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Enhancing flood susceptibility mapping in Meghna River basin by introducing ensemble Naive Bayes with stacking algorithms

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ABSTRACT

This article intends to assess flood susceptibility mapping in Meghna River basin (MRB) and identified flood susceptible regions using three benchmark models including random forest (RF), support vector machine (SVM) and bagging with Naïve Bayes (NB) stacking ensemble algorithms (e.g. RF-NB; SVM-NB and Bagging-NB). The flood sample was partitioned into a training set (70%), and a validation set (30%), and the capability of prediction of flood-influencing variables was quantified by the multi-collinearity test. Several statistical metrics and Area Under the Receiver Operating Characteristics (AUROC) technique were applied to evaluate the techniques' performance and precision. The outcomes showed that the significant factors influencing flash floods include rainfall, distance from the river and river density. The NB-Bagging outperforms (≈ a prediction accuracy of 95.1%) than other models in predicting the risk of flooding in the MRB. Results obtained from NB-Bagging showed that 12% and 21% of the basin were demarcated as having high and very high flood susceptibility, respectively. This article identified that rainfall and distance from the river were the two most driving factors influencing flooding in the MRB. The present work will aid decision-makers and local authorities determine flood

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conditioning problems and efficient flood risk management to lessen the consequences.

1. Introduction

Flood is a natural hazard that can seriously devastate people's livelihood, socioeconomics, and ecosystems (Costache, Crăciun, et al. 2024; Vahid Razavi-Termeh et al. 2025). Flood events have emerged as one of the most frequent natural hazards around the globe (Islam et al. 2024). Every year, about 20,000 people are killed by floods worldwide (Ruidas et al. 2024). Flood is responsible for more than 90% of property damages and disruption of life throughout Asia (Kumar and Jha 2024; Shah and Ai 2024). Therefore, flood susceptibility mapping (FSM) studies concentrated on basins or regional scales are crucial for mitigating and controlling potentially hazardous conditions.

The fundamental concept of FSM relies on the linkage among flood events and driving factors to build a flood susceptibility prediction model, which produces a spatial map of flood susceptibilities (Li and Hong 2023; Liu et al. 2025). Developing a comprehensive strategy for understanding flood potential requires the examination of multiple conditioning factors that affect flood susceptibility (Widya et al. 2024). The identification of the most relevant and influential conditioning factors associated with flood formation is essential for FSM using machine learning techniques (Mia et al. 2023). The capacity to forecast complex relationships within large data sets presents a valuable method for integrating various parameters, including rainfall, land use, elevation, soil properties, and geological factors (Liu et al. 2025). Factors associated with rainfall significantly influence the flood events (Islam et al. 2023). However, factors such as slope, plan curvature, and elevation are less critical for FSM tasks. Floods typically occur over extensive areas, representing a regional phenomenon; therefore, the spatial scale of factors conditioning floods must be taken into account (Ruidas et al. 2024). The limitation of existing flood conditioning factors may result in susceptibility outcomes from machine learning models exhibiting a generalization effect, thereby weakening their capacity to identify flood-prone areas in regions with minor elevation variations (Costache, Pal, et al. 2024). Improving prediction accuracy necessitates the exploration of factors such as rainfall, distance from the river and river density, which account for flood flow accumulation characteristics and enhance FSM (Halder et al. 2024). Thus, multiple key factor analysis facilitates a nuanced understanding of the interactions among these variables and their effects on the FSM.

Research on predicting FSM has utilized various approaches, primarily statistical methods, physically based models and machine learning techniques (Costache et al. 2023; Liu et al. 2025). Statistical methods, such as frequency ratio (Chowdhury 2024), are conventional approaches grounded in linear modeling that necessitate severe statistical assumptions. The complex mechanisms of flood disasters often challenge these assumptions (Shah and Ai 2024), leading to decreased accuracy in the results (Costache et al. 2023). Physically based models can simulate inundation areas and depths through the calculation of overland flood extents (Ghosh et al. 2023). The intricate architecture of these physically based models necessitates sophisticated input data and substantial computational resources (Diaconu et al. 2024), thereby constraining their applicability in data-scarce and extensive regions (Costache, Pal, et al. 2024). Machine learning models are being developed for FSM to address these challenges, owing to their superior predictive capabilities (Vahid Razavi-Termeh et al. 2025). The models discussed encompass traditional machine learning techniques such as support vector machines (SVMs) (Hao et al. 2024), Naive Bayes (Habibi et al. 2023), Bagging (Chowdhury et al. 2025) and decision trees (Akay 2024), ensemble methods including random forests (Riaz and Mohiuddin 2025) and extreme gradient boosting (Bammou et al. 2024), as well as deep learning approaches such as convolutional neural networks (Hao et al. 2024) and multilayer perceptron (Costache et al. 2022). Recent advancements in FSM have emphasized the importance of integrating machine learning models with diverse data sets to enhance prediction accuracy and address regional variations in flood potential (Costache, Arabameri, et al. 2024; Mangkhaseum et al. 2024). Studies by Islam et al. (2021) and Prasad et al. (2022) have highlighted the critical role of hybrid ensemble models in improving flood prediction capabilities, while Costache, Arabameri, et al. (2024) demonstrated the efficiency of combining machine learning techniques with remote sensing data for precise FSM assessments. Similarly, Demissie et al. (2024) and Zhao et al. (2024) have underscored the importance of advanced statistical validation methods, such as ROC-AUC and Taylor diagrams, to ensure the robustness of model outputs. The operational mechanism of FSM utilizing machine learning involves establishing nonlinear relationships between flood triggers and environmental factors derived from historical flood data sets (Costache et al. 2022; Gholami et al. 2025). Nonetheless, limited research has concentrated on improving the precision of FSM by examining flood conditioning factors. The accuracy of historical flood inventory and flood conditioning factors directly influences the performance of machine learning models (Ruidas et al. 2024).

Bangladesh has faced severe floods historically due to significant rainfall in the upper and lower Ganges–Brahmaputra–Meghna (GBM) River basins (Abrar et al. 2024). Among three river basins, the Meghna River basin is highly susceptible to flooding in the monsoon season, as water flow exceeds the capacity of rivers, canals, beels, haors, and low-lying areas, leading to extensive inundation and damage to crops, homes, roads, and other properties (Chowdhury 2024). In June 2022, significant rainfall resulted in river overflow and substantial flooding (Kader et al. 2024). The overflow caused the inundation of roads and highways, resulting in the loss of several lives of individuals who were trapped. In 2022, a significant flash flood commenced in May, followed by a second wave in mid-June, impacting approximately 7.2 million individuals (Rudra and Sarkar 2023). Flash floods in the MRB exhibit rapid onset, significant intensity, lack of warning, and particular geographic conditions, triggering them some of the deadliest natural disasters (Rifath et al. 2024; Chowdhury et al. 2025). For example, several studies have been conducted in the GBM River basins to assess the FSM in the Padma River basin (Mia et al. 2023; Abrar et al. 2024), Teesta River basin (Islam et al. 2021; Sarkar et al. 2022) and Brahmaputra River basin (Mia et al. 2023). Nonetheless, hardly such research has been conducted to assess the FSM in the MRB using hybrid ensemble machine learning models and extensive field surveys. Hence, creating an FSM and identifying factors influencing flood events for the MRB using appropriate methods are crucial for flood management in this basin.

Based on the discussion above, this study has raised the following questions: (a) How is the performance of the proposed ensemble Naïve Bayes algorithms for FSM in the MRB area? (b) What are the factors that influence flood susceptibility in the study area? Therefore, the prime objectives of the present research are (a) to explore and assess the performance of the ensemble Naïve Bayes with stacking algorithms (NB-RF, NB-SVM and NB-Bagging) models to predict FSM, and (b) to reveal the factors that affect flood susceptibility in the MRB area to generate FSM.

The novelty of this research lies in its development of an advanced benchmark methodology to create highly accurate FSM for a flood-prone region in northeastern Bangladesh. For the first time, the Meghna River Basin has been mapped precisely using an innovative integration of RF, SVM, Bagging and stacking ensemble NB models. The study employs five robust statistical indicators, including the AUC Curve, alongside several other indices, to validate the accuracy of its results. This approach not only advances FSM techniques but also provides valuable insights for local and regional governments and policy-makers, enabling the formulation of effective measures to mitigate the detrimental impacts of flash floods and enhance disaster management strategies.

