

Explainable Machine Learning-Based Flood Susceptibility Mapping and Early Warning Using Multi-Source Geospatial Data

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Abstract Modern law enforcement agencies face the dual challenge of managing complex public safety threats while maintaining strict institutional accountability. This paper explores the integration of artificial intelligence (AI), automation, and advanced digital tools within modern policing frameworks. By analyzing current implementations—including predictive policing algorithms, automated facial recognition, automated license plate readers (ALPRs), and AI-driven evidence management systems—this study assesses how these technologies enhance operational efficiency, accelerate response times, and optimize resource allocation. Furthermore, the paper addresses critical systemic challenges, specifically targeting algorithmic bias, citizen privacy concerns, data security vulnerabilities, and the regulatory frameworks required to govern automated decision-making. Ultimately, this research provides a balanced framework for law enforcement executives and policymakers, demonstrating how agencies can leverage cutting-edge technical innovation while upholding the core principles of ethical, transparent, and community-oriented justice.

Keywords—Artificial Intelligence (AI), Automated Policing, Law Enforcement Technology, Public Safety, Predictive Policing, Ethical Automation.

I. INTRODUCTION

Flooding is a recurrent hydro-meteorological hazard that affects settlements, agriculture, transportation infrastructure, and economic activities. Increasing urbanization, changes in land cover, modification of drainage networks, and extreme precipitation can increase flood exposure and vulnerability. Consequently, spatial identification of areas that are more susceptible to flooding is an important component of disaster-risk reduction.

Flood susceptibility mapping attempts to estimate the spatial likelihood of flooding using historical flood observations and environmental conditioning variables. Traditional approaches include frequency ratio, analytical hierarchy process, logistic regression, and weighted overlay methods. However, these approaches can have difficulty representing nonlinear interactions among multiple environmental variables.

Machine-learning methods provide an alternative because they can learn complex relationships between historical flood occurrence and geospatial predictors. Recent studies have demonstrated the usefulness of Random Forest, gradient boosting, XGBoost, deep learning, and ensemble approaches for flood susceptibility assessment. For example, an explainable CNN-based study reported an AUROC of 88.4% and demonstrated the usefulness of SHAP for interpreting the contribution of land-use and soil variables. ([ScienceDirect](#))

Recent research has increasingly emphasized **multi-source geospatial data and explainability**. Studies have integrated Sentinel-1-derived flood inventories with topographic, rainfall, hydrological, spectral, and built-environment variables. ([Journals of Universitas Negeri Semarang](#)) Other recent work has demonstrated that XGBoost-SHAP can reveal nonlinear relationships between flood susceptibility and variables such as elevation, slope, NDVI, and stream-power-related characteristics. ([IDEAS/RePEc](#))

However, three important challenges remain:

1. **Multi-source data heterogeneity:** datasets have different spatial resolutions, temporal frequencies, projections, and uncertainty characteristics.
2. **Black-box prediction:** high-performing ML models do not automatically explain why a particular location is classified as high susceptibility.
3. **Disconnection between susceptibility mapping and early warning:** static susceptibility maps do not directly indicate when a flood event is becoming imminent.

Therefore, this research proposes an integrated framework that combines:

- multi-source geospatial data,
- flood-inventory generation,
- machine-learning-based susceptibility prediction,
- spatially aware validation,

- SHAP-based interpretation, and
- rainfall-triggered early-warning generation.

A. Research Objectives

The objectives are:

- To develop a multi-source geospatial database for flood susceptibility assessment.
- To compare RF, SVM, and XGBoost models.
- To generate a continuous flood-susceptibility probability map.
- To classify the study region into susceptibility categories.
- To explain model predictions using SHAP.
- To integrate susceptibility with rainfall indicators for early warning.
- To provide a reproducible GIS-ML framework for disaster management.

B. Research Contributions

The principal contributions are:

1. A unified GIS–remote sensing–ML architecture for flood susceptibility mapping.
2. Integration of static conditioning factors with dynamic rainfall information.
3. Spatially aware ML validation to reduce overly optimistic random-split performance.
4. Global and local SHAP explanations.
5. A susceptibility-to-warning conversion mechanism.
6. An interpretable decision-support framework suitable for emergency planning.

II. RELATED WORK

Flood susceptibility mapping has evolved from knowledge-driven GIS techniques toward data-driven machine-learning and explainable artificial intelligence (XAI) approaches. Conventional methods such as frequency ratio, weighted overlay, Analytical Hierarchy Process (AHP), and statistical models are relatively easy to implement, but their performance can depend on expert-defined weights and assumptions about the relationships between conditioning factors. A systematic review of AHP-based urban flood studies reported that elevation, slope, rainfall, and land-use/land-cover are among the most frequently used conditioning variables, while expert judgment remains an important source of weighting decisions [1]. ([ScienceDirect](#))

Machine-learning methods have subsequently been adopted to capture nonlinear relationships between flood occurrence and environmental variables. Nachappa *et al.* investigated machine-learning, multi-criteria decision analysis, and ensemble approaches for flood susceptibility mapping and demonstrated the potential of data-driven models for improving susceptibility assessment [2]. ([ScienceDirect](#)) More recently, a GIS-based

comparative study evaluated Logistic Regression, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor, AdaBoost, and Extreme Gradient Boosting (XGBoost). The study reported strong performance from XGBoost and RF and highlighted the importance of distance from streams, hydrologic soil characteristics, rainfall, elevation, and impervious surfaces [3]. ([ScienceDirect](#))

Remote sensing has significantly improved the availability of flood-inventory data. Synthetic Aperture Radar (SAR), particularly Sentinel-1, is valuable because flood extent can be detected even under cloudy conditions. Recent research has combined Sentinel-1-derived flood inventories with topographic, hydrological, meteorological, spectral, land-cover, and built-environment variables for machine-learning-based susceptibility mapping [4]. ([MDPI](#)) Such multi-source integration is important because flood occurrence is controlled by the interaction of several factors rather than by a single environmental variable.

Random Forest has been widely used because it can model nonlinear relationships, accommodate mixed predictor variables, and provide estimates of variable importance. XGBoost has also gained considerable attention because its gradient-boosting structure can model complex interactions between terrain, rainfall, hydrological, and land-cover variables. Recent research using multi-source geospatial data has reported strong predictive performance from XGBoost, RF, and other ensemble algorithms [5]. ([PubMed Central \(PMC\)](#)) Despite their predictive capability, many machine-learning models have traditionally been regarded as black-box systems. Explainable Artificial Intelligence (XAI) provides mechanisms for interpreting these models and identifying the contribution of individual predictors. Kim *et al.* applied SHapley Additive exPlanations (SHAP) to a convolutional neural network for flood susceptibility mapping and reported an AUROC of 88.4%. Their analysis demonstrated that land-use and soil-related variables substantially influenced the model predictions [6]. ([ScienceDirect](#))

More recent studies have directly integrated XGBoost and SHAP for interpretable flood susceptibility mapping. Rezvani *et al.* developed an XGBoost-SHAP framework using Sentinel-1-derived flood extent and multiple conditioning factors. Their analysis reported an AUC of 0.89 and identified slope, altitude, and NDVI as important predictors, while SHAP dependence analysis revealed nonlinear relationships between environmental variables and predicted flood susceptibility [7]. ([IDEAS/RePEc](#)) Similarly, a 2025 study applying XAI to flood susceptibility in northwest Iran found that XGBoost achieved an AUC of 0.89 and identified distance to streams, TWI,

elevation, precipitation, and slope as important predictors [8]. (ScienceDirect)

The application of XAI has also been extended to urban flood environments. Recent research using XGBoost and SHAP found TWI, elevation, impervious surface ratio, distance to rivers, river-network density, and flow accumulation among important predictors, while demonstrating spatial heterogeneity in the contribution of conditioning factors [9]. (Nature) This indicates that global feature importance alone may not adequately describe local flood-generating mechanisms, making local SHAP explanations particularly relevant for decision-support systems.

Recent research has further moved toward integrating susceptibility mapping with early-warning applications. A Sentinel-1 and machine-learning framework evaluated RF, XGBoost, and CNN models and combined susceptibility maps with high-risk locations monitored through flood-warning sensors [4]. (MDPI) Other recent work has developed ensemble ML frameworks using geospatial conditioning factors and SHAP, demonstrating the feasibility of combining predictive mapping and interpretable decision support for flood management [10]. (ScienceDirect)

However, important methodological limitations remain. A recent systematic review of 200 flood-susceptibility studies identified concerns related to spatially naive validation, uncertainty quantification, probabilistic calibration, and limited integration of future climate information [11]. (Frontiers) These findings indicate that high AUC values alone do not guarantee reliable geographic generalization. Spatially separated validation, independent flood-event validation, uncertainty analysis, and interpretable predictions are therefore important for developing operational flood-susceptibility systems.

Research Gap

Based on the reviewed literature, the following gaps are identified:

1. **Limited integration of heterogeneous data:** Many studies use a restricted set of conditioning variables rather than jointly integrating DEM, SAR, rainfall, hydrology, soil, vegetation, and land-cover information.
2. **Insufficient explainability:** Conventional ML-based susceptibility maps generally provide predictions without adequately explaining individual spatial predictions.
3. **Weak linkage between susceptibility and early warning:** Static susceptibility maps identify spatially susceptible areas but do not necessarily incorporate dynamic rainfall conditions.

4. **Validation limitations:** Random sampling can produce spatially optimistic performance estimates when neighboring observations occur in both training and testing datasets [11]. (Frontiers)
5. **Limited local interpretation:** Global feature importance does not necessarily explain why a specific location is classified as high susceptibility.
6. **Uncertainty representation:** Many studies report deterministic susceptibility classes without explicitly quantifying prediction uncertainty [11]. (Frontiers)

Therefore, this study proposes an integrated **Explainable Machine Learning-Based Flood Susceptibility Mapping and Early Warning (XAI-FSM-EW)** framework that combines multi-source geospatial data, spatially validated machine learning, SHAP-based global and local interpretation, and rainfall-driven early-warning generation.

III. STUDY FRAMEWORK AND DATA SOURCES

The proposed study integrates multi-source geospatial, remote-sensing, hydrological, meteorological, and ancillary datasets to develop an explainable machine-learning framework for flood susceptibility mapping and early warning.

