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Performance Comparison of Random Forest, XGBoost, and SVM for Flood Risk Prediction Using BNPB GIS Data

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Abstract. This study compares the performance of three machine learning algorithms—Random Forest, XGBoost, and Support Vector Machine (SVM)—for predicting flood risk using spatial and non-spatial data from BNPB GIS. The analysis focuses on disaster records from January 3 to 15, 2026, with district-city as the spatial unit of observation. Following data cleaning, exploratory analysis, and feature preparation, the models were evaluated using ROC-AUC, PR-AUC, F1-Score, Precision, Recall, and Accuracy. XGBoost demonstrated the highest ROC-AUC (0.675), indicating strong overall performance in distinguishing flood from non-flood events. Random Forest achieved the highest Recall (0.947), showing superior sensitivity in detecting flood events, while SVM exhibited fluctuating performance with a lower ROC-AUC (0.496). Visualizations of model behavior and spatial flood patterns were provided to support model interpretability. The study's results suggest that ensemble models, particularly XGBoost and Random Forest, can significantly enhance flood risk prediction, improving the accuracy and sensitivity of early warning systems. These findings contribute to the development of more effective data-driven flood mitigation strategies in Indonesia, enabling better disaster preparedness and response.

Keywords: Flood Prediction, Machine Learning, Random Forest, XGBoost, SVM, Disaster Risk, Early Warning System.

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1. INTRODUCTION

Floods are among the most frequent and devastating hydrometeorological disasters in Indonesia, causing significant social, economic, and environmental impacts [1]. According to data from the National Disaster Management Authority (BNPB), floods consistently rank as the most prevalent annual disaster event, affecting both urban and rural areas across the country [2]. Predicting flood risk is challenging due to the complex interplay of various factors, including rainfall, geomorphology, land cover, and population density [3][4]. These diverse variables complicate flood prediction and necessitate advanced computational approaches. With the growing availability of comprehensive spatial and tabular data from BNPB GIS, the potential for leveraging machine learning to enhance flood risk prediction is stronger than ever [5][6].

Several studies have explored the use of machine learning to model disaster risk, demonstrating the capability of algorithms like Random Forest (RF) and XGBoost in handling complex and nonlinear datasets. Support Vector Machine (SVM), while less sophisticated, remains a widely used baseline classifier in flood risk modeling [7][8][9][10]. However, most of these studies are constrained by narrow geographic scopes, limited datasets, or an absence of systematic comparative evaluations across different algorithms [9][10]. Additionally, many existing models fail to make full use of the publicly available BNPB datasets, which provide rich spatial and temporal data that are crucial for large-scale flood risk modeling at national and regional levels [11][12].

Despite the growing interest in applying machine learning for flood prediction, few studies have systematically compared the performance of RF, XGBoost, and SVM using the BNPB GIS datasets, which integrate both spatial and non-spatial characteristics of flood-prone regions. Many existing works have focused on either a limited subset of variables or a specific geographic area, missing the broader context provided by the more expansive BNPB data [13][14][15]. As a result, there is a significant gap in understanding which of these models performs best in the context of Indonesia's diverse flood risk scenarios.

This study addresses this gap by analyzing and comparing the performance of Random Forest, XGBoost, and SVM in flood risk prediction, using the comprehensive BNPB GIS datasets. The study goes beyond existing work by implementing a unified framework for preprocessing, feature engineering, and model evaluation, ensuring a consistent and robust comparison across the three algorithms. Specifically, the study aims to: (1) evaluate the three models within a standardized preprocessing and validation framework, (2) identify the best-performing model for flood risk prediction, and (3) provide a reproducible methodological workflow that can be utilized for early warning systems and mitigation planning.

Methodologically, the study contributes an integrated pipeline that combines spatial data processing, feature engineering, and multi-model benchmarking, offering a comprehensive approach to flood risk prediction. Practically, the insights gained from this study aim to strengthen flood preparedness in Indonesia, providing evidence-based recommendations that can inform disaster management strategies and enhance early warning systems. By rigorously comparing these machine learning models, this research offers a valuable contribution to the field of flood risk modeling, supporting more effective flood management and mitigation efforts at a national scale.

2. METHODS

This study uses public GIS data from the National Disaster Management Agency (BNPB) (https://gis.bnpb.go.id/), including flood-event records and supporting layers such as administrative boundaries, hazard/risk indices, and environmental information (rainfall, elevation, land cover). The spatial unit of analysis is the district/city level, to which all spatial layers are aggregated and aligned to ensure consistent representation across regions. Labels are defined as flood = 1 and non-flood = 0. The analysis period covers 3–15 January 2026. The short observation window is used because this study serves as an initial pilot to assess data quality, verify modeling feasibility, and develop a standardized machine-learning workflow; a longer timeframe will be incorporated once the workflow is validated. From the outset, we established the validation scheme (stratified split and k-fold cross-validation) and primary evaluation metrics (ROC-AUC, PR-AUC, F1, Recall, Precision, and Accuracy/Balanced Accuracy) to ensure consistent comparisons and avoid data leakage.