2. Materials and methods

2.1. Study area

The Meghna River Basin (MRB) is a significant river system in South Asia, including regions of eastern Bangladesh. It is an essential component of the Ganges–Brahmaputra–Meghna (GBM) river system, constituting one of the biggest global river networks (Figure

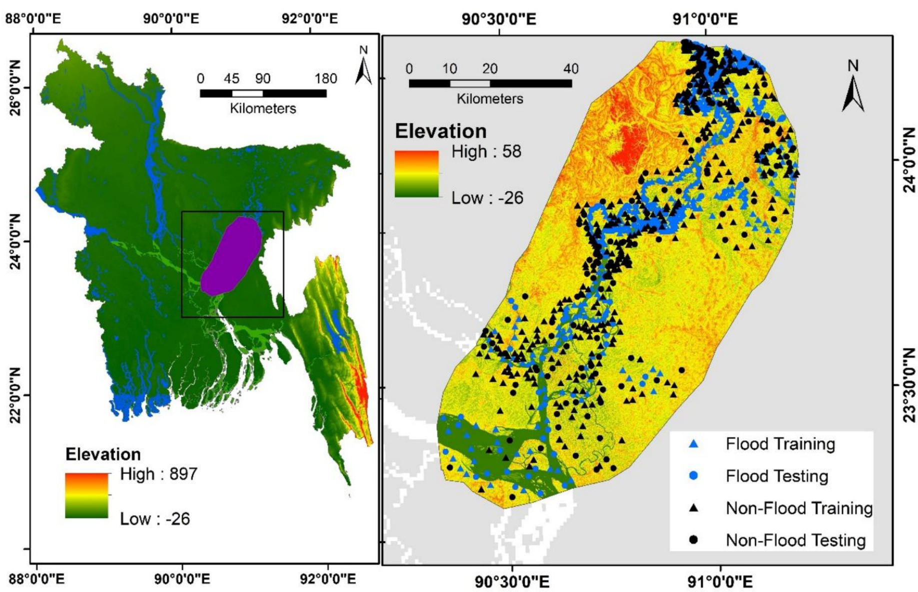

Figure 1. Study area map showing the Meghna River basin, Bangladesh.

1). The MRB comes from the Barak River in Assam, a northeastern state of India, which divides into two distributaries, the Surma and the Kushiyara, in the Sylhet district of Bangladesh, which subsequently merge to create the MRB. Significant tributaries of northeastern Bangladesh are the Surma, Kushiyara, Manu, Dhalai and the Haor systems (wetlands) (Brammer 2016). The MRB converges with the Ganges and Brahmaputra rivers downstream to create the Bengal Delta, the most significant delta globally, before discharging into the Bay of Bengal (Chowdhury 2024).

The basin exhibits numerous landforms, including expansive floodplains in Bangladesh, including wetlands, low-lying flood-prone regions and heavily inhabited plains (Rudra and Sarkar 2023). The MRB has a tropical monsoon climate characterized by dry and wet periods. Annual precipitation exhibits considerable variation across the basin, with some areas, particularly in Meghalaya, receiving over 5,000 mm, ranking among the planet's wettest locations (Khairul et al. 2022). The MRB facilitates agriculture, fishery, navigation and hydropower generation. Its wetlands and abundant wildlife make it an ecological hotspot, while its deltaic plains rank among the most productive areas globally. Nonetheless, the basin has issues like climate change, water management conflicts and the effects of population increase. Flood occurs every year in this basin, with the worst flood happening on May 2022 during the monsoon season (Figure 2). The current study only examined the middle and lower portions of the MRB region in Bangladesh.

2.2. Methodology

The proposed methodological flowchart (Figure 3) shows the summary of the current study. Flood inventory, identification of flood conditioning parameters and creation of a geospatial database, using the multi-collinearity technique, as well as FSM techniques by introducing ensemble Naive Bayes with stacking algorithms (NB-RF, NB-SVM and NB-Bagging) were included in the proposed framework.

2.2.1. Flood inventory map

Association between floods and the components that influence to occur floods is established by the map of flood inventory. Using the following data sources for the years 1988 through 2021, we developed a flood inventory database including (i) historical flood data set from government along with private organizations (Rahman et al. 2021; Islam et al. 2023), (ii) literature and (iii) Landsat 5-8, Sentinel-1 and MODIS satellite pictures the inventories were prepared by binary classification, with floods assigned to (30 m 30 m) grid cells as well as non-floods assigned to '0′ (Rahman et al. 2021).

2.2.2. Database splitting

The resulting flood inventory was randomly partitioned in two separate data types: 70% of the data from 364 flood prone areas was applied to develop the algorithm, while 30% of the data from 156 flood-prone areas was utilized to confirm the techniques (Islam et al. 2023). It is assumed to collect negative samples or non-flood sites near flood areas. In order to prevent preference, earlier studies were suggested using the equivalent amount of non-flood data points as definitive or flood data set (Diaconu et al. 2024) according to the

Figure 2. Recent flash floods in Meghna River Basin, northeastern Bangladesh (source: field survey, June 20, 2022).

map of topography, information of flood history and field observation (Islam et al. 2021). Furthermore, a corresponding number of non-flood areas among the MRB were taken for validation (30%) and training (70%) (Rahman et al. 2021).

2.2.3. Flood conditioning parameter preparations

Following 18 conditioning factors were assessed based on previous studies (Islam et al. 2021; Mia et al. 2023; Kader et al. 2024) as well as the watershed characteristics

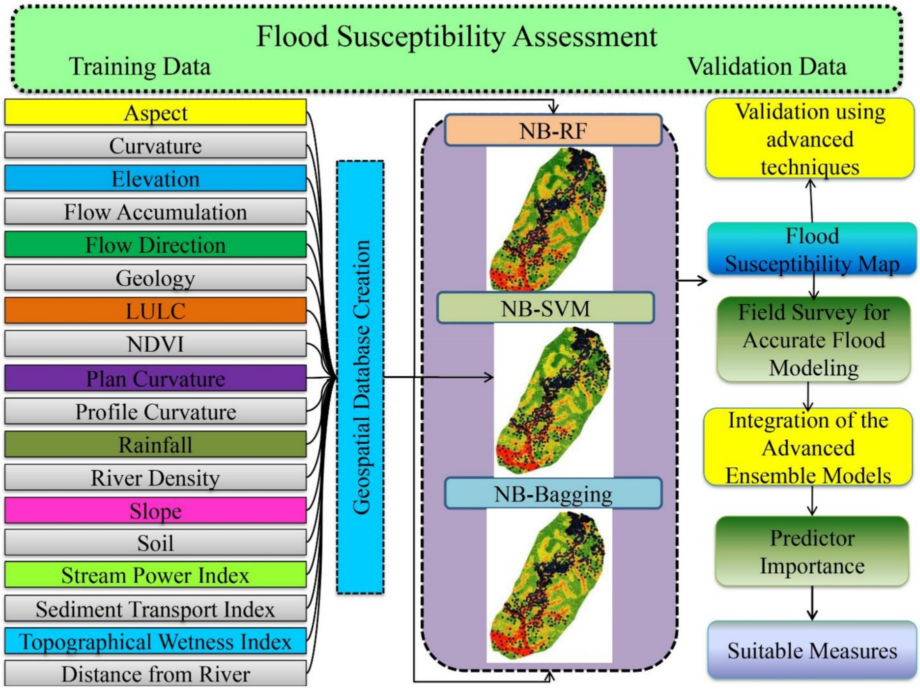

Figure 3. The proposed methodology flowchart adopted for this study.

of MRB regions: aspect, curvature, elevation (m), flow accumulation, flow direction, geology, land use and land cover (LU/LC), normalized difference vegetation index (NDVI), plan curvature, profile curvature, mean annual rainfall (mm), river density (RD), slope angle (degree), soil, stream power index (SPI), sediment transport index (STI), topographic wetness index (TWI) and distance to the rivers (m). Figure 4 shows the information on the flood-influencing factors, aspect, angle, slope, elevation curvature, profile and plan curvature, TWI, STI, SPI, distance to rivers, River Density flow accumulation and direction, that were extracted by using 30-m resolution ALOS-digital elevation model (DEM). The required information was extracted *via* https://chrsdata.eng.uci.edu/. The map illustrating mean annual rainfall was created by the Kriging spatial interpolation tool (https://chrsdata.eng.uci.edu/) in the GIS environment from 2000 to 2020. Kriging interpolation is strongly suggested if the MRB region of the sampling site is insufficient (Mia et al. 2023). NDVI and land cover map was collected through the site (https://earthexplorer.usgs.gov/). Maps of Geology (1:100,000) were obtained through the website of USGS at (https://www.usgs.gov/programs/energy-resources-program). The Food and Agriculture Organization of the United Nations (https://www.fao.org) produced a soil texture map (scale of 1:5000 000). It is worth mentioning that decreasing the inconsistency related to various spatial resolutions is a study endeavor. About 30 m constant grid size was predicted by satisfactory outcomes; thus, all variable components were sampled (Ghosh et al. 2023). Furthermore, strong-resolution spatial variables like DEMs as well as their variations do not considerably increase mapping accuracy of the FSM (Rahman et al. 2021). In our study, the rainfall map was generated using data from 35 meteorological stations distributed across the MRB, with historical records spanning 20 years (2000–2020).