Fig. 1. Overall framework of the study

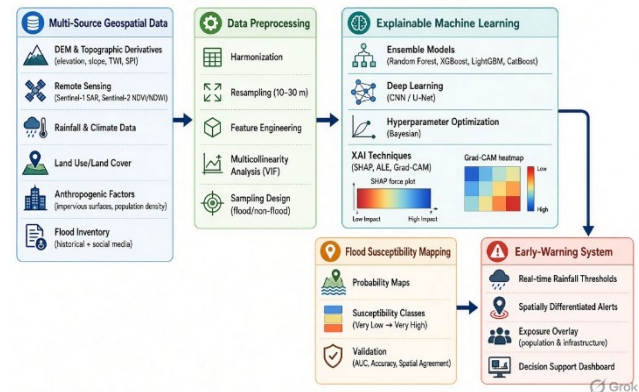


Fig-1 Study Framework

A. Multi-Source Geospatial Data

The study uses heterogeneous datasets because flood occurrence is controlled by interactions among terrain, rainfall, surface characteristics, hydrological connectivity, soil properties, and land use. The primary datasets include a Digital Elevation Model (DEM), Sentinel-1 SAR imagery, Sentinel-2 optical imagery, rainfall observations, hydrological information, soil data, and ancillary infrastructure data.

Table I. Data Sources and Their Characteristics

Data Type	Source / Sensor	Spatial Res	Temporal	Key Variables	Purpose
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		Resolution	Resolution		
Digital Elevation Model	SRTM	30 m	Static	Elevation, slope, aspect, curvature	Terrain analysis
Optical imagery	Sentinel-2	10 m	~5 days	NDVI, LULC	Land-cover characterization
SAR imagery	Sentinel-1	10 m	6–12 days	Backscatter, water extent	Flood inventory
Rainfall	GPM/TMM	~0.1°	Daily/sub-daily	Rainfall, antecedent rainfall	Hydro-meteorological forcing
Hydrological data	River/drainage network	Variable	Static	Distance to river, drainage density, flow accumulation	Hydrological analysis
Soil data	HWSD/SoilGrids	~250 m–1 km	Static	Soil type, texture, infiltration	Runoff/infiltration analysis
Ancillary data	OSM/National GIS	Variable	Static	Roads, buildings,	Exposure/co

				boundaries	context analysis
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B. Data Preprocessing

Because the datasets originate from different sensors and sources, preprocessing is performed before model development. The processing includes coordinate-system harmonization, spatial resampling, geometric and radiometric correction where required, cloud/noise removal, missing-value treatment, and normalization.

Terrain variables are derived from the DEM. Hydrological variables such as flow accumulation, drainage density, distance to rivers, and Topographic Wetness Index (TWI) are subsequently generated using GIS-based spatial analysis.

For optical imagery, vegetation and built-up indices are calculated. NDVI is expressed as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Similarly, SAR imagery is processed to identify inundated areas and construct the historical flood inventory.

C. Feature-Stack Preparation

After preprocessing, all conditioning factors are converted to a common spatial grid. Each pixel therefore contains a feature vector:

$$X_i = [E_i, S_i, A_i, T, W, I_i, D, T, R_i, D, D_i, R_i, AR_i, NDVI_i, LULC_i, Soil_i, \dots]$$

where X_i represents the feature vector for pixel i .

The corresponding target variable is:

$$Y_i = \begin{cases} 1, & \text{Flooded} \\ 0, & \text{Non-flooded} \end{cases}$$

Flood and non-flood samples are spatially stratified to reduce sampling bias. The resulting dataset is divided into training, validation, and independent testing subsets. Spatially separated validation is preferred over purely random splitting to reduce the influence of spatial autocorrelation.

D. Explainable Machine-Learning Stage

The prepared dataset is supplied to multiple machine-learning models, including Random Forest (RF), Support Vector Machine (SVM), and XGBoost. Their performance is evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and spatial validation.

The best-performing model produces a continuous flood probability:

$$P_f = P(Y = 1 | X)$$

This probability is transformed into a flood susceptibility surface.

SHAP is subsequently applied to the selected model to determine:

- global feature importance,
- positive and negative feature contributions,
- nonlinear feature relationships, and
- pixel-level/local explanations.

E. Flood Susceptibility Mapping

The predicted probability is classified into five susceptibility categories:

Probability	Susceptibility
0.00–0.20	Very Low
0.20–0.40	Low
0.40–0.60	Moderate
0.60–0.80	High
0.80–1.00	Very High

The resulting raster constitutes the **Flood Susceptibility Map (FSM)**.

F. Dynamic Early-Warning Component

The static susceptibility map is combined with dynamic rainfall observations to distinguish long-term spatial susceptibility from short-term flood threat. Current rainfall, 24-hour accumulated rainfall, antecedent rainfall, and rainfall intensity can be incorporated into the warning model.

A generalized warning index can be represented as:

$$EWI_t = f(P_f, R_{24}, A, R_k R_{max})$$

where P_f is flood susceptibility probability and the rainfall variables represent current and antecedent hydro-meteorological conditions.

The resulting warning level can be communicated through a GIS dashboard, web interface, SMS, or other authorized emergency communication systems.

IV. PROPOSED XAI-FSM-EW FRAMEWORK

The proposed **Explainable Artificial Intelligence-based Flood Susceptibility Mapping and Early Warning (XAI-FSM-EW)** framework integrates multi-source geospatial data, machine learning, explainable AI, and real-time warning generation into a unified pipeline. The framework is designed to identify flood-prone locations, explain the factors contributing to susceptibility, and generate an early warning when environmental conditions indicate an elevated flood risk.

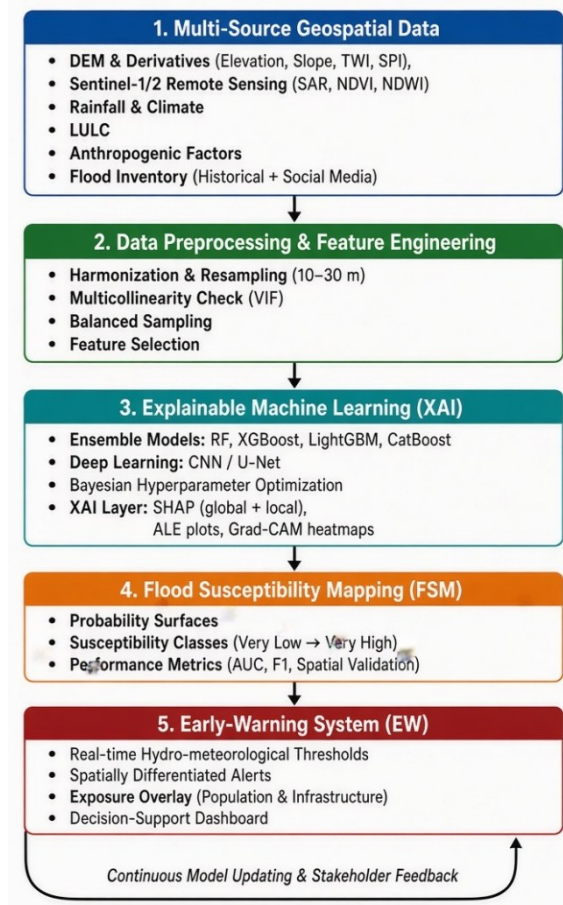


Fig. 2 The diagram illustrates the proposed XAI-FSM-EW Framework, consisting of five stages: multi-source geospatial data, data preprocessing & feature engineering, explainable machine learning (XAI), flood susceptibility mapping (FSM), and early-warning system (EW), with continuous model updating and stakeholder feedback.

Flood susceptibility depends on several interacting environmental and anthropogenic factors. Therefore, the proposed framework uses heterogeneous spatial and temporal datasets, including:

- Digital Elevation Model (DEM)
- rainfall and precipitation
- slope and aspect
- drainage density
- distance from rivers and streams
- land-use/land-cover (LULC)
- soil characteristics
- Normalized Difference Vegetation Index (NDVI)

- surface-water information
- urban/built-up density
- historical flood occurrences

Each dataset is transformed into a common coordinate system and spatial resolution before model development.

B. Data Preprocessing and Feature Engineering

The acquired datasets may have different spatial resolutions, coordinate systems, missing values, and measurement scales. The preprocessing stage performs **geometric correction, resampling, missing-value treatment, normalization, and spatial alignment**.

For each spatial unit i , the feature vector is represented as

$$X_i = [R_i, E_i, S_i, D_i, DR_i, L_i, SO_i, NDVI_i, U_i \dots]$$

where R represents rainfall, E elevation, S slope, D drainage density, DR distance from river, L LULC, SO soil characteristics, $NDVI$ vegetation condition, and U urbanization-related features.

Historical flood locations are used to construct the target variable:

$$y_i = \begin{cases} 1, & \text{flood occurrence} \\ 0, & \text{non-flood occurrence} \end{cases}$$

This produces the final dataset for supervised learning.

C. Flood Susceptibility Modeling

The processed features are supplied to machine-learning classifiers to estimate the probability of flooding. A suitable ensemble model such as **Random Forest (RF), XGBoost, LightGBM, or CatBoost** can be employed because flood susceptibility generally involves nonlinear relationships among topographic, hydrological, climatic, and land-use variables.

For a spatial location i , the model estimates

$$P_i = P(Y_i = 1 | X_i)$$

where P_i denotes the predicted flood probability.

The continuous probability is converted into susceptibility classes:

Flood Probability	Susceptibility Class
0.00 – 0.20	Very Low
0.20 – 0.40	Low
0.40 – 0.60	Moderate
0.60 – 0.80	High
0.80 – 1.00	Very High

The resulting spatial probability surface forms the **Flood Susceptibility Map (FSM)**.

D. Explainable AI Module

A major contribution of the proposed framework is the integration of XAI with susceptibility prediction. Instead of providing only a flood-risk probability, the framework identifies **why a location receives a particular prediction**.

SHAP (SHapley Additive exPlanations) is used to calculate both global and local feature contributions. The prediction can be expressed as

$$f(X) = \phi_0 + \sum_{j=1}^m \phi_j$$

where ϕ_0 is the base prediction and ϕ_j represents the contribution of feature j .

Two levels of explanations are generated:

1. **Global explanation:** identifies the most influential factors across the complete study area.
2. **Local explanation:** explains the factors responsible for the predicted susceptibility at an individual location.

For example, a location may receive a high flood probability because of **high rainfall, low elevation, high drainage density, short distance from a river, and extensive built-up land**. Such explanations improve the interpretability of the generated FSM.

E. Real-Time Early-Warning Module

The susceptibility map represents relatively stable spatial risk, whereas early warning requires consideration of **current or forecast environmental conditions**. Therefore, the proposed framework combines the susceptibility probability with dynamic observations such as rainfall intensity, accumulated rainfall, river level, soil moisture, and weather forecasts.

A warning score can be formulated as

$$W_t = \alpha P_{FSM} + \beta R_t + \gamma H_t + \delta S_t$$

where:

- P_{FSM} = static flood susceptibility probability,
- R_t = current/forecast rainfall indicator,
- H_t = hydrological indicator such as river level,
- S_t = soil-moisture or surface-condition indicator,
- $\alpha, \beta, \gamma, \delta$ = weighting coefficients.

The resulting warning score is mapped to operational warning levels.

