ISSN: 2623-1662 (online), 2460-092X (printed)
DOI: https://doi.org/10.19109/jusifo.v11i2.32227
Vol. 11, No. 2 (2025), p.141-152

JUSIFO
JURNAL SISTEM INFORMASI

Research Article [OPEN ACCESS]

Hybrid Fuzzy-AHP and Machine Learning with Sensitivity Analysis for Urban Flood Risk Assessment

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ABSTRACT

Urban flooding poses a growing challenge in rapidly urbanizing regions due to the combined effects of climate variability, land-use change, and infrastructure limitations. This study proposes a hybrid framework integrating the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP), ensemble machine learning, and sensitivity analysis to support urban flood risk assessment. Fuzzy-AHP is employed to incorporate expert judgment and address uncertainty through triangular fuzzy numbers, while Random Forest and XGBoost are used to capture non-linear relationships and temporal patterns in heterogeneous flood-related data. The framework is applied to 1,008 observations from 12 districts in Bekasi City, Indonesia, covering the period 2018–2024. Model performance indicates strong discriminatory capability in distinguishing flood and non-flood conditions. Sensitivity analysis is explicitly positioned as a policy-oriented diagnostic and prioritization tool, enabling the identification of influential variables relevant for seasonal planning and early warning strategies. The results highlight the dominant role of climate-related factors, particularly rainfall and temporal variables, in shaping urban flood risk. Overall, the proposed framework demonstrates the complementary integration of expert knowledge and data-driven learning, offering a transferable methodological reference for flood risk assessment in complex urban environments.

Keyword: Fuzzy-AHP, random forest and xgboost, urban flood risk assessment

Received: November 27, 2025; Revised: December 29, 2025; Accepted: December 30, 2025

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1. INTRODUCTION

Urban flooding has emerged as a critical and recurring natural hazard in rapidly developing cities, driven by the combined effects of climate change, accelerated urbanization, and insufficient infrastructure planning (Ghasemzadeh et al., 2021; Prashar et al., 2023). The growing frequency and severity of urban flood events pose substantial challenges for municipal governance, often resulting in significant economic losses, social disruption, and environmental degradation. These risks are inherently complex, as urban flooding is shaped by the interaction of hydrological processes, environmental conditions, and socio-economic dynamics, which are difficult to represent using conventional assessment approaches (Huang & Wang, 2025; Zhou et al., 2025). This complexity is particularly pronounced in developing countries, where high population density, rapid land-use transformation, and limited adaptive capacity amplify flood vulnerability. In Indonesia, metropolitan areas such as Bekasi exemplify this challenge, facing compounded risks from internal factors, including land subsidence and inadequate drainage systems, as well as external pressures such as upstream flood inflows (Yuanita & Sagala, 2025).

In response to these challenges, flood risk assessment methodologies have progressively shifted from single-criterion or static approaches toward integrated multi-criteria frameworks. The Analytical Hierarchy Process (AHP) has been widely adopted for urban flood vulnerability mapping, including applications in Indonesia (Mujib et al., 2021; Perdinan et al., 2023), Brazil and India (Pimenta et al., 2025; Sar et al., 2025), due to its structured decision-making capabilities. However, conventional AHP is limited by its reliance on precise judgments and its sensitivity to subjectivity and uncertainty in expert assessments. To address these limitations, fuzzy logic has been incorporated into AHP, enabling the use of linguistic variables and improving robustness in pairwise comparisons (Toth & Vacik, 2018; Wieckowski et al., 2024). Empirical studies indicate that Fuzzy-AHP enhances flood risk assessment by better accommodating uncertainty and imprecision (Benaiche et al., 2025; Cikmaz et al., 2025; Demirel et al., 2025). Nevertheless, most Fuzzy-AHP-based models remain largely static and continue to depend on expert-defined weighting schemes, restricting their ability to capture dynamic environmental changes and complex interdependencies among flood-related factors.