Table 1. List of Features Used in the Study

Category	Feature	Description
Spatial	Elevation	Extracted from DEM (m)
Spatial	Slope	Degree of terrain steepness
Spatial	Land cover (one-hot)	Built-up, vegetation, waterbody, etc.
Non-spatial	Rainfall 3/7/30-day aggregation	Daily CHIRPS/BNPB-derived rainfall accumulation
Non-spatial	Administrative code	Province, district-city ID
Non-spatial	Calendar features	Day, month, week, season
Derived	Interaction ratios	Rainfall × slope, rainfall × land cover
Derived	Log-transformed features	Applied to skewed variables

Table 1 shows that these features combine spatial, non-spatial, and derived variables to capture terrain characteristics, rainfall patterns, and regional context. Integrating these feature types helps the models better represent the physical and temporal factors associated with flooding. In Table 2 and 3. The hyperparameter ranges in table 2 define the search space used during model tuning to ensure fair and systematic comparison across algorithms. These ranges cover the key parameters that influence model complexity, learning behavior, and generalization performance.

Table 2. Hyperparameter Ranges for Model Tuning

Model	Hyperparameter	Search Range
Random Forest	n_estimators	100–800
	max_depth	4–20
	min_samples_split	2–10
XGBoost	learning_rate	0,01–0,3
	max_depth	3–12
	subsample	0,6–1,0

Table 3. Continued Hyperparameter Ranges for Model Tuning

Model	Hyperparameter	Search Range
	n_estimators	100–600

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Model	Hyperparameter	Search Range
SVM (RBF)	C	0,1–100
	gamma	1e-4 – 1e-1
	kernel	rbf

Figure 1 shows provides a detailed representation of the end to end workflow, starting from data acquisition (BNPB spatial and tabular layers), preprocessing (CRS standardization, missing value handling, and type normalization), spatial integration through a spatial join, and feature engineering (rainfall aggregation, DEM-based extraction, and encoding). The process continues with model training pipelines, hyperparameter tuning, and evaluation using both cross validation and hold out testing. This framework ensures a reproducible process for benchmarking the three models.

