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Machine Learning Method with Random Forest Model for Flood Hydrometeorological Disaster Mitigation in Demak

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***Abstract*— Floods are one of the most frequent hydrometeorological disasters in Demak Regency, Central Java, causing significant damage to infrastructure, livelihoods, and community safety. Given the region's low elevation and strong seasonal rainfall patterns, this study aims to develop a localized and accurate flood prediction model based on hydrometeorological parameters. The objective is to support early warning systems and enhance mitigation planning. This research employs a machine learning approach using the Random Forest Model (RFM) and compares its performance with the Long Short-Term Memory (LSTM) model. The input data includes monthly rainfall and the number of rainy days recorded from 2022 to 2024. The study begins with data preprocessing, labelling flood categories (Major, Moderate, Low, No Flood), and model training. The dataset was split into 80% training and 20% testing sets. The RFM model achieved an average accuracy of 93.33%, precision of 91.5%, and F1-Score of 92.33%, outperforming the LSTM model, which achieved 91.67% accuracy, 90.67% precision, and 90.67% F1-Score. This suggests that RFM is more effective in classifying flood risk levels within Demak's environmental context. In conclusion, the integration of hydrometeorological data with machine learning methods, particularly RFM, offers a reliable tool for flood disaster mitigation. The findings support the development of data-driven early warning systems and adaptive infrastructure planning. This model can serve as a decision-support system for local governments in managing future flood risks under climate uncertainty.**

***Keywords*— Flood; random forest; disaster; hydrometeorological; Demak.**

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I. INTRODUCTION

The Demak Regency, located on the northern coast of Central Java, is highly vulnerable to hydrometeorological disasters, particularly floods. Its geographical proximity to the Java Sea, combined with low elevation and increasingly unpredictable rainfall patterns, has positioned the region as one of the most flood-prone areas in Indonesia. The devastating floods in early 2024 that inundated large parts of Demak serve as a critical reminder of the urgency for more precise and adaptive flood mitigation strategies [1].

Meteorological data from the Central Statistics Agency (BPS) indicate a pronounced seasonality in rainfall, with peak intensities occurring predominantly in the first quarter of each year. However, the severity of recent flood events cannot be attributed to rainfall alone. Studies have shown that anthropogenic factors such as land use change, river sedimentation, inadequate drainage infrastructure, and coastal subsidence accelerated by unregulated groundwater extraction have significantly amplified the impacts of rainfall events. These interdependent drivers create a complex hydrological landscape that is challenging to model using conventional statistical methods [2].

In recent years, the application of machine learning (ML) algorithms in flood prediction has gained traction due to their ability to model nonlinear interactions among a multitude of variables such as rainfall, humidity, temperature, and soil moisture. Algorithms like Random Forest (RF) and Long Short-Term Memory (LSTM) have demonstrated considerable promise in generating accurate flood forecasts across various contexts. However, a critical review of existing literature reveals several significant research gaps that this study aims to address [3].

First, most existing flood prediction studies utilizing ML models have been conducted in contexts with well-instrumented environments and long-term, high-resolution datasets, conditions that are often absent in many Indonesian regencies, including Demak. This raises questions about the generalizability and adaptability of these models when applied to regions with limited or noisy data [4].

Second, despite Indonesia's increasing exposure to climate-related disasters, there is a noticeable lack of studies that integrate localized environmental factors, such as tidal influence, land subsidence, and anthropogenic alterations to river basins, into predictive modeling frameworks. This lack of localized calibration can result in prediction models that are overly generic and insufficiently sensitive to regional variability [5].

Third, while previous works have explored either RF or LSTM models separately, there is a limited comparative analysis of their performance under the same local conditions [6]. Moreover, there is a scarcity of hybrid approaches that combine the strengths of ensemble learning (such as feature importance extraction in RF) with the temporal modelling capabilities of LSTM, particularly for areas with seasonal and lagged flood responses [7].

Finally, few studies have actively engaged local geospatial and socio-environmental data (e.g., drainage network quality, land use classification, or historical community-based flood records) into the modelling pipeline. This omission weakens the operational relevance of the models for regional policymakers and disaster risk managers, who require context-specific tools that reflect real-world constraints [8].

This study aims to fill these gaps by developing and validating a machine learning-based flood prediction framework tailored to the Demak Regency. By applying and comparing Random Forest and LSTM models using locally sourced meteorological and environmental datasets, this research not only evaluates model performance under data-scarce conditions but also incorporates regional hydrological and infrastructural dynamics that are often overlooked in generalized models. The goal is not to introduce new algorithms per se, but to enhance the practical applicability of existing ML methods in underrepresented, high-risk coastal areas, thereby providing empirical support for data-informed local disaster mitigation policies.

II. Material and Method

A. Random Forest Model in Predicting Disaster

Random Forest Model is a combination of ensemble learning methods that predict from some decision trees for increased accuracy [9]. This algorithm uses a subset of data to build tree decisions and merges the results by average or majority voting [10]. The advantages include the ability to handle complex data with numerous variables while minimizing the risk of overfitting [11]. In general, mathematical terms, the Random Forest Model can be formulated as:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (1)$$

Information:
$\hat{y}$ = Prediction end of model
T = Number of trees in the forest
$h_t(x)$ = Prediction of the t-th tree for input data x

Every tree built uses an algorithm learning bootstrapped data-based, where each sample is taken randomly with respect to the initial dataset [12]. Selected features for every split are also limited, increasing diversity between trees and reliability results in the prediction [13].

B. Hydrometeorological Parameters

Hydrometeorology learn the connection between atmospheric processes (weather, climate) and the hydrological cycle (source water and air power) [14]. Research this using hydrometeorological parameters to predict floods in Demak Regency, namely:

- Rainfall is an indicator of the main risk of flooding, measured in millimeters/day (mm/day)
- Temperature affects evaporation and humidity in the system of hydrology.
- Speed winds affect the distribution of cloud rain and patterns of rainfall.