The spatial distribution of these stations was sufficient to ensure reliable Kriging interpolation and provide an accurate representation of rainfall variability across the region. However, this study identifies that increasing the density of meteorological stations could further improve the precision of the interpolation and the overall reliability of the rainfall map. This clarification has been incorporated into the manuscript to address the comment and enhance its comprehensiveness.

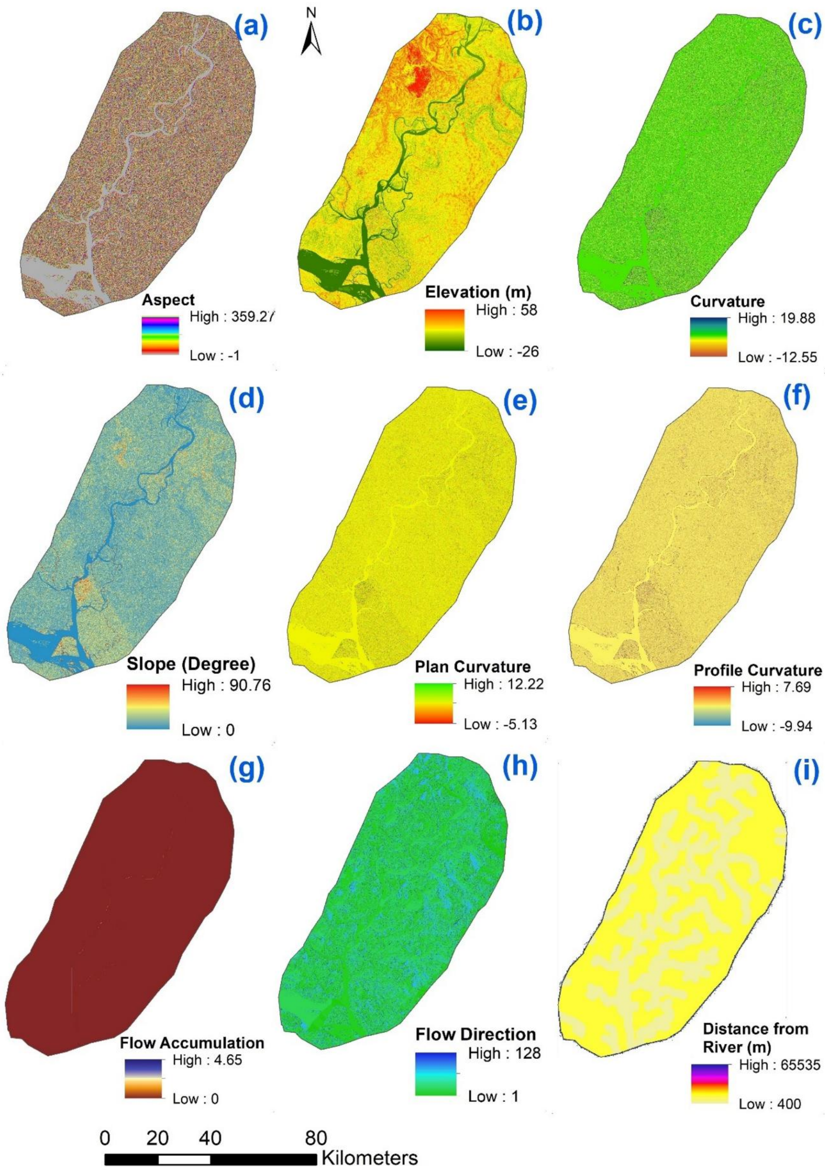

Figure 4. Conditioning parameters including (a) aspect, (b) elevation (m), (c) curvature, (d) slope angle (degree), (e) plan curvature, (f) profile curvature, (g) flow accumulation, (h) flow direction, (i) distance to the rivers, (j) river density (RD), (k) mean annual rainfall (mm), (l) soil, (m) stream power index (SPI), (n) topographic wetness index (TWI), (o) sediment transport index (STI), (p) geology, (q) land use and land cover (LU/LC), and (r) normalized difference vegetation index (NDVI).

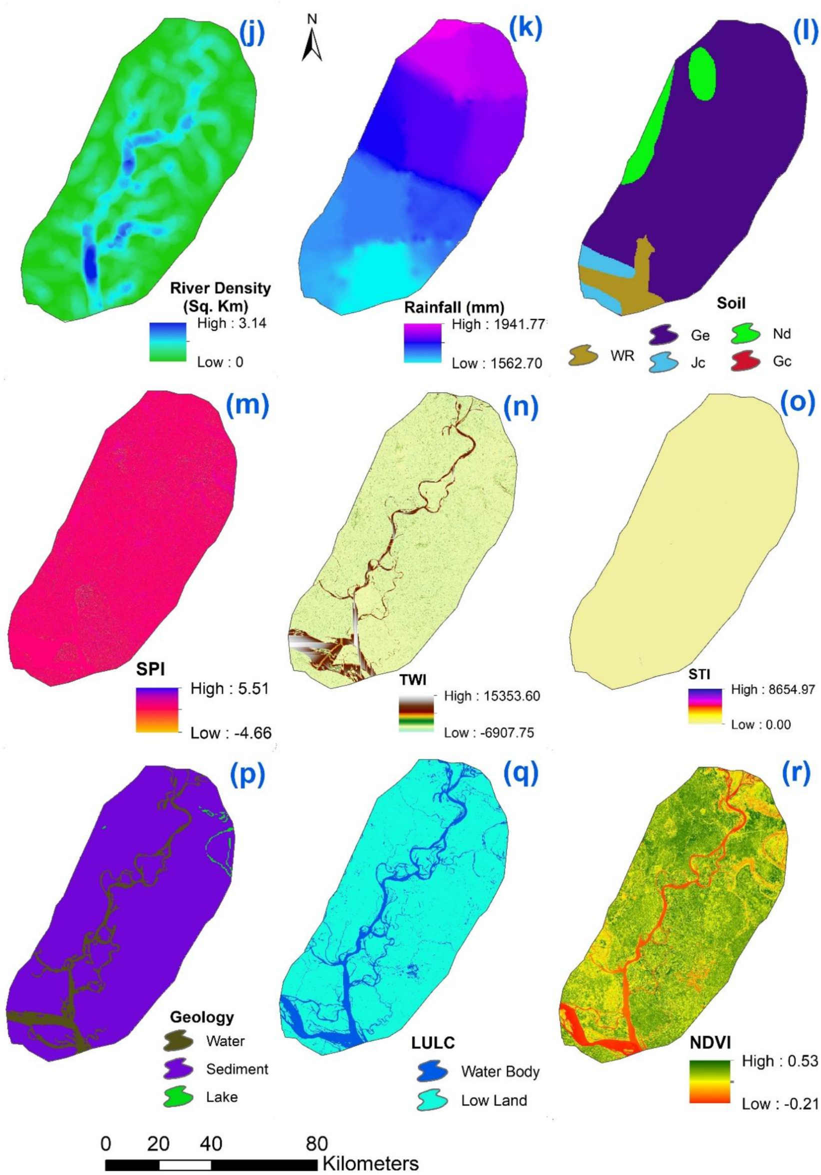

Figure 4. Continued.

2.3. Method for susceptibility of flood mapping models

2.3.1. Naive Bayes

Naive Bayes is a statistical classification technique and a special, simple case of a Bayesian Network where single node is defined as feature and other attribute nodes, with the assumption, feature nodes are not dependent of one another (Habibi et al. 2023). It is one of the conventional machine learning algorithms that is based on probability theory (c) (Costache et al. 2022).

On the basis of the intrinsic properties of probability (particularly probability division), the Naive Bayes approach provides favorable outcomes after initial practice. Bayes proposes a method for calculating the posterior probability, P (c | x), using the prior probabilities, P (c), P (x) and P (x | c). The Naive Bayes classifier considers the influence of the predictor cost (x) on a particular category (c) of the various predictor values to be neutral. This is referred to as conditional independence in the following Equations (1) and (2):

$$P(c|x) = \frac{P(c|x)*P(c)}{P(x)} \tag{1}$$

$$P(c|X) = P(x_1|c)*P(x_2|c)*....*P(x_n|c) \tag{2}$$

Here, $P(c|x)$ is the posterior probability of the target, $P(c)$ is the prior probability of the class and $P(x)$ is the prior probability of the predictor (Janizadeh et al. 2021).

2.3.2. Random forest

Random forest (RF) model is an ensemble learning algorithm that uses a large number of decision trees to explain the spatial correlations between the incidence of floods and the associated classification and regression parameters (Kumar and Jha 2024). Breiman pioneered the RF technique, which depends on random resampling of the input training data (Tang et al., 2021). The incorporation of a massive number of trees makes it one of the most powerful ensemble learning models. RF has a number of advantages, including its ability to be unaffected by noise, that incorporate a wide range of data and identify the most critical factors (Youssef et al. 2022).