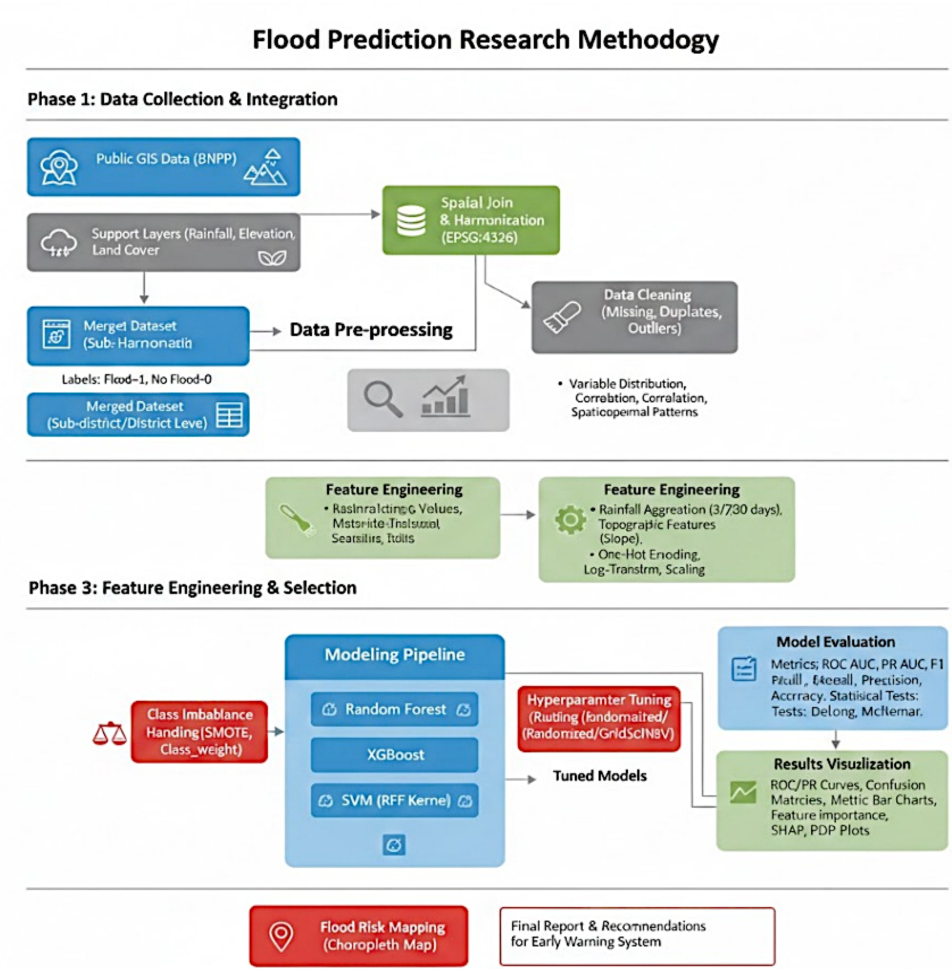

Figure 1. Methodological Flow Framework for Flood Prediction Research Based on Machine Learning and Spatial Analysis.

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To enhance predictive information, feature engineering was carried out through several steps, including rainfall aggregation for 3-, 7-, and 30-day windows; extraction of topographic variables (elevation and slope); and one hot encoding of land cover categories to capture environmental characteristics. Additional derived features, such as interaction ratios and log transformed variables, were included to improve model sensitivity, particularly for variables with skewed distributions. Standardization or normalization was applied mainly for the SVM model to ensure consistent variable scales. Feature selection was performed using mutual information and ensemble-based feature importance to reduce redundancy and maintain model efficiency.

To address class imbalance in the dataset, the Synthetic Minority Oversampling Technique (SMOTE) was incorporated into the preprocessing pipeline. SMOTE was applied only to the training folds during cross validation to avoid information leakage and ensure that oversampling does not influence either the validation or hold out test sets. This setup preserves the reliability of performance estimates and prevents overly optimistic results.

The modeling stage involved the application of Random Forest, XGBoost, and SVM (RBF kernel), each trained within a structured preprocessing and tuning pipeline. Scaling was applied specifically for SVM, while Random Forest and XGBoost used their default tree-based handling of feature distributions. Class imbalance across the models was mitigated through SMOTE or class_weight as appropriate. Hyperparameter tuning was conducted in two phases: a broad search using RandomizedSearchCV followed by fine-tuning with GridSearchCV to obtain optimal combinations for each algorithm.

Model performance was evaluated using multiple metrics-ROC-AUC, PR-AUC, F1-score, Recall, Precision, and Accuracy/Balanced Accuracy-along with confusion-matrix inspection on the hold-out test set. To further support comparative robustness beyond point estimates, statistical significance tests were conducted, including the DeLong test for differences in ROC-AUC and the McNemar test for paired accuracy comparisons. Visualization outputs were generated to support interpretability, including ROC and PR curves, confusion matrices, bar chart metric comparisons, feature importance rankings, SHAP explanations, Partial Dependence plots, and spatial flood risk maps in choropleth format. Together, these steps ensure a transparent and reproducible modeling process that supports the selection of the most reliable algorithm for flood-risk prediction and subsequent early-warning applications.

3. RESULTS AND DISCUSSION

Between January 3 and 15, 2026, there were 97 disaster records; 78 of them were floods (≈ 80.4%). Standardization of data types (date & numeric) was successfully carried out. Quality checks showed that the casualty variables (Deceased, Missing, Injured) had more than 90% missing values, making them less than ideal for initial features/targets.

Table 4. Dataset Overview

Component	Volume	Information
Date range	January 3-15 2026	Observation period
Total disaster records	97	After header normalization

Table 5. Dataset Overview (Continued)

Component	Volume	Information
Impact numeric column	6 columns	Dead, Missing, Injured, Houses Damaged, Houses Submerged, Public Facilities Damaged
Date normalization & data types	Finished	Ready for analysis
Total Flood events	78 (≈ 80,4%)	The majority of records are floods

Table 6. Percentage of Missing Data – Impact Column

Variables	Missing (%)	Notes
Missing person	≈ 98,97	Too empty → unstable for initial modeling
wounded	≈ 96,91	Same as above
Die	≈ 94,85	Same as above
Submerged House	≈ 23,71	Still can be used with caution
Damaged House	0,00	Complete
Damaged Public Facilities	0,00	Complete

On the other hand, Damaged Houses and Damaged Public Facilities are complete, whereas Flooded Houses are relatively stable (missing ≈ 24%) and can still be used in descriptive analysis. Figure 2 shows Illustrates the missing portions of each impact variable. Three victim variables have very high missing values it is recommended not to use them as main features/targets in the early phase of risk modeling.