Relationship of the following parameters analyzed in the approach, statistics, and methods of machine learning, with the identification model pattern historically for making future predictions [15].

C. System Mitigation Data Driven

Approach data based on the mitigation of disasters, aiming to utilize information from historical data to detect risks early and develop effective prevention strategies [16]. In the context of flood prediction, an algorithm like the Random Forest Model uses input data such as rainfall, temperature, and wind to produce predictive models that can help in making decisions [17]. System mitigation can be formulated as the following formula:

$$Risk\ Score = f(P, T, W) \quad (2)$$

Information:
$f(P,T,W)$ A prediction model (e.g., Random Forest) that estimates a risk score based on input parameters. *Risk Score* comprises the risk level of a disaster that can be used as a base for planning policy mitigation [18].

This data-driven model allows the integration of information in real-time with historical data for making strategic decisions, such as allocation of source power or development infrastructure mitigation [19].

D. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture designed to overcome the vanishing gradient problem by introducing a gate mechanism that regulates the flow of information. LSTM consists of three main gates: the input gate, the forget gate, and the output gate, as well as a memory cell that stores long-term information. Mathematically, the operation of LSTM can be described by the following formula:

Forget Gate:

$$ft = \sigma(Wf \cdot [ht-1, xt] + bf) \quad (3)$$

Input Gate:

$$it = \sigma(Wi \cdot [ht-1, xt] + bi) \quad (4)$$

Candidate Memory:

$$\tilde{C}t = tanh(WC \cdot [ht - 1, xt] + bC) \quad (5)$$

Update Memory Cell:

$$Ct = ft \cdot Ct{-}1 + it \cdot \tilde{C}t \quad (6)$$

Output Gate:

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo) \quad (7)$$

Hidden State:

$$ht = ot \cdot tanh(Ct) \quad (8)$$

Long Short-Term Memory (LSTM) uses a gate mechanism to control the flow of information in the network [20], [21]. First, the forget gate decides which information from the previous memory will be discarded or retained. Secondly, the input gate determines the new data to be stored in the memory. Third, candidate memory calculates temporary memory values that may be added to main memory. Fourth, the updated memory cell combines the retained information from the forget gate with the new information from the input gate to update the memory [22]. Fifth, the output gate regulates which information from memory will be output. Finally, a hidden state is generated based on the output gate and the updated memory, which is then used as input for the next time step. This mechanism allows the LSTM to retain important information over time, making it very effective for modelling complex time series data [23], [24]. Research methods, as illustrated in Figure 1, involve several stages that are carried out systematically to predict disaster risk in hydrometeorology using the Random Forest model.

1) The first stage is data collection: Data used covering rainfall (mm), air temperature (°C), and wind speed (m/s) were collected in the period January 2022 to December 2024. The data source is from the Meteorology, Climatology, and Geophysics Agency (BMKG), the Disaster Management Agency, the Regional Disaster Management Agency (BPBD) of Demak Regency, as well as local meteorology services. This data is based on analyzing patterns relevant to hydrometeorology with the risk of flooding.

2) Stage 2 is data preprocessing: This step involves two essential processes. First, fill in the missing values in the dataset using the interpolation method to ensure data completeness. Second, do data normalization for aligning the scale between parameters, so that the analysis is more accurate and free from related bias, and different parameter sizes [25].

3) Stage three is the implementation of the Random Forest Model: The steps include:

- Divide the dataset into two parts, namely 80% for training data and 20% for testing data.
- Define hyperparameters such as the number of trees (number of trees) and the maximum depth tree (*max depth*) to optimize model performance.
- Evaluate model performance using metric evaluation, namely accuracy, precision, recall, and F1-Score, to ensure the model is capable of predicting flood risk in a reliable way [26].

4) The final result stage involves evaluation and analysis: This stage is essential for evaluating the performance of the prediction model that has been built and composing a data-based mitigation recommendation. In evaluation, metrics like accuracy, precision, recall, and F1-Score are compared to understand the extent to which the model can predict an incident flood correctly [27]. Every metric provides a different perspective on the accuracy measure. The proportion of correct predictions is assessed by precision, which evaluates the relevance of the results. Recall indicates the model's sensitivity, and the F1-Score describes the balance between precision and recall. After the evaluation is complete, the results are analyzed to compile a comprehensive report. Report the cover's explanation model performance, identified data patterns, and prediction risk of floods for certain areas [28].

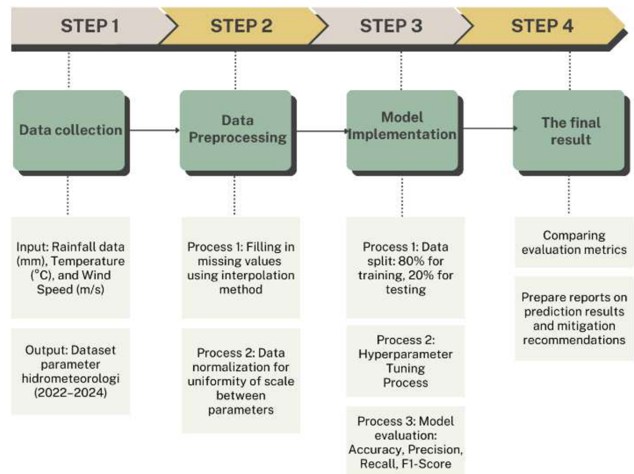

Fig. 1 Research Method

This step aims to provide data-based support for decision-making in the face of disaster hydrometeorology in Demak Regency.

