Enhancing the Generalization of Flood Susceptibility Models: A Leakage-Aware Ensemble Framework for Deltaic Landscapes

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Abstract

Flood susceptibility mapping (FSM) is a cornerstone of disaster risk reduction in low-lying deltaic regions; however, conventional machine learning (ML) applications frequently suffer from spatial data leakage, resulting in inflated performance metrics and unreliable hazard predictions. To address this critical methodological shortcoming, this study develops a robust, leakage-aware ML framework for FSM in the highly vulnerable Greater Noakhali region of Bangladesh. Utilizing a flood inventory derived from Sentinel-1 SAR imagery of the catastrophic August 2024 event, we integrated twelve spatially explicit conditioning factors representing topographic, hydrological, and anthropogenic drivers. To ensure true model generalization and mitigate the effects of spatial autocorrelation, eight ensemble algorithms were evaluated using a rigorous 10-fold blocked spatial cross-validation strategy. The spatially constrained evaluation provided realistic performance estimates, in contrast to the overly optimistic ROC-AUC values typical of conventional random splits, with Random Forest demonstrating the highest generalization capability (ROC-AUC = 0.627) and XGBoost achieving the optimal balance between precision and recall (F1 = 0.451). Furthermore, SHAP (SHapley Additive exPlanations) analysis of the ensemble models identified land use, vegetation density (NDVI), and drainage density as the primary physical drivers of flood susceptibility in this coastal tract. By demonstrating that spatially robust validation is essential for credible geospatial AI, the resulting maps identify critical high-risk zones along the Meghna estuary and provide a physically plausible, operationally relevant tool for regional disaster management.

Keywords: Flood susceptibility mapping, Spatial data leakage, Spatial cross-validation, Machine learning, Random Forest, XGBoost, SHAP analysis, Remote sensing, Bangladesh, Noakhali region.

Introduction

Floods are one of the most common and damaging natural hazards globally shaped by overflowing water standing, caused as an effect of more volume of water to rest due to a lot of rain, river flooding storm surges or dam failure (Shampa et al. 2025). These events disrupt ecosystems, damage infrastructure, and endanger human lives predicting significant economic losses along with long term socioeconomic impacts (Yao et al. 2026).

Among flood-prone countries, Bangladesh stands out due to its unique geographical and hydrological setting (Paszkowski et al. 2025). The country lies at the meeting point of the Ganges, Brahmaputra and Meghna river systems, which channel large upstream flows into the

seaward direction during monsoon seasons (Paszkowski et al. 2025). This environment, when taken together with its predominantly low-lying alluvial floodplains and elevation in relation to potential coastal storm surges from the Bay of Bengal, renders wide areas of the country vulnerable to frequent flooding (Elahi et al. 2025).

The southeastern coastal belt of Bangladesh, especially Greater Noakhali (Noakhali, Lakshmipur and Feni Districts) is one of the most vulnerable flood-prone zones in Bangladesh (Sarker and Jahan 2026). Flood vulnerability is, however, exacerbated still further due to the region's low elevation, flat topography and dense drainage network as well as strong tidal forces (Piya et al. 2026). Previous catastrophic events such as August 2024 flash flood in this region, which affected more than 550,000 further underlines the need for solidifying a unique methodology with proper flood assessment frameworks (Huang 2025).

Flood susceptibility mapping (FSM) is a crucial disaster risk reduction tool that assists in land-use planning, early warning systems, and climate adaptation strategies (Rashid et al. 2026). Existing standard flood modelling approaches are physically based hydrodynamic models; however, their high computational requirement and data-intensive nature limit the applicability, especially in data-scarce environments (Aniramu et al. 2026). On the other hand, machine learning (ML) techniques can be a flexible and fast alternative that has great potential for modelling complex nonlinear relationships between flood occurrence and conditioning factors such as topography, hydrology, land use, and climate variables (Ganiyu et al. 2026). Ensemble-based approaches such as Random Forest, XGBoost and LightGBM have been reported to be highly accurate across different geographical locations (Rahman and Yasuhara 2026).

Yet, a key methodological issue for geospatial ML applications relates to spatial data leakage which is caused by spatial autocorrelation between samples (Grekousis 2025). Popular train–test splits often introduce spatial proximity between samples that nonetheless appear in both datasets, giving rise to biassed and overly optimistic performance estimates which are contrary to what a true generalization of the model will yield (Li et al. 2023). This problem is most evident in low-lying flood-sensitive areas such as Bangladesh, where spatial dependency is high yet neglected (Alif et al. 2025).

These limitations have been addressed by spatially explicit validation strategies (i.e. spatial cross-validation, block-based holdout) that restrict geographic proximity of data for training and evaluation to obtain more realistic estimates of model performance (Islam et al. 2026). These approaches are effective yet not commonly applied in deltaic environments where reproducible and reliable modeling frameworks are urgently needed (Nnam et al. 2026).

In this scenario, the current study proposed a leakage aware flood susceptibility mapping framework using classical machine learning techniques under strict spatial holdout design for Greater Noakhali area (Tella et al. 2026). A systematic evaluation of eight popular models, Decision Tree, Random Forest, Extra Trees, AdaBoost, Gradient Boosting, HistGradientBoosting, XGBoost and LightGBM, is conducted using a block-based spatial partitioning scheme (Rahimi et al. 2026). Flood inventory is obtained from Sentinel-1 and conditioning factors are constructed with terrain, hydrological, and land-use datasets (Asrade et al. 2026). A consistent preprocessing pipeline is used, with one-hot-encoding of land use/land cover, cyclic transformation of aspect variables, and median imputation with missing-indicator features to maintain reproducibility and prevent feature-level leakage (Elmotawakkil et al. 2025). Additionally, SHAP analysis is used to explain the predictions of the model and measure how important some conditioning factors are (Gupta et al. 2026).

The objective of this study is to assess the performance of classical machine learning models using strict spatial validation, create a reproducible geospatial modeling workflow free from leakage and evaluate tree-based ensemble techniques for flood susceptibility mapping. It also aims to produce realistic susceptibility maps for regional planning and disaster risk management. This research that focuses on computation efficient interpretable models places an emphasis on leakage aware evaluation and shows moderate performance metrics to be the most credible foundations for assessment of regularly occurring flood susceptibility in coastal Bangladesh.