Each decision tree in the RF learning technique is instructed using a random sample drawn from the training data set. All of the predictive variables used to divide nodes are also chosen randomly. The RF approach requires the determination of two properties: the number of selected variables for each decision tree (mtry) and the number of generated decision trees (DTs) (ntree) (Janizadeh et al. 2021). However, a large value of Ntree may lengthen the modeling process, whereas small values result in error. The primary steps of RF technique are to (1) explore the primary data set employing bootstrap to make subsets of equal size, (2) apply subsets to build decision trees, as well as (3) merge the prediction or classification findings of all the decision trees to get the concluding outcomes (Prasad et al. 2022).

2.3.3. Support vector machine

The SVM is a recent machine-learning technique based on statistical learning (Islam et al. 2023). The SVM model is frequently used in FSM (Saha et al. 2021; Seleem et al. 2022). The primary goal of this algorithm is to find the best possible hyperplane to separate the flooded class from the non-flooded class (Seleem et al. 2022). It is a supervised classification method that uses the training data to construct a separating hyperplane between two distinct classes. The classification strategy increases the distance between the class and the classification hyperplane to reduce noise and improve generalization (Youssef et al. 2022). Using the statistical learning theory as its foundation, the SVM transforms the data set into a high-dimensional feature space using nonlinear transformers in order to provide the most accurate hyperplane. The best hyperplane is possible when the margins between the problem's designated classes are at their maximum (Arabameri et al. 2022). An appropriate mathematical kernel function (such as a polynomial, sigmoid, radial basis function (RBF) or linear) must be chosen to transform the nonlinear data into linear data in order to obtain effective SVM training and high classification accuracy (Talukdar et al. 2020). The nonlinear classifier or regression line properties of the RBF kernel function make it more common in SVM than the others (Islam et al. 2021). The RBF is as follows Equation (3):

$$K(x,y) = \exp(-\gamma P X_i - X_j P^2) \tag{3}$$

Here, γ is the gamma operator. The way γ is estimated influences the results. The training set of data was the same as that used for other models, and a gamma operator of 0.9 was chosen (Shahabi et al., 2020).

2.3.4. Bagging

Bootstrap aggregating is called "Bagging" by Breiman, who is a famous American statistician (Talukdar et al. 2020). It is one of the earliest methods of creating many sub-data sets and combining distinct base classifiers (Pham et al. 2021). It is one of the most widely used techniques for creating ensembles. Each training set in Bagging is formed by creating a bootstrap replica of the primary training set (Chowdhury et al. 2025). The Bagging method can reduce the classification variance, resulting in better ensemble model performance. Bagging is generated in bootstrap subsets using an initial training data set with sizes equal to the actual training data set (Ghosh et al. 2023). A base classifier is trained using these bootstrapped sub-data sets, also referred to as bootstrapped sub-data. The results are then added by utilizing the majority voting procedure, which is denoted by Equation 4:

$$\beta(x) = \underset{y \in \{-1,1\}}{\arg} \sum_{b} \delta_{sgn\left(C^b(x)\right).y} \tag{4}$$

Here, $\delta_{i,j}$ is the Kronecker symbol, $C^b(x)$ represents the constructed classifier and $y \in \{-1, 1\}$ is the class labels (i.e. flood and unflood) (Pham et al. 2021).

2.4. Stacking ensemble

The stacking approach is a widely used method in heterogeneous ensemble learning (Islam et al. 2021). It involves using metamodels to combine numerous sub-classifiers, resulting in strong prediction conforming to the aggregations of those sub-classifiers (Islam et al. 2023). An important aspect to mention, three steps are involved in developing and implementing the stacking ensemble. The process involves three main steps: (i) training the primary classifier techniques, namely Bagging, RF and SVM (Costache, Crăciun, et al. 2024); (ii) collecting the features from the base classifiers' outputs creates a fresh data of training and (iii) training the meta-classifier technique using NB. Stacking ensembles allow for the simultaneous estimation of computed errors for all base classifiers. This is achieved by applying the fundamental learning processes and reducing residual errors using meta-learning procedures.

2.5. Multi-collinearity test assessment

The multi-collinearity test was performed in this research to eliminate influencing variables from the model in order to reduce the possibility of errors. Here, the Variance Inflation Factor (VIF) and tolerance are important in determining the errors. The VIF and tolerance were calculated using Equations (5) and (6).

$$\text{Tolerance} = 1 - r^2 \tag{5}$$

$$VIF = 1/\text{Tolerance} \tag{6}$$

A VIF number greater than 10 and a tolerance value of 0.1 suggest a multi-collinearity problem (Halder et al. 2024). This investigation's criteria for forecasting flood susceptibility was less than 5 (VIF value).

2.6. Statistical metrics

Each constructed model's accuracy and predictive efficacy on the testing data were examined using predefined validation criteria (Saha et al. 2021). In the current research, the reliability of the employed machine learning models was evaluated using five statistical measures: sensitivity, specificity, negative-predictive value (NPV), positive-predictive value (PPV), as well as receiver operating characteristics curve (ROC)-AUC analysis (Talukdar et al. 2020). The four statistical measures, true-negative (TN), true-positive (TP), false-negative (FN) and false-positive (FP), were used to determine the validation approaches. The effectiveness of the above-mentioned models is proportional to the outcomes of the various validation strategies, where better performance was seen for larger numbers (Ruidas et al. 2022).

Specificity (Sp) is the rate of true negatives and is conventionally stated as a function of true negatives (TN) and false positives (FP) in the following Equation (7):

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{7}$$

Sensitivity (Sn) equals the true positive rate and is represented as a function of true positives (TP) and false negatives (FN) (Saha et al. 2021) in the following Equation (8):

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

PPV is the percentage of units for the true conditions with the expected positive outcome in the below Equation (9).

$$\text{PPV} = \frac{\text{TP}}{\text{FP} + \text{TP}} \tag{9}$$

Similarly, NPV can be written as follows in Equation (10):

$$\text{NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{10}$$

The ROC-AUC curve area falls in the range 0.5 and 1, representing a range of model performance (Talukdar et al. 2020). The values of two statistical indices, 'sensitivity' and 'specificity' can be plotted on the ordinate and abscissa, respectively, to generate this curve. The following Equation (11) was used to determine the ROC-AUC approach:

$$\text{AUC} = \sum\nolimits_{k=1}^{n} (X_{k+1} - X_k)(S_{k+1} - S_k - S_k/2) \tag{11}$$

AUC denotes the area under the curve, and S_k and X_k signify sensitivity and specificity, respectively.

3. Results

3.1. Multi-collinearity assessment

The multicollinearity assessment revealed that all conditioning factors, except for soil, exhibited VIF values below the commonly accepted threshold of 5. The soil factor displayed a VIF value of 5.208, which slightly exceeds the threshold. However, it was retained in the analysis due to its critical role in influencing flood susceptibility through its impact on infiltration and runoff characteristics. Previous studies (Lin and Billa 2021; Islam et al. 2021) have noted that VIF values up to 10 may still be acceptable, particularly when the variable is highly relevant to the phenomenon being studied. For instance, Wang et al. (2023) and Khosravi et al. (2019) has noted that VIF values up to 10 may still be acceptable, particularly when a variable plays a critical role in the studied phenomenon. Additionally, the ensemble machine learning models employed in this study are designed to handle multicollinearity effectively, as demonstrated by Islam et al. (2021) and Arabameri et al. (2020). This inclusion ensures the comprehensiveness and accuracy of the model. The analysis confirmed that plan curvature exhibits a VIF value of 1.122 and a tolerance value of 0.891, well within acceptable thresholds. These findings demonstrate that plan curvature does not suffer from multicollinearity and is adequate for mapping flood susceptibility. This correction enhances the model's robustness and ensures consistency in the selection of conditioning factors.

3.2. Flood susceptibility assessment

The three stacking machine learning models (NB-RF, NB-SVM, and NB-Bagging) were used to produce FSM for each pixel in the MRB. Based on the testing findings, the NB-Bagging model was tested to be the best-performing prediction technique among each benchmark techniques for data sets. ArcGIS 10.3.1 offers to reclassify the FSM, for instance, manual methodology, equal interval, quantile, natural break, regular interval. Within these strategies, quantile as well as natural break techniques were frequently described in analyzing of FSM (Ruidas et al. 2022; Halder et al. 2024). One of the best reclassifying techniques is quantile that can impart robust outcomes compared to other reclassifying models. Hence, the quantile reclassifying strategy was used for this research. The FSM have been demarcated into five classes: very low, low, moderate, high and very high (Figure 5). The quantile classification method was chosen for its simplicity and effectiveness in dividing the FSM into discrete classes, facilitating interpretation and practical application for policy-makers and stakeholders. This approach ensures an equal distribution of areas across categories, making it easier to identify and prioritize high-risk zones. While we acknowledge the potential subjectivity of this method, its clarity and accessibility make it a valuable tool for flood risk management in diverse regions.