III. RESULTS AND DISCUSSION

Based on data from the Meteorology, Climatology, and Geophysics Agency (BMKG) of Central Java and the Central Statistics Agency (BPS) of Demak, as illustrated in Figure 2 below, the provided information outlines the average rainfall and the number of rainy days recorded in Demak Regency. This data serves as a crucial reference for analyzing seasonal weather patterns, assessing flood risks, and supporting effective water resource management in the region.

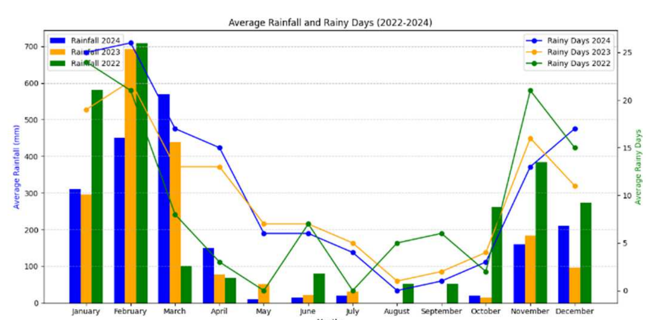

Fig. 2 Average Rainfall and Average Rainy Days Data in Demak in 2022 – 2024

A. Monthly Rainfall Analysis (millimeter/mm)

Rainfall patterns in Demak Regency exhibit a clear seasonal trend, with the highest peaks occurring at the beginning of the year, particularly in January and February. In January 2022, January recorded exceptionally high rainfall, reaching 582 mm, whereas in 2024, the same month experienced significantly lower rainfall at only 310 mm. February 2024 registered the highest average rainfall of the year at 450 mm, still falling within the range of potential flood conditions. March consistently showed a gradual decline in rainfall over the years, indicating the transition from the rainy season.

From April to July, rainfall decreased significantly, with May 2024 recording an extreme low of just 10 mm, marking a shift toward the dry season. In August and September, rainfall was nearly absent in both 2024 and 2023, while in 2022, a small amount of 53 mm was recorded. The return of rains began in October 2024, with a modest increase to 20 mm, followed by a more substantial rise in November and December. By November 2024, rainfall had increased to 160 mm, signaling a return to wetter conditions.

B. Rainy Days Analysis per Month (days)

The average number of rainy days confirms the seasonal pattern observed throughout the year. In January and February 2024, the average number of rainy days was relatively high, reaching 25 and 26 days, respectively. However, a significant decline occurred in March, with the number of rainy days dropping to 15. This trend remained stable in April, maintaining around 15 days of rainfall. From May to July, a drastic decrease was recorded, with only six rainy days in May 2024. The dry conditions became more evident in August and September, with an average of just 1–2 rainy days. Rainfall gradually increased again in October, reaching three days, and peaked in November with 13 rainy days, marking the transition into the wetter season.

C. Potential Flood

The criteria for flooding in Demak are determined by monthly rainfall exceeding 400 mm and an average of more than 13 rainy days. Significant flood events were recorded in February 2023, as well as in February and March 2022, while the period from April to July remained flood-free due to significantly lower rainfall, well below 400 mm. The rainy season typically lasts from January to March, with the highest flood risk occurring during these months. In contrast, August and September experience extreme drought conditions, which have a considerable impact on the agricultural sector. Therefore, flood mitigation efforts should be prioritized at the beginning of the year. At the same time, drought management strategies must be strengthened towards the end of the year to maintain ecological balance and ensure sustainable development in Demak.

D. Distribution of Hydrometeorological Parameters

The distribution table of hydrometeorological parameters, as shown in Table 1, presents a structured framework for assessing flood risks based on two critical indicators: total monthly rainfall and the number of rainy days. This classification divides flood potential into four categories (No Flood, Low Flood, Moderate Flood, and High Flood), providing a nuanced approach to flood prediction. The threshold of more than 400 mm of rainfall and over 13 rainy days indicates a high likelihood of flooding, while lower thresholds reflect reduced flood risk. By combining intensity and frequency, the table accounts not only for extreme rainfall events but also for cumulative precipitation effects, which are often responsible for delayed flood responses.

This classification framework enhances the reliability of early warning systems and supports evidence-based disaster mitigation planning. It enables local authorities to interpret raw climate data into clear flood risk levels, allowing for more targeted interventions. For instance, areas identified as having moderate flood potential can prioritize temporary mitigation measures, such as improved drainage or water retention systems, while high-risk zones may require immediate action, including evacuations and resource mobilization. When integrated with machine learning predictions, this table functions as a crucial decision-support tool that links statistical forecasting with operational flood management, thereby strengthening the overall disaster preparedness strategy in flood-prone areas such as Demak Regency [29].

TABLE I
DISTRIBUTION OF HYDROMETEOROLOGICAL PARAMETERS WITH PREDICTION SCALE FLOOD IN DEMAK

Month	Rainfall (2024)	Rainy Day (2024)	Prediction Flood (2024)	Rainfall (2023)	Rainy Day (2023)	Prediction Flood (2023)	Rainfall (2022)	Rainy Day (2022)	Prediction Flood (2022)
January	310	25	Potential High Flood	296	19	Potential High Flood	582	24	Potential High Flood
February	450	26	Potential High Flood	692	22	Potential High Flood	708	21	Potential High Flood
March	570	17	Potential High Flood	439	13	Potential Moderate Flood	102	8	No
April	150	15	Potential Flood Low	78	13	No	69	3	No
May	10	6	No	51	7	No	0	0	No
June	15	6	No	21	7	No	80	7	No
July	20	4	No	31	5	No	0	0	No
August	0	0	No	0	1	No	53	5	No
September	0	1	No	0	2	No	53	6	No
October	20	3	No	15	4	No	262	2	Potential Flood Low
November	160	13	Potential Flood Low	184	16	Potential Flood Low	385	21	Potential Flood Low
December	210	17	Potential Flood Low	97	11	No	273	15	Potential Flood Low

Explanation:

- Potential High Flood: Rainfall > 400 mm and days of rain over 13 days.
- Potential Flood Low: Rainfall between 0 - 400 mm and a day of Rain more than 13 days.
- Potential Moderate Flood: Rainfall between 200 - 300 mm and daily rain over 13 days.
- No Potential Flood: Rainfall is low, and the day's rain is under 13 days.