Study Area

The study was performed at the Greater Noakhali region, located in the southeastern coastal zone of Bangladesh. Three administrative districts - Noakhali, Lakshmipur and Feni constitute this region. Geographically, the study area is defined roughly between 22°30′N to 23°15′N latitude and 90°45′E to 91°45′E longitude, covering one of the low-lying deltaic landscapes bordering northern Bay of Bengal.

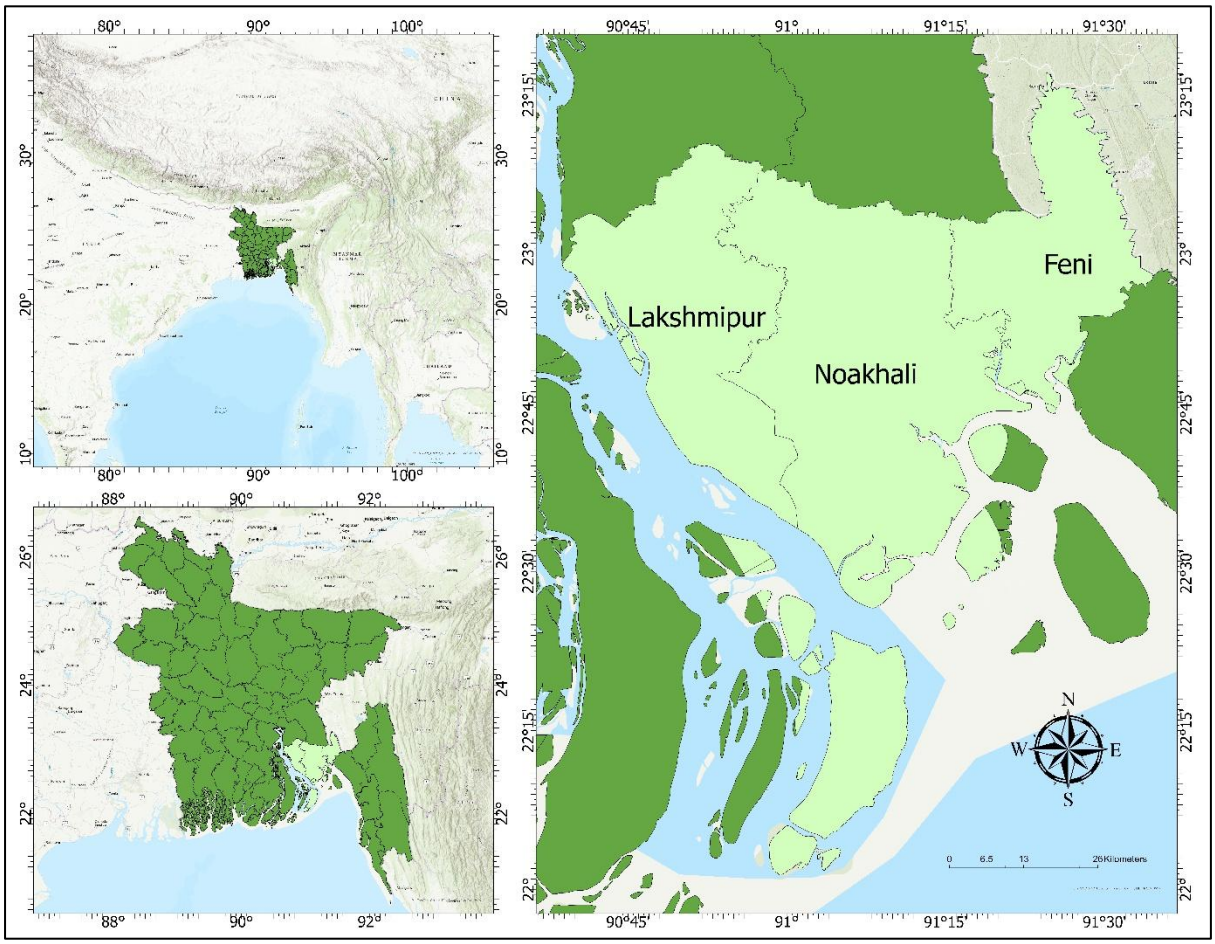

Figure 1: Study Area Map

This region is almost flat and low elevated geomorphology with all the areas lying in 0–5 m above mean sea level is vulnerable to inundation (Sorna et al. 2025). Majority of the landform are recent alluvial deposits, formed through dynamic interaction between Meghna River system and coastal sediment transfer (Ali et al. 2025). The region belongs to the Ganges–Brahmaputra–Meghna (GBM) delta, with perpetual geomorphological evolution characterized

by ongoing pro-cesses of accretion and erosion that further modulate flood dynamics (Khan 2021).

The study area is a highly dense, interconnected system of rivers tidal channels and canals (locally called khals) with the western and southern edges bounded by the Meghna estuar (Valentine and Wilson 2023). I think it is this intertwined drainage which makes a stage of flood regime both from the upstream and downstream tidal propagation (Elahi et al. 2025). As a result, the region is vulnerable to both fluvial flooding due to upstream discharge in times of high monsoon flow as well as tidal flooding and storm surges from the Bay of Bengal (Elahi et al. 2025).

The region is characterized by tropical monsoon climate with most annual precipitation occurring between June and September (Das et al. 2021). Heavy rainfall during this period often overlaps with high river discharge and tidal phase, thus posing additional flood risk. Besides, temporality extreme flooding incidents are established to be associated with cyclonic activities in the Bay of Bengal, especially in coastal and estuarial regions (Dutta et al. 2025).

Over the last decades, accelerated agricultural intensification and land-use changes such as more settlements, urbanization, and infrastructure have modified the alteration of natural hydrological response within that area (Dixit et al. 2024). These modifications have diminished the natural drainage capability and have amplified the surface runoff, making the region more flood sensitive.