To overcome these constraints, recent research has increasingly explored the integration of multi-criteria decision-making techniques with machine learning models for flood risk assessment (Ekmekcioğlu et al., 2021; He et al., 2025; Hidayatulloh & Bahrawi, 2025). Machine learning methods are particularly well suited for identifying non-linear relationships and temporal patterns within large and heterogeneous datasets. Despite this potential, machine learning is often employed primarily as a predictive component, with limited conceptual clarity regarding its analytical complementarity to expert-based weighting approaches. As a result, the added analytical value of machine learning within hybrid flood risk frameworks is not always explicitly articulated, which may weaken methodological transparency and theoretical coherence.

Beyond model integration, another notable limitation in existing studies concerns the role of sensitivity analysis. Sensitivity analysis is commonly applied as a post-hoc diagnostic technique to assess how variations in individual input parameters affect model outputs (Xu et al., 2024). When sensitivity analysis is treated merely as an auxiliary evaluation step without influencing analytical interpretation or decision support, discrepancies can arise between stated methodological claims and actual implementation. Positioning sensitivity analysis as a policy-oriented prioritization and diagnostic instrument—rather than solely as a validation tool—remains insufficiently explored, particularly in the context of seasonal flood management and early warning systems in urban environments.

Addressing these methodological gaps, this study proposes a hybrid urban flood risk assessment framework that integrates Fuzzy-AHP, ensemble machine learning, and sensitivity analysis. Fuzzy-AHP is employed to systematically incorporate expert knowledge while accounting for uncertainty through triangular fuzzy numbers. Ensemble machine learning models, namely Random Forest and XGBoost, are used to analyze historical flood-related data and capture dynamic, non-linear relationships among environmental and socio-economic variables. Random Forest is selected for its robustness in handling noisy and heterogeneous inputs, whereas XGBoost is utilized to model complex interactions and temporal effects. Importantly, the joint use of these models is intended to support methodological triangulation rather than performance maximization alone. Sensitivity analysis is explicitly framed as a policy-relevant prioritization tool, enabling the identification of influential parameters to inform targeted mitigation strategies and seasonal flood preparedness. This integrated design ensures conceptual consistency between expert-driven judgment, data-driven learning, and decision-oriented analysis within a unified flood risk assessment framework.

Accordingly, this study aims to: (1) develop a conceptually coherent hybrid framework for urban flood risk assessment that integrates Fuzzy-AHP and ensemble machine learning; (2) clarify the complementary analytical roles of expert-based weighting and data-driven learning within flood risk analysis; and (3) operationalize sensitivity analysis as a diagnostic and prioritization mechanism for policy-oriented decision support. The study is guided by the following research questions: *How does the integration of Fuzzy-AHP and ensemble machine learning enhance analytical robustness in urban flood risk assessment?* and *How can sensitivity-based prioritization support seasonal planning and early warning strategies in flood-prone urban areas?*.

2. MATERIALS AND METHODS

2.1 Materials

The empirical study was conducted in Bekasi City, Indonesia, a rapidly urbanizing metropolitan area that is highly vulnerable to recurrent flooding due to climate variability, land subsidence, and upstream hydrological pressures. The dataset comprises 1,008 observations collected from 12 districts during the period 2018–2024, providing sufficient spatial and temporal coverage for urban flood risk modeling.

The study utilizes both primary and secondary data sources. Secondary quantitative data were obtained from authoritative national and local agencies. Meteorological variables, including monthly rainfall, were sourced from the Meteorological, Climatological, and Geophysical Agency (BMKG). Flood occurrence records were obtained from the Regional Disaster Management Agency (BPBD). Spatial and physical-environmental data, such as land cover, topography, and distance to rivers, were derived from the Geospatial Information Agency (BIG). Socio-economic indicators, including population density and economic activity, were obtained from Statistics Indonesia (BPS). Data reliability was ensured through cross-validation with historical flood reports and available field survey records.

The input variables were grouped into three main categories reflecting the multidimensional nature of urban flood risk. Climate-related variables include monthly rainfall (mm), climate variability indices, and external flood events represented as binary indicators. Physical-environmental variables consist of land cover percentage, groundwater subsidence rate (cm/year), distance to river networks (meters), and topography classified based on elevation. Socio-economic variables include population density (persons/km^2), drainage infrastructure condition expressed as a quality index, and economic activity indicators. The target variable is flood occurrence, defined as a binary outcome indicating the presence or absence of flooding within a given district and time period.