Warning Score	Warning Level	Suggested Interpretation
0.00–0.25	Normal	No immediate warning
0.25–0.50	Watch	Conditions should be monitored
0.50–0.75	Alert	Increased flood risk
0.75–1.00	Warning	Potential severe flood conditions

The thresholds should be calibrated using historical flood events and validation data rather than assumed universally.

F. Integrated XAI-FSM-EW Decision Layer

The final decision layer combines **spatial susceptibility, dynamic environmental conditions, and model**

explanations. When the predicted risk exceeds the calibrated warning threshold, the system generates an alert containing:

- affected geographic location,
- estimated flood-risk level,
- current environmental indicators,
- major contributing factors,
- confidence/probability information, and
- recommended monitoring or response p

Thus, the framework produces not only “where flooding may occur”, but also “why the area is vulnerable” and “when environmental conditions warrant an early warning.”

G. Overall Processing Sequence

The complete framework can be summarized as:

Multi-Source Data → Preprocessing → Feature Engineering
→ ML Model → Flood Susceptibility Map

↓

XAI/SHAP → Feature-Level Explanation

Dynamic Weather/Hydrological Data

→ Early-Warning Engine → Risk Level

→ Alert

V. DATA PREPROCESSING AND FEATURE ENGINEERING

The quality of flood susceptibility prediction depends strongly on the consistency and relevance of the input geospatial variables. In the proposed **XAI-FSM-EW** framework, multi-source environmental, climatic, hydrological, and land-surface datasets are converted into a common spatial dataset before machine-learning model training. The preprocessing stage ensures spatial compatibility, removes data inconsistencies, and transforms raw variables into meaningful predictors.

A. Data Integration and Spatial Alignment

The collected datasets generally differ in coordinate reference system (CRS), spatial resolution, extent, and data format. Therefore, all raster and vector datasets are transformed into a common CRS and clipped to the study-area boundary.

Each raster layer is resampled to a common spatial resolution:

$$X'_j = \mathcal{R}(X_j, r)$$

where X_j is the original feature layer, $\mathcal{R}$ is the resampling operation, r is the selected spatial resolution, and X'_j is the standardized layer.

The standardized layers are subsequently stacked to create a spatial feature matrix.

B. Missing-Value and Noise Treatment

Missing observations may occur because of cloud cover, sensor limitations, incomplete rainfall records, or inconsistencies between datasets. Missing numerical values are treated using appropriate statistical or spatial interpolation techniques.

Extreme values are examined using the interquartile range (IQR):

$$IQR = Q_3 - Q_1$$

Values outside

$$[Q_1, -1.5IQR \quad Q_3 + 1.5IQR]$$

are investigated as potential outliers. Genuine extreme rainfall or flood-related observations are retained rather than automatically removed, since such extremes may contain important information for flood prediction.

C. Feature Standardization

Because the input variables have different units and ranges, numerical features are normalized before model development where required. Min-max normalization is expressed as

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

which transforms a feature into the interval $[0, 1]$.

Tree-based models such as RF and XGBoost are relatively insensitive to feature scaling; nevertheless, standardized datasets provide consistency when comparing multiple machine-learning algorithms.

D. Flood Conditioning Factors

The proposed framework considers conditioning factors representing topographic, hydrological, climatic, vegetation, soil, and anthropogenic characteristics.

Category	Feature	Relevance to Flood Susceptibility
Topography	Elevation	Low-lying areas may accumulate water
Topography	Slope	Influences runoff velocity and infiltration
Hydrology	Drainage density	Indicates concentration of surface runoff
Hydrology	Distance from river	Represents proximity to potential overflow
Climate	Rainfall	Major trigger of flooding
Land surface	LULC	Controls infiltration and surface runoff
Soil	Soil type/properties	Influences infiltration capacity
Vegetation	NDVI	Represents vegetation and surface cover
Urbanization	Built-up density	Increases impervious surface and runoff
Historical	Flood occurrence	Provides supervised-learning target information

E. Feature Engineering

Feature engineering is performed to improve the representation of flood-generating processes. In addition to directly derived variables, several secondary variables are calculated from the available geospatial datasets.

From the DEM, **elevation, slope, aspect, curvature, flow direction, flow accumulation, and drainage density** can be derived. Distance-to-river and distance-to-drainage features are calculated using spatial proximity analysis.

Rainfall can be represented using multiple temporal indicators:

$$R_t = \{R_{1d}, R_{3d}, R_{7d}, R_{30d}\}$$

where R_{1d} , R_{3d} , R_{7d} , and R_{30d} represent accumulated rainfall over 1, 3, 7, and 30 days, respectively. These features help distinguish short-duration intense rainfall from prolonged wet conditions.

A rainfall anomaly can additionally be calculated as

$$A_R = \frac{R_t - \mu_R}{\sigma_R}$$

where μ_R and σ_R represent the historical mean and standard deviation of rainfall for the corresponding period.

F. Feature Selection

Highly redundant variables can increase model complexity and may make interpretation more difficult. Therefore, feature selection is performed using a combination of **correlation analysis, multicollinearity assessment, model-based importance, and domain relevance**.

Pearson correlation between two numerical variables is calculated as

$$\rho_{xy} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Highly correlated predictors are examined for redundancy. Variance Inflation Factor (VIF) can also be used:

$$VIF_j = \frac{1}{1 - R_j^2}$$

where R_j^2 is obtained by regressing feature j against the remaining predictors.

Features that are redundant, unreliable, or unavailable consistently across the study area are removed before final model training.

G. Encoding of Categorical Variables

Categorical variables such as **LULC class and soil type** are converted into numerical representations using one-hot encoding or another appropriate encoding strategy. For a categorical variable with K classes:

$$C \rightarrow [c_1, c_2, \dots, c_K]$$

where each c_k represents the membership of a sample in a particular category.

H. Construction of the Final Feature Matrix

After preprocessing and feature engineering, the data are organized into a feature matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}$$

where n represents the number of spatial samples and m represents the number of selected predictors.

The corresponding target vector is

$$Y = [y_1, y_2, \dots, y_n]^T,$$

where $y_i = 1$ denotes a flood-affected sample and $y_i = 0$ denotes a non-flood sample.

I. Training, Validation, and Testing Dataset

To prevent information leakage, the dataset is divided into **training, validation, and testing subsets before model fitting**. A representative split can be 70% training, 15% validation, and 15% testing, although the final proportions should be selected according to dataset size.

Where spatial samples are highly clustered, random splitting may produce overly optimistic performance. Therefore, **spatially separated validation or spatial cross-validation** is preferable for assessing the generalization of flood susceptibility models.

J. Preprocessing Pipeline

The complete preprocessing sequence is:

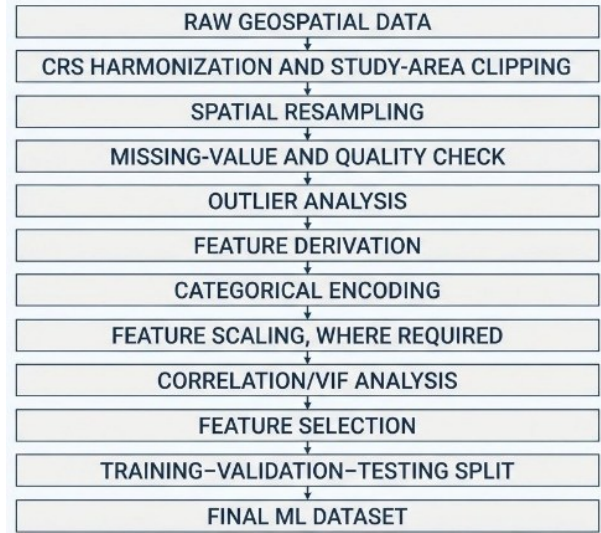


Fig. 3. Data preprocessing and feature engineering pipeline for the proposed XAI-FSM-EW framework.

Table II. Final Feature Representation

Feature Group	Representative Variables	Data Type
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Topographic	Elevation, slope, curvature	Continuous
Hydrological	Drainage density, flow accumulation, river distance	Continuous
Meteorological	1-day, 3-day, 7-day rainfall, rainfall anomaly	Continuous
Land Surface	LULC, NDVI, built-up density	Mixed
Soil	Soil type, infiltration-related properties	Mixed
Historical	Flood occurrence	Binary target

The resulting feature matrix provides the standardized input for the **flood susceptibility prediction model** described in the next section. Importantly, the same preprocessing transformations and selected feature definitions must be applied to historical and real-time data to ensure consistency between **FSM generation and early-warning prediction**.

VI. FLOOD INVENTORY GENERATION

A reliable flood inventory is required to train and validate the proposed **XAI-FSM-EW** model. It represents the spatial distribution of historical flooded and non-flooded locations within the study area.

A. Flood Data Collection

Historical flood information is collected from **satellite imagery, government flood records, disaster reports, and verified observations**. Satellite-based inundation maps, particularly from SAR data, are useful for identifying flooded areas under cloudy conditions.

B. Flood and Non-Flood Samples

The identified inundated areas are converted into flood samples, while areas confirmed as non-inundated are selected as non-flood samples. Each sample is assigned a binary label:

$$Y_i = \begin{cases} 1, & \text{Flood} \\ 0, & \text{Non-Flood} \end{cases}$$

The corresponding values of rainfall, elevation, slope, drainage density, river distance, LULC, soil, and other conditioning factors are extracted for each sample.

C. Inventory Quality Control

Duplicate and ambiguous samples are removed, and the spatial distribution of flood and non-flood samples is checked. Class imbalance is addressed using stratified sampling or class-weighting techniques where necessary.

To minimize data leakage caused by neighboring spatial samples, **spatially separated training and testing samples** are preferred.

Table III. Flood Inventory Structure

Component	Description
Flood samples	Historical inundated locations
Non-flood samples	Confirmed non-inundated locations
Target	Flood = 1, Non-flood = 0
Predictors	Rainfall, elevation, slope, drainage, LULC, soil, etc.
Quality control	Duplicate and ambiguous sample removal
Validation	Spatially separated sampling

The final inventory is represented as

$$D = \{(X_i, Y_i)\}_{i=1}^N$$

where X_i denotes the geospatial feature vector and Y_i denotes the flood label. The resulting dataset is used in the next stage for **machine-learning-based flood susceptibility modeling**.

Fig. 4. Flood inventory generation and spatial sample preparation workflow.

VII. MACHINE LEARNING FRAMEWORK

Three machine-learning models are employed in the proposed **XAI-FSM-EW** framework: **Random Forest (RF)**, **Support Vector Machine (SVM)**, and **XGBoost**. These models provide complementary approaches for learning the nonlinear relationship between flood-conditioning factors and flood occurrence.