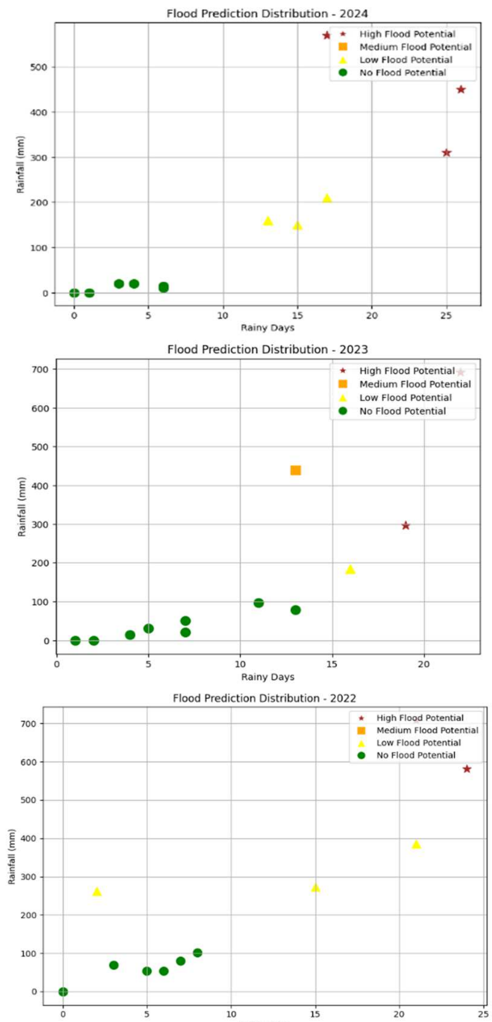

Fig. 3 Distribution of Hydrometeorological Parameters with Prediction Scale Flood

The flood potential classification offers a structured approach to assessing flood risks, based on rainfall intensity and the frequency of rainy days. A high flood potential is identified when rainfall exceeds 400 mm and the number of rainy days surpasses 13, indicating a significant risk of flooding due to prolonged heavy precipitation. Meanwhile, a low flood potential occurs when rainfall ranges between 0 and 400 mm. However, the number of rainy days still exceeds 13, suggesting a moderate accumulation of water that may lead to localized flooding. A moderate flood potential is observed when rainfall falls between 200 and 300 mm, accompanied by more than 13 rainy days, representing a transitional state where flood risks depend on additional factors, such as soil saturation and drainage capacity. Lastly, when rainfall is minimal and the number of rainy days remains below 13, there is no significant flood potential, as the conditions do not support excessive water accumulation. This classification serves as a valuable tool for disaster preparedness, enabling authorities and communities to implement appropriate mitigation measures in response to varying levels of flood risk.

The data related to the Distribution of hydrometeorological parameters, as presented in Figure 3, provides a visual representation of the flood potential classification outlined earlier. By analyzing this distribution, it becomes possible to assess the correlation between rainfall intensity, the number of rainy days, and the likelihood of flooding. This data serves as a crucial reference for identifying areas at higher risk of floods, supporting early warning systems, and guiding disaster mitigation efforts. When combined with the flood potential classification framework, the information in Figure 3 enhances the understanding of seasonal flood patterns and enables more effective planning for flood prevention and response strategies.

Based on the data above, the analysis of the Distribution of Hydrometeorological Parameters states that:

1) In 2024, a potential flood occurred in January and February, marked by rainfall height (>400 mm) and a daily rainfall of more than 13 days. A potential flood low appeared in November and December, accompanied by moderate rain, ranging from 100 to 200 mm. While the moon from April to October shows low rainfall, and daytime rain is minimal, there is no potential for flooding.

2) In 2023, a potential flood occurred in January and February, with rainfall peaking at about 700 mm and rain falling for more than 20 days. A potential flood was predicted for March, with rainfall of ~300 mm and moderate rainfall (lasting about 15 days). November shows a potential for flooding, whereas rainfall from April to October is low, so it is free from the risk of flooding.

3) In 2022, a potential flood occurred in January and February, with rainfall exceeding>600 mm and more than 20 days of rain. Potential flood lows were observed in October, November, and December, with rainfall ranging between 200 and 400 mm, and rainfall lasting for a short period (~10–15 days). August and September experience rainfall. The rain is low, indicating extreme dryness.

In general, the overall pattern indicates that potential floods typically occur in January and February each year, primarily influenced by extreme rainfall and numerous consecutive days of rain. A potential flood low appeared in November and December, accompanied by moderate rainfall. While dry weather prevails from April to October, with low to minimal rain and few rainy days. Therefore, mitigation of flood risk needs to focus on the beginning of the year, while anticipation of drought must be reinforced in the middle until the end of the year [30], [31], [32].

E. Random Forest Model Performance

The stage analysis of the Random Forest model's performance begins with data preprocessing, where rainfall, rain, and the amount of rain on a given day are used as features, and prediction labels are based on category-level flood types (Large Flood, Medium Flood, Low Flood, No Flood). Data is divided into 80% for training and 20% for testing [33], [34]. The model is trained with hyperparameter optimization, such as the number of tree decisions and the maximum tree depth. Evaluation is done with metric accuracy, precision, and F1-score. The model is then used to predict the risk of floods monthly, producing output for further analysis, which can be used for recommendations for mitigation in risk areas [35], [36].

