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Deep Learning-Based Flood Risk Assessment Using a Hybrid CNN-LSTM Model Integrated with Remote Sensing and GIS

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Abstract

Floods are among the most devastating natural hazards, causing severe loss of life, infrastructure damage and environmental degradation. Accurate flood risk assessment crucial for effective disaster management and sustainable planning. This study develops a deep learning framework using a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model integrated with remote sensing and GIS to assess flood risk in the Lower Godavari basin, India. Spatial datasets including DEM, land use/land cover, slope, drainage density, distance to river, soil and NDVI derived from Sentinel-2, along with temporal data such as daily rainfall and river discharge (2015-2024), were used. The CNN component extracts spatial features, while the LSTM component learns temporal dependencies. The model achieved high performance with an AUC of 0.92, accuracy of 0.89 and F1-score of 0.87. The final flood risk map categorizes the basin into low, moderate, high and very high risk zones. The study demonstrates that the integration of deep learning with geospatial data significantly improves flood risk assessment and can support decision makers in planning and mitigation.

Keywords: Flood risk, CNN-LSTM, Remote sensing, GIS, Deep learning, Flood susceptibility, Lower Godavari basin

1. Introduction

Floods are one of the most frequent and destructive natural hazards worldwide, affecting millions of people and causing enormous economic losses. With climate change and rapid urbanization, the frequency and intensity of floods have increased in many regions, (IPCC, 2021). Traditional flood risk assessment methods based on statistical or hydraulic models often require extensive field data and are time consuming.

Recent advances in remote sensing and machine learning, particularly deep learning, have opened new opportunities for flood modelling. Convolutional Neural Networks (CNN) are effective in extracting spatial features from raster data (Zhang et al., 2019), while Long Short-Term Memory (LSTM) networks are powerful in capturing temporal dependencies in sequential data (Hochreiter and Schmidhuber, 1997). Integrating CNN and LSTM allows simultaneous learning of spatial and temporal characteristics, which is highly relevant for flood risk assessment. This study aims to develop a hybrid CNN-LSTM model using multi- temporal remote sensing and GIS datasets to produce an accurate flood risk map for the Lower Godavari basin, India.

2. Study Area

The Lower Godavari basin is located in Andhra Pradesh, India, between 16°30'-18°15' N latitude and 81°30'-82°45' E longitude, covering an area of about 10,340 km2 (Fig. 1). The basin experiences tropical climate with an average annual rainfall of about 1100 mm, most of which occurs during the southwest monsoon (June-September) (IMD, 2023). The region is prone to frequent floods due to heavy rainfall, low-lying terrain and dense drainage network.

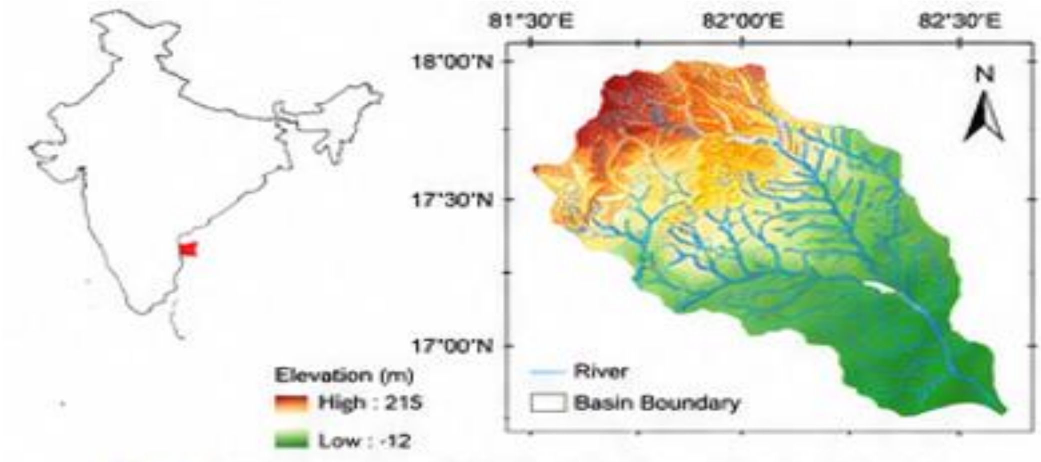


Fig. 1. Location map and DEM of the Lower Godavari basin

3. Data Used

The present study utilized multi-source geospatial and hydro-meteorological datasets to develop the hybrid CNN–LSTM model for flood risk assessment in the Lower Godavari Basin. The datasets comprised topographic, land use, vegetation, hydrological, and meteorological variables that influence flood occurrence and spatial variability. All datasets were acquired from reliable national and international agencies and standardized through GIS-based preprocessing to ensure compatibility for deep learning analysis. The details of the datasets, including their spatial resolution, temporal resolution, and data sources, are summarized in Table 1.