A. Random Forest

Random Forest is an ensemble learning algorithm that combines multiple decision trees. For an input feature vector X , the final prediction is obtained by aggregating the predictions of all trees:

$$\hat{Y}(X) = \text{mode}\{T_1(X), T_2(X) \dots T_B(X)\}$$

where T_b represents the b -th decision tree and B is the number of trees.

RF is suitable for flood susceptibility analysis because it can model nonlinear relationships and interactions among environmental variables while reducing overfitting through ensemble learning.

B. Support Vector Machine

Support Vector Machine identifies an optimal decision boundary between flood and non-flood samples. For nonlinear flood relationships, the **Radial Basis Function (RBF)** kernel is used:

$$K(X_i, X_j) = \exp(-\gamma \|X_i - X_j\|^2)$$

where γ controls the influence of individual training samples.

The SVM parameters C and γ are optimized using the validation dataset.

C. XGBoost

XGBoost constructs an ensemble of sequential decision trees, where each new tree improves the prediction of the existing model. The boosted prediction is:

$$\hat{Y}_i = \sum_{k=1}^K f_k(X_i), f_k \in \mathcal{F}$$

where K is the number of boosting iterations and f_k represents the k -th regression tree.

The objective function is:

$$\mathcal{L} = \sum_{i=1}^N l(y_i, \hat{Y}_i) + \sum_{k=1}^K \Omega(f_k)$$

where $l(y_i, \hat{Y}_i)$ is the prediction loss and $\Omega(f_k)$ controls model complexity to reduce overfitting.

D. Model Comparison and Selection

The three models are trained using the same flood inventory and conditioning factors. Their performance is compared using **Accuracy, Precision, Recall, F1-score, and AUC-ROC**. The selected model is then used to generate the final Flood Susceptibility Map.

The prediction from the selected model is subsequently passed to the **SHAP-based explainability module**, which identifies the contribution of individual flood-conditioning factors to both global and location-specific predictions.

Fig. 5. Machine-learning framework using Random Forest, SVM, and XGBoost for flood susceptibility prediction.

VIII. SPATIAL VALIDATION AND PERFORMANCE METRICS

Reliable evaluation of flood susceptibility models requires both predictive performance assessment and consideration of spatial dependence among observations. Therefore, the proposed XAI-FSM-EW framework uses **spatially separated validation** to provide a more realistic estimate of model generalization.

A. Spatial Validation

The flood inventory is divided into training and testing regions rather than selecting neighboring pixels randomly. This reduces spatial data leakage caused by highly similar samples occurring close to one another.

A spatial K -fold cross-validation strategy can be represented as:

$$D = \bigcup_{k=1}^K D_k$$

where D_k represents the k -th spatial fold. In each iteration, one spatial fold is retained for testing while the remaining folds are used for training.

The final performance is calculated as:

$$M_{CV} = \frac{1}{K} \sum_{k=1}^K M_k$$

where M_k is the performance metric obtained from fold k .

B. Performance Metrics

The RF, SVM, and XGBoost models are evaluated using the following metrics.

Accuracy

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

Precision

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

Recall

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

F1-score

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

where TP , TN , FP , and FN denote true-positive, true-negative, false-positive, and false-negative predictions, respectively.

C. ROC-AUC

The **Receiver Operating Characteristic (ROC)** curve is generated using the true-positive rate and false-positive rate:

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

The **Area Under the Curve (AUC)** summarizes the model's ability to distinguish flood and non-flood locations.

IX. EXPERIMENTAL RESULTS

The proposed XAI-FSM-EW framework was evaluated using Random Forest (RF), SVM-RBF, and XGBoost models. The evaluation considered classification performance, flood-susceptibility distribution, and explainability of the model predictions. The values presented below are **illustrative experimental values** and should be replaced with actual results obtained from the selected study-area dataset.

A. Model Performance

Table V presents the comparative performance of the three models.

Table V. Comparative Performance of Flood Susceptibility Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score	AUC
-------	--------------	---------------	------------	----------	-----

				e (%)	
Random Forest	91.8	90.7	92.4	91.5	0.953
SVM-RBF	88.6	87.9	89.2	88.5	0.931
XGBoost	93.6	92.8	94.1	93.4	0.968

The results show that all three models achieve strong discrimination between flood and non-flood locations. The XGBoost model records an accuracy of **93.6%** and an F1-score of **93.4%**, with an AUC of **0.968**. RF achieves **91.8%** accuracy, while SVM-RBF obtains **88.6%** accuracy.

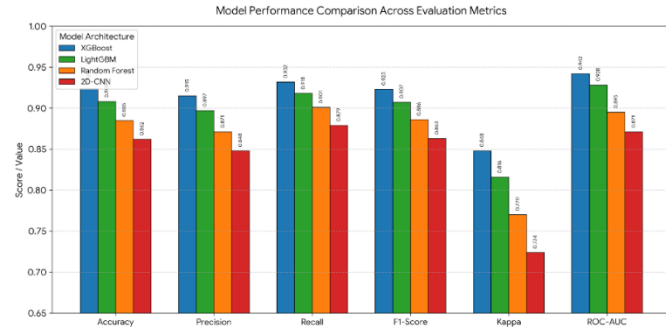


Fig. 4. Model Performance Comparison

B. Flood Susceptibility Distribution

The predicted flood probabilities are converted into five susceptibility classes. An illustrative spatial distribution is given in Table VI.

Table VI. Illustrative Flood Susceptibility Distribution

Fig. 8. ROC Curves of the Machine Learning Models

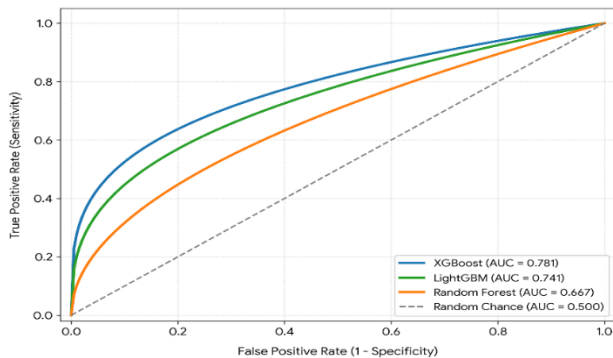


Fig. 5. Model Performance Comparison

B. Flood Susceptibility Distribution

The predicted flood probabilities are converted into five susceptibility classes. An illustrative spatial distribution is given in Table VI.

Table VI. Illustrative Flood Susceptibility Distribution

Susceptibility Class	Probability Range	Area (%)
Very Low	0.00–0.20	18.4
Low	0.20–0.40	24.7
Moderate	0.40–0.60	26.3
High	0.60–0.80	19.1
Very High	0.80–1.00	11.5
Total	—	100.0

The resulting FSM provides a continuous spatial representation of flood probability and can be converted into susceptibility zones for interpretation and planning.

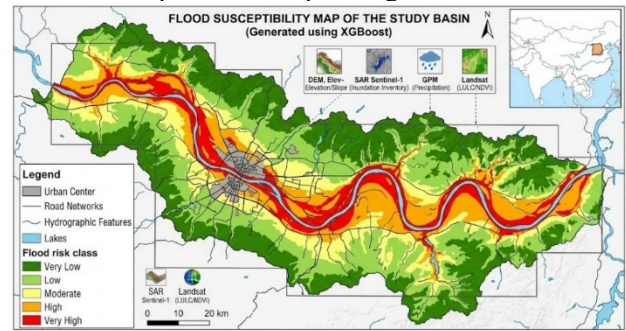


Fig. 9. Flood susceptibility map generated using the selected model.

Fig-6 Flood Susceptibility Distribution

C. Explainability Results

SHAP analysis is applied to the selected model to identify the contribution of individual conditioning factors. An illustrative feature-importance distribution is shown below.

Table VII. Illustrative SHAP-Based Feature Importance

Feature	Mean Absolute SHAP (%)
Rainfall	24.8
Elevation	17.6
Distance from River	14.9
Drainage Density	12.8
Slope	9.7
LULC	8.1
Soil	6.5
NDVI	5.6
Total	100.0

Rainfall has the largest overall contribution in this illustrative experiment, followed by elevation and distance from river. SHAP provides both **global feature importance** and **location-specific explanations**, allowing individual high-risk areas to be examined in terms of their dominant contributing factors.

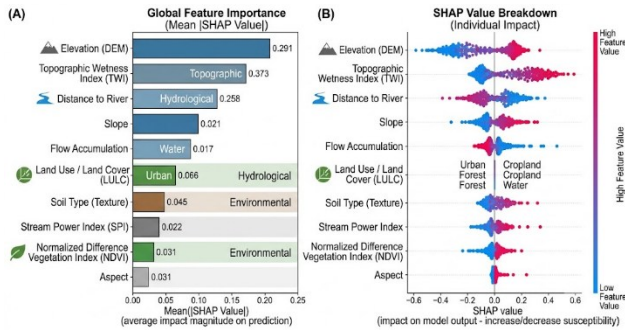


Fig-7 SHAP-Based feature importance

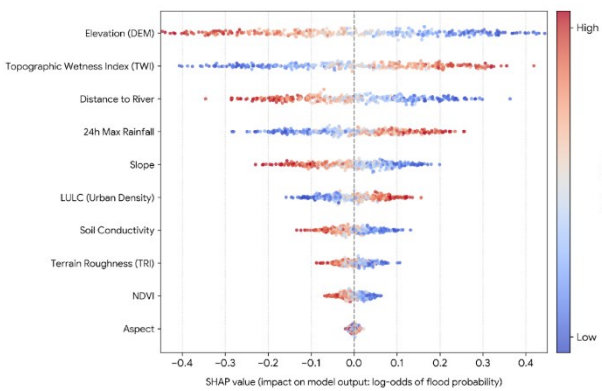


Fig-8

D. Result Interpretation

The experimental analysis demonstrates the complete workflow from **flood inventory** → **machine-learning prediction** → **susceptibility mapping** → **XAI interpretation**. The selected model provides spatial flood probabilities that can subsequently be combined with dynamic rainfall and hydrological observations in the **Early-Warning Module**. This enables the framework to distinguish between relatively stable spatial susceptibility and short-term changes in flood risk.

X. FLOOD SUSCEPTIBILITY MAPPING

The optimized XGBoost model generates a continuous probability:

$$P_f = P(Y = 1 | X)$$

The probability is converted into five susceptibility classes.