In addition to quantitative data, expert knowledge was incorporated to support the multi-criteria decision-making component of the study. Expert input was collected through Focus Group Discussions involving five experts with backgrounds in hydrology, environmental engineering, and urban planning. These experts contributed to the formulation of the hierarchical decision structure and provided pairwise comparison judgments for the Fuzzy-AHP analysis.

2.2 Methods

This study develops a hybrid analytical framework that integrates the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP), ensemble machine learning, and sensitivity analysis to support urban flood risk assessment. The overall research workflow, illustrated in Figure 1, consists of sequential stages including data collection, expert-based weighting, data preprocessing, machine learning modeling, and sensitivity analysis. This structured workflow is designed to ensure methodological rigor and conceptual coherence between expert judgment, data-driven learning, and decision-oriented analysis.

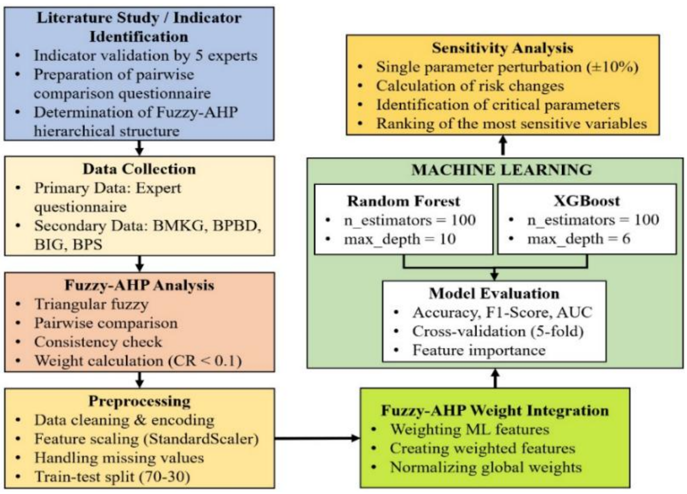

Figure 1. Research methodology

Fuzzy-AHP was first applied to derive relative importance weights for flood-related variables under uncertainty. A three-level hierarchical structure was developed based on expert discussions, consisting of the overall goal of urban flood risk assessment, three main criteria (climate, physical environment, and socio-economic factors), and their respective sub-criteria. Expert preferences were elicited using pairwise comparison questionnaires based on the Saaty scale (1–9) (Liu, 2022). To account for uncertainty and subjectivity in expert judgment, the crisp Saaty scale values were converted into triangular fuzzy numbers following established fuzzy AHP procedures (Coffey & Claudio, 2021). The fuzzy membership function and scale conversion are defined in Equations (1) and (2).

$$\acute{\alpha}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \qquad (1)$$

$$\cancel{1} = (1,1,1), \cancel{2} = (1,2,3), \cancel{3} = (2,3,4), \ldots, \cancel{9} = (8,9,9) \qquad (2)$$

The consistency of expert judgments was evaluated using the Consistency Ratio (CR), calculated using Equation (3), where the Random Index (RI) depends on the size of the comparison matrix. A CR value below 0.1 was considered acceptable, indicating consistent judgments. Fuzzy weights were computed using the geometric mean method (Equation 4), and defuzzification was performed using the centroid method to obtain crisp weights suitable for integration with machine learning models.

$$CI = \frac{\lambda_{max} - n}{n-1}, \quad CR = \frac{\mathrm{CI}}{RI} \qquad (3)$$

$$r_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}, \quad w_i = \frac{r_i}{\sum_{j=1}^{n} r_j} \qquad (4)$$

Prior to machine learning modeling, data preprocessing was conducted to ensure data quality and methodological rigor. Missing values were handled using k-nearest neighbor (KNN) imputation. Categorical variables were encoded based on their characteristics, with flood occurrence and external flood events binarized, district and month variables label-encoded, and topography encoded ordinally according to elevation. Numerical features were normalized using standardization based on the StandardScaler formulation (Equation 5). The dataset was then divided into training and testing subsets using a 70:30 stratified split on the target variable to preserve class distribution.

$$X_{scaled} = \frac{X - \mu}{\sigma} \qquad (5)$$

The crisp weights obtained from the Fuzzy-AHP analysis were integrated into the machine learning feature set through weighted feature engineering (Equation 6). This approach ensures that variables identified as more important by expert judgment exert proportionally greater influence during model learning, while still allowing the models to capture data-driven relationships.