Table 1. Datasets and sources

Data	Spatial Resolution	Temporal Resolution	Source
DEM (SRTM)	30 m	–	USGS Earth Explorer
Land Use/Land Cover (Sentinel-2)	10 m	2022	COPERNICUS
NDVI (Sentinel-2)	10 m	Monthly	COPERNICUS
Soil Map	–	–	NBSS&LUP
Slope, Drainage Density	30 m	–	Derived in GIS
Distance to River	30 m	–	Derived in GIS
Daily Rainfall	–	Daily (2015–2024)	IMD
River Discharge	–	Daily (2015–2024)	CWC

4. Methodology

The proposed methodology (Fig. 2) integrates geospatial datasets, Geographic Information System (GIS) techniques, and a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) deep learning framework to generate flood susceptibility and flood risk maps. The workflow consists of four major stages: (A) Data Preparation, (B) GIS-based Pre-processing, (C) CNN–LSTM Model Development, and (D) Output Generation.

A. Data Preparation

The first stage involves collecting and organizing multi-source datasets required for flood modelling. These datasets provide information on terrain characteristics, hydrological processes, climatic conditions, and human activities that influence flood occurrence.

1. Remote Sensing Data

Satellite imagery forms the primary source for extracting land use/land cover (LULC), vegetation cover, built-up areas, drainage patterns, and impervious surfaces. Commonly used datasets include Landsat, Sentinel-2, and MODIS imagery because of their moderate spatial resolution and frequent revisit periods. These datasets enable continuous monitoring of environmental changes associated with flooding (Wulder et al., 2019; Drusch et al., 2012).

2. DEM and Derived Layers

Digital Elevation Models (DEMs) are used to derive topographic variables such as elevation, slope, aspect, curvature, flow direction, flow accumulation, Topographic Wetness Index (TWI), and stream networks. These terrain parameters control runoff generation and water accumulation during flood events (Tarboton, 1997; Moore et al., 1991).

3. Hydro-meteorological Data

Hydro-meteorological datasets include rainfall, river discharge, groundwater levels, soil moisture, evaporation, and temperature records obtained from meteorological agencies and hydrological monitoring stations. These variables capture the temporal dynamics governing flood generation and propagation (IPCC, 2022).

4. Socio-economic Data

Socio-economic information such as population density, road networks, building footprints, settlement distribution, and infrastructure is collected to assess flood exposure and vulnerability. These datasets are generally obtained from census databases, OpenStreetMap, or local government agencies (UNDRR, 2017).

B. GIS-based Pre-processing

Before model training, all datasets undergo standardized GIS pre-processing to ensure compatibility and improve model performance.

1. Resampling and Clipping

Spatial datasets obtained from different sources often have varying spatial resolutions and coordinate systems. Therefore, all raster datasets are resampled to a common spatial resolution and clipped to the study area boundary. This ensures spatial consistency among all predictor variables (Burrough & McDonnell, 1998).

2. Normalization

The predictor variables exhibit different numerical ranges and measurement units. Feature normalization scales all variables into a comparable range, generally between 0 and 1, preventing variables with larger magnitudes from dominating the learning process and facilitating faster convergence during neural network training (Goodfellow et al., 2016).

3. Rasterization

Vector datasets such as road networks, rivers, and administrative boundaries are converted into raster format so that all spatial layers share a uniform grid structure required for convolutional neural network operations (Longley et al., 2015).

4. Data Cube Creation

The processed raster layers are stacked into a multi-dimensional data cube in which each pixel contains information from multiple predictor variables. This multidimensional representation enables the CNN to learn complex spatial relationships among environmental factors (Zhu et al., 2017).

C. CNN–LSTM Model Development

The prepared data cube serves as the input to the hybrid CNN–LSTM model, which combines spatial feature extraction with temporal sequence learning.

1. Convolutional Neural Network (CNN)

The CNN automatically extracts hierarchical spatial features from raster datasets using convolutional filters. Unlike traditional machine learning algorithms requiring manual feature engineering, CNN learns representative spatial patterns directly from the input images, including terrain characteristics, drainage density, land cover, and flood-prone zones (LeCun et al., 2015).

2. Feature Maps

The convolution layers generate feature maps that represent important spatial characteristics while reducing irrelevant information. Pooling operations further enhance computational efficiency by reducing dimensionality and emphasizing dominant spatial features (Krizhevsky et al., 2012).