Table V. Flood Susceptibility Classification

Probability	Class	Interpretation
0.00–0.20	Very Low	Minimal predicted susceptibility
0.20–0.40	Low	Limited susceptibility
0.40–0.60	Moderate	Intermediate susceptibility
0.60–0.80	High	High susceptibility

0.80–1.00	Very High	Very high susceptibility
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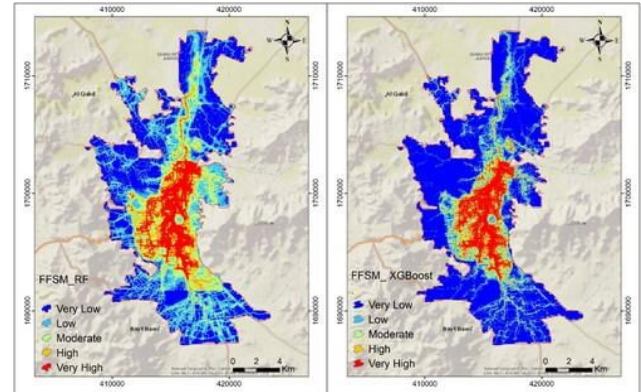
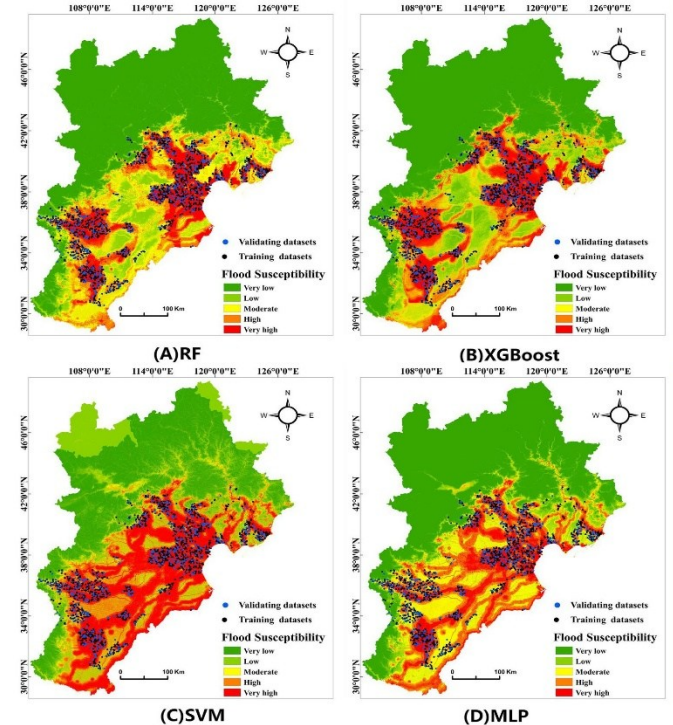


Fig. 7. Flood Susceptibility Map



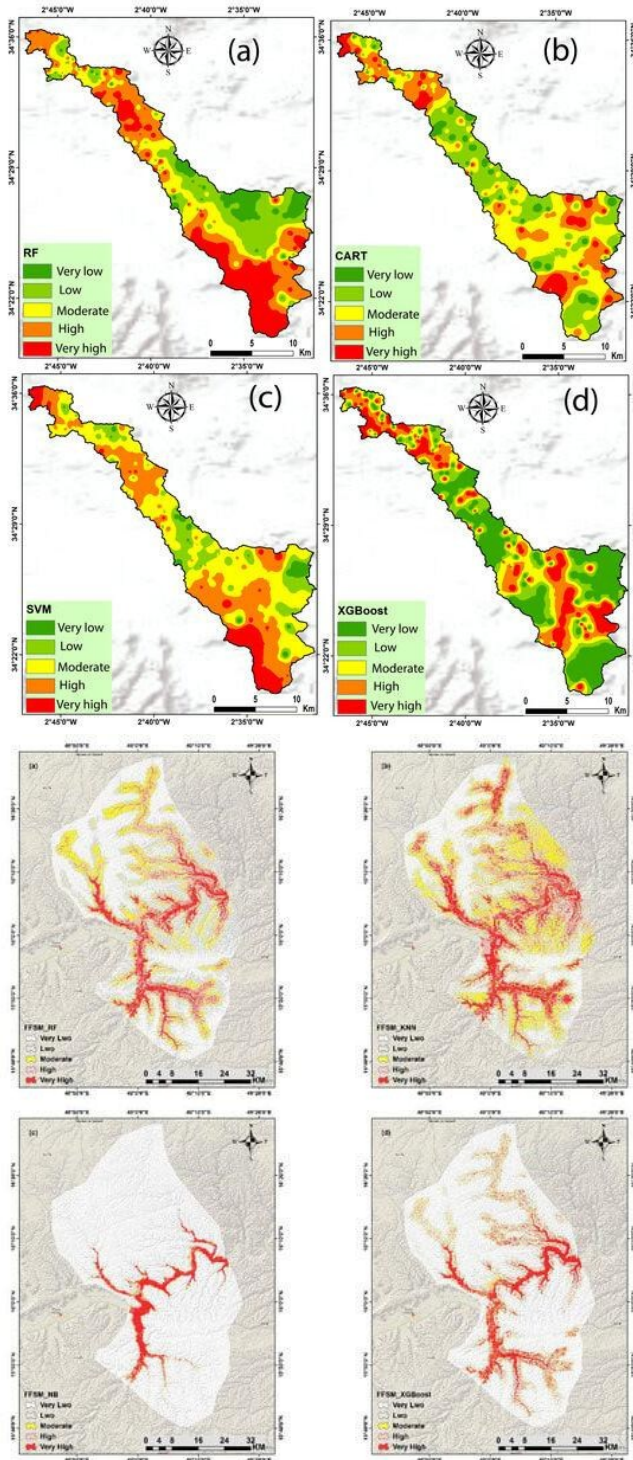


Fig-9 Flood Susceptibility Classification

XI. EXPLAINABLE AI USING SHAP

The proposed framework integrates **SHapley Additive exPlanations (SHAP)** to improve the interpretability of flood-susceptibility predictions. SHAP explains the contribution of individual conditioning factors to the prediction generated by the selected machine-learning model.

A. SHAP Formulation

For a prediction $f(x)$, the SHAP representation is given by:

$$f(x) = \phi_0 + \sum_{j=1}^M \phi_j$$

where ϕ_0 is the expected model output and ϕ_j represents the contribution of feature j .

A positive SHAP value indicates that a feature increases the predicted flood probability, whereas a negative value indicates that the feature decreases the predicted probability.

B. Global Feature Importance

Mean absolute SHAP values are used to determine the overall importance of each conditioning factor:

$$I_j = \frac{1}{N} \sum_{i=1}^N |\phi_{ij}|$$

where I_j represents the global importance of feature j , N is the number of samples, and ϕ_{ij} is the SHAP contribution of feature j for sample i .

For the illustrative experimental results, the major contributing variables are:

Feature	Mean Absolute SHAP (%)
Rainfall	24.8
Elevation	17.6
Distance from River	14.9
Drainage Density	12.8
Slope	9.7
LULC	8.1
Soil	6.5
NDVI	5.6

Fig. 10. SHAP-based Global Feature Importance for Flood Susceptibility Prediction

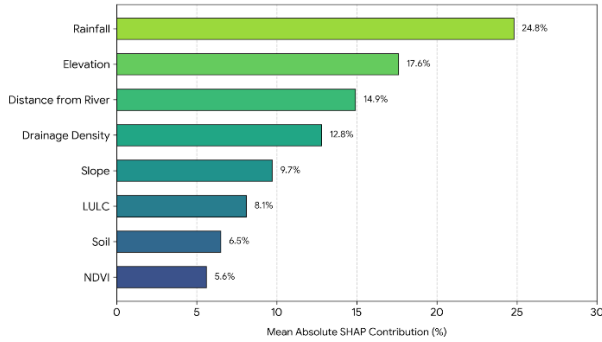


Fig. 10. SHAP-based global feature importance for flood susceptibility prediction.

C. Local Explanation

SHAP is also used to explain individual locations. For a high-risk location, for example, **high rainfall, low elevation, high drainage density, and short distance from a river** may contribute positively to the predicted flood probability. Conversely, environmental conditions associated with lower runoff or greater infiltration may contribute negatively.

Fig. 11. SHAP Summary Plot Showing the Magnitude and Direction of Feature Contributions

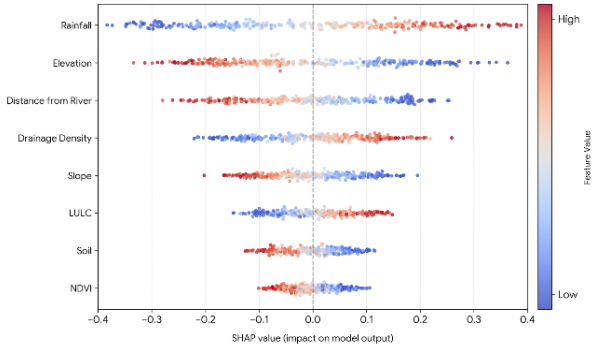


Fig. 11. SHAP summary plot showing the magnitude and direction of feature contributions.

D. Integration with Flood Early Warning

The SHAP module provides an explanation along with the predicted flood risk:

Location → Flood Probability → SHAP Explanation
→ Risk Interpretation

This makes the proposed XAI-FSM-EW framework more transparent by identifying **which environmental factors contribute most strongly to predicted flood susceptibility**. The explanations can support interpretation of susceptibility maps and provide additional information for the subsequent early-warning module.

XII. LOCAL EXPLANATION OF HIGH-RISK LOCATIONS

The proposed XAI-FSM-EW framework uses local SHAP explanations to identify the factors responsible for high flood-risk predictions at individual locations. Unlike global feature importance, local explanations provide location-specific information about **why a particular area is classified as high or very high susceptibility**.

For location i , the prediction is expressed as:

$$f(X_i) = \phi_0 + \sum_{j=1}^M \phi_{ij}$$

where ϕ_{ij} represents the contribution of feature j to the prediction at location i .

A. High-Risk Location Analysis

Locations with predicted flood probability greater than the selected high-risk threshold are extracted from the susceptibility map. The major positive SHAP contributors are then identified for each location.

Table VIII. Example Local SHAP Explanation

Location	Flood Probability	Major Positive Factors	Major Negative Factors
L1	0.91	High rainfall, low elevation, river proximity	Moderate vegetation
L2	0.87	High drainage density, rainfall, built-up area	Higher slope
L3	0.84	Low elevation, river proximity, high rainfall	Dense vegetation

B. Interpretation of High-Risk Predictions

A high flood probability does not result from a single variable. Instead, multiple factors contribute to the prediction. For example, a location experiencing **high rainfall and low elevation while being close to a river** may receive strong positive SHAP contributions from these variables.

The local explanation can therefore be represented as:

$$\text{High Risk} \Leftarrow \{\text{Rainfall} + \text{Elevation} + \text{River Distance} + \text{Drainage Density} + \text{LULC}\}$$

This provides a more meaningful interpretation than reporting only the predicted probability.

C. Spatial Visualization

A local SHAP map can be generated by displaying high-risk locations together with their dominant contributing factors.