Methodology

The overall workflow of this study follows a structured, leakage-aware machine learning pipeline for flood susceptibility mapping, consisting of data collection, preprocessing, feature analysis, model development, evaluation, and interpretation.

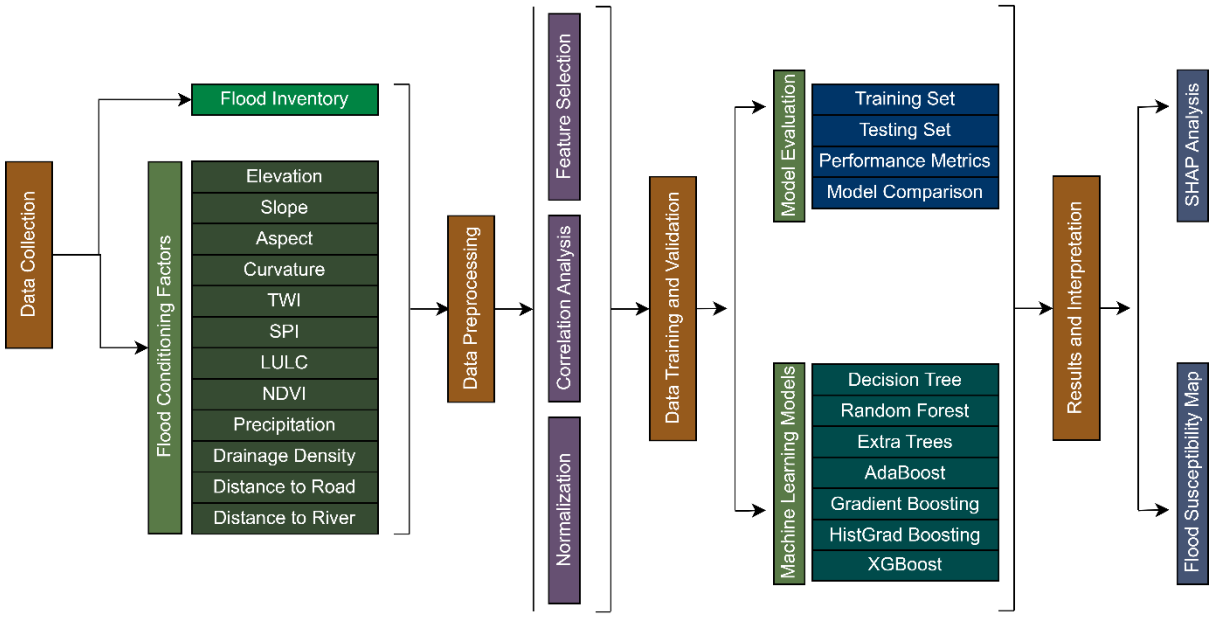

Figure 2: Methodology Flowchart

The data collection step consists of a flood inventory dataset and many conditioning factors compiled from remote sensing and geospatial sources. The flood inventory obtained from

Sentinel-1 SAR Imagery and twelve factors, i.e. elevation, slope, aspect, curvature, Topographic Wetness Index (TWI), Stream Power Index (SPI), Land use Land cover (LULC), NDVI, Precipitation, Drainage density distance to roads and Distance to rivers used as topographic-hydrological-environmental-anthropogenic influences were all prepared in a GIS environment.

After data acquisition, all variables are preprocessed to ensure they are compatible with the model. This involves missing value imputation, categorical variable encoding (LULC), cyclical feature transformations (aspect), and continuous variable normalization. Operations of this manner are done only on the training data to avoid data leakage.

In the next step, feature analysis via correlation and statistical metrics is performed to identify redundant or highly collinear variables that would enhance model robustness, focus on key predictors of interest, improve interpretability whilst mitigating overfitting.

Next building dataset dividing in a train and test subset with a spatially aware strategy subject to avoid spatial autocorrelation. Metrics include using ROC-AUC, precision, recall and F1 score to evaluate models against testing set after training on the training set.

Multiple machine learning algorithms are used in the model development stage such as Decision Tree, Random Forest, Extra Trees, and Boosting methods like AdaBoost, Gradient Boosting, HistGradient Boosting and XGBoost that follow a similar pipeline to enable standard comparison amongst different models.

Based on the evaluation description and predictive stability, the model with the best performance is selected. SHAP (SHapley Additive exPlanations) analysis is then performed to interpret model behavior and deduce the contribution of each conditioning factor. Finally, a final model is applied to produce the flood susceptibility map.

Flood Inventory and SAR Imagery

A consistent flood inventory is an essential component of supervised flood susceptibility modelling (Murad et al. 2025). In this study, the flood inventory was prepared based on the August 2024 flood event which inundated most of the districts such as Noakhali, Lakshmipur and Feni in Greater Noakhali region.

Land flood area contours using multi-temporal Sentinel-1 Synthetic Aperture Radar (SAR) images is widely used in tropical and monsoon-dominated countries for its all-day, all-weather imaging ability (Hussain et al. 2023). SAR, unlike optical sensors, is able to penetrate cloud cover and therefore is notably useful for monitoring flood extent during high rainfall events (Shatov et al. 2026).

Backscatter differences from pre- and post-event scattering coefficients were used to extract inundated areas from processed SAR images, where floodwater typically has a low backscatter signature due to specular reflection. This combined flood extent map was subsequently sampled at point locations representing flood (1) and non-flood (0) classes.

After filtering data with missing values in target, we would have 14,988 labeled samples collected. Out of these, 4,109 samples are related to floods having a positive class ratio of 27.42%, and the remaining refers to non-flood conditions.

Spatially stratified random sampling generated non-flood samples defining various regions of the study area ensuring sufficient spatial coverage and minimizing bias. To prevent spatial duplication and clustering effect, special caution was spent to make sure each sample represents unique geography.

Such a flood inventory yields an ample and spatially balanced set of training and evaluation data that can be used for training and evaluating machine learning models under strict conditions of spatial validation.