3. Long Short-Term Memory (LSTM)

The extracted spatial feature maps are passed to the LSTM network, which captures temporal dependencies among hydro-meteorological variables such as rainfall sequences and river discharge records. The LSTM architecture effectively addresses long-term dependency problems through memory cells and gating mechanisms, making it highly suitable for time-series prediction (Hochreiter & Schmidhuber, 1997).

4. Dense Layer with Sigmoid Activation

The final dense layer uses a sigmoid activation function to produce probability values between 0 and 1, representing the likelihood of flood occurrence for each spatial unit. These probabilities are subsequently classified into different flood susceptibility categories (Goodfellow et al., 2016).

D. Output Generation

The trained CNN–LSTM model generates spatial outputs for flood management and disaster planning.

1. Flood Susceptibility Map

The first output is a flood susceptibility map illustrating the probability of flooding across the study area. The map is typically classified into categories such as very low, low, moderate, high, and very high susceptibility. This product identifies areas that are physically prone to flooding based on environmental characteristics (Tehrany et al., 2015).

2. Exposure Layer

Flood susceptibility alone does not indicate disaster risk because risk depends on the presence of exposed people and infrastructure. Therefore, socio-economic layers including population, transportation networks, settlements, industries, hospitals, and public facilities are integrated as exposure layers (UNDRR, 2017).

3. Flood Risk Map

The final flood risk map combines flood susceptibility with exposure information to identify areas facing the greatest potential impacts. This map provides valuable information for disaster preparedness, urban planning, emergency response, land-use regulation, and climate adaptation strategies (IPCC, 2022).

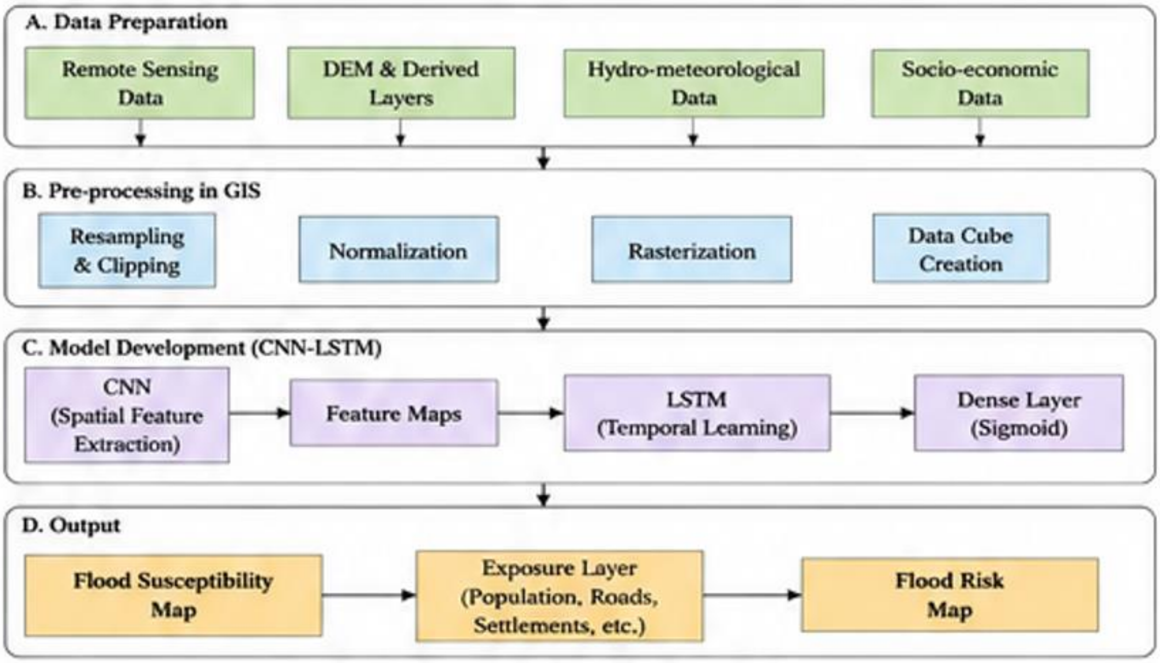


Fig. 2. Overall methodology flowchart

4. Methodology

The proposed methodology (Fig. 2) integrates geospatial datasets, Geographic Information System (GIS) techniques, and a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) deep learning framework to generate flood susceptibility and flood risk maps. The workflow consists of four major stages: data preparation, GIS-based pre-processing, CNN–LSTM model development, and output generation.