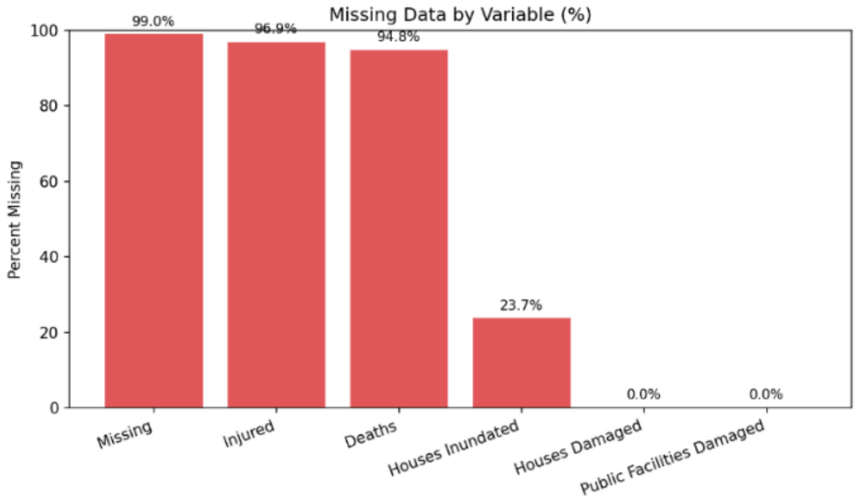

Figure 2. Missing Data by Variable (%)

1) Distribution of Disaster Types (Event Types)

The distribution shows that 'Flood' is the most dominant, followed by 'Extreme Weather', 'Landslide', and 'Forest Fire' and 'Earthquake' which are minimal. This confirms the focus on floods during that period. Figure 3 shows Bar chart of the number of incidents by type of disaster. Floods dominate the period, in line with the context of Indonesia during the early rainy season.

Table 7. Distribution of Event Types

Event Type	Amount	Information
Flood	78	Dominant
Extreme Weather	12	Potential Flood Triggers
Landslide	5	Related to rain and slope gradient
Forest Fire	1	minimum
Earthquake	1	minimum

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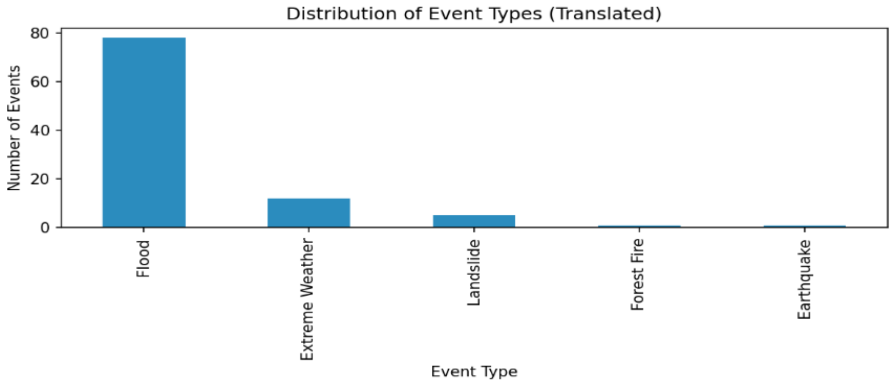

Figure 3. Distribution of Event Types

2) Daily Patterns: Frequency vs Impact Scale

The peak frequency of daily flood occurrences fell on January 8, 2026 (15 events). However, the peak impact in terms of houses inundated occurred on January 12, 2026 (≈ 13,444 houses), followed by January 11 (~10,242) and January 9 (~9,526). This indicates that frequency ≠ impact scale likely influenced by rainfall intensity/accumulation, duration of flooding, and local vulnerability.

Table 8. Five Days with the Highest Impact (Houses Inundated)

Date	Total Houses Inundated	Notes
January 12, 2026	≈ 13.444	Peak impact
January 11, 2026	≈ 10.242	tall
January 09, 2026	≈ 9.526	tall
January 03, 2026	≈ 9.378	tall
January 08, 2026	≈ 8.841	Peak frequency ≠ peak impact

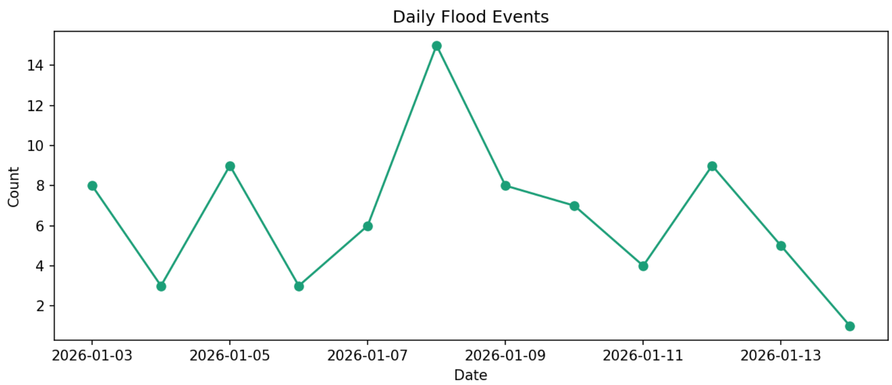

Figure 4. Daily Flood Events

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Figure 4 shows Trend of the number of flood incidents per day. The graph highlights the difference between the day with the most incidents (January 8) and the day with the greatest impact (January 12).