The three FSM techniques with five categories are shown in Figure 5. The areal coverage of very high to high flood susceptible regions in the NB-RF model was 1397.69 and 566.63 km^2, respectively, and these zones were primarily situated southern section of the MRB. The remaining part of this area was associated with moderate, low, as well as very low susceptibility zones, while areal coverages were 660.17 (11.01%), 970.17 (16.18%) and 2401.43 km^2 (40.05%), respectively (Figures 5(a) and 6). The very high,

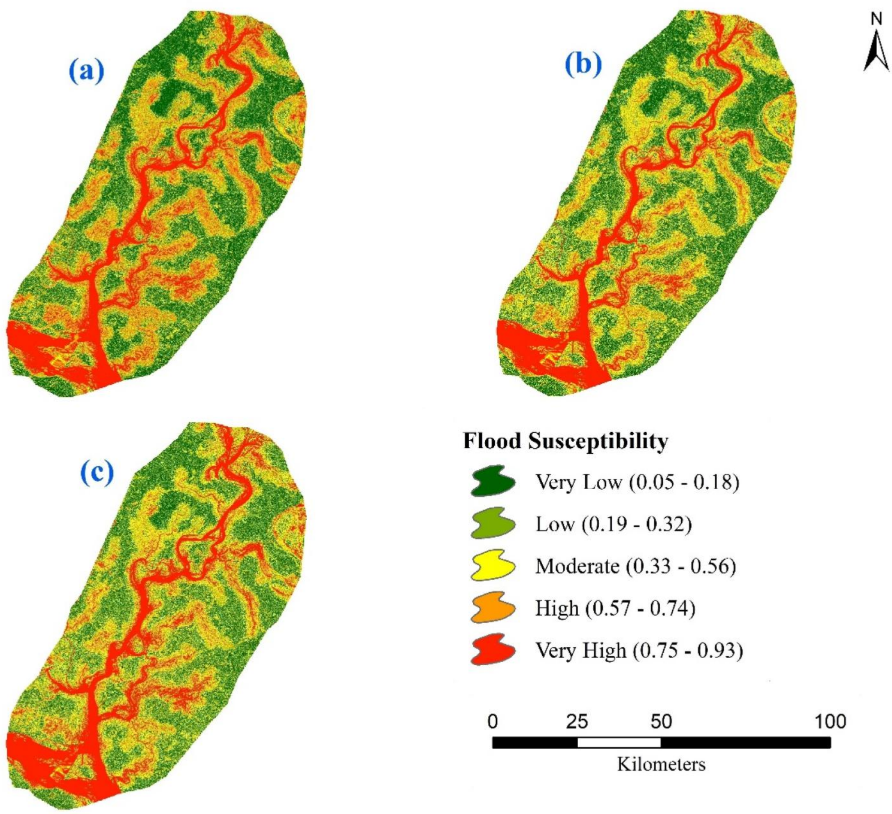

Figure 5. Flood susceptibility assessment using an ensemble of NB-RF (a), NB-SVM (b), and NB–Bagging (c) models.

high and moderate flood susceptibility zones were associated primarily in the middle and southern portions of the watershed in the NB-SVM model, with areal coverage of these zones being 1324.33 (22.09%), 617.00 (10.29%) and 658.97 km^2 (10.99%), respectively. The other part was engaged with low and very low flood-sensitive areas, with area coverage of 1339.72 (22.34%) and 2056.05 km^2 (34.29%), respectively (Figures 5(b) and 6). The areal coverage of very high, high and moderate flood-susceptible areas in the NB-Bagging model was 1222.60 (20.49%), 684.15 (11.47%) and 728.22 km^2 (12.21%), with these vulnerable zones primarily located in the watershed's eastern, middle and southern portions. Aside from that, the remainder of this region was connected with low to very low flood susceptible zones, with areal extents of 1570.05 (26.32%) and 1761.05 (29.52%), respectively (Figures 5(c) and 6).

It can be found on all maps in this region with a floodplain near a big river, as well as areas with extremely high and high flood-prone zones. The same findings were observed in Islam et al. (2023). Furthermore, the very high as well as high susceptible classifications are largely placed in the MRB's southern and southwestern sections. However, this suggests that the NB-Bagging model produces more practical results with more precision and reliability than other models. This finding might reduce the time and expense of mitigation plan in the MRB, which is utilized fort land-use planning and policy implications.

3.3. Validation

We utilized area under receiver operating characteristics curve (AUROC) to validate the three flood-prone models based on the validation and training factors (Figure 7). The AUROCs showed that all of the algorithms performed well (>0.9) on both data

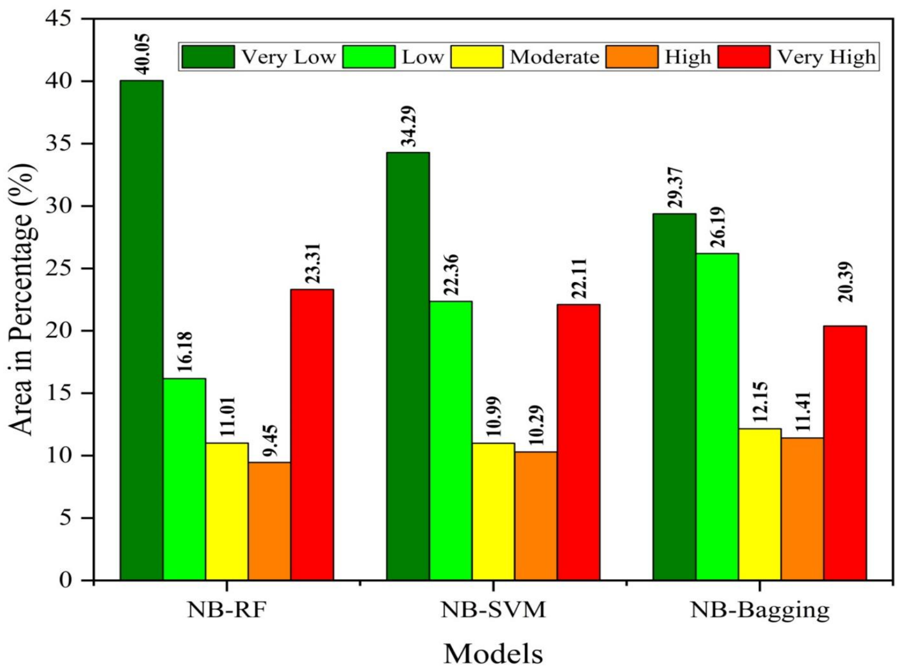

Figure 6. Areal percentage of different flood susceptibility classes.

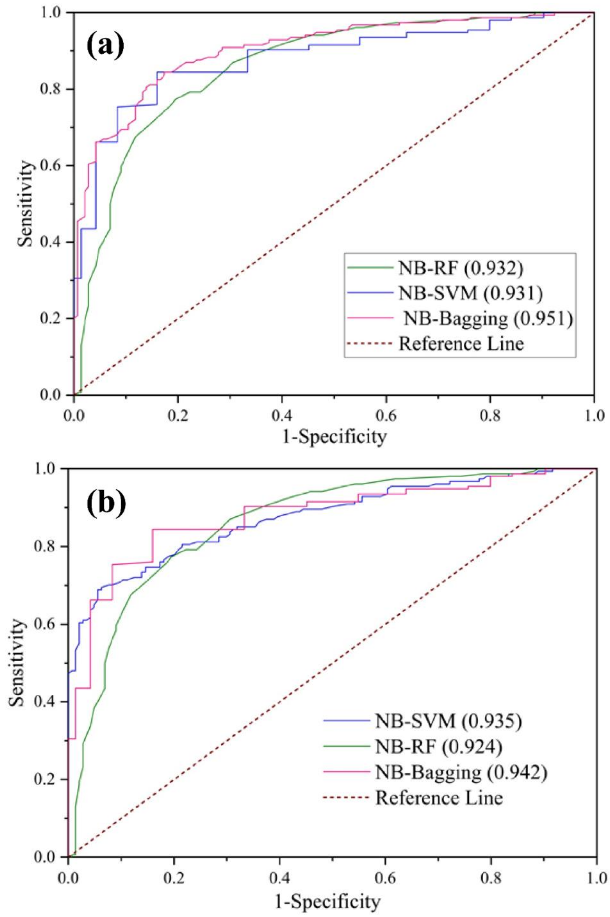

Figure 7. ROC curve using training (a) and validation (b) data sets.

sets of training and validation. However, the NB–Bagging technique performed best on the validation sets of data (AUROC = 0.951). The validation of flood-sensitive maps has been examined that was constructed using models and data sets of training points (for real flood events, the success rate curve) and validation points (for predicted flood events, the prediction rate curve).