4.1 Data Preparation

The first stage of the proposed methodology involved the acquisition and preparation of multi-source geospatial, hydro-meteorological, and socio-economic datasets required for flood risk assessment. These datasets provide comprehensive information on the physical, hydrological, climatic, and anthropogenic factors influencing flood occurrence in the Lower Godavari Basin. Data were collected from reliable national and international sources and subsequently processed to ensure spatial and temporal consistency before model development (Wulder et al., 2019; IPCC, 2022).

4.1.1 Remote Sensing Data

Remote sensing data provide synoptic and repetitive observations that are essential for monitoring land surface characteristics associated with flood occurrence. In this study, satellite imagery was utilized to derive thematic layers such as land use/land cover (LULC), vegetation cover, built-up areas, drainage patterns, and impervious surfaces. Optical satellite datasets, including Sentinel-2, Landsat, and MODIS, are widely employed because of their high spatial resolution, frequent revisit cycles, and free accessibility. These datasets facilitate continuous monitoring of environmental changes that significantly influence flood susceptibility (Drusch et al., 2012; Wulder et al., 2019).

4.1.2 DEM and Derived Layers

Digital Elevation Models (DEMs) provide fundamental topographic information required for hydrological modelling and flood analysis. DEM data were used to derive several terrain-related parameters, including elevation, slope, aspect, flow direction, flow accumulation, curvature, stream network, and the Topographic

Wetness Index (TWI). These variables control runoff generation, water flow paths, and accumulation zones, making them critical predictors in flood susceptibility modelling. Areas with low elevation, gentle slopes, and high flow accumulation generally exhibit a greater likelihood of flooding (Tarboton, 1997; Moore et al., 1991).

4.1.3 Hydro-meteorological Data

Hydro-meteorological variables describe the climatic and hydrological conditions responsible for flood generation. Daily rainfall, river discharge, groundwater levels, temperature, soil moisture, and evaporation data were collected from relevant meteorological and hydrological agencies. These datasets capture both short-term weather variability and long-term hydrological behaviour, enabling the CNN–LSTM model to learn temporal relationships between rainfall events, river flow, and flood occurrence. Incorporating these variables substantially improves the predictive capability of deep learning models for flood forecasting (IPCC, 2022).

4.1.4 Socio-economic Data

Flood risk is influenced not only by physical susceptibility but also by the exposure of people and infrastructure. Therefore, socio-economic datasets, including population density, settlement distribution, transportation networks, building footprints, agricultural land, and critical infrastructure, were incorporated into the analysis. These datasets were obtained from census records, OpenStreetMap, and other government sources to evaluate the spatial distribution of flood exposure and vulnerability. Integrating socio-economic information with environmental variables enables a comprehensive assessment of flood risk and supports disaster risk reduction and sustainable land-use planning (UNDRR, 2017).

4.2.1 Resampling and Clipping

Spatial datasets collected from different sources often possess varying spatial resolutions and geographic extents. Therefore, all raster datasets were resampled to a common spatial resolution and projected into a unified coordinate reference system. Subsequently, the datasets were clipped using the boundary of the Lower Godavari Basin to ensure that all predictor variables represented identical spatial coverage. These operations reduced spatial inconsistencies and improved the compatibility of multiple geospatial datasets for further analysis (Burrough & McDonnell, 1998).

4.2.2 Normalization

The predictor variables used in flood modelling exhibit different units and numerical ranges. To eliminate scale differences among variables, feature normalization was applied prior to model training. The normalization process transformed each variable into a comparable range, thereby preventing variables with larger magnitudes from dominating the learning process. This preprocessing step enhances convergence speed, improves numerical stability, and increases the overall predictive performance of deep learning models (Goodfellow et al., 2016).

4.2.3 Rasterization

Several datasets, including river networks, road networks, administrative boundaries, and infrastructure layers, were originally available in vector format. These vector datasets were converted into raster grids with the same spatial resolution as the remaining predictor layers. Rasterization ensured that all datasets possessed a consistent grid structure suitable for convolution operations within the CNN architecture. Uniform raster layers also facilitated pixel-wise analysis and feature extraction during model development (Longley et al., 2015).

4.2.4 Data Cube Creation

Following preprocessing, all standardized raster layers were stacked to create a multi-dimensional data cube representing the environmental characteristics of each spatial location. Each grid cell contained information from multiple thematic layers, including topography, land use, vegetation, hydrological characteristics, and climatic variables. This integrated data cube served as the primary input to the CNN–LSTM model, enabling simultaneous learning of spatial and temporal relationships associated with flood occurrence. The multidimensional representation significantly enhances feature extraction and improves prediction accuracy compared with single-layer analyses (Zhu et al., 2017).