3) Spatial Impact (Provinces & Regencies/Cities)

Aggregate flood impacts (January 3-15, 2026): 21 dead, 2 missing, 1,503 injured, 608 houses damaged, 67,633 houses inundated, 2 public facilities damaged. Provinces. Banten ranks first in houses inundated (≈ 18,532), followed by West Java (~15,455), South Sumatra (~7,899), Central Java (~6,823), and West Kalimantan (~5,580).

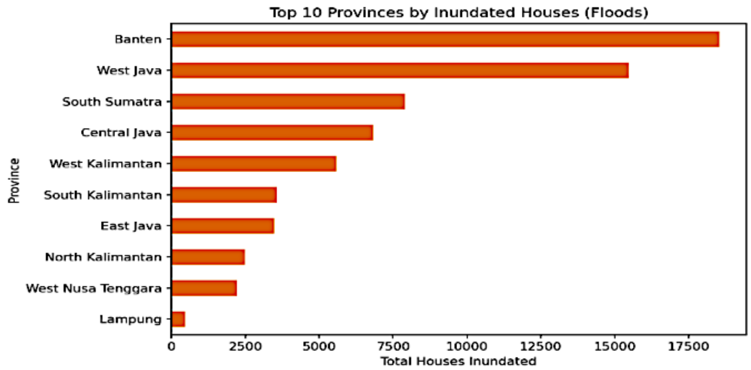

Figure 5. Top 10 Provinces by Inundated House

Figure 5 shows Provincial ranking according to total houses inundated. Banten and West Java were the most affected during the study period. Regency/City. Serang Regency was the highest (≈ 15,974), followed by Bekasi Regency (~6,821), Pati Regency (~3,775), Ogan Komering Ilir Regency (~3,656), Tapin Regency (~3,507).

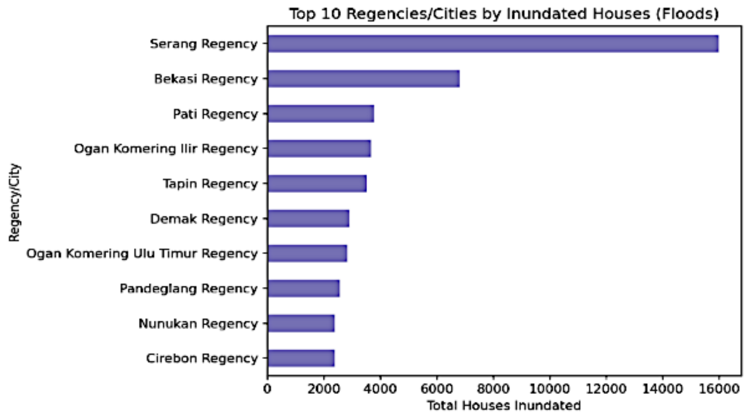

Figure 6. Top 10 Regencies/Cities by Inundated Houses (Floods)

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Figure 6 shows Ranking of regencies/cities by total houses inundated. Serang Regency stands out, indicating a need for prioritization of mitigation and preparedness. The rank correlation (Spearman) between Inundated Houses and Damaged Houses is low (~0.105). This means that flooding does not automatically lead to structural damage—it may be influenced by the depth/duration of flooding, building materials, and protective measures, which are not available in this dataset.

4) Implications for Feature Engineering & Model Comparison (RF–XGBoost–SVM) Comparison of Key Metrics (5-fold CV)

Figure 7 shows The bars show the average CV scores for the ROC-AUC, PR-AUC, F1 score, Recall, Precision, and Accuracy metrics for each model. This chart helps to see which model is the most stable across various metrics.