$$X_{weighted} = \mathrm{X} \times \mathrm{W} \qquad (6)$$

Two ensemble machine learning algorithms, Random Forest and XGBoost, were employed to model urban flood risk. The use of machine learning in this study is intended to complement expert-based weighting by capturing complex non-linear relationships and interaction effects among heterogeneous flood-related variables. Random Forest was selected for its robustness to noise, ability to handle high-dimensional data, and stable generalization performance in environmental modeling contexts (Khumaidi et al., 2024). The Random Forest model is configured with parameters including (n_estimators = 100) to ensure sufficient ensemble diversity, (max_depth = 10) to control model complexity, and (min_samples_split = 5) to prevent overly specific node partitioning.

XGBoost is employed as a representative boosting-based ensemble algorithm with high predictive capacity and efficient optimization. Unlike Random Forest, which relies on independent tree construction, XGBoost builds trees sequentially by minimizing a regularized objective function, enabling the model to capture complex non-linear interactions and subtle temporal patterns within the data. In this study, XGBoost is justified as a high-capacity learner designed to identify intricate relationships and interaction effects among flood-related variables that may not be captured through expert-based weighting or bagging-based ensembles alone. The XGBoost model is configured with (n_estimators = 100), (max_depth = 6) to balance expressiveness and generalization, and (learning_rate = 0.1) to ensure stable convergence during training. Both models were initialized with a fixed random state to ensure reproducibility. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics, with the F1-score emphasized due to moderate class imbalance. Model robustness was further assessed using 5-fold stratified cross-validation.

Feature importance analysis was conducted to examine the contribution of individual variables to model predictions. Random Forest feature importance was derived using the mean decrease in impurity, while XGBoost employed gain-based importance metrics. The comparison between machine learning–derived importance scores and Fuzzy-AHP weights was used as an internal analytical check to identify convergence or divergence between expert judgment and data-driven patterns.

Finally, single-parameter sensitivity analysis was conducted to identify influential variables within the flood risk system. Each input variable was independently perturbed by ±10% from its baseline value while holding other variables constant. Sensitivity was quantified using Equation (7), which measures the relative change in predicted flood risk resulting from these perturbations (Xu et al., 2024). In this study, sensitivity analysis is explicitly positioned as a diagnostic and policy-oriented prioritization tool, rather than as an adaptive or self-updating modeling mechanism. The results are intended to support seasonal flood planning, early warning strategies, and targeted mitigation measures by identifying key leverage points within the urban flood system.

$$S_i = \max\left(\left|\frac{R_{i+} - R_0}{R_0}\right|, \left|\frac{R_{i-} - R_0}{R_0}\right|\right) \qquad (7)$$

3. RESULTS AND DISCUSSION

3.1 Exploratory Data Analysis and Dataset Characteristics

The exploratory data analysis provides an overview of the key characteristics of the dataset, which comprises 1,008 observations collected from 12 districts in Bekasi City over the period 2018–2024. As illustrated in Figure 2, the distribution of flood occurrences indicates that 41% of the observations correspond to flood events, while 59% represent non-flood conditions, reflecting a moderate class imbalance in the dataset. Table 1 summarizes the descriptive statistics of the numerical variables, revealing substantial variability across key flood-related factors. Monthly rainfall exhibits a wide range, varying from 89.1 mm to 312.5 mm, with an average of 185.4 mm, indicating pronounced spatial and temporal variability in precipitation patterns within the study area. Climate variability, with a mean value of 2.1 and a standard deviation of 0.8, suggests moderate fluctuations in climatic conditions throughout the observation period.