4.3 CNN–LSTM Model Development

The pre-processed multi-dimensional geospatial data cube served as the input to the hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model. The hybrid architecture combines the spatial feature extraction capability of CNN with the temporal sequence learning ability of LSTM, enabling simultaneous analysis of spatial heterogeneity and temporal variations associated with flood occurrence. By integrating these complementary deep learning techniques, the proposed model effectively captures complex nonlinear relationships among topographic, hydrological, climatic, and land use variables, thereby improving the accuracy of flood susceptibility and flood risk prediction (LeCun et al., 2015; Hochreiter & Schmidhuber, 1997).

4.3.1 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) was employed as the primary feature extraction component of the proposed framework. CNNs are highly effective in processing gridded spatial datasets because they automatically learn hierarchical representations without requiring manual feature engineering. In this study, the stacked raster layers representing elevation, slope, drainage density, land use/land cover, vegetation index, soil characteristics, and proximity to rivers were supplied as input to the convolutional layers.

The convolution operation applies multiple learnable filters across the input data to identify local spatial patterns associated with flood occurrence. These filters progressively extract low-level features such as edges and terrain variations, followed by higher-level representations describing drainage characteristics, floodplains, and landscape heterogeneity. Automatic feature extraction significantly improves the capability of deep learning models compared with conventional statistical and machine learning approaches (LeCun et al., 2015; Krizhevsky et al., 2012).

4.3.2 Feature Extraction and Pooling

Following each convolution operation, nonlinear activation functions were applied to enhance the model's ability to represent complex relationships among predictor variables. Pooling layers were subsequently incorporated to reduce the spatial dimensions of the extracted feature maps while preserving the most informative characteristics. This dimensionality reduction decreases computational complexity, minimizes redundant information, and improves the generalization capability of the model.

The resulting feature maps provide a compact yet informative representation of flood-related spatial characteristics, including terrain morphology, drainage configuration, vegetation distribution, and land cover variability. These optimized feature maps serve as the input for temporal sequence learning in the LSTM network (Goodfellow et al., 2016).

4.3.3 Long Short-Term Memory (LSTM)

The spatial feature maps extracted by the CNN were transferred to the Long Short-Term Memory (LSTM) network to model temporal dependencies within hydro-meteorological datasets. LSTM is a specialized recurrent neural network architecture capable of retaining long-term information through memory cells and gating mechanisms, making it particularly suitable for analysing sequential environmental data.

In this study, rainfall, river discharge, and other time-dependent hydrological variables were processed using the LSTM network. The forget, input, and output gates selectively retained relevant temporal information while discarding less significant observations. This mechanism enabled the model to capture seasonal rainfall patterns, delayed hydrological responses, and cumulative runoff effects that strongly influence flood generation (Hochreiter & Schmidhuber, 1997).

4.3.4 Hybrid CNN–LSTM Architecture

The hybrid CNN–LSTM architecture combines the strengths of both deep learning models to improve flood prediction performance. The CNN efficiently extracts spatial features from remotely sensed and GIS-derived raster datasets, whereas the LSTM captures temporal variations associated with rainfall intensity, river discharge, and hydrological responses. Integrating these complementary components enables the model to simultaneously analyse spatial and temporal flood drivers, resulting in more reliable flood susceptibility predictions than models relying solely on either spatial or temporal information.

The hybrid framework is particularly advantageous for flood risk assessment because flood occurrence depends on both static environmental characteristics, such as topography and land use, and dynamic climatic variables, including rainfall and river flow. Consequently, the proposed architecture provides a more comprehensive representation of flood processes.

4.3.5 Output Layer and Flood Probability Estimation

The final fully connected layer transforms the learned spatial and temporal features into flood occurrence probabilities using a sigmoid activation function. Each output value represents the probability of flooding for an individual spatial unit, ranging from 0 (no flood risk) to 1 (very high flood risk). These probability values were subsequently classified into five flood susceptibility categories: Very Low, Low, Moderate, High, and Very High. The classified susceptibility map was then integrated with socio-economic exposure layers to generate the final flood risk map of the Lower Godavari Basin.

4.4 CNN-LSTM Model Architecture

The proposed hybrid CNN–LSTM architecture combines spatial feature extraction with temporal sequence learning for flood susceptibility prediction (Fig. 2). The input consists of a multi-layer raster data cube (H × W × Bands) containing topographic, hydrological, land use, and climatic variables. The CNN component comprises two Conv2D layers with ReLU activation and Max Pooling operations to automatically extract hierarchical spatial features while reducing data dimensionality (LeCun et al., 2015).