As a result, flood validation and training spots were placed on flood inundation maps. The areas can describe the reliability of the models of the AUROC. The greater the AUROC, the better the model's prediction performance. The AUROC of the NB-Bagging model (0.951) was higher than that of the NB-RF (0.932) and NB-SVM (0.931) models (Figure 7(a) and Table 1). Similarly, the NB-Bagging model had a better AUROC (0.942) than the NB-RF (0.924) and NB-SVM (0.935) models (Figure 7(a) and Table 1). The findings suggest that, while all three flood susceptibility models had good prediction accuracy (AUROC >0.90), the NB-Bagging model is the strongest for flood susceptibility modeling for this research region, since it increased prediction performance from 0.951 to 0.942 (Table 1). Figure 8(a) and Table 1 demonstrate that NB–Bagging and NB-SVM sensitivity had the highest value,

Table 1. Validation of the models.

Models	Stage	Parameters					
		Sensitivity	Specificity	PPV	NPV	F Score	AUC
NB-RF	Training	0.92	0.87	0.89	0.96	0.89	0.932
	Validation	0.87	0.79	0.76	0.87	0.83	0.924
NB-SVM	Training	0.95	0.88	0.92	0.94	0.91	0.938
	Validation	0.96	0.70	0.75	0.91	0.81	0.935
NB–Bagging	Training	0.95	0.93	0.93	0.96	0.94	0.951
	Validation	0.92	0.76	0.76	0.92	0.83	0.942

whereas NB-RF had the lowest sensitivity. On the other hand, Figure 8(b) and Table 1 show that NB-SVM had the highest value and NB-RF had the lowest value.

Taylor diagrams are used in this study to evaluate the models. As a graphical evaluation metric, the Taylor diagram is extremely important in model validation (Mia et al. 2023). As a consequence, these graphic displays virtually the same outcomes as the prior modeling techniques (Figure 9). NB-Bagging has the highest correlation among the other two models. This model that outperforms generates a correlation value near 1 and a standard deviation close to 0.

Depending on training and testing data, the analysis performance of three flood-vulnerable models using root mean square error (RMSE). The lower the RMSE values, the higher the accuracy of the models. This work demonstrated tuning parameters of the NB-Bagging, NB-SVM and NB-RF algorithms using boosting iterations and RMSE, while tree depth was taken into consideration (Figure 10). The relationship between Boosting iterations and RMSE was evaluated using the mean, median and optimal value from boosting based on the three models mentioned aforementioned.

3.4. Importance of the flood conditioning variables

Figure 11 depicts the 18 factors' assessed relevance in all anticipated categories. The most significant factors in the NB-RF model for assessing the FSM were rainfall (80), distance from the river (74) and river density (70), respectively. In the case of NB-SVM, the dominant factors for FSM were rainfall (81), river density (70) and distance from the river (60). However, in the case of NB-Bagging, the most dominating factor was rainfall (90), which enhances the flood, distance from the river (72) and river density (70) responsible, respectively (Figure 11). Other factors in all proposed categories showed linked with moderate to low relevance for determining the FSM.

In the MRB, we identified two most influencing factors that affect the FSM using correlation- based feature selection method. In the MRB, distance to the river drives a prime contribution in occurring flood hazards. It is also a critical parameter for spatial prediction of flood susceptible areas in the basin. Consequently, the likelihood of flooding is higher when the distance is shorter, especially when the river does not have a large storage capacity. In distance to the river bed, we selected the DEM map using the multi-ring buffer tool in ArcGIS platform. Usually, the least infiltration rate in the MRB lies in rapid runoff adjacent to river in heavy rainfall events, which results in detrimental flooding with low topographic gradients. In this article, the

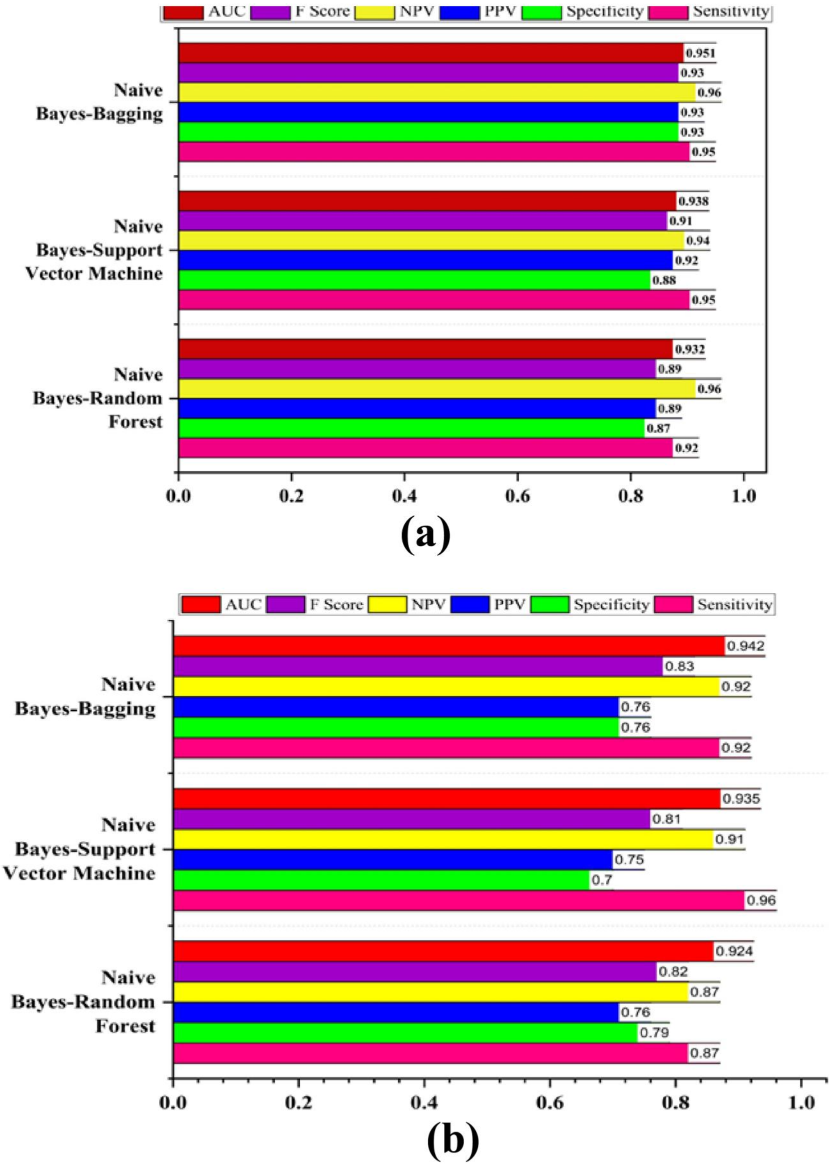

Figure 8. Validation of the models considering training (a) and validation (b) data sets.

distance range was between 400 and 65535 m (Figure 12), which means that the distance to rivers up to 65535 m was the most influential distance to flood events.

Rainfall plays a prominent and direct effect on flood risks. Extreme rainfall leads to a strong possibility of flood events. In this study, rainfall up to 1942 mm had the most prominent influence on flooding phenomena (Figure 13), while rainfall above 1942 mm demonstrated a substantial effect. The rainfall of nearly 1563 mm is associated with a strong chance of flood events in the MRB. Moran's I is an efficient tool for assessing the effects of regional pattern on rainfall in the study region, aiding research in hydrology. The Morans' I index proves the statement as the *p*-value is

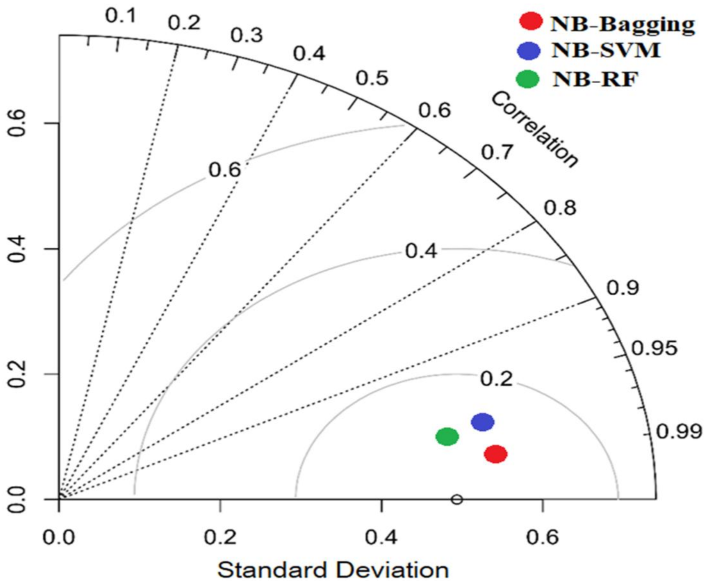

Figure 9. Taylor diagram for this study.