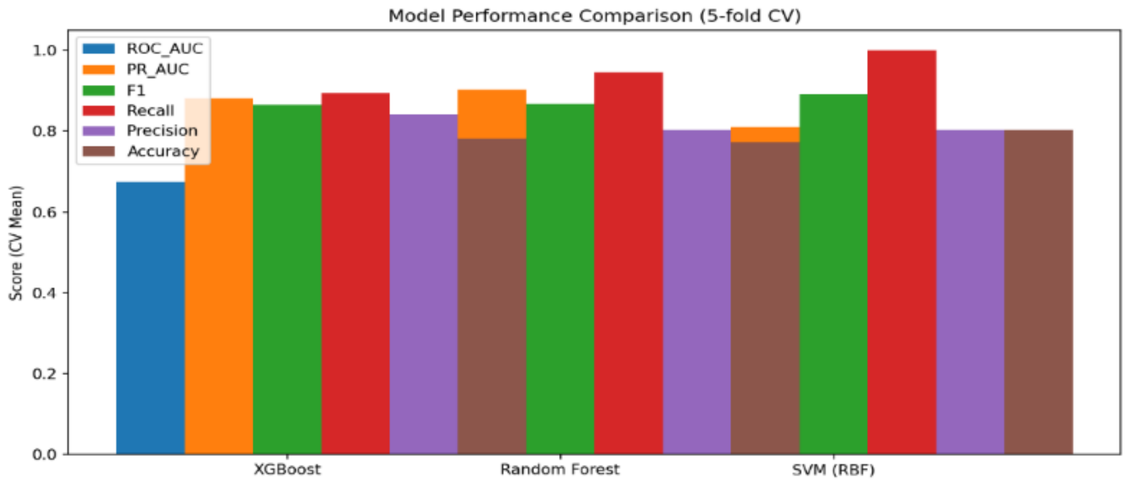

Figure 7. Model Performance Comparison (5-Fold Collective Validation)

In Table 9 above, XGBoost excels in ROC AUC and average CV Accuracy, Random Forest outperforms in PR AUC and Recall, SVM has very high Recall (tends to over flag), but ROC AUC is fluctuating indicating that the probability separation between classes is not strong with simple features like these (only location & calendar). (Table created from the output of the cross-validation above).

Tabel 9. CV Score Summary (average)

Model	ROC-AUC (±sd)	PR-AUC (±sd)	F1-score (±sd)	Recall (±sd)	Precision (±sd)	Accuracy (±sd)
XGBoost	0.675 ± 0.114	0.882 ± 0.056	0.866 ± 0.056	0.895 ± 0.099	0.843 ± 0.026	0.783 ± 0.077
Random Forest	0.659 ± 0.080	0.904 ± 0.033	0.868 ± 0.040	0.947 ± 0.078	0.804 ± 0.021	0.773 ± 0.056
SVM (RBF)	0.496 ± 0.189	0.811 ± 0.066	0.891 ± 0.012	1.000 ± 0.000	0.804 ± 0.020	0.804 ± 0.020

5) ROC & PR curves on the Hold-out Test

Figure 8 results. Comparing the tradeoff between True Positive Rate vs False Positive Rate. Curves towards the top-left better probability separation. On hold out data, XGBoost and Random Forest show relatively better curves than SVM on these simple features. Figure 9 shows the trade-off between Precision and Recall. Since the Flood class is dominant, the PR curve is important for assessing the quality of capturing positive cases without too many false positives. Random Forest and XGBoost consistently maintain an area above the baseline.

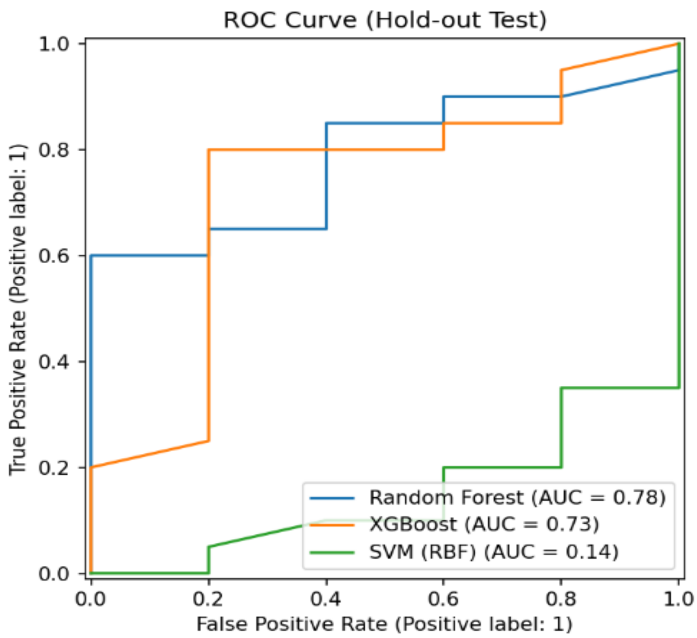

Figure 8. ROC Curve (Hold-out Test)