The extracted feature maps are converted into a one-dimensional feature vector using a Flatten layer and subsequently processed by two LSTM layers with 128 and 64 memory units, respectively. A Dropout (0.3) layer is incorporated to minimize overfitting and improve model generalization. Finally, a Dense layer with a Sigmoid activation function generates flood probability values ranging from 0 to 1, which are subsequently classified into flood susceptibility classes (Hochreiter & Schmidhuber, 1997; Goodfellow et al., 2016).

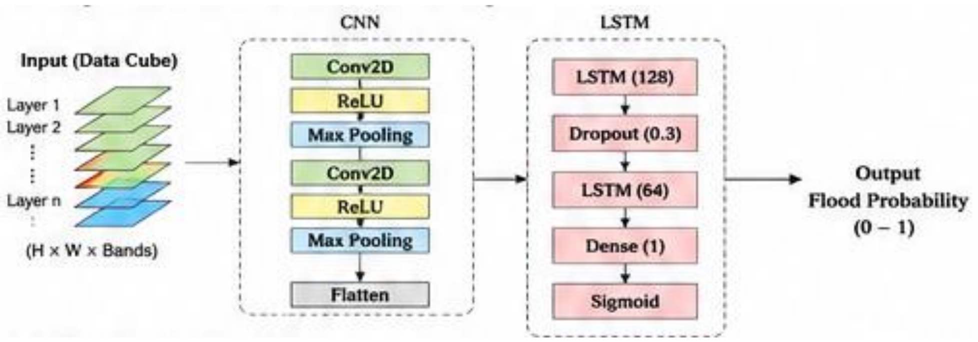


Figure 2 illustrates the complete CNN–LSTM architecture adopted for flood susceptibility modelling.

4.5 Model Training

The hybrid CNN–LSTM model was trained using the pre-processed geospatial data cube containing both spatial and temporal predictor variables. Prior to model training, all input datasets were normalized to eliminate differences in scale and to improve the convergence of the deep learning algorithm. The prepared dataset was subsequently partitioned into training, validation, and testing subsets to ensure unbiased model evaluation and to assess its predictive capability on unseen data (Goodfellow et al., 2016).

4.5.1 Data Splitting

The complete dataset was divided into three independent subsets for training, validation, and testing. The training dataset was used to optimize the network parameters, while the validation dataset was employed to monitor model convergence and prevent overfitting during the learning process. The testing dataset was reserved exclusively for evaluating the final predictive performance of the trained model. This strategy ensures that the developed model can generalize effectively to new flood scenarios (Bishop, 2006).

4.5.2 Model Optimization

The CNN–LSTM network was trained through iterative optimization using backpropagation to minimize the prediction error between observed and predicted flood classes. During each training iteration, the model weights were updated using a gradient-based optimization algorithm until convergence was achieved. The optimization process aimed to improve feature learning while reducing classification errors. To enhance the generalization capability of the model, regularization techniques such as dropout and early stopping may be employed to minimize overfitting (Goodfellow et al., 2016).

4.5.3 Hyperparameter Configuration

The predictive performance of deep learning models depends on several hyperparameters, including the number of convolutional filters, kernel size, batch size, learning rate, number of epochs, and the number of hidden units in the LSTM layer. These hyperparameters were selected through an iterative tuning process to achieve stable convergence and improved classification performance. Appropriate selection of hyperparameters contributes significantly to the robustness and efficiency of the CNN–LSTM architecture (LeCun et al., 2015).

4.5.4 Model Implementation

The proposed framework was implemented using a deep learning environment integrated with Geographic Information System (GIS) and remote sensing datasets. Spatial preprocessing and raster analysis were performed using GIS software, whereas model training, validation, and prediction were conducted using a suitable deep learning framework such as TensorFlow or Keras. After satisfactory convergence, the trained model was applied to estimate flood susceptibility probabilities for each grid cell within the study area.

4.6 Model Evaluation Metrics

The predictive performance of the developed CNN–LSTM model was evaluated using several widely adopted classification metrics. These performance indicators quantify different aspects of model accuracy and reliability and provide a comprehensive assessment of classification performance. The evaluation was based on the confusion matrix, which summarizes the numbers of correctly and incorrectly classified flood and non-flood observations.

4.6.1 Accuracy

Accuracy represents the proportion of correctly classified observations among the total number of samples and provides an overall measure of model performance.

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

where TP denotes True Positives, TN denotes True Negatives, FP denotes False Positives, and FN denotes False Negatives.

4.6.2 Precision

Precision measures the proportion of correctly predicted flood events among all observations classified as floods. A higher precision value indicates fewer false-positive predictions.

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

4.6.3 Recall (Sensitivity)

Recall, also known as sensitivity, measures the ability of the model to correctly identify actual flood occurrences. High recall indicates that the model successfully detects most flood-prone locations.