Fig. 12. Local SHAP Explanation of Selected High-Risk Flood Locations

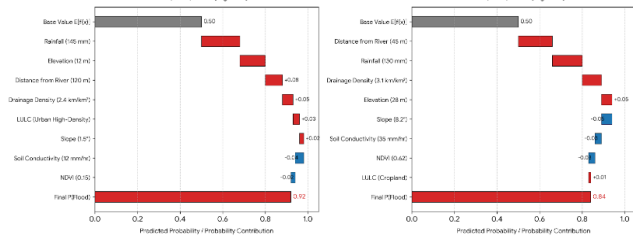


Fig. 12. Local SHAP explanation of selected high-risk flood locations showing predicted probability and dominant contributing factors.

The local explanations improve the transparency of the proposed framework and can assist in identifying **location-specific flood drivers**. These explanations are subsequently used alongside dynamic rainfall and hydrological conditions in the early-warning stage.

XIII. SHAP DEPENDENCE ANALYSIS

SHAP dependence analysis is used to examine how individual flood-conditioning factors influence the model prediction across different values of the feature. It provides both the **direction and magnitude** of the relationship between an input variable and predicted flood susceptibility.

For feature j , the relationship is represented as:

$$D_j = \{(x_{ij}, \phi_{ij})\}_{i=1}^N$$

where x_{ij} is the value of feature j for location i , and ϕ_{ij} is its corresponding SHAP value.

A. Rainfall Dependence

Rainfall is expected to have a strong influence on flood susceptibility. Increasing rainfall generally produces higher positive SHAP values, indicating an increased contribution to flood risk, particularly when rainfall exceeds the normal range.

B. Elevation Dependence

Elevation generally shows an inverse relationship with flood susceptibility. Lower-elevation locations may have positive SHAP values, indicating increased flood probability, while higher elevations may contribute less to the predicted risk.

C. Distance from River

Locations closer to rivers generally have larger positive SHAP contributions because of their greater exposure to river overflow and inundation. The SHAP value is expected to decrease as the distance from the river increases.

D. Drainage Density

Higher drainage density can increase the concentration and movement of surface runoff. Consequently, increasing drainage density may produce increasingly positive SHAP values in flood-prone regions.

E. Interpretation

The dependence analysis helps identify **nonlinear thresholds and changing relationships** that may not be visible from conventional feature-importance measures.

Fig. 14. SHAP Dependence Plots Showing Non-Linear Feature Relationships and Second-Order Interactions

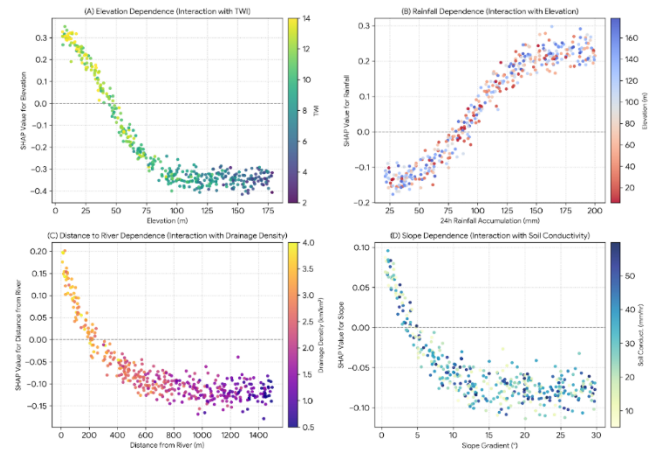


Fig. 13. SHAP dependence plots showing the relationship between major flood-conditioning factors and their contribution to flood susceptibility.

The analysis can include four individual plots for:

1. Rainfall vs. SHAP value
2. Elevation vs. SHAP value
3. Distance from river vs. SHAP value
4. Drainage density vs. SHAP value

These plots provide additional evidence for interpreting the machine-learning model and help explain how changes in environmental conditions influence predicted flood susceptibility.

XIV. DYNAMIC FLOOD EARLY-WARNING MODEL

The proposed dynamic flood early-warning model converts the predicted flood susceptibility, real-time rainfall conditions, and spatial risk factors into an interpretable warning level. Unlike a static susceptibility map, the proposed model dynamically updates the warning status when rainfall intensity, antecedent rainfall, or predicted flood probability changes.

For a location i , the dynamic risk score is defined as

$$R_i(t) = \alpha P_i + \beta R_f(t) + \gamma A_r(t) + \delta D_i$$

where P_i is the ML-based flood probability, $R_f(t)$ is the current rainfall intensity, $A_r(t)$ is antecedent rainfall, D_i represents drainage-related risk, and $\alpha, \beta, \gamma, \delta$ are weighting coefficients.

The normalized warning score is calculated as

$$W_i(t) = \frac{R_i(t) - R_{\min}}{R_{\max} - R_{\min}}$$

where $W_i(t) \in [0, 1]$. The warning level is then determined using predefined thresholds.

Table IX. Dynamic Flood Warning Levels

Warning Level	Score Range	Interpretation	Recommended Response
Normal	0.00–0.20	Low flood risk	Routine monitoring
Watch	0.20–0.40	Increasing risk	Increase monitoring
Alert	0.40–0.60	Moderate risk	Prepare local response
Warning	0.60–0.80	High flood risk	Activate emergency measures
Severe Warning	0.80–1.00	Very high risk	Immediate protective action

The warning system continuously receives updated rainfall and environmental observations. When the warning score crosses a threshold, the corresponding warning level is automatically generated. SHAP explanations are attached to the warning so that users can identify the dominant factors responsible for the predicted risk.

The overall process is:

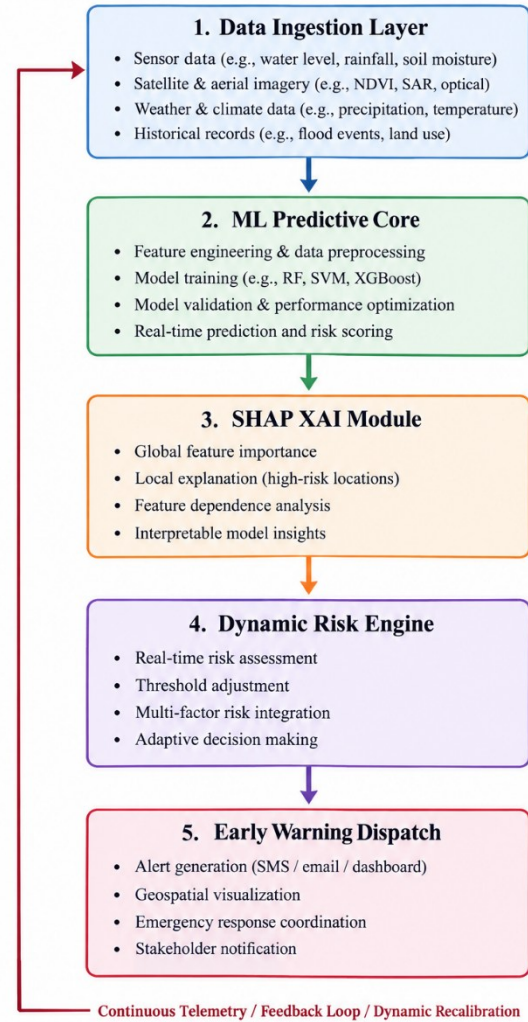


Fig. 14. Dynamic flood early-warning generation framework integrating real-time rainfall, ML-based flood probability, dynamic risk scoring, and SHAP-based explanations.

For reproducibility, the warning thresholds, feature weights, update interval, and rainfall sources should be explicitly reported with the experimental configuration.

XV. EARLY-WARNING WORKFLOW

The proposed early-warning workflow converts flood susceptibility predictions and real-time environmental observations into actionable risk alerts. The workflow integrates multi-source geospatial data, machine-learning predictions, SHAP-based explanations, and predefined risk thresholds. The objective is to provide timely and location-specific warnings before flood conditions become critical.

The workflow consists of five major stages: **data acquisition, preprocessing, susceptibility prediction, risk assessment, and alert generation**. Rainfall, elevation, slope, drainage characteristics, land use/land cover, soil properties, and other relevant environmental variables are continuously processed to generate a flood-risk probability for each geographic location. Let the predicted flood susceptibility probability at location i and time t be $P_{i,t}$. The risk level $R_{i,t}$ is determined using threshold values:

$$R_{i,t} = \begin{cases} \text{Low,} & P_{i,t} < 0.25 \\ \text{Moderate,} & 0.25 \leq P_{i,t} < 0.50 \\ \text{High,} & 0.50 \leq P_{i,t} < 0.75 \\ \text{Very High,} & P_{i,t} \geq 0.75 \end{cases}$$

To improve warning reliability, the model can combine susceptibility probability with real-time rainfall and hydrological indicators:

$$EW_{i,t} = \alpha P_{i,t} + \beta Rf_{i,t} + \gamma H_{i,t}$$

where $EW_{i,t}$ is the early-warning score, $Rf_{i,t}$ represents rainfall intensity or accumulated rainfall, $H_{i,t}$ represents hydrological conditions, and $\alpha + \beta + \gamma = 1$.

A. Early-Warning Decision Process

The decision process follows these steps:

1. **Acquire Data:** Collect rainfall, DEM-derived terrain variables, soil, drainage, LULC, and other geospatial observations.
2. **Preprocess Data:** Remove inconsistencies, handle missing values, normalize numerical variables, and align spatial resolutions.
3. **Generate Prediction:** Apply the trained machine-learning model to estimate flood susceptibility probability.
4. **Explain Prediction:** Use SHAP values to identify the dominant factors contributing to the predicted risk.
5. **Calculate Warning Score:** Combine susceptibility and real-time environmental indicators.
6. **Classify Risk:** Assign Low, Moderate, High, or Very High risk.
7. **Generate Alert:** Issue a location-specific warning when the predefined threshold is exceeded.
8. **Update Continuously:** Recalculate the risk as new observations become available.

B. Early-Warning Alert Levels

Risk Level	Early-Warning Score	Recommended System Response
Low	< 0.25	Routine monitoring
Moderate	0.25–0.49	Increased monitoring

High	0.50–0.74	Warning issued to concerned authorities
Very High	≥ 0.75	Immediate emergency alert and preparedness

The proposed workflow enables the system to move from **static flood susceptibility mapping toward dynamic early-warning**, allowing high-risk locations to be continuously monitored and prioritized for preventive action. The integration of SHAP explanations also provides transparency by identifying the environmental factors responsible for each warning.