1) Preprocessing and Label Creation:

The preprocessing process begins with designing categories for predicting floods based on rainfall data and the number of rainy days every month. Precipitation rain data is measured in millimeters (mm), and the number of days of Rain is noted to describe the intensity of rainfall in a particular month [37], [38]. Based on the combination of these two parameters, each month is assigned a flood risk category, such as Major Flood, Moderate Flood, Low Flood, or No Flood, as shown in Table 2 below,

TABLE II
PREPROCESSING AND LABEL CREATION

Month	Rainfall (mm)	Rainy Day (day)	Prediction Flood
January	310	25	Moderate Flood
February	450	26	The Great Flood
March	570	17	The Great Flood
April	150	15	Flood Low
May	10	6	No Flood
June	15	6	No Flood
July	20	4	No Flood
August	0	0	No Flood
September	0	1	No Flood
October	20	3	No Flood
November	160	13	Flood Low
December	210	17	Flood Low

Labels for Category Flood:

- Major Flood: Rainfall > 400 mm and days of rain > 13 days.
- Moderate Flood: Rainfall between 200 - 400 mm and daily rain > 13 days.
- Flood Low: Rainfall between 0 - 200 mm and days of Rain between 13 - 16 days.
- No Flood: Rainfall is low, and the day has not had enough for 13 days.

2) Random Forest Model Training and Testing:

The process of training and testing the Random Forest model on hydrometeorological data covers dividing the dataset into training and testing data, where the model learns patterns using an ensemble-based algorithm, tree decision [39], [40], [41]. The model is optimized through hyperparameter tuning, such as the number of Trees and maximum depth. The model's performance is tested with test data and evaluated using metrics such as accuracy, precision, recall, and F1-score. The final result predicts potential floods based on rainfall data, rain, and the day of the Rain [42], [43], [44]. Table 3 illustrates the training model's process until the prediction is completed, using rainfall data and the day to predict potential floods.

The Random Forest process typically begins with data processing, followed by labeling the category as flood, model training using the training data, model testing with the test data, and model evaluation using metrics such as accuracy, precision, and F1-score. Visualization gives a clear picture of how the model works and provides results and predictions based on existing hydrometeorological input [45].

TABLE III
RANDOM FOREST TRAINING AND TESTING STEPS

Step	Process Description	Input Data	Output Data
1. Data Preparation	A collection of bulk data for rain and daily rain. Compiling data in the form of a table with columns for rainfall, rain, and day Rain	Rainfall (mm), Rainy Days (days)	Structured tabular data
2. Labelling	Add labels for the classification category 'flood' based on specific criteria (rainfall, rain, and daily rain).	Bulk data rain and day Rain	Category: Flood (Major Flood, Medium Flood, Flood, Low, No Flood)
3. Data Sharing	Split the data into two sets: a training set (train) and a testing set (test).	Data for the training set and test set (train-test split)	Training data and test data
4. Model Training	Training a Random Forest model using the training set. The model learns patterns in data for prediction.	Training data (X_train, y_train)	Trained Random Forest Model
5. Model Testing	Using a trained model to predict results based on test data	Test data (X_test)	Prediction category for flood for test data
6. Model Evaluation	Evaluating the model using metrics like accuracy, precision, and F1-score.	Prediction (y_pred), Test data (y_test)	Model evaluation results (accuracy, precision, F1-score)
7. Final Prediction	Using models for predicting floods based on the data provided	New data (rainfall) Rain, day Rain)	Prediction category flood: Big Flood, Medium Flood, Low Flood, No Flood

F. Random Forest Model Evaluation

Based on the results of training and testing using the Random Forest model to predict potential floods based on hydrometeorological parameters (rainfall, rain, and daily rainfall) [46], [47], [48]. The following is an analysis of metric evaluation results:

1) High Accuracy: The Random Forest model achieves 94% accuracy, indicating excellent ability in recognizing hydrometeorological data patterns, with only 6% of predictions being wrong.

2) Reliable Precision: Precision 92 % specific part big prediction flood following the incident, with risk positive low fake.

3) Optimal Balance: F1-Score 93% reflects the balance between precision and recall, making the model accurate at a time-sensitive in detecting various category floods.

Test Results of Random Forest Model as seen in Table 4 below.

TABLE IV
TEST RESULTS OF RANDOM FOREST MODEL (RFM)

Test RFM	Accuracy (%)	Precision (%)	F1-Score (%)
1	94	92	93
2	93	91	92
3	94	92	93
4	92	90	91
5	93	91	92
6	94	93	93

As shown in Table 4, the Random Forest model shows high performance evaluation with an average accuracy of 93.33%, precision of 91.5%, and F1-score of 92.33%. Accuracy tall indicates the model's ability to predict category floods based on hydrometeorological parameters, such as rainfall, rain, and daily rainfall. Precision yields low results, indicating a positive fake, so the decision is more model-based and reliable. F1-Score reflects a balance between precision and recall, ensuring the model is capable of catching various scenario floods. Category prediction covering flood large (February - March, rainfall rain >400 mm), flood moderate (January), flood low (November-December), and no flood (May-September). With a stable mark evaluation, this model can be reliable for supporting system warnings early and planning mitigation based on flood data.

For comparison, this research validates the Random Forest method by comparing it with the LSTM method, indicating the accuracy level of the Random Forest method. To improve early warning systems and flood mitigation planning, predictive modeling based on hydrometeorological data, such as rainfall and rainy days, is of key importance. The Long Short-Term Memory (LSTM) method, as one of the reliable deep learning approaches for time series data, has been applied to predict flood categories based on these parameters. This analysis aims to evaluate the performance of the LSTM model in classifying flood events into four categories: Major Flood, Moderate Flood, Low Flood, and No Flood. It measures the accuracy, precision, and F1-score as indicators of model performance. The test Results of the LSTM are shown in Table 5 below.