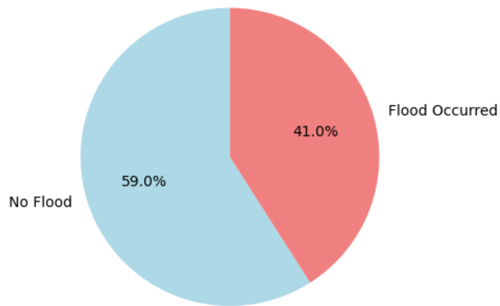

Figure 2. Distribution of flood events

The correlation analysis in Table 1 reveals intriguing patterns, with rainfall showing the highest positive correlation with flood occurrence (r = 0.68), confirming the dominance of precipitation factors in flood genesis in urban areas (Tierolf et al., 2021). Conversely, land cover shows a significant negative correlation (r = -0.61), emphasizing the crucial role of vegetation and green spaces in flood mitigation through increased infiltration and reduced runoff (Taşkın & Manioğlu, 2024). Groundwater subsidence shows a moderate positive correlation (r = 0.59), indicating its contribution to water accumulation, especially in low-elevation areas.

Table 1. Descriptive statistics of numerical variables in the dataset

Variable	Mean	Std Dev	Min	Max	Correlation with Flood
Rainfall (mm)	185.4	45.2	89.1	312.5	0.68
Climate Variability	2.1	0.8	1.0	4.5	0.54
Land Cover (%)	62.3	18.7	25.4	89.2	-0.61
Groundwater Subsidence (cm/year)	8.2	3.1	2.5	15.8	0.59
Distance to River (m)	450.3	215.6	85.2	1250.4	-0.52
Population Density (persons/km^2)	12,580	3,450	6,250	21,500	0.48

The temporal flood occurrence patterns (Figure 3) reveal significant seasonal variations, with peak occurrences in January and December, consistent with the monsoon rainfall pattern in Indonesia (Mulsandi et al., 2024). The high population density distribution (mean = 12,580 persons/km^2) with a wide range (6,250-21,500 persons/km^2) reflects demographic heterogeneity across districts, contributing to variations in social vulnerability to flood impacts.

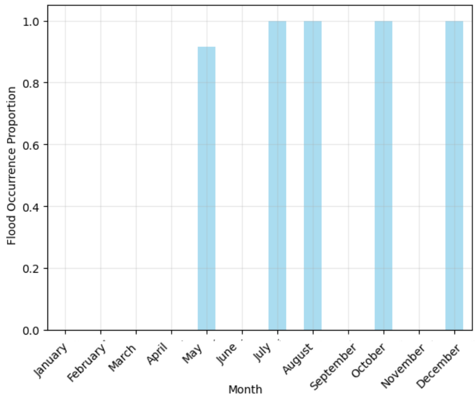

Figure 3. Monthly flood occurrence patterns

The correlation analysis among variables (Figure 4) reveals complex relationships between flood-causing factors. The highest positive correlation is observed between rainfall and climate variability (r = 0.91), while land cover shows a negative correlation with population density (r = -0.67), confirming the impact of urbanization on water absorption capacity through the conversion of open land to built-up areas (Pugara et al., 2021).

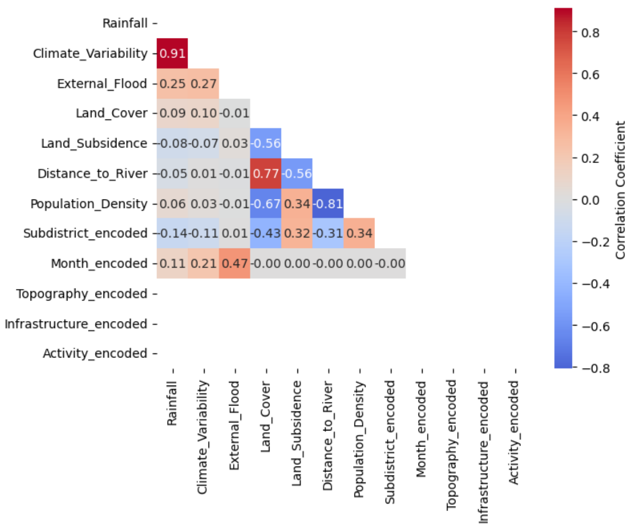

Figure 4. Feature correlation matrix

3.2 Fuzzy-AHP Weighting Results and Consistency Analysis

The Fuzzy-AHP weighting results (Figure 5) revealed a clear priority structure in flood risk assessment. Climate factors emerged as the dominant contributor (52.78%), followed by physical environment (33.25%) and socio-economic factors (13.96%). At the sub-criteria level, rainfall (0.1897) and external flooding (0.1756) were identified as the most critical factors, confirming the dominance of hydrometeorological factors in urban flooding.