Flood Conditioning Factors

Flood Event is a result of intricate topographic, hydrologic, climatic and anthropogenic interactions (Dal Seno et al. 2024). Out of a total of twenty-five candidate variables, twelve conditioning factors deemed useful based on their common use in flood susceptibility studies and availability for the study area were selected out and grouped into three categories:

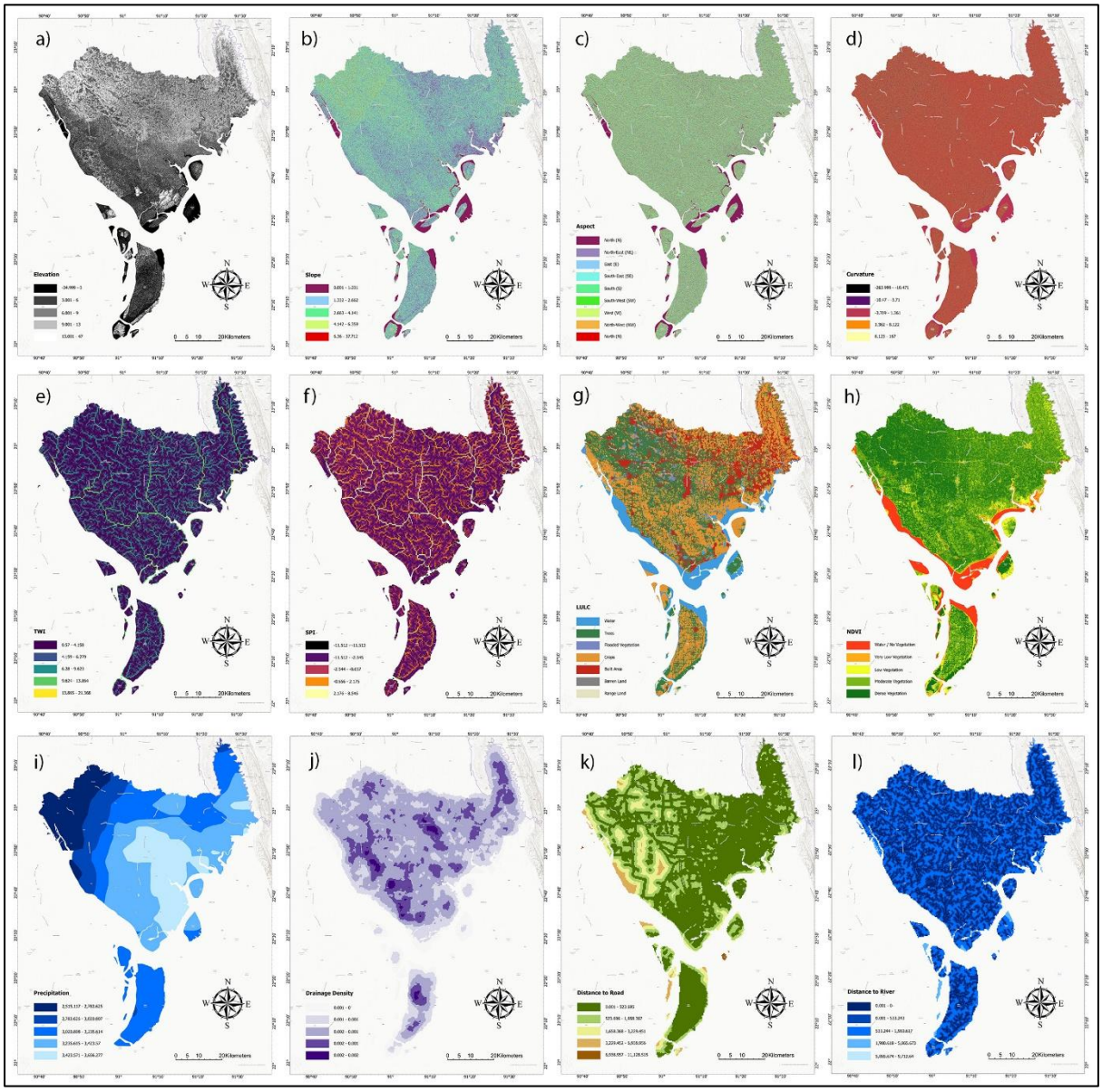

Figure 3: Flood Conditioning Factors: a)Elevation, b)Slope, c)Aspect, d)Curvature, e)TWI, f)SPI, g)LULC, h)NDVI, i)Precipitation, j)Drainage Density, k)Distance to Road, l)Distance to River.

Hydrological Factors

Topographic Wetness Index (TWI): TWI is a measure of the spatial variability and potential accumulation of soil moisture (Murad et al. 2026). It is defined as:

$$TWI = \ln\left(\frac{A_s}{\tan\beta}\right) \quad (1)$$

Stream Power Index (SPI): SPI is a surrogate variable for the erosive power of flowing water, directly computable from slope and flow accumulation (Ghasemian et al. 2022).

Drainage density: This indicates the total length of a stream unit area and its related areas (Das and Lepcha 2019).

Distance to River: The distance from rivers is an important measure of flood risk as the closer a location is to river channels, the higher the chances of flooding during peak discharge periods (Habumugisha et al. 2022).

Environmental and Anthropogenic Factors

Land Use/Land Cover (LULC): LULC affects infiltration, runoff and water retention. Urban or built-up areas often cause surface runoff to escalate, while active vegetated areas increase infiltration and reduce the risk of flooding (Dahim et al. 2023).

Distance to Road: Road infrastructure can also disturb natural drainage patterns and provide barriers to water flow (Abedin et al. 2020).

Normalized Difference Vegetation Index (NDVI): NDVI is a key representor of vegetation density and health. Infiltration and evapotranspiration are higher in areas with a higher NDVI, leading to reduced propensity for flooding (Ren et al. 2024).

Precipitation: Precipitation is a direct driver of flood events (Kumar et al. 2026). Spatial variability in rainfall intensity significantly influences flood occurrence (Kumar et al. 2026).