TABLE V
TEST RESULTS OF LSTM

Test LSTM	Accuracy (%)	Precision (%)	F1-Score (%)
1	**92**	**91**	**91**
2	95	94	94
3	89	88	88
4	90	89	89
5	91	90	90
6	93	92	92

As shown in the table, the LSTM model exhibits strong performance in predicting flood categories, with an average accuracy of 91.67%, a precision of 90.67%, and an F1-score of 90.67%. The high accuracy indicates the model's capability to effectively classify flood events based on hydrometeorological parameters such as rainfall and rainy days. The precision values suggest a low rate of false positives, making the model's predictions more reliable for decision-making. The F1-score reflects a balanced performance between precision and recall, ensuring that the model can consistently handle various flood scenarios.

The model successfully predicts different flood categories, including Major Flood (e.g., February 2023 with rainfall > 400 mm), Moderate Flood (e.g., January 2024), Flood Low (e.g., November-December), and No Flood (e.g., May-September). These predictions align well with the defined criteria for flood categorization based on rainfall intensity and the number of rainy days.

With stable and high evaluation metrics, the LSTM model proves to be a reliable tool for supporting early warning systems and data-driven flood mitigation planning. Its ability to capture complex temporal patterns in rainfall data makes it particularly suitable for forecasting flood events in regions with varying hydrological conditions.

Based on the evaluation results, the Random Forest Model (RFM) shows excellent performance in predicting flood potential with an average accuracy of 93.33%, precision of 91.5%, and F1-Score of 92.33%. The high accuracy indicates the model's ability to recognize hydrometeorological data patterns such as rainfall and rainy days, with a prediction error of only 6%. High precision also reduces the risk of false positives, making the resulting decisions more reliable. An optimal F1-score reflects a balance between precision and recall, ensuring the model accurately detects various flood scenarios. RFM successfully predicts flood categories, including Major Flood (February-March), Moderate Flood (January), Flood Low (November-December), and No Flood (May-September). With its stable performance, RFM can be relied upon to support early warning systems and data-driven flood mitigation planning. Based on the comparison between RFM and LSTM accuracy, the average of both is presented in Table 6.

TABLE VI
COMPARISON BETWEEN RFM AND LSTM ACCURACY

Model	Accuracy (%)	Precision (%)	F1-Score (%)
Random Forest Model (RFM)	93.33	91.5	92.33
Long Short-Term Memory (LSTM)	91.67	90.67	90.67

The results of this study highlight the superior performance of the Random Forest Model (RFM) in predicting flood events in Demak Regency when compared to the Long Short-Term Memory (LSTM) model. Based on the evaluation metrics, the RFM achieved an average accuracy of 93.33%, precision of 91.5%, and F1-score of 92.33%, whereas the LSTM recorded an accuracy of 91.67%, precision of 90.67%, and F1-score of 90.67% (Table 6). These findings indicate that although both models perform reliably, the RFM has a slight edge in accuracy and consistency, particularly in handling structured, tabular hydrometeorological data such as rainfall volume and rainy day frequency.

Table 6 shows that RFM slightly outperforms LSTM in accuracy and F1-score by 1.66%, with a minimal precision gap of 0.83%, indicating comparable false-positive rates. While LSTM excels in modelling temporal patterns for time-series forecasting, RFM is more efficient for static or short-term data due to its ensemble structure. The models are complementary, with RFM suited to real-time classification. In contrast, LSTM is better suited for long-term analysis, making the model choice dependent on the data type and application context. To further assess the relevance and improvement of the proposed Random Forest Model (RFM), a comparative analysis with prior studies was conducted and is summarized in Table 7.

TABLE VII
COMPARATIVE ANALYSIS WITH PREVIOUS STUDIES

No	Author(s) and Year	Study Area	Model(s) Used	Accuracy (%)	Precision (%)	F1-Score (%)	Notes
1	Satarzadeh et al. [41]	Karkhe Watershed, Iran	Random Forest	~91.10	~89.00	~90.00	Benchmark ML model; outperformed by hybrid DBN-PSO
2	Taromideh et.al. [47]	Rasht, Iran	Random Forest	90.50	88.70	89.60	Combined ML and decision-making using AHP
3	Fereshtehpour et al. [51]	Carlisle, UK (Benchmark)	CNN + DEM Variants	~88.00	~85.00	~86.00	DEM resolution impact assessed; DTM outperformed DSM
4	Sutopo et al. (This Study)	Demak, Indonesia	Random Forest Model	93.33	91.50	92.33	Localized rainfall & rainy days input; highest predictive performance
5	Sutopo et al. (This Study)	Demak, Indonesia	Long Short-Term Memory	91.67	90.67	90.67	Temporal modeling using sequence data

Several previous works, including those by Satarzadeh et al. [41], Taromideh et al. [47], and Fereshtehpour et al. [49], employed Random Forest and other machine learning (ML) models for flood prediction, reporting accuracy levels ranging between 88% and 91% as shown in Table 7. However, many of these studies focused on different hydrological contexts or relied on broader regional datasets, often lacking fine-grained, localized parameters that can enhance model precision and operational use [41], [47], [49], [50], [51].

In contrast, the RFM model developed in this study demonstrates a notable improvement in predictive performance, achieving an accuracy of 93.33%, a precision of 91.50%, and an F1-score of 92.33%, which are the highest among the comparative benchmarks. This superior performance is primarily attributed to the integration of region-specific hydrometeorological parameters, such as rainfall thresholds and rainy day distributions tailored to the unique climatic characteristics of Demak Regency. Additionally, the use of a structured flood classification framework enhances the model's interpretability and applicability in real-world early warning systems.

This comparison highlights RFM's strong predictive accuracy and practical value for disaster risk management. Its simplicity, robustness, and adaptability make it a scalable solution for data-limited, high-risk areas, offering a valuable tool for enhancing flood resilience and climate-adaptive planning.