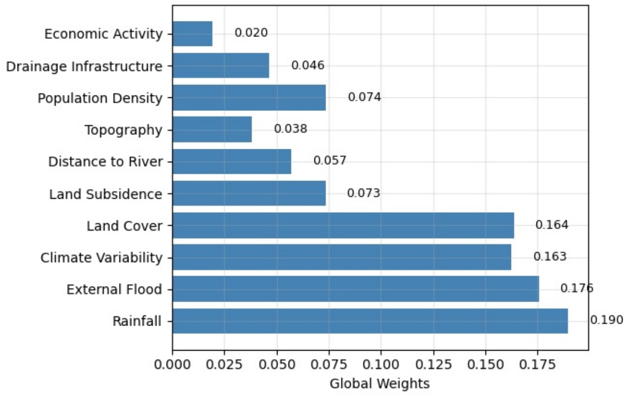

Figure 5. Fuzzy-AHP global weights

Consistency analysis (Figure 6) showed that all hierarchical levels had an aggregate Consistency Ratio (CR) below the threshold of 0.1, indicating consistency. The indicator level (CR = 0.046), physical environment (CR = 0.037), and socio-economic level (CR = 0.046) demonstrated high consistency across all respondents. The aggregate matrix remained consistent (CR = 0.005), which aligns with the robust findings of the geometric mean in handling individual inconsistencies (Mushwani et al., 2024).

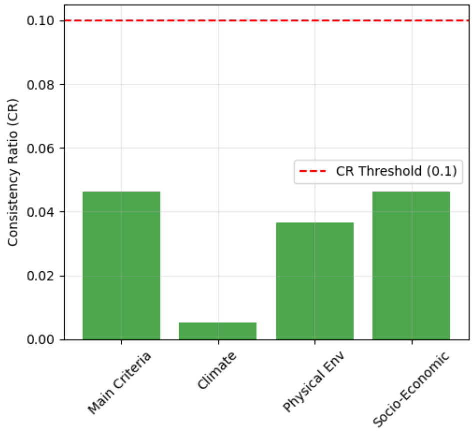

Figure 6. Consistency ratio by hierarchy level

3.3 Performance of Integrated Machine Learning Models

The integration of Fuzzy-AHP weights with ensemble machine learning resulted in high predictive performance, as summarized in Table 2. Both Random Forest and XGBoost achieved accuracy, F1-score, and AUC values of 1.00 on the test dataset. These results indicate that the models were able to effectively distinguish between flood and non-flood events within the observed dataset.

Table 2. Machine learning model performance for flood risk prediction

Model	**Accuracy**	**F1-Score**	**AUC Score**	**Cross-Val F1 (Mean ± SD)**	**Precision**	**Recall**
Random Forest	1.00	1.00	1.00	1.00 ± 0.00	1.00	1.00
XGBoost	1.00	1.00	1.00	1.00 ± 0.00	1.00	1.00

It is important to clarify that the reported performance reflects the combined effect of expert-based weighting and data-driven learning applied to a well-structured and domain-specific dataset. Prior to model training, the dataset was partitioned into training and testing subsets, and all preprocessing steps, including feature scaling and integration of Fuzzy-AHP weights, were conducted in accordance with the defined modeling pipeline. This sequential process was designed to minimize the risk of information leakage between training and testing data and to preserve methodological rigor.

To further assess model robustness, a 5-fold stratified cross-validation strategy was employed, yielding consistent performance across folds with negligible variance. While perfect classification performance is uncommon in real-world urban flood studies, similar outcomes have been reported in domain-specific applications where expert-informed feature weighting is integrated with ensemble learning techniques (He et al., 2025). Nevertheless, the authors acknowledge that such results should be interpreted cautiously, particularly with respect to potential overfitting and dataset specificity.

The ROC curves for both models, presented in Figure 7, demonstrate strong discriminative capability across classification thresholds. Rather than emphasizing absolute performance metrics alone, this study focuses on the analytical consistency between expert-derived Fuzzy-AHP weights and machine learning–based feature importance patterns. The alignment observed between these two perspectives suggests that the integrated framework captures meaningful relationships inherent in the urban flood system.