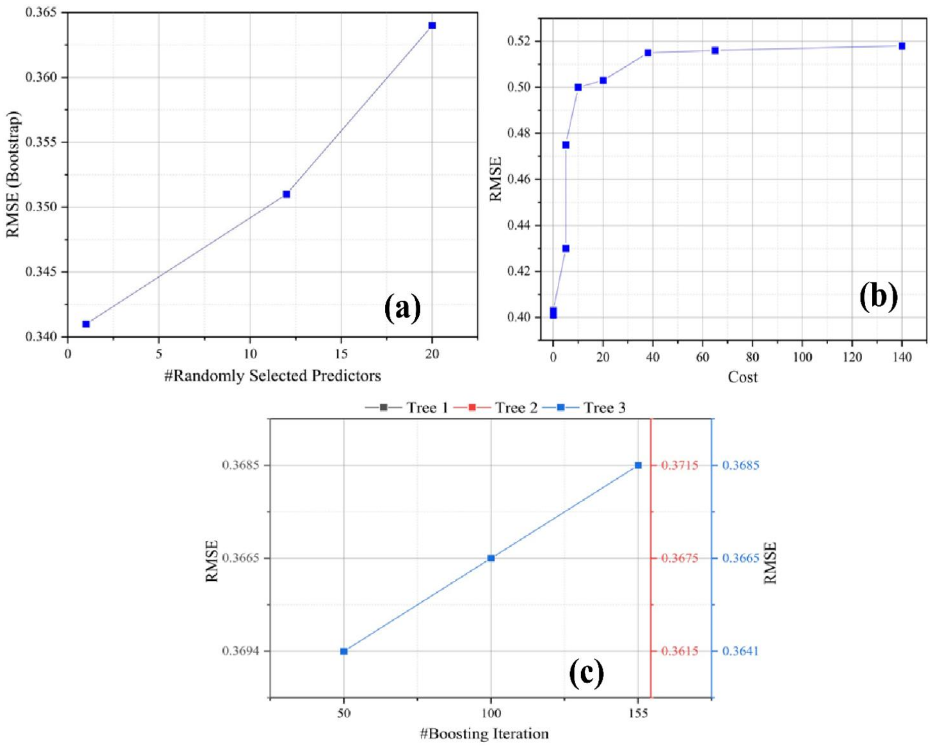

Figure 10. Result of tune parameters in three machine learning models: RF (a), SVM (b) and NB (c).

Parameters	NB-RF	NB-SVM	NB-Bagging
Aspect	10	12	8
Curvature	20	17	25
Elevation	60	50	57
Flow Accumulation	40	45	35
Flow Direction	30	25	32
Geology	15	18	10
LULC	50	43	55
NDVI	30	40	30
Plan Curvature	25	25	20
Profile Curvature	25	24	30
Rainfall	80	81	90
River Density	70	70	70
Slope	65	60	66
Soil	15	32	17
SPI	40	45	40
STI	25	20	20
TWI	8	15	5
Distance from River	74	60	72

Figure 11. Importance of the 18 variables through modeling process.

significant, which indicates the strong relationship between flooding and rainfall in this case.

4. Discussion

Understanding the factors influencing flood phases is an essential first step in FSM (Liu et al. 2025). It is important to use a multicollinearity test among the main factors because their interactions have a big impact on the prediction model's results (Gholami et al. 2025). Adding more factors that could be important to the model makes the data dimensions more complicated, which makes the model less useful and less able to generalize (Costache, Crăciun, et al. 2024). Therefore, we must establish an ideal factor combination by eliminating associated and inconsequential factors. This research examined 19 conditioning factors for FSM using the available data set. The multicollinearity test findings indicated 18 important factors (Table 2). To produce FSMs, it is essential to provide a high level of independence among the factors, hence enhancing the robustness of FSM evaluation.

This study employed an ensemble stacking model to identify factors with significant predictive potential and to assess multicollinearity among these factors (Islam et al. 2021). The ensemble stacking models showed that rainfall, distance from the river and river density all made it much easier to predict where flood risk would be most likely to happen (Figure 11). Previous studies have emphasized the potential influence of rainfall on flood risks, linking its effects to the hydrological cycle *via*

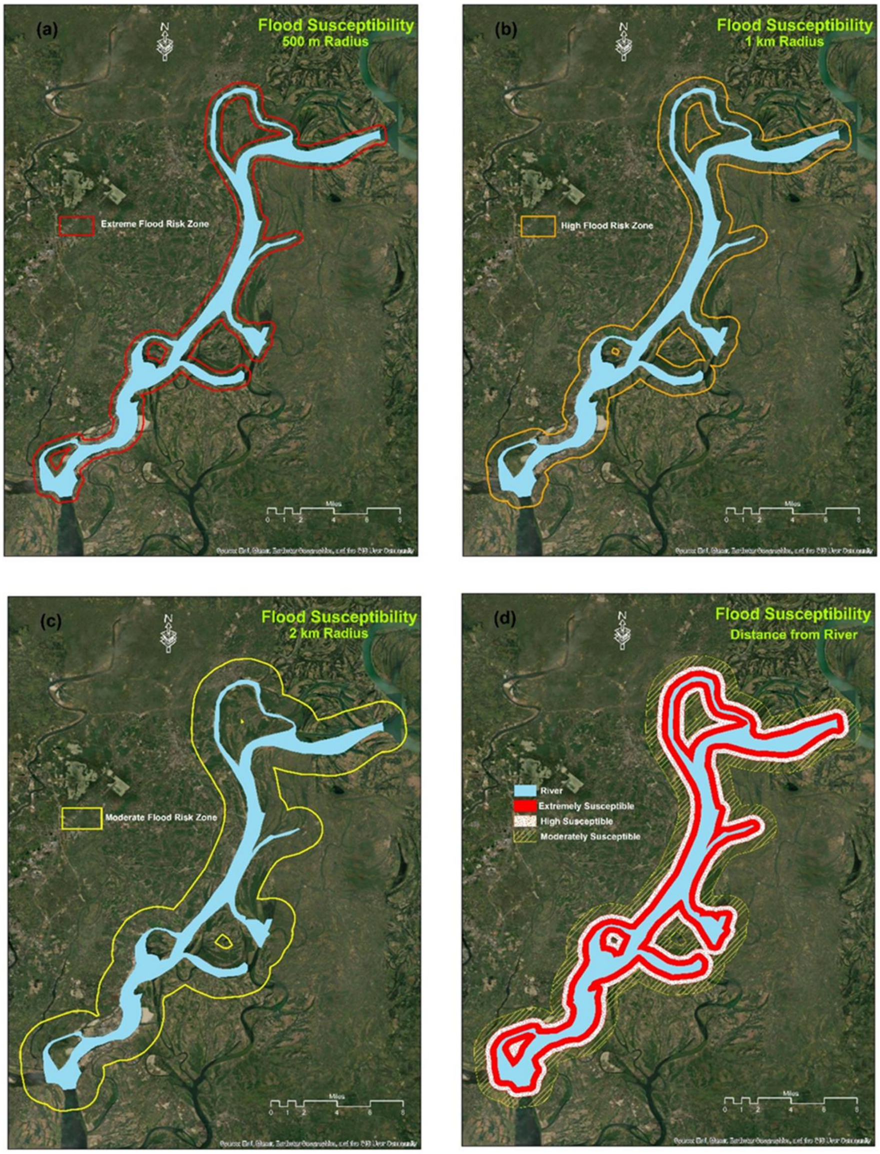

Figure 12. Flood susceptibility mapping factor the distance from the river.

evapotranspiration and infiltration, which leads to heightened runoff (Burayu et al. 2023; Abrar et al. 2024). Prior research on the FSM has highlighted the critical influence of river proximity and density alongside factors such as elevation, LULC, slope, SPI and flow accumulation in regulating runoff (Mia et al. 2023; Saini et al. 2023; Chowdhury et al. 2025). This study illustrates the strong correlation between rainfall and FSM, emphasizing the potential risk associated with heavy rainfall. The FSMs indicated potential flood events in areas with agricultural fields and residential plantations (Chowdhury 2024). Integrating land use data into the FMM enhances understanding of the hydrological impacts and potential flood risks associated with