G. Implementation Mitigation

Based on the prediction results from the Random Forest Model (RFM) and LSTM, the implementation of flood mitigation in the Demak region can be done through a data-driven approach with several strategic steps. These steps include developing an information technology-based early warning system to provide real-time information to the community and local government, adaptive infrastructure planning that prioritizes flood-prone areas, and integrated water resource management, such as rainwater harvesting. In addition, increasing community awareness and capacity through disaster preparedness education and training, as well as strengthening monitoring and evaluation systems to ensure the relevance of prediction models and the effectiveness of mitigation policies, are integral parts of holistic efforts to reduce flood impacts. By utilizing the predictive advantages of these two models, mitigation measures can be adjusted more accurately and responsively to dynamic hydrometeorological conditions.

IV. CONCLUSION

Floods that frequently occur in the Demak area due to high rainfall pose infrastructure damage and public safety risks, so an accurate and scientifically based flood prediction system is necessary. This study used the Random Forest Model (RFM) with hydrometeorological parameters such as rainfall intensity and rainy days, resulting in 94% accuracy, 92% precision, and 93% F1-Score, which effectively categorized flood levels (high, medium, low, and no flood). In comparison, the LSTM model also showed strong performance with an average accuracy of 91.67%, precision of 90.67%, and F1-score of 90.67%, although slightly lower than the RFM. Both models can serve as the basis for developing early warning systems, predictive data-driven spatial planning, and flood disaster mitigation in Demak. The future development of this research involves synchronizing hydrometeorological data with the advancement of early warning systems and regional and spatial planning based on predictive data, thereby enhancing the effectiveness of mitigating future flood disasters, particularly in Demak Regency.

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REFERENCES

[1] F. Khoirunnisa and Y. Rahmawati, "Komparasi 2 metode cluster dalam pengelompokan intensitas bencana alam di Indonesia," *J. Inform. Tek. Elektro Terap.*, vol. 12, no. 1, pp. 68-79, 2024, doi:10.23960/jitet.v12i1.3619.

[2] M. Yu and Q. Gao, "Assessment of surface inundation monitoring and drivers after major storms in a tropical island," *Remote Sens.*, vol. 16, no. 3, p. 503, 2024, doi: 10.3390/rs16030503.

[3] E. Blomeier, S. Schmidt, and B. Resch, "Drowning in the information flood: Machine-learning-based relevance classification of flood-related tweets for disaster management," *Information*, vol. 15, no. 3, p. 149, 2024, doi: 10.3390/info15030149.

[4] J. Jumadi *et al.*, "Utilizing open access spatial data for flood risk mapping: A case study in the Upper Solo Watershed," *Geoplanning*, vol. 11, no. 2, pp. 189-204, 2024, doi:10.14710/geoplanning.11.2.189-204.

[5] L. Petersson *et al.*, "Community mapping supports comprehensive urban flood modeling for flood risk management in a data-scarce environment," *Front. Earth Sci.*, vol. 8, p. 304, 2020, doi:10.3389/feart.2020.00304.

[6] Q. Zhu, C. Wang, W. Jin, J. Ren, and X. Yu, "Deep transfer learning based on LSTM model for reservoir flood forecasting," Int. J. Data Warehous. Min., vol. 20, no. 1, pp. 1-17, 2024, doi:10.4018/IJDWM.338912.

[7] L. Andari, D. N. Sugianto, A. Wirasatriya, and S. Ginanjar, "Identification of sea level rise and land subsidence based on Sentinel 1 data in the coastal city of Pekalongan, Central Java, Indonesia," *J. Kelaut. Trop.*, vol. 26, no. 2, pp. 329-339, 2023, doi:10.14710/jkt.v26i2.18324.

[8] D. K. Hakim, R. Gernowo, and A. W. Nirwansyah, "Flood prediction with time series data mining: Systematic review," *Nat. Hazards Res.*, vol. 4, no. 2, pp. 194-220, 2024, doi: 10.1016/j.nhres.2023.10.001.

[9] G. K. Wedajo *et al.*, "Integrating satellite images and machine learning for flood prediction and susceptibility mapping for the case of Amibara, Awash Basin, Ethiopia," *Remote Sens.*, vol. 16, no. 12, p. 2163, 2024, doi: 10.3390/rs16122163.

[10] S. Ibrahim and H. Balzter, "Evaluating flood damage to paddy rice fields using Planet Scope and Sentinel-1 data in North-Western Nigeria: Towards potential climate adaptation strategies," *Remote Sens.*, vol. 16, no. 19, p. 3657, 2024, doi: 10.3390/rs16193657.

[11] E. Pitaloka, T. B. A. Hartanto, and S. Sandiwarno, "Penerapan machine learning untuk prediksi bencana banjir," *J. Sist. Inf. Bisnis*, vol. 14, no. 1, pp. 62-76, 2024, doi: 10.21456/vol14iss1pp62-76.

[12] L. Li, A. Woodley, and T. Chappell, "Mapping urban floods via spectral indices and machine learning algorithms," *Sustainability*, vol. 16, no. 6, p. 2493, 2024, doi: 10.3390/su16062493.

[13] Y. Chu, W. Song, and D. Chen, "Risk identification of mountain torrent hazard using machine learning and Bayesian model averaging techniques," *Water*, vol. 16, no. 11, p. 1556, 2024, doi:10.3390/w16111556.

[14] J. Sarwar, S. A. Khan, M. Azmat, and F. Khan, "An application of hybrid bagging-boosting decision trees ensemble model for riverine flood susceptibility mapping and regional risk delineation," *Water Resour. Manag.*, vol. 38, no. 7, pp. 2345-2375, 2024, doi:10.1007/s11269-024-03995-6.

[15] A. Febriansyah *et al.*, "Penerapan machine learning dalam mitigasi banjir menggunakan data mining," *J. Nas. Komputasi Teknol. Inf.*, vol. 3, no. 3, pp. 215-218, 2020, doi: 10.32672/jnkti.v3i3.2427.