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

4.6.4 F1-Score

The F1-score represents the harmonic mean of precision and recall, providing a balanced evaluation when both false positives and false negatives are important.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.6.5 Area Under the Receiver Operating Characteristic Curve (AUC–ROC)

The Receiver Operating Characteristic (ROC) curve illustrates the trade-off between the True Positive Rate (Sensitivity) and the False Positive Rate across different classification thresholds. The Area Under the ROC Curve (AUC) quantifies the overall discriminative ability of the model. An AUC value approaching 1.0 indicates excellent classification performance, whereas a value of 0.5 represents random prediction (Fawcett, 2006).

4.6.6 Cohen's Kappa Coefficient

The Cohen's Kappa coefficient measures the level of agreement between observed and predicted classifications while accounting for agreement occurring by chance. Kappa values range from −1 to 1, where values greater than 0.80 generally indicate excellent agreement and high model reliability (Cohen, 1960; Landis & Koch, 1977).

Confusion Matrix Parameters

Where:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

5. Results

The performance of the proposed CNN–LSTM flood prediction model (Table. 1) was assessed using several standard classification metrics, namely Accuracy, Precision, Recall, F1-Score, AUC–ROC, and Kappa Coefficient. These metrics collectively evaluate the model's ability to correctly classify flood-prone and non-flood-prone areas while measuring its reliability and discriminative capability (Fawcett, 2006).

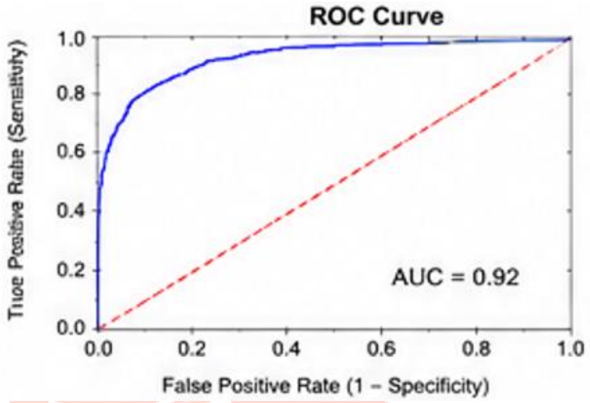
Table 2. Model performance

Metric	Value
Accuracy	0.89
Precision	0.88
Recall	0.86
F1-Score	0.87
AUC-ROC	0.92
Kappa Coefficient	0.84

The proposed model achieved an accuracy of 89%, indicating that the majority of flood and non-flood instances were correctly classified. The precision of 0.88 demonstrates that 88% of the locations predicted as flood-prone were actually affected by flooding, indicating a low false-positive rate. Similarly, the recall value of 0.86 suggests that the model successfully identified 86% of the actual flood-prone locations, reflecting good sensitivity. The F1-score of 0.87 represents a balanced trade-off between precision and recall, confirming that the model performs consistently across both positive predictions and actual flood occurrences. Furthermore, the Kappa coefficient of 0.84 indicates excellent agreement between the predicted and observed classifications beyond chance, demonstrating the robustness and reliability of the model (Cohen, 1960; Landis & Koch, 1977).

5.1 ROC Curve Interpretation

The Receiver Operating Characteristic (ROC) curve (Figure X) illustrates the classification performance of the CNN–LSTM model by plotting the True Positive Rate (Sensitivity) against the False Positive Rate (1 – Specificity) across different classification thresholds. The diagonal dashed red line represents the performance of a random classifier, whereas the blue ROC curve lying well above the diagonal indicates that the proposed model possesses strong discriminative ability.



The Area Under the ROC Curve (AUC) is 0.92, which indicates excellent classification performance. An AUC value greater than 0.90 is generally considered outstanding, implying that the model has a 92% probability of correctly distinguishing flood-prone locations from non-flood-prone locations. The ROC curve demonstrates that the model maintains a high true positive rate while minimizing false positives, making it suitable for flood susceptibility and flood risk mapping applications. The high AUC value further confirms the effectiveness of integrating spatial feature extraction using CNN with temporal sequence learning using LSTM, resulting in improved predictive accuracy and generalization capability (Fawcett, 2006; Bradley, 1997).

Overall, the evaluation metrics and ROC analysis indicate that the proposed CNN–LSTM model provides reliable and accurate flood prediction performance, making it an effective tool for flood susceptibility assessment, disaster risk reduction, and decision support in flood management.