Despite the strong performance observed, this study does not claim universal generalizability of the trained models beyond the study area. The results are intended to demonstrate the feasibility and analytical robustness of the proposed hybrid framework within the context of Bekasi City. Future studies are encouraged to validate the framework using independent datasets, alternative temporal partitions, or external urban contexts to further assess transferability and robustness.

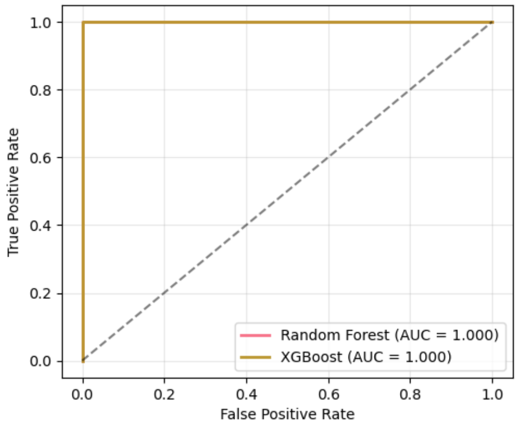

Figure 7. ROC curve analysis

3.4 Sensitivity Analysis and Policy Implications

Single-parameter sensitivity analysis is conducted to identify critical variables influencing urban flood risk. The applied approach follows a systematic perturbation scheme, where each input variable is independently increased and decreased by ±10% from its baseline value while other variables are held constant. Sensitivity is quantified using Equation (7), which measures the relative change in predicted flood risk in response to perturbations of individual input parameters. This method is widely used to evaluate the influence of specific variables on model outputs and to support interpretative analysis of complex systems (Xu et al., 2024).

In this study, sensitivity analysis is explicitly positioned as a diagnostic and policy-oriented prioritization tool, rather than as a component of an adaptive or self-updating modeling mechanism. The analysis is conducted after model development and evaluation, and its primary purpose is to identify leverage points that are most relevant for decision-making, seasonal planning, and early warning strategies.

The sensitivity results, summarized in Table 3, indicate that temporal variables, particularly Month_encoded, exhibit the highest sensitivity score, followed by rainfall and land cover. Although the absolute magnitude of sensitivity values is relatively modest, with maximum changes in predicted risk remaining below 1.5%, such values remain meaningful in urban flood management contexts, where small variations in risk probability can have substantial cumulative impacts during repeated seasonal flood events (Yuanita & Sagala, 2025).

The prominence of temporal variables highlights the importance of seasonality in urban flood risk dynamics, supporting the development of preparedness measures and early warning systems that explicitly account for monthly and seasonal patterns. Rainfall sensitivity further reinforces the dominant role of hydrometeorological drivers, while the negative sensitivity associated with land cover emphasizes the mitigating effect of vegetation and permeable surfaces.

From a policy perspective, sensitivity analysis functions as a prioritization mechanism, assisting decision-makers in focusing monitoring and intervention efforts on variables with higher influence on risk outcomes. Rather than implying direct causality, the sensitivity results provide structured guidance for policy formulation, resource allocation, and operational flood management planning. Overall, the integration of sensitivity analysis enhances the practical relevance of the proposed framework by translating model outputs into actionable, policy-relevant insights, while maintaining methodological transparency and analytical credibility.

Table 3. Sensitivity analysis results for the top 10 variables

Rank	Variable	Sensitivity Score	Max Change (%)	Direction of Change
1	Month_encoded	0.0056	+1.37	Positive
2	Rainfall	0.0017	+0.41	Positive
3	Land Cover	0.0004	-0.10	Negative
4	Distance to River	0.0003	-0.08	Negative
5	Population Density	0.0003	+0.07	Positive
6	Groundwater Subsidence	0.0001	+0.03	Positive
7	District_encoded	0.0000	0.00	Neutral
8	Climate Variability	0.0000	0.00	Neutral
9	External Flooding	0.0000	0.00	Neutral
10	Topography_encoded	0.0000	0.00	Neutral

3.5 Discussion on Hybrid Methodology Integration

The proposed hybrid framework integrates Fuzzy-AHP and ensemble machine learning to address the complexity of urban flood risk assessment, where uncertainty, data heterogeneity, and interacting environmental factors pose significant analytical challenges. Fuzzy-AHP provides a structured mechanism for incorporating expert judgment and uncertainty into multi-criteria weighting, which has been widely adopted in flood and environmental risk studies to support transparent prioritization (Huang & Wang, 2025; Rana & Routray, 2018). In data-constrained urban contexts, such expert-based approaches remain essential for representing local knowledge and stakeholder perspectives.

