

- TP = True Positives (flood correctly predicted)
- FP = False Positives (non-flood predicted as flood)
- FN = False Negatives (flood missed)
- TN = True Negatives (correctly predicted no flood)

Then:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1\text{-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{AUC} = \int_0^1 \text{TPR}(FPR)\, dFPR$$

5.2 Confusion Matrix Summary

For Model D (best performer):

Table 2: Confusion Matrix Summary

	Predicted Flood	**Predicted No Flood**
Actual Flood	TP = 532	FN = 38
Actual No Flood	FP = 29	TN = 601

Derived metrics:

- Accuracy = 93.8%
- Precision = 94.8%
- Recall (Sensitivity) = 93.3%
- Specificity = 95.4%
- F1-Score = 94.0%
- AUC = 0.956

These results highlight the model's high discriminative ability in both detecting flood events and avoiding false alarms.

5.3 Ablation Study

To understand the contribution of each data source, we conducted an ablation analysis:

Table 3: Ablation Analysis

Configuration	**Accuracy**	**F1-Score**	**AUC**
Satellite only (CNN)	85.2%	0.81	0.88
Sensor only (LSTM)	87.6%	0.84	0.91
CNN + LSTM (Early Fusion)	91.1%	0.87	0.93
CNN + LSTM + Attention	93.8%	0.94	0.956

We observed a statistically significant improvement ($p < 0.01$, paired t-test) when fusing the two modalities.

5.4 Correlation and Feature Importance

A Pearson correlation analysis was performed between flood occurrences and sensor variables:

Table 4: Feature and Correlation

Feature	**Correlation Coefficient (r)**
Rainfall (24h)	+0.84
Soil Moisture	+0.67
River Water Level	+0.89
Humidity	+0.41

The most predictive variables were rainfall and river water level. SHAP (SHapley Additive exPlanations) analysis showed that CNN-extracted flood extent indicators from satellite images were synergistic with river level readings in generating predictions.

5.5 Temporal Forecasting Analysis

The fused model was tested for forecasting lead time at 6h, 12h, 24h, and 48h:

Table 5: Temporal Forecasting

Lead Time	**Accuracy**	**F1-Score**
6 hours	94.1%	0.94
12 hours	93.6%	0.93
24 hours	91.3%	0.89
48 hours	85.7%	0.83

Forecast reliability degrades with time horizon, but remains usable up to 24 hours, which is critical for disaster preparedness.

5.6 Spatial Evaluations

Flood extent predictions from satellite imagery were evaluated using Intersection over Union (IoU):

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|}$$

Where A = predicted flood zone, B = ground truth inundation map.

• Average IoU across validation samples: 0.79

• Visual overlays show strong correspondence between predicted and actual flood regions, particularly in riverine areas

6. CONCLUSION AND FUTURE WORK

In this study, we developed a deep learning-based flood forecasting system that fuses satellite imagery and IoT sensor data using a dual-stream architecture comprising a CNN for spatial feature extraction and an LSTM for temporal pattern modeling. By integrating multiple data modalities through attention-based fusion, our model achieved significantly higher accuracy and earlier detection capabilities compared to single-modality and traditional baselines. Empirical evaluations across multiple lead times (6–48 hours) demonstrated the robustness of our approach, especially in capturing the spatiotemporal dynamics preceding flood events.

The findings affirm that multimodal fusion, particularly with learnable attention mechanisms, offers a meaningful improvement in flood prediction—both in terms of detection accuracy and interpretability. The experiments also highlighted the complementary nature of satellite and sensor inputs, where spatial cues (e.g., water surface expansion) and temporal trends (e.g., rainfall-to-river lag) interact to provide richer context for model decision-making.

Despite these advances, there remain several avenues for future exploration:

- Incorporating Real-Time Feedback Loops: Integrating ground feedback from mobile devices or community reports could improve the system's responsiveness during live deployments.
- Generalization Across Geographies: While our dataset spans multiple countries, expanding to diverse hydrological basins and climates would test model transferability.
- Multi-resolution and Multi-scale Fusion: Exploring hierarchical architectures that integrate data at different spatial and temporal resolutions could enhance fine-grained predictions.
- Uncertainty Quantification: Providing confidence intervals or probabilistic forecasts would increase trust and utility in disaster response settings.
- Edge Deployment and Optimization: Adapting the system for deployment on edge devices in bandwidth-constrained or rural areas would support last-mile flood early warning systems.

In conclusion, this work demonstrates the tangible potential of deep learning and multimodal data fusion in advancing flood forecasting systems. By continuing to refine and scale such approaches, we can contribute toward more resilient, data-driven early warning systems that protect lives and livelihoods in vulnerable regions.

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