Table 1: Factors' Data Source and Resolution

Factor	Source of Data	Spatial Resolution (m)
Elevation	https://earthexplorer.usgs.gov/ SRTM DEM	30 m × 30 m
Slope	https://earthexplorer.usgs.gov/ Derived from SRTM DEM	30 m × 30 m
Aspect	https://earthexplorer.usgs.gov/ Derived from SRTM DEM	30 m × 30 m
Curvature	https://earthexplorer.usgs.gov/ Derived from SRTM DEM	30 m × 30 m
SPI	https://earthexplorer.usgs.gov/ Derived from SRTM DEM	30 m × 30 m
TWI	https://earthexplorer.usgs.gov/ Derived from SRTM DEM	30 m × 30 m
NDVI	https://earthexplorer.usgs.gov/ Landsat 8 Level-2 Surface Reflectance	30 m × 30 m
LULC	https://livingatlas.arcgis.com/landcover/ Esri Sentinel-2 Land Cover	10 m × 10 m
Rainfall	https://www.chc.ucsb.edu/data/chirps CHIRPS Precipitation Dataset	5000 m × 5000 m
Drainage Density	https://earthexplorer.usgs.gov/ Derived from SRTM DEM	30 m × 30 m
Distance to River	https://earthexplorer.usgs.gov/ Derived from drainage network (SRTM DEM)	30 m × 30 m
Distance to Road	https://www.openstreetmap.org/ OpenStreetMap Road Network	30 m × 30 m

Modeling and Spatial Cross-Validation

To assess flood susceptibility, eight different classical machine learning models were implemented, including the Decision Tree, Random Forest, Extra Trees, AdaBoost, Gradient Boosting, HistGradientBoosting and two very efficient tree ensemble methods, XGBoost and LightGBM (Arrogante-Funes et al. 2024). Instead of conventional random splitting methods, this study adopts a blocked spatial cross-validation strategy to tackle the issue of spatial data leakage stemming from spatial autocorrelation. The study area was split into 10 spatial folds, with a geographically distinct block of 5000 units from the total number of pixels within this fold used for validation and testing respectively, while all other folds were used for training. Such rigid spatial separation guarantees that model evaluation samples do not correlate with training data in space, avoiding over-optimistic performance estimates and forcing to generalize relationships between flood occurrence and environmental predictors (Dal Seno et al. 2024). All the models were trained on data seamless pre-processing pipeline and its hyperparameter tuning was performed on validation fold to provide a leak free evaluation framework. Finally, SHAP analysis is employed on some models to interpret feature contributions and improve model interpretability.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4)$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Results

Performance Assessment

For continued validation results, it was found that XGBoost (ROC-AUC = 0.6256) performed best, with LightGBM (0.6254) and Random Forest (0.6270) closely behind.

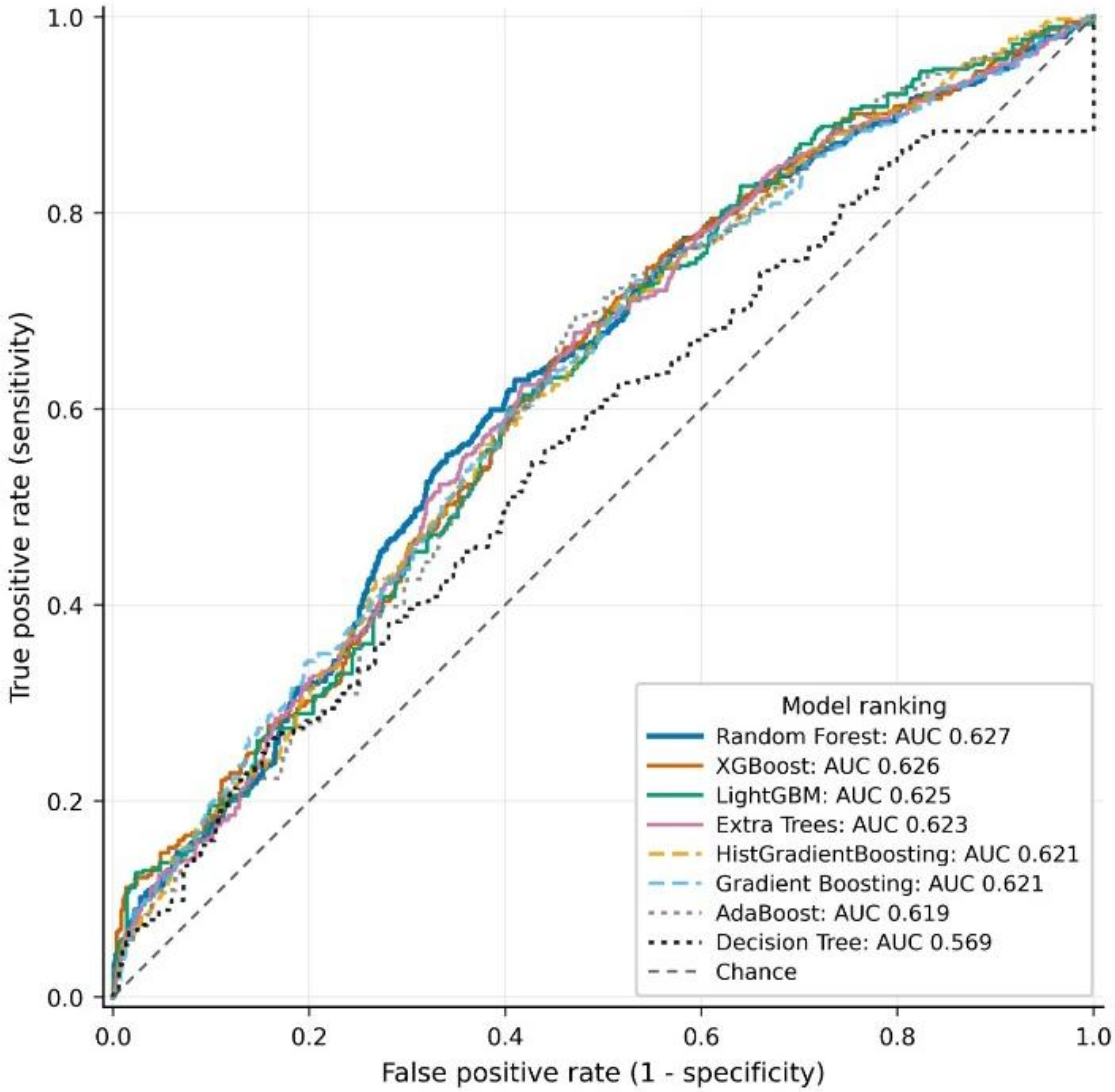

Figure 4: ROC-AUC Curves for models

Notice that XGBoost also yielded the highest average precision and F1-score (which capture its ability for modeling nonlinear relationships and handling class-imbalances), the second-highest ROC-AUC score and lowest root-relative error. Other ensemble models performed just a bit worse but competitively like HistGradientBoosting and Gradient Boosting.