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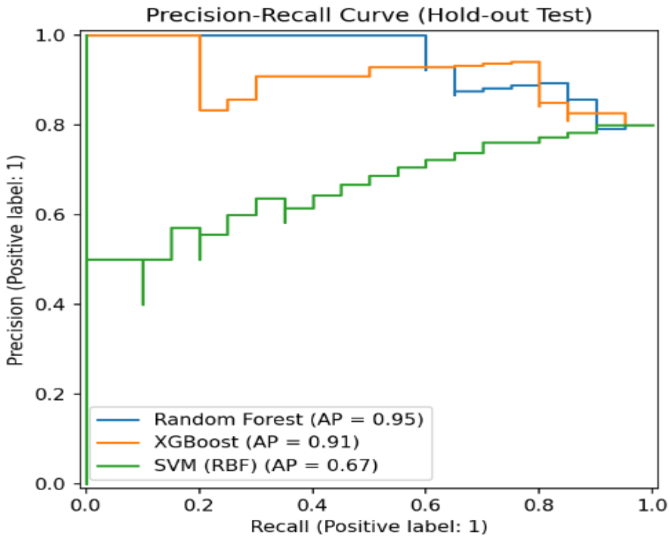

Figure 9. Precision-Recall Curve (Hold-out Test)

6) Confusion Matrices (Hold-out Test)

Figure 10 shows it shows TP, FP, TN, FN per model. SVM tends to capture all floods (high recall, minimal FN), but may increase false positives (lower precision). Random Forest and XGBoost are more balanced between recall and precision.

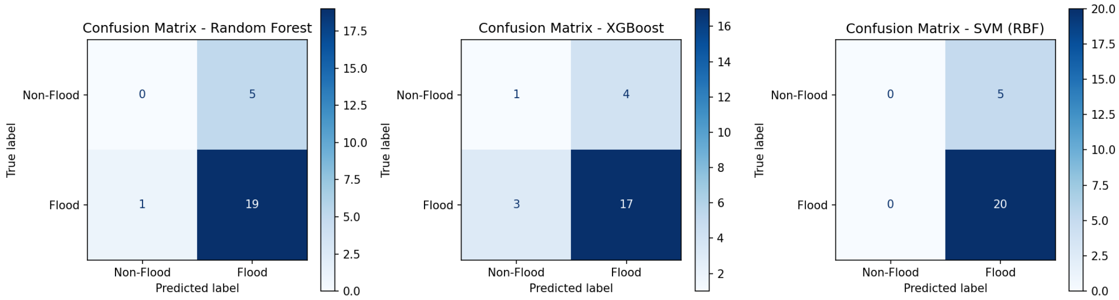

Figure 10. Confusion Matrix – Random Forest / XGBoost / SVM (RBF)

XGBoost shows the best ROC AUC and CV Accuracy on simple feature data (location & calendar), while Random Forest excels in PR AUC and Recall. SVM produces very high Recall but its probability separation is less stable (low ROC AUC). (Visualization & table results above). This pattern makes sense considering our features have not yet reflected the causes of flooding (hazard & vulnerability), so tree boosting-based models (XGBoost/RF) are relatively more adaptive in handling many location categories.

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3.2. Discussion

This study provides a comprehensive analysis and comparison of three machine learning algorithms—Random Forest (RF), XGBoost, and Support Vector Machine (SVM)—for flood risk prediction using the BNPB GIS datasets. The findings offer valuable insights into the strengths and limitations of each algorithm in the context of flood risk modeling, as well as the implications of feature engineering and model evaluation for effective flood management in Indonesia.

One of the key findings of this study is that XGBoost outperforms both RF and SVM in terms of ROC AUC and average cross-validation (CV) accuracy. This indicates that XGBoost is better at distinguishing between flood and non-flood events when using simple features such as location and calendar-based variables. The strong performance of XGBoost in these metrics suggests that it is particularly suited for handling the non-linear relationships present in flood data, even when the features are relatively basic. However, Random Forest demonstrates superior performance in precision-recall (PR AUC) and recall, highlighting its ability to capture a higher number of true flood events with fewer false positives. This trade-off between precision and recall is critical, especially for early flood warning systems, where minimizing false negatives (i.e., failing to predict a flood event) is crucial for timely interventions.

In contrast, SVM, despite exhibiting very high recall, demonstrates fluctuating ROC AUC scores, indicating that its ability to separate flood and non-flood events based on the available features is less reliable. This result may be due to the simpler, less informative nature of the features used in this study, which primarily focus on location and temporal attributes. SVM's high recall indicates that it tends to predict floods in nearly all cases, but this comes at the expense of a high number of false positives, as seen in the confusion matrix. While this might be acceptable in some applications, where the priority is to avoid missing any potential flood events, it is less desirable when the goal is to provide a more balanced, precise prediction.