Nevertheless, expert-derived weighting methods are inherently limited in their ability to capture complex non-linear relationships and interaction effects among flood-related variables. Previous studies have highlighted that hierarchical multi-criteria approaches may oversimplify dynamic systems when used in isolation (Ekmekcioğlu et al., 2021; Tierolf et al., 2021). In response to these limitations, data-driven machine learning techniques have been increasingly integrated into flood risk assessment frameworks to enhance analytical depth and pattern recognition (Guan et al., 2024).

Within the proposed framework, machine learning is explicitly positioned as a complementary analytical component rather than a replacement for Fuzzy-AHP. Ensemble models such as Random Forest and XGBoost are capable of learning non-linear interactions, threshold effects, and temporal dependencies directly from historical data, which cannot be fully represented through expert-based pairwise comparisons alone. By integrating expert-derived weights into the machine learning feature space, the framework enables expert knowledge to guide model learning while allowing empirical data to reveal additional interaction structures.

A key observation emerging from this hybrid integration is the divergence between expert-based Fuzzy-AHP weights and machine learning–derived feature importance for certain variables. Such discrepancies should not be interpreted as methodological inconsistency, but rather as an indication of complex contextual dependencies and non-linear interactions captured through data-driven learning, as also discussed in comparative studies of expert-based and machine learning approaches in flood risk assessment. This divergence underscores the analytical value of combining expert judgment with empirical modeling to obtain a more comprehensive understanding of flood risk dynamics.

The concurrent use of Random Forest and XGBoost further enhances the robustness of the framework through methodological triangulation. While Random Forest offers stability and robustness under heterogeneous and noisy data conditions, boosting-based approaches such as XGBoost provide higher capacity for modeling complex non-linear relationships. Employing multiple ensemble strategies reduces dependence on a single modeling assumption and aligns with recent recommendations for improving robustness and interpretability in flood risk modeling.

Importantly, the contribution of machine learning within this framework should not be evaluated solely in terms of predictive performance. Its primary added value lies in enriching analytical interpretation, validating or challenging expert-based assumptions, and revealing interaction effects that support more informed planning and policy decisions. By explicitly defining the complementary roles of Fuzzy-AHP and ensemble machine learning, the proposed framework avoids redundancy and clarifies its methodological contribution to urban flood risk assessment.

4. CONCLUSION

This study proposes a hybrid framework integrating Fuzzy-AHP, ensemble machine learning, and sensitivity analysis to support urban flood risk assessment in complex urban environments. By combining expert-based weighting with data-driven learning, the framework addresses limitations inherent in single-method approaches and enhances analytical interpretability.

The integration of Random Forest and XGBoost complements Fuzzy-AHP by capturing non-linear interactions and temporal patterns that cannot be fully represented through hierarchical weighting alone. Sensitivity analysis, explicitly positioned as a policy-oriented diagnostic and prioritization tool, provides actionable insights for seasonal planning and early warning strategies without being interpreted as an adaptive modeling mechanism.

The primary contribution of this study lies in the coherent methodological integration of expert judgment, ensemble learning, and sensitivity analysis within a single analytical framework. While the findings are based on a localized urban dataset, the proposed approach offers a transferable methodological reference for flood risk assessment in developing urban contexts. Future research may focus on validating the framework using independent datasets and broader geographic settings.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ACKNOWLEDGEMENTS

This research was financially supported by a Research Grant from the Directorate of Research and Community Service, Directorate General of Research and Development, Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia, under contract number 0070/C3/AL.04/2025 (Penelitian Dosen Pemula). The authors sincerely appreciate the financial support that facilitated the successful completion of this study. Special thanks are also extended to the Bekasi City BMSDA (Environmental Management and Natural Resources Agency), the Bekasi City BPBD (Disaster Management Agency), and other relevant departments for their invaluable contributions and cooperation throughout the research process.

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