Table 2: Performance Overview

Model	Family	Roc-Auc	Average Precision	Accuracy	Balanced Accuracy	Precision	Recall	F1	Mcc
Random Forest	Tree Ensemble	0.6270	0.3879	0.6025	0.6014	0.3565	0.5990	0.4470	0.1805
XGBoost	Boosting	0.6256	0.4024	0.5718	0.5989	0.3440	0.6574	0.4516	0.1753
LightGBM	Boosting	0.6254	0.3971	0.6331	0.5684	0.3499	0.4289	0.3854	0.1290
Extra Trees	Tree Ensemble	0.6227	0.3738	0.5977	0.5941	0.3505	0.5863	0.4387	0.1676
HistGradient Boosting	Boosting	0.6208	0.3686	0.6501	0.5624	0.3551	0.3731	0.3639	0.1228
Gradient Boosting	Boosting	0.6207	0.3707	0.5970	0.5856	0.3453	0.5609	0.4275	0.1529
AdaBoost	Boosting	0.6193	0.3749	0.5943	0.5877	0.3456	0.5736	0.4313	0.1564
Decision Tree	Tree	0.5689	0.3410	0.4425	0.5371	0.2894	0.7411	0.4163	0.0708

As demonstrated in table 3, ROC-AUC and average precision performance on the test dataset indicates that ensemble methods outperform single-tree models across the board; random forest leads in ROC-AUC performance while XGBoost leads high precision-recall performance.

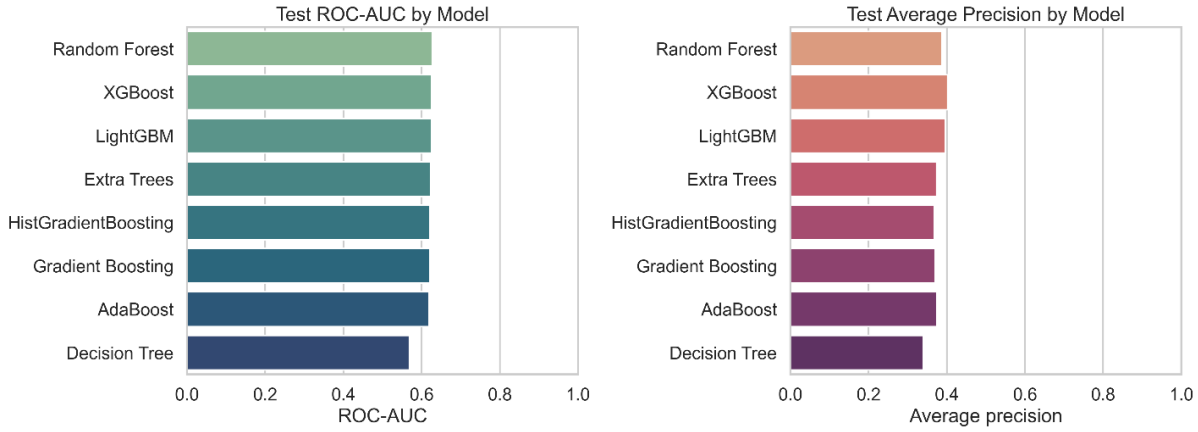

Figure 5: ROC-AUC and Average Precision

In Conclusion Based on Overall Performace Random Forest was chosen as Final Model. While XGBoost had higher average precision and F1-score, Random Forest produced better ROC-AUC and more consistent generalization under spatial evaluation, making it favorable for regional-scale susceptibility mapping.

Model Interpretability (SHAP Analysis)

To enhance the interpretability of the selected model, SHAP (SHapley Additive exPlanations) analysis was conducted on the Random Forest model to quantify the contribution of individual conditioning factors to flood susceptibility predictions. SHAP provides a unified framework

for interpreting complex machine learning models by assigning each feature an important value based on its marginal contribution to the prediction outcome.