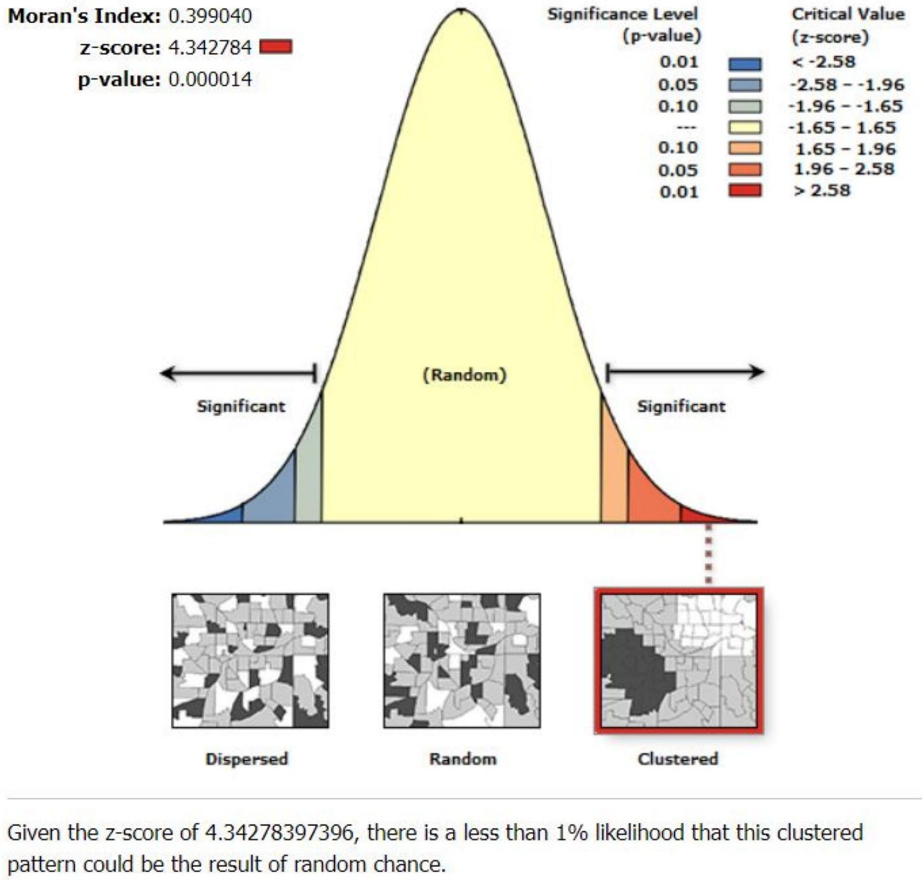

Figure 13. Physical representation of rainfall influencing factor in Meghna River basin.

urbanization (Rudra and Sarkar 2023; Rifath et al. 2024). The FSM indicated an increased risk of flooding in regions with low slopes. An earlier investigation revealed that slope is a significant factor in FSM, with lower slopes correlating with increased flood occurrence (Kader et al. 2024).

The FSM were generated using Bagging-NB, SVM-NB and RF-NB models, exhibiting comparable patterns with AUROC values of 95.1%, 93.5% and 92.4%, respectively. The precision of the three hybrid stacking models presented in this work suggests their potential as benchmarks for future research, mainly aimed at assessing FSM in the MRB. Naïve Bayes is one of the eminent neighborhood classifier techniques, which is very easy to use and intensely competent in different fields (Habibi et al. 2023). Bagging is an ensemble meta-algorithm in machine learning to enhance the stability and accuracy of algorithms used in statistical classification and regression. It reduces variance and mitigates overfitting. It is often used in decision tree methodologies. Combining the Bagging technique and the Naïve Bayes classifier enabled surmounting the shortcomings and generating a feasible flood model. The value of AUROC (0.951) of the proposed NB–Bagging technique represents the performance of this model, which is the best for predicting flood susceptibility. This hybrid

Table 2. Multicollinearity assessment test.

	Collinearity statistics	
Parameters	Tolerance	VIF
Aspect	0.569	1.757
Curvature	0.238	4.202
Elevation	0.567	1.764
Flow accumulation	0.804	1.244
Flow direction	0.864	1.157
Geology	0.774	1.293
LULC	0.433	2.311
NDVI	0.463	2.159
Plan curvature	0.563	1.776
Profile curvature	0.891	1.122
Rainfall	0.668	1.497
River density	0.553	1.808
Slope	0.206	4.854
Soil	0.192	5.208
SPI	0.329	3.040
STI	2.315	0.432
TWI	0.551	1.816
Distance from river	0.471	2.125

stacking technique might considerably enhance the prediction accuracy of Naïve Bayes as a primary classifier. The validation method revealed that the ensemble NB–Bagging technique performed the best in the training phase (AUROC = 0.951), PPV=.093, NPV = 0.96, F score = 94) and had the lowest RMSE and highest correlation. About 9.45%–20.49% is covered by high as well as very high flood susceptibility of total area of the MRB. Similar outcomes such as this current research were investigated by Kurugama et al. (2024), Amiri et al. (2024), Diaconu et al. (2024), and Costache, Crăciun, et al. (2024). Hence, the results of the current research work are strongly associated with past literature (Talukdar et al. 2020; Khairul et al. 2022; Pal et al. 2022).

Nevertheless, several works have shown elevated AUROC values for hybrid models in FSM. For example, a flood susceptibility model using a genetic algorithm based on support vector regression achieved an AUROC of 75% (Dodangeh et al. 2020). A Bagging model using 12 significant components, as shown by Talukdar et al. (2020), exhibited strong efficacy in FSM of the Teesta River basin, achieving an AUROC of 85.2%. A recent study of flood susceptibility in the Brahmaputra River basin, Bangladesh, using an ensemble ANN-RF algorithm, achieved an AUROC score of 88.9%, signifying exceptional predictive accuracy (Islam et al. 2023). Stacking algorithms may improve the efficacy of machine-learning models (Islam et al. 2021; Seleem et al. 2022; Costache et al. 2023; Abrar et al. 2024; Zhao et al. 2024). Research on the performance of stacking learning models has shown that their prediction ability is affected by the proportion of training to testing data set (Widya et al. 2024). Therefore, using the NB–Bagging model for other natural disaster prediction is strongly suggested to acquire high-precision findings. Compared to field surveys, the proposed machine learning model gives decision-makers an inexpensive and shorter time-spending pathway for quantifying flood occurrences and risk.

This article illustrates the use of ensemble learning techniques for FSM, emphasizing the limitations of existing methods. The limitation is the need for advance novel techniques to enhance hyperparameter optimization. The findings of the present research help identify the influencing factors that affect FSM. However, our research encountered additional limitations due to the unavailability of rainfall distribution data sets for our study basin. Furthermore, there is an absence of high-quality contemporary weather maps for the MRB. The absences may have influenced the precision of the flood susceptibility model outcomes. Similarly, the disparity in resolution between the soil texture map (1:5,000,000) and the geological map (1:100,000) presents a notable limitation in this study. The coarse scale of the soil map may oversimplify variations in soil properties, potentially underrepresenting localized effects on flood susceptibility, such as infiltration and runoff. This scale mismatch could lead to inconsistencies when integrating soil data with higher-resolution layers, impacting the precision of spatial analysis. To mitigate this, all layers were resampled to a uniform 30-m resolution; however, this approach does not fully recover the finer spatial details. Future research should aim to utilize higher-resolution soil texture data to enhance model accuracy and reliability. The inclusion of factors like aspect, curvature and TWI, while showing lower importance, was retained to capture potential subtle influences on flood susceptibility that may not be fully addressed by other variables. Although these factors had lower significance in this analysis, their presence does not adversely affect the model's performance due to the robust machine learning algorithms employed, which can handle less impactful variables without compromising accuracy. Lastly, there was a paradox on which model to select to the close AUROC values. Future research should investigate optimization strategies to determine FSM. Recent advancements in ensemble learning optimization techniques have the ability to enhance predictive accuracy and refine the model (Talukdar et al. 2020; Sarkar et al. 2022). Moreover, integrating other geographical data sets, including meteorological information and human activities, might enhance FSM.

5. Conclusion

The current research intends to propose ensemble naive bayes with stacking algorithms (NB–Bagging, NB-SVM and NB-RF) to assess the flood susceptibility within MRB area, Bangladesh. During the first phase of the study, a total of 364 sites were obtained *via* a comprehensive field survey, where previous flooding records had taken place within the MRB. Concurrently, a total of 18 flood conditioning factors were chosen as input data for the ensemble machine learning models. The effectiveness of these models in predicting floods was evaluated using the multi-collinearity test approach. Through the implementation of the prediction capacity assessment approach, it was determined that all suggested parameters have a pivotal role, to varying degrees, in the occurrence of floods. The testing findings revealed no multicollinearity issues existed among the chosen conditioning factors.

The modeling processing through NB–Bagging results showed that rainfall (90), distance from the river (72) and river density (70) all had a significant impact on flood occurrence in the MRB. The main results of this article were that the NB-Bagging achieved an AUROC value of 0.951, indicating good accuracy compared to other models. Thus, the NB–Bagging model was used to develop flood mapping modeling in the MRB. This study found that rainfall, river distance and river density significantly affect the studied basin's floods. Major innovation of this study is the integration of techniques such as SVM, RF,and Bagging, with stacking ensemble Naïve Bayes and field survey. The use of the FSM technique may serve as a valuable tool for planners, decision-makers and academics to effectively execute suitable administrative strategies in the study basin. Hence, it is advisable to use these characteristics and models to conduct FSM over a larger geographical domain to enhance policy formulation and alleviate the consequences of flooding. Furthermore, the findings of this research might be significantly valuable for the regional to national authorities responsible for implementing flood prevention measures as well as other basins in the world. Future research can apply these models to flood forecasting and LULC predictions to offer a foundation for comprehensively comparing the model's performance.

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Data availability statement

Data will be made available on request.

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