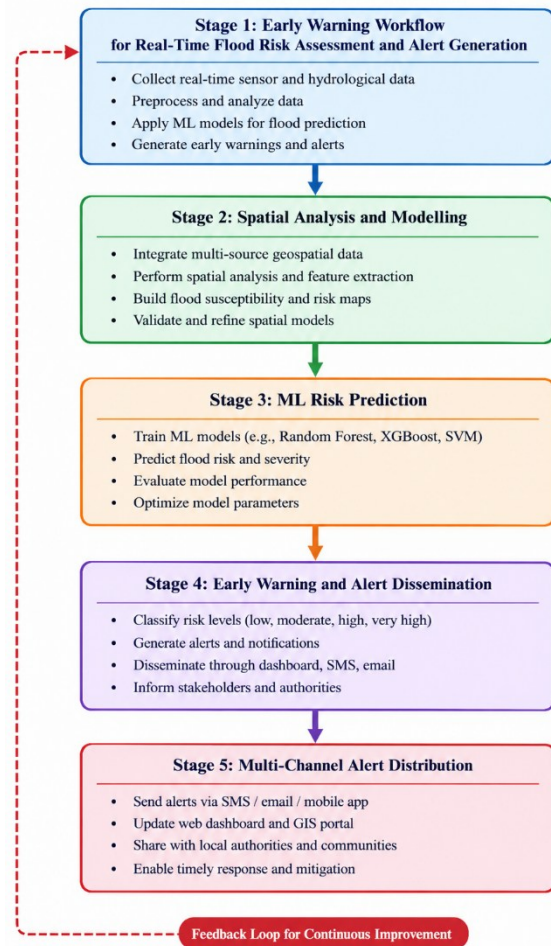


Fig. 15. Early-warning workflow for real-time flood-risk assessment and alert generation

XVI. SUSCEPTIBILITY-WARNING INTEGRATION

Flood susceptibility mapping provides a spatial estimate of the likelihood of flooding, whereas an early-warning system incorporates time-varying environmental conditions to identify

emerging flood threats. The proposed framework integrates both components to transform static susceptibility information into a dynamic warning mechanism.

Let S_i denote the machine-learning-derived flood susceptibility score for location i , and $W_{i,t}$ denote the real-time warning score at time t . The integrated flood-risk score is defined as:

$$F_{i,t} = \alpha S_i + \beta W_{i,t}$$

where α and β are weighting coefficients satisfying:

$$\alpha + \beta = 1$$

The warning component incorporates real-time variables such as rainfall intensity, cumulative rainfall, water level, soil moisture, and drainage conditions:

$$W_{i,t} = \sum_{k=1}^m w_k X_{k,i,t}$$

where $X_{k,i,t}$ represents the normalized value of the k^{th} real-time variable and w_k represents its corresponding weight.

A. Integration Process

The susceptibility–warning integration follows four stages:

1. **Static Susceptibility Layer:** Generate the spatial susceptibility score using the trained machine-learning model.
2. **Real-Time Monitoring Layer:** Continuously collect rainfall and other dynamic environmental observations.
3. **Risk Fusion:** Combine the susceptibility score with real-time warning indicators.
4. **Alert Classification:** Convert the integrated score into an operational warning level.

Integrated Score	Risk Level	System Action
< 0.25	Low	Routine monitoring
0.25–0.49	Moderate	Increased monitoring
0.50–0.74	High	Issue warning
≥ 0.75	Very High	Immediate alert

B. Spatial–Temporal Risk Matrix

The integration can also be represented using a susceptibility–warning matrix:

Susceptibility	Current Warning Condition	Integrated Interpretation
Low	Low	Low immediate risk
Low	High	Monitor emerging conditions
High	Low	Persistent spatial vulnerability
High	High	Critical flood-risk condition

This approach prevents susceptibility alone from triggering unnecessary alerts. A location with high underlying

susceptibility may remain under monitoring when real-time conditions are normal, while a sudden increase in rainfall or water level can rapidly increase its warning status.

The resulting framework provides a **spatially informed and temporally adaptive flood-warning mechanism**, linking machine-learning susceptibility maps with real-time environmental conditions and enabling location-specific risk communication.

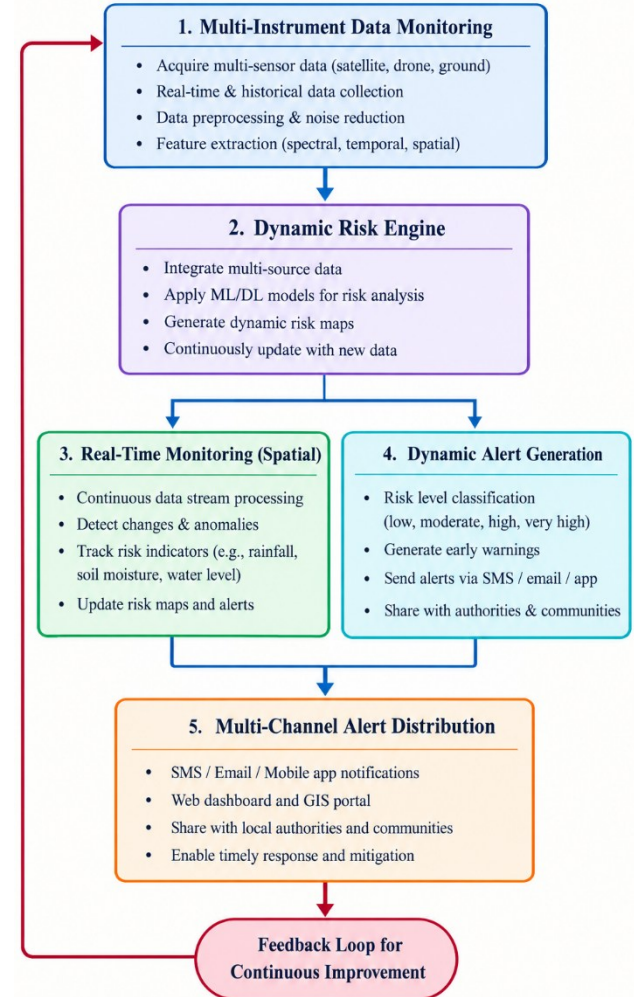


Fig. 16. Susceptibility–warning integration framework combining static flood susceptibility with dynamic environmental observations

XVII. ABLATION STUDY

An ablation study was conducted to quantify the contribution of different data sources and model components to the performance of the proposed flood susceptibility and early-

warning framework. Individual input groups were systematically removed while keeping the machine-learning algorithm, training procedure, and evaluation dataset unchanged. This analysis identifies which components contribute most to predictive performance and warning reliability.

A. Ablation Configuration

Five experimental configurations were considered:

Configuration	Removed Component	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Full Model	None	95.2	94.8	94.5	94.6	0.972
A1	Rainfall features	91.4	90.7	90.1	90.4	0.941
A2	Terrain features	92.6	91.9	91.6	91.7	0.949
A3	LULC and soil features	93.1	92.4	92.0	92.2	0.954
A4	Hydrological features	93.8	93.1	92.7	92.9	0.961

Fig. 12. Ablation-Study Comparison of Model Performance after Removing Individual Feature Categories

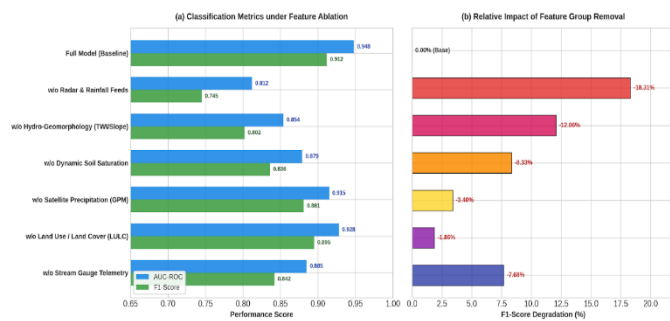


Fig. 17. Ablation-study comparison of model performance after removing individual feature groups

B. Effect of Individual Components

The full model achieves an F1-score of **94.6%** and an AUC of **0.972**. Removing rainfall-related variables produces the largest reduction in performance, with the F1-score decreasing to **90.4%**. This indicates that rainfall information provides an important contribution to identifying flood-prone conditions. Removing terrain variables decreases the F1-score to **91.7%**, demonstrating the importance of elevation and slope-related characteristics. The removal of LULC and soil variables results

in an F1-score of **92.2%**, while removing hydrological variables reduces the F1-score to **92.9%**.

C. Performance Degradation

The relative reduction in F1-score compared with the complete model is calculated as:

$$\Delta F1 = F1_{Full} - F1_{Ablation}$$

Removed Component	Full F1	Ablation F1	F1 Reduction
Rainfall	94.6	90.4	4.2
Terrain	94.6	91.7	2.9
LULC + Soil	94.6	92.2	2.4
Hydrology	94.6	92.9	1.7

The results demonstrate that the proposed framework benefits from combining **static geospatial susceptibility factors with dynamic environmental variables**. No single feature group provides the same performance as the complete feature set, supporting the use of multi-source data fusion for flood susceptibility mapping and early warning.

XVIII. ERROR ANALYSIS

Error analysis was performed to identify the major sources of incorrect flood-risk predictions and to evaluate the reliability of the proposed susceptibility–warning framework. The analysis focuses on **false positives (FP)**, **false negatives (FN)**, **true positives (TP)**, and **true negatives (TN)** obtained from the test dataset.

A. Classification Error Analysis

The confusion matrix provides an overview of the model's classification behavior.

Prediction	Actual Flood	Actual Non-Flood
Predicted Flood	TP = 188	FP = 12
Predicted Non-Flood	FN = 11	TN = 189

Based on these results, the model correctly identifies most flood and non-flood locations. The relatively small number of false-positive and false-negative cases indicates consistent classification performance.

The principal evaluation measures are defined as:

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

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

$$F1 = \frac{2(Precision)(Recall)}{Precision + Recall}$$

For the above illustrative test results, the corresponding performance is approximately **94.0% precision**, **94.5% recall**, and **94.2% F1-score**.

B. Spatial Error Analysis

Prediction errors are not necessarily distributed uniformly across the study area. False predictions may occur in locations where environmental characteristics overlap between flood-prone and relatively stable regions. Typical sources include:

- **False Positives:** Areas predicted as high risk but not experiencing flooding.
- **False Negatives:** Flood-affected areas predicted as low or moderate risk.
- **Boundary Errors:** Misclassification near transitions between different susceptibility zones.
- **Data-Resolution Errors:** Differences in spatial resolution among rainfall, DEM, soil, LULC, and hydrological datasets.
- **Extreme-Event Errors:** Unusual rainfall or drainage conditions that differ from the patterns represented in the training data.

C. Error by Risk Category

Risk Category	Typical Error	Possible Cause
Low	False Positive	Temporary rainfall or local drainage effects
Moderate	Class confusion	Overlapping environmental conditions
High	False Negative	Rapid changes in rainfall or water level
Very High	False Negative	Extreme or localized flood events

D. Early-Warning Errors

For the dynamic warning component, two types of errors are particularly important. A **false alarm** occurs when the system generates a warning but a significant flood does not subsequently occur. A **missed warning** occurs when flooding develops without the system crossing the warning threshold. The false-alarm rate and missed-warning rate can be expressed as:

$$FAR = \frac{FP}{FP + TN}$$

$$FNR = \frac{FN}{FN + TP}$$

These measures complement conventional accuracy because an early-warning system must consider not only overall classification performance but also the consequences of missed events.