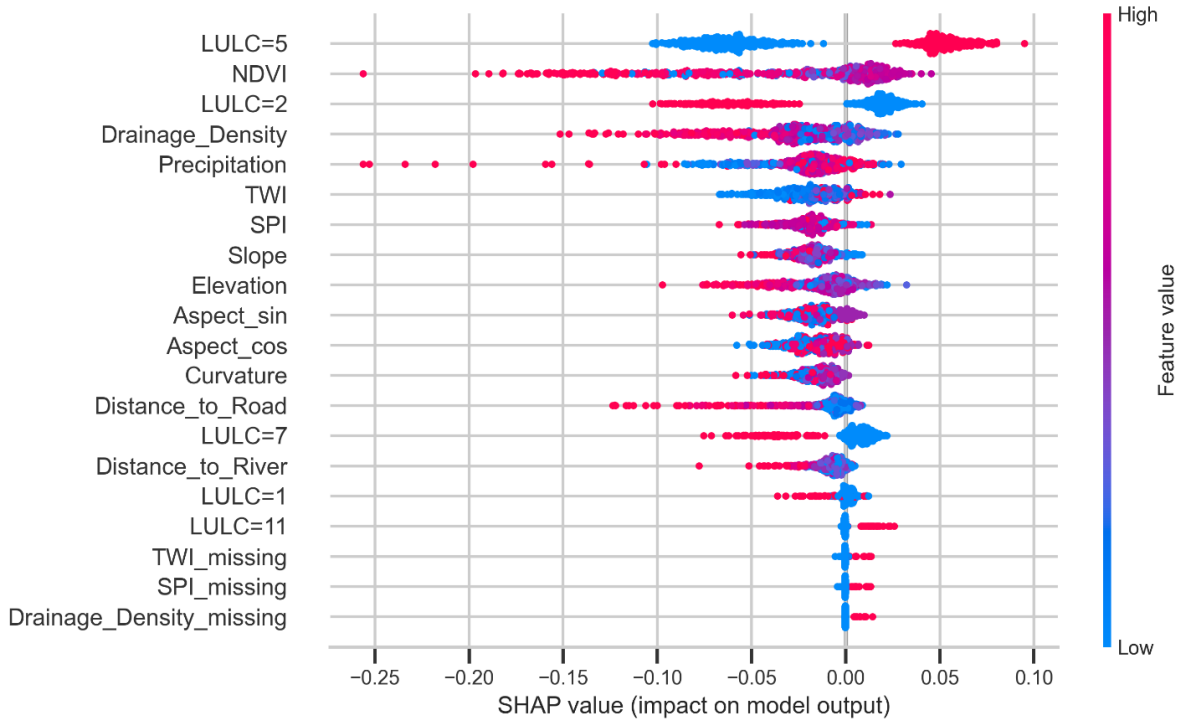

Figure 6: SHAP Result

Figure X shows the SHAP summary plot, features are ranked by mean absolute value and the distribution of SHAP values indicates both simultaneous impact on flood occurrence magnitude & direction. The color gradient (from red to blue) corresponds to feature values: higher states are in red and lower states are in blue.

These findings suggest that among the most important predictors are Land Use/Land Cover (LULC), NDVI and drainage density. Some land-use and land-cover (LULC) classes (e.g., LULC=5 and LULC=2) are positively strong contributors to flood susceptibility, indicating that those types of land use likely low-lying agricultural or built-up areas are more susceptible to inundation, while others have weak positive contributions or appear to reduce the likelihood of inundation.

NDVI has been found to be inversely proportional to flood susceptibility: the more vegetation cover there is, the lower a location is with respect to susceptible areas to floods; likely maybe due more infiltration and less surface run off (Aldiansyah and Wardani 2023).

Within the hydrological parameters, the drainage density, precipitation and TWI are prominent. The use of these variables indicates an increased susceptibility to flooding, because higher values of these variables are associated with a greater accumulation of runoff and more effective water retention (Al-Kindi and Alabri 2024).

Topographic variables like elevation and slope follow expected patterns where lower elevation means higher flood susceptibility and flatter slopes correspond to more flooding risk while higher elevation will mean reduced flooding probability, as well as steeper slopes (Hajji et al. 2025).

Predictions are also influenced by distance-based variables such as distance to rivers and roads (Yuan et al. 2023). There are more complex effects for road distance, as close proximity to

roads actually appears to increase susceptibility even though mere distance from rivers is correlatively less susceptible and areas immediately adjacent a river show the most relative vulnerability likely due to localized changes in drainage pathways (Hajji et al. 2025).

In summary, the SHAP analysis confirms that the model is indeed able to capture meaningful relationships of environmental factors regulating flood occurrence capturing complex interactions between hydrological processes and land-use characteristics that shape flood proneness in Greater Noakhali.

Flood Susceptibility Mapping

Based on the performance assessment, the Random Forest model was selected to generate the final flood susceptibility map for the Greater Noakhali region. The model output, initially obtained as continuous probability values, was reclassified into five susceptibility classes: very low, low, medium, high and very high to improve readability and guide on-ground decision-making.

In Figure 7, it shows that flood risk is significantly higher in the regions of Meghna estuary and nearby distributaries due to merging effects of river discharge and tidal effects. Likewise, areas of high susceptibility inland are also observed in places with high drainage density, low elevation and land use intensity which carry surface runoff and accumulate within the field.

Moderate susceptibility zones are further scattered across transitional landscapes, driven by minor terrain variation and the domain of extensive land use types that influence localized flood processes. On the contrary, low and very low susceptibility areas are mostly located within largely elevated urban regions under better natural drainage condition.

The spatial patterns of susceptibility map are consistent with the SHAP analysis result. Crucial controlling factors (e.g. LULC, NDVI, drainage density and precipitation) exhibit major dominance in flood-prone zones which validates the physical topology of model output results. Low NDVI areas and specific land-use types, for example, have the tendency to closely align with high-susceptibility clusters and regions subjected to higher elevation and slope tend to correspond well with low-risk zones.

Additionally, Random Forest model outputs are spatially coherent and smooth, thus preventing fragmentation and noise in the surface of predictions. This feature improves the applicability of the map to regional-scale planning and flood risk management.