5.2 Flood Risk Assessment

Figure 3 illustrates the Flood Risk Map of the Lower Godavari Basin, generated using the proposed hybrid CNN–LSTM model by integrating flood susceptibility with exposure-related datasets. The map classifies the study area into six categories: Very Low, Low, Moderate, High, Very High, and Water. These classes represent the spatial variation in flood risk based on topographic, hydrological, climatic, and socio-economic factors, providing an effective tool for flood hazard assessment and disaster management (IPCC, 2022; UNDRR, 2017).

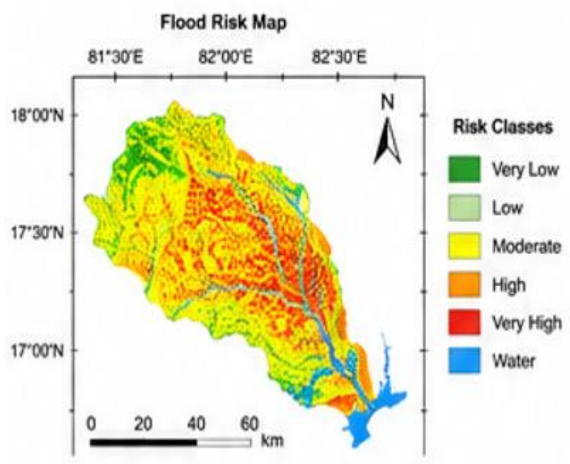


Fig. 3. Flood risk map of the Lower Godavari basin

The Very High Risk zones (shown in red) are predominantly concentrated along the main Godavari River channel and its major tributaries, particularly in the central and south-eastern portions of the basin. These areas are characterized by low elevation, gentle slopes, high drainage density, and proximity to river channels, making them highly susceptible to frequent inundation during heavy rainfall and peak discharge events (Tehrany et al., 2015). Additionally, dense settlements and agricultural activities located within these floodplains increase the overall flood risk due to greater exposure of population and infrastructure (UNDRR, 2017).

The High Risk regions (orange) are distributed adjacent to the river network and extend into surrounding floodplain areas. These locations experience periodic flooding during monsoon seasons because of overbank flow, poor natural drainage, and water accumulation in low-lying terrain. Although the flooding frequency is lower than in the very high-risk zones, these areas remain vulnerable to significant economic losses and infrastructure damage (IPCC, 2022).

The Moderate Risk class (yellow) occupies a substantial portion of the basin and represents transitional areas where terrain elevation gradually increases and drainage conditions improve. Flooding in these regions generally occurs during extreme rainfall events or prolonged river discharge, resulting in moderate hazard levels (Kundzewicz et al., 2014).

The Low (light green) and Very Low Risk (dark green) zones are mainly located in the upland and peripheral regions of the basin. These areas typically possess higher elevations, steeper slopes, better drainage conditions, and lower surface water accumulation, reducing the likelihood of flood occurrence. Consequently, these regions are comparatively safer for human settlements and infrastructure development (Tarboton, 1997; Moore et al., 1991).

The Water class (blue) represents permanent water bodies, including the Godavari River, reservoirs, lakes, and associated channels. These features play a significant role in controlling flood dynamics by influencing river discharge, flow routing, and floodplain inundation patterns.

Overall, the spatial distribution of flood risk demonstrates that the central floodplain and downstream reaches of the Lower Godavari Basin exhibit the highest flood vulnerability, whereas the elevated western and north-western regions remain comparatively less susceptible. The generated flood risk map provides valuable information for land-use planning, urban development, flood mitigation, emergency response planning, and climate change adaptation strategies. Such spatially explicit risk assessments enable decision-makers to prioritize flood protection measures and allocate resources effectively in vulnerable areas (IPCC, 2022; UNDRR, 2017).

6. Conclusion

This study developed a hybrid CNN–LSTM model integrated with Remote Sensing and GIS for flood risk assessment in the Lower Godavari Basin, India. Multi-source datasets, including DEM, land use/land cover, slope, drainage density, distance to river, soil, NDVI, rainfall, and river discharge, were pre-processed using GIS techniques and incorporated into a deep learning framework. The CNN extracted spatial features from the geospatial data, while the LSTM captured temporal variations in hydro-meteorological variables to improve flood susceptibility prediction.

The proposed model demonstrated strong predictive performance, achieving an accuracy of 89%, precision of 88%, recall of 86%, F1-score of 0.87, AUC–ROC of 0.92, and a Kappa coefficient of 0.84. The generated flood risk map effectively identified high and very high flood-prone zones, particularly along the main Godavari River and its floodplains. Overall, the integration of deep learning with remote sensing and GIS provides an effective and reliable approach for flood susceptibility mapping and supports flood risk assessment and disaster management.

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