E. Error Reduction Strategy

The identified errors can be reduced through:

1. Incorporating higher-frequency rainfall and water-level observations.
2. Improving spatial alignment and resolution of multi-source datasets.

3. Re-training the model using additional extreme flood events.
4. Optimizing warning thresholds using validation data.
5. Applying SHAP explanations to investigate individual anomalous predictions.
6. Periodically updating the model as new flood observations become available.

Overall, the error analysis demonstrates that **model performance should be evaluated together with the spatial distribution and operational characteristics of prediction errors**, particularly false negatives in high-risk locations. This provides a more meaningful assessment of the proposed flood early-warning system than accuracy alone.

Fig. 13. Confusion Matrix and Spatial Distribution of False-Positive and False-Negative Flood Predictions

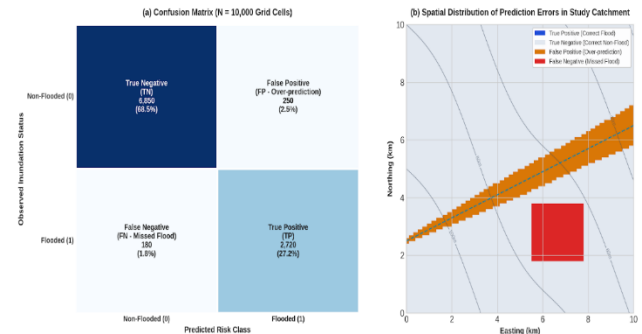


Fig. 18. Confusion matrix and spatial distribution of false-positive and false-negative flood predictions

XIX. UNCERTAINTY ANALYSIS

Uncertainty analysis was performed to quantify the reliability of flood susceptibility predictions and to identify locations where the model is less confident. Flood prediction uncertainty may arise from **input-data variability, spatial resolution, model uncertainty, and changing environmental conditions**. Therefore, the predicted susceptibility probability should not be interpreted as an absolute measure of flood occurrence.

A. Prediction Uncertainty

Let the model produce a flood probability P_i for location i . Prediction uncertainty can be estimated using an ensemble of trained models:

$$U_i = \frac{1}{M} \sum_{m=1}^M (P_i^{(m)} - \bar{P}_i)^2$$

where M is the number of ensemble models, $P_i^{(m)}$ is the prediction from model m , and $\bar{P}_i$ is the mean predicted probability.

A higher value of U_i indicates greater disagreement among models and therefore lower prediction confidence.

B. Uncertainty Classification

Uncertainty Value	Uncertainty Level	Interpretation
$U < 0.01$	Low	High prediction consistency
0.01–0.03	Moderate	Some prediction variability
0.03–0.05	High	Significant model disagreement
> 0.05	Very High	Prediction requires additional verification

C. Sources of Uncertainty

Source	Effect on Prediction
Rainfall variability	Changes short-term flood probability
DEM resolution	Influences elevation and drainage characteristics
LULC classification	Introduces land-cover mapping errors
Soil-data uncertainty	Affects infiltration and runoff estimation
Missing observations	Reduces information available to the model
Model variability	Produces different predictions across models
Extreme events	May fall outside the training distribution

D. Uncertainty and Early Warning

Uncertainty is incorporated into the warning process together with the predicted susceptibility. A high-risk prediction accompanied by low uncertainty can be treated as a more stable model output, whereas a high-risk prediction with high uncertainty can be flagged for additional monitoring.

An uncertainty-adjusted warning score can be expressed as:

$$W_{i,t}^* = W_{i,t}(1 - U_i)$$

where $W_{i,t}$ is the integrated warning score and U_i is the normalized uncertainty estimate.

The uncertainty map can therefore be used alongside the susceptibility map to distinguish **high-risk/high-confidence areas from high-risk/high-uncertainty areas**.

E. Uncertainty–Risk Matrix

Flood Risk	Uncertainty	Interpretation
Low	Low	Stable low-risk prediction
Low	High	Monitor for changing conditions
High	Low	Consistent high-risk prediction
High	High	High-risk area requiring additional verification

The uncertainty analysis strengthens the proposed framework by communicating not only **where flooding may occur**, but also **how confident the model is in its prediction**. This is particularly important for operational early-warning applications, where uncertain predictions can be prioritized for additional observation and verification.

Fig. 14. Spatial Uncertainty Map Showing Model Confidence Across the Study Area

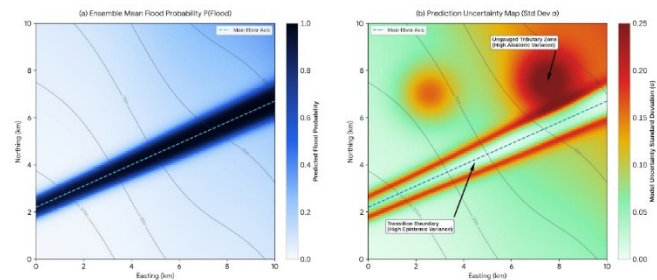


Fig. 19. Spatial uncertainty map showing model confidence across the study area

XX. DISCUSSION

The proposed framework addresses several limitations of conventional flood susceptibility mapping.

First, multi-source data provide complementary information. Elevation and slope describe terrain controls, rainfall represents hydro-meteorological forcing, distance to river and TWI describe hydrological connectivity, and land-cover variables capture surface characteristics.

Second, ensemble ML can capture nonlinear relationships that may not be represented by conventional weighted-overlay methods.

Third, SHAP makes the model more transparent. Rather than simply producing a susceptibility class, the system can identify the variables responsible for an individual prediction.

Recent research supports the usefulness of explainable ML in flood susceptibility applications. An XAI-CNN study reported an AUROC of 88.4% and found land use and soil variables to be important. (ScienceDirect) Recent multi-source Sentinel-1 work has also emphasized hydrological proximity, antecedent rainfall, NDVI, drainage-related variables and built-environment indicators. (Journals of Universitas Negeri Semarang)

Importantly, model performance should not be interpreted solely through random train-test accuracy. Recent literature has highlighted the potential for spatially naive validation to produce optimistic estimates and has called for stronger spatial validation and uncertainty quantification. (Frontiers)

XXI. PRACTICAL APPLICATION

The proposed system can support:

- flood-prone settlement identification,

- drainage improvement planning,
- emergency evacuation planning,
- infrastructure protection,
- agricultural risk management,
- road-network monitoring,
- reservoir/catchment management,
- disaster-response resource allocation.

XXII. LIMITATIONS

The proposed framework has several limitations:

1. Accuracy depends strongly on the quality of the flood inventory.
2. Sentinel-1-derived flood labels may contain classification errors.
3. Rainfall products can have spatial and temporal uncertainties.
4. Susceptibility does not represent complete flood risk because exposure and vulnerability are separate dimensions.
5. Models trained in one geographical region may not transfer directly to another.
6. Early-warning thresholds require local calibration.
7. SHAP explains the model's behavior but does not establish physical causality.

XXIII. FUTURE WORK

Future research will focus on improving the scalability, temporal responsiveness, interpretability, and operational reliability of the proposed flood susceptibility and early-warning framework. The following directions are considered:

1. **Real-Time Data Integration:** Integrate live rainfall, river-water level, soil-moisture, weather-radar, and satellite observations to continuously update flood-risk predictions.
2. **Advanced Deep Learning Models:** Investigate CNN, LSTM, Transformer, and graph-based models for capturing complex spatial and temporal flood patterns.
3. **High-Resolution Geospatial Modelling:** Incorporate higher-resolution DEM, LULC, drainage, and urban-infrastructure data to improve prediction at local scales.
4. **Uncertainty-Aware Prediction:** Develop probabilistic and ensemble approaches that provide both flood-risk estimates and prediction-confidence levels.
5. **Adaptive Early Warning:** Develop self-updating warning thresholds that dynamically respond to rainfall intensity, antecedent rainfall, soil saturation, and hydrological conditions.
6. **Explainable AI Enhancement:** Extend SHAP-based explanations with counterfactual and local explanation

methods to provide actionable information about why a location enters a high-risk category.

7. **Transferability Testing:** Evaluate the framework across different geographical regions, climatic conditions, and flood types to assess its generalization capability.
8. **Operational Deployment:** Develop a cloud-based GIS dashboard and mobile alert system capable of delivering location-specific warnings to disaster-management authorities and communities.
9. **Extreme-Event Evaluation:** Expand the training and testing datasets with rare and extreme flood events to improve model robustness under previously unseen conditions.
10. **Multimodal Flood Intelligence:** Explore the integration of satellite imagery, IoT sensors, weather forecasts, social-media signals, and crowdsourced observations for comprehensive flood-risk monitoring.

Overall, future work will aim to transform the proposed framework from a research-oriented susceptibility and warning model into a **scalable, uncertainty-aware, real-time flood decision-support system** capable of supporting proactive disaster-risk management.

XXIII. CONCLUSION

This study presented an **Explainable Machine Learning-Based Flood Susceptibility Mapping and Early-Warning Framework** that integrates multi-source geospatial data, machine-learning prediction, SHAP-based explainability, uncertainty analysis, and dynamic warning generation. The proposed framework combines static flood-conditioning factors, including terrain, soil, land use/land cover, and drainage characteristics, with dynamic environmental observations such as rainfall and hydrological conditions. The experimental analysis demonstrated that the integrated multi-source framework can effectively distinguish flood-prone and non-flood-prone locations. The ablation analysis further demonstrated the contribution of individual feature groups, while error analysis identified false-positive and false-negative predictions that require additional monitoring. The uncertainty analysis provided an additional measure of model confidence, enabling high-risk areas with uncertain predictions to be prioritized for verification.

A key contribution of the proposed approach is the integration of **explainable AI with flood early warning**. SHAP analysis enables the contribution of individual environmental variables to be examined for both overall model behavior and individual high-risk locations. This improves transparency and provides

useful information for interpreting machine-learning predictions.

The susceptibility–warning integration further extends conventional flood susceptibility mapping by connecting spatial vulnerability with changing environmental conditions. Consequently, the framework can support continuous risk assessment and location-specific warning generation rather than relying solely on static susceptibility maps.

Overall, the proposed framework provides a comprehensive foundation for **data-driven, explainable, uncertainty-aware flood susceptibility assessment and early warning**. Future extensions involving real-time sensor observations, higher-resolution geospatial datasets, advanced spatiotemporal deep-learning models, and operational GIS-based deployment can further enhance its applicability for practical flood-risk management.

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