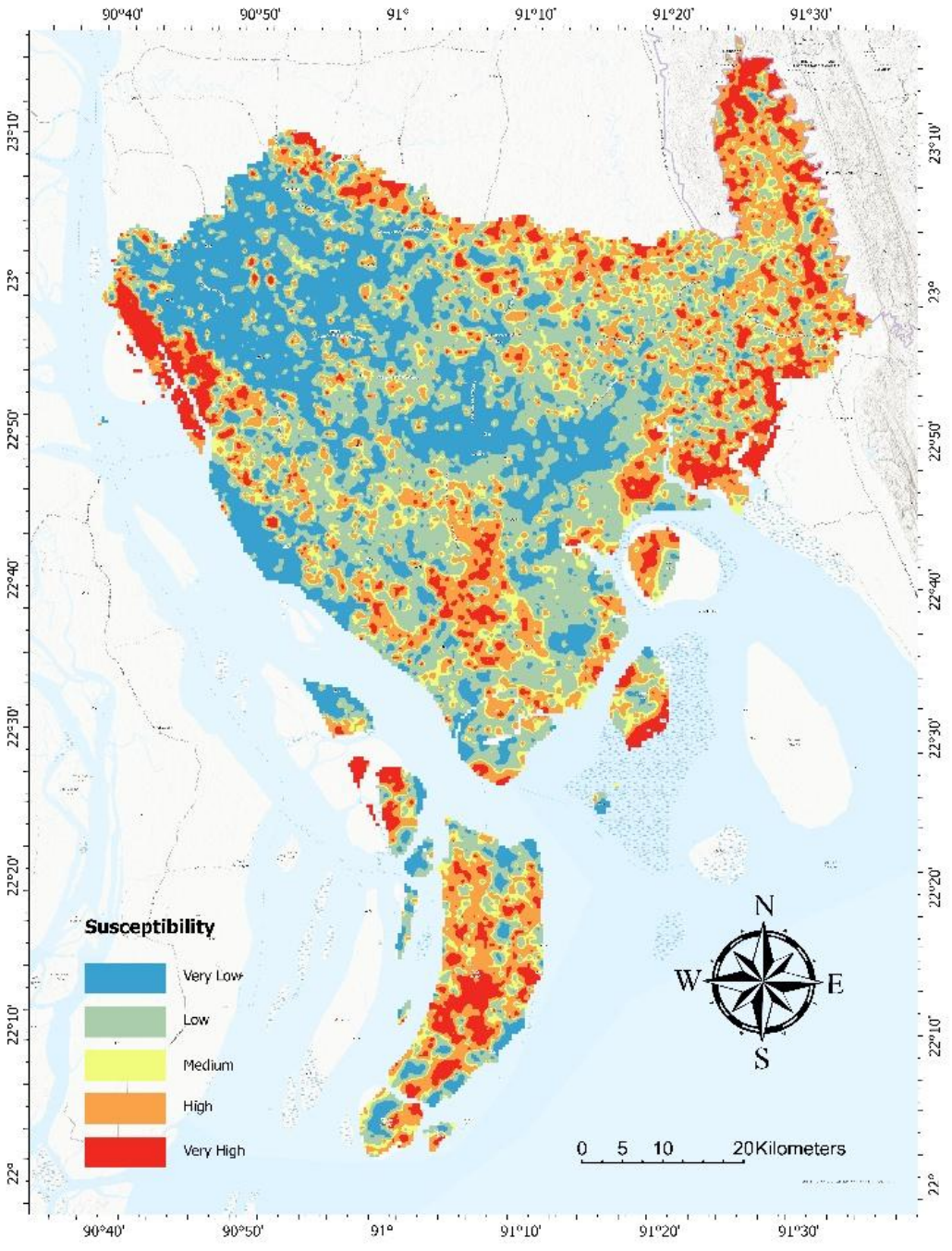

Figure 7: Flood Susceptibility Map

Overall, the generated flood susceptibility map provides a realistic representation of flood-prone areas in the Greater Noakhali region and demonstrates the effectiveness of leakage-aware machine learning in capturing spatial flood dynamics. The map can serve as a valuable tool for land-use planning, disaster preparedness, and climate adaptation strategies in this highly vulnerable coastal region.

Discussion

This study highlights a crucial shift needed in geospatial flood modelling: moving from simple "memorization" to more realistic "generalization". Unlike traditional flood susceptibility research in Bangladesh, which often reports very high ROC-AUC scores (>0.90) with random train-test splits, our findings show more moderate scores (around 0.62–0.63). Although lower

in number, these scores offer a more accurate assessment of model performance in areas not seen during training. Using a blocked spatial cross-validation approach, we reduced bias caused by spatial autocorrelation, enabling the models to learn true physical relationships rather than relying on proximity patterns (Vainio et al. 2021). One reason for the moderate scores is that we considered the dataset imbalanced without creating synthetic data to balance it, because most cases in the natural hazards dataset are inherently imbalanced (Eltehewy et al. 2023).

Among the ensemble architectures, bagging-based Random Forest and boosting-based XGBoost demonstrated superior stability. While XGBoost excelled in precision and F1 score, suggesting a high sensitivity to flood-positive pixels, Random Forest was selected for final mapping due to its superior ROC-AUC (0.6270) and more coherent spatial prediction behavior. This suggests that while boosting models are adept at capturing complex minority-class patterns, bagging-based approaches may offer the robustness required for regional-scale hazard assessment under strict spatial constraints.

The SHAP analysis provided a physically interpretable "glass-box" view into these ensemble models. The dominance of LULC, NDVI, and drainage density highlights the combined influence of anthropogenic modifications and natural hydrological networks (Bhattarai et al. 2025). Specifically, the strong inverse relationship between NDVI and flood susceptibility confirms that vegetation cover acts as a natural buffer by enhancing infiltration and slowing surface runoff. Furthermore, the spatial alignment of high-susceptibility zones with the Meghna estuary and low-lying coastal tracts confirms the model's ability to capture the dual influence of fluvial discharge and tidal propagation characteristic of deltaic environments (Jamei et al. 2022).

Despite the rigor of the leakage-aware framework, limitations remain. The reliance on a single flood event (August 2024) and the 30m resolution of the SRTM DEM may omit hyper-local drainage nuances. Future research should explore multi-temporal inventories and integrate high-resolution soil moisture data to further refine these predictive surfaces.

Conclusion

This study successfully establishes a stringent, leakage-aware machine learning framework for flood susceptibility mapping in the Greater Noakhali region of Bangladesh. By moving beyond standard random validation techniques, this research directly addresses the pervasive issue of spatial data leakage that plagues geospatial modelling, often leading to misleading and over-optimistic hazard assessments. Our comparative evaluation confirms that tree-based ensemble models, specifically Random Forest and XGBoost, deliver credible and stable flood-risk predictions under strict spatial holdout validation in a dynamic deltaic landscape. Integrating Sentinel-1 SAR imagery with SHAP-based interpretability yielded a transparent methodology that identified hydrological density, vegetation cover, and land-use patterns as the foremost drivers of inundation. The resulting susceptibility map accurately delineates critical high-risk zones concentrated along coastal and riverine corridors, supplying a realistic and operationally viable decision-support tool for land-use planning and early warning systems. Ultimately, this research underscores the absolute necessity of adopting spatially robust validation as a foundational standard for geospatial AI, ensuring the reliability of flood risk interventions and climate adaptation strategies in highly vulnerable regions.

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