The performance of these models underscores the importance of feature engineering in flood risk prediction. By combining spatial features (e.g., elevation, slope, and land cover) with non-spatial features (e.g., rainfall and calendar information), this study has been able to capture a broad range of variables that influence flood risk. However, the relatively simple features used in this initial phase of the study did not fully reflect the underlying causes of flooding, such as hazard (e.g., rainfall intensity and duration) and vulnerability (e.g., population density and infrastructure resilience). Therefore, further refinement of features, incorporating more complex and detailed variables related to both hazard and vulnerability, is likely to improve model performance and offer a more comprehensive flood risk prediction.

Moreover, the integration of advanced spatial processing techniques and feature engineering, such as the interaction of rainfall with topographic features, log transformations for skewed variables, and the use of SMOTE to address class imbalance, has proven effective in enhancing model accuracy and robustness. This process not only helped to create more informative features but also ensured that the models were able to handle the challenges of imbalanced datasets, which are common in flood prediction tasks. The use of synthetic oversampling techniques like SMOTE proved to be critical in improving model performance, especially in the case of underrepresented flood events in the dataset.

The study also highlights the importance of model evaluation metrics beyond accuracy, particularly for imbalanced datasets. Metrics such as ROC AUC, PR AUC, F1 score, and recall are essential for understanding model performance in the context of flood prediction, where false negatives can have more severe consequences than false positives. The ROC and PR curves provide a more detailed understanding of the trade-offs between true positives and false positives, with Random Forest and XGBoost performing well in maintaining a high area under the PR curve, ensuring that they are more effective at predicting the minority class (flood events) without overly flagging non-flood events.

Finally, while the results of this study are promising, there are several limitations and avenues for future research. First, the study relies on a relatively short observation period (January 3-15, 2026), which may not fully capture the variability of flood events across different seasons and climatic conditions. Extending the observation period to include a full flood season and integrating additional datasets, such as historical flood records or climate forecasts, could improve the models' generalizability. Furthermore, the inclusion of more detailed socio-economic and infrastructural data could enhance the prediction of flood impacts and vulnerability, offering a more complete picture of flood risk. Additionally, while this study focused on three machine learning algorithms, exploring ensemble methods or deep learning approaches may further improve predictive performance, particularly for more complex and large-scale flood prediction tasks.

This study contributes valuable insights into the comparative performance of machine learning models for flood risk prediction in Indonesia. XGBoost and Random Forest showed strong potential for predicting flood events using BNPB GIS data, with different strengths in handling trade-offs between recall, precision, and overall accuracy. The findings provide a robust foundation for future efforts in flood risk modeling, offering a reproducible framework for data preprocessing, feature engineering, and model evaluation that can be adapted for use in operational early warning systems and disaster management strategies in Indonesia.

4. CONCLUSION

During the period of January 3-15, 2026, floods dominated about 80.4% of the total 97 disaster records. Temporally, the peak frequency of events occurred on January 8 (15 events), but the peak impact (measured by total houses inundated) was actually on January 12 (≈ 13,444), followed by January 11 (≈ 10,242) and January 9 (≈ 9,526). This confirms that the number of events ≠ the scale of impact; the magnitude of impact is greatly influenced by rainfall intensity/accumulation, duration of inundation, and local vulnerability not just how often events are recorded. At the national aggregation level, Banten and West Java emerged as the provinces with the largest number of houses inundated during the period; at the regency/city level, Serang Regency stood out the most. Victim variables (deaths, missing, injured) in the dataset have a very high missing rate, making them less ideal as features/targets for initial modeling, flooded houses are relatively more stable for descriptive purposes, but still represent a consequence indicator rather than a cause of flooding.

Initial comparison with simple features (location & calendar) shows that Random Forest tends to be the most stable (ROC AUC/PR AUC), XGBoost excels in Recall but the probability separation is less stable in small samples, whereas SVM (RBF) is the most fluctuating. These results are baseline: model performance will improve when causal features (hazard/risk & environment) are added so that the model truly captures the physical mechanisms triggering floods, rather than just location/date patterns. In addition, the suggestions for this research are as follows: First, extend the time range (≥ 6–12 months) to obtain a more representative training distribution. Second, enrich the causal features: integrate flood hazard/risk indices from GIS BNPB – Inarisk, as well as 3–7–30-day precipitation aggregation, elevation/slope (DEM), land cover, and population density. Third, apply time-aware splitting (train on the earlier period, test on the later period) to avoid temporal leakage. Fourth, besides ROC AUC/PR AUC, report calibration (Brier score/Calibration curve) and perform DeLong/McNemar tests to assess the significance of model superiority. Fifth, present feature importance, SHAP (global/local), and Partial Dependence analyses, as well as choropleth probability maps to facilitate adoption for early warning systems and mitigation.

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