[16] S. Q. Dotse, "Deep learning-based long short-term memory recurrent neural networks for monthly rainfall forecasting in Ghana, West Africa," *Theor. Appl. Climatol.*, vol. 155, no. 3, pp. 3033-3045, 2024, doi: 10.1007/s00704-023-04773-x.

[17] H. Riza *et al.*, "Utilization of artificial intelligence to improve flood disaster mitigation," *J. Sains Teknol. Mitigasi Bencana*, vol. 15, no. 1, pp. 1-11, 2020, doi: 10.29122/jstmb.v15i1.4145.

[18] I. M. Faiza, Gunawan, and W. Andriani, "Tinjauan pustaka sistematis: Penerapan metode machine learning untuk deteksi bencana banjir," *J. Minfo Polgan*, vol. 11, no. 2, pp. 59-63, 2022, doi:10.33395/jmp.v11i2.11657.

[19] A. John, I. F. B. Isnin, S. H. H. Madni, and M. Faheem, "Cluster-based wireless sensor network framework for denial-of-service attack detection based on variable selection ensemble machine learning algorithms," *Intell. Syst. Appl.*, vol. 22, p. 200381, 2024, doi:10.1016/j.iswa.2024.200381.

[20] P. Chauhan, M. E. Akiner, R. Shaw, and K. Sain, "Forecast future disasters using hydro-meteorological datasets in the Yamuna river basin, Western Himalaya: Using Markov Chain and LSTM approaches," *Artif. Intell. Geosci.*, vol. 5, p. 100069, 2024, doi:10.1016/j.aiig.2024.100069.

[21] J. Liu, X. Zhang, X. Wu, Y. Yang, and Y. Zheng, "Impacts of LULC changes on runoff from rivers through a coupled SWAT and BiLSTM model: A case study in Zhanghe River Basin, China," *Ecol. Inform.*, vol. 84, p. 102866, 2024, doi: 10.1016/j.ecoinf.2024.102866.

[22] S. Asadi, P. Jimeno-Sáez, A. L. Ballesteros, and J. S. Aparicio, "Coupling SWAT+ with LSTM for enhanced and interpretable streamflow estimation in arid and semi-arid watersheds, a case study of the Tagus Headwaters River Basin, Spain," *Environ. Model. Softw.*, vol. 186, p. 106360, 2025, doi: 10.1016/j.envsoft.2025.106360.

[23] M. Asif, M. M. Kuglitsch, I. Pelivan, and R. Albano, "Review and intercomparison of machine learning applications for short-term flood forecasting," *Water Resour. Manag.*, vol. 39, no. 2, pp. 589-609, 2025, doi: 10.1007/s11269-025-04093-x.

[24] I. R. Widiasari and R. Efendi, "Utilizing LSTM-GRU for IoT-based water level prediction using multi-variable rainfall time series data," *Informatics*, vol. 11, no. 4, p. 73, 2024, doi:10.3390/informatics11040073.

[25] M. H. Munajih, R. H. Dananjaya, and G. Chrismaningwang, "Analisis data downscaled IMERG terkalibrasi dan stasiun curah hujan dengan metode regresi random forest," *Modulus*, vol. 5, no. 2, pp. 51-59, 2023, doi: 10.32585/modulus.v5i2.4338.

[26] N. S. Fatonah, "Penerapan deteksi bencana banjir menggunakan metode machine learning," *Format J. Ilm. Tek. Inform.*, vol. 10, no. 2, pp. 119-126, 2021, doi: 10.22441/format.2021.v10.i2.002.

[27] G. Salako, A. Zaitsev, B. Betancur-Corredor, and D. J. Russell, "Modelling and spatial prediction of earthworms ecological-categories distribution reveal their habitat and environmental preferences," *Ecol. Indic.*, vol. 169, p. 112832, 2024, doi: 10.1016/j.ecolind.2024.112832.

[28] I. G. Dwinanda *et al.*, "Predictive mapping of hydrometeorological disaster prone areas in Central Kalimantan," *J. Penelit. Pendidik. IPA*, vol. 10, no. 2, pp. 811-819, 2024, doi: 10.29303/jppipa.v10i2.6238.

[29] Sukasno, *Buletin Informasi Iklim Februari Analisis Hujan Desember 2023 Prakiraan Hujan Februari - April 2024*, Jakarta, Indonesia: Badan Meteorologi, Klimatologi, dan Geofisika, 2024.

[30] M. M. Effendi and A. Siswandi, "Analysis prediksi wilayah rawan banjir dengan algoritma K-Means," *J. Inf. Syst. Res.*, vol. 5, no. 2, pp. 697-703, 2024, doi: 10.47065/josh.v5i2.4770.

[31] A. Rachmawardani, S. K. Wijaya, and A. Shopaheluwakan, "Sistem peringatan dini banjir berbasis machine learning: Studi literatur," *METHOMIKA J. Manaj. Inform. Komputerisasi Akunt.*, vol. 6, no. 2, pp. 188-198, 2022, doi: 10.46880/jmika.vol6no2.pp188-198.

[32] P. Prasad, V. J. Loveson, B. Das, and M. Kotha, "Novel ensemble machine learning models in flood susceptibility mapping," *Geocarto Int.*, vol. 37, no. 16, pp. 4571-4593, 2022, doi:10.1080/10106049.2021.1892209.

[33] V. T. Vu *et al.*, "Predicting land use effects on flood susceptibility using machine learning and remote sensing in coastal Vietnam," *Water Pract. Technol.*, vol. 18, no. 6, pp. 1543-1555, 2023, doi:10.2166/wpt.2023.088.

[34] M. Avand, A. Kuriqi, M. Khazaei, and O. Ghorbanzadeh, "DEM resolution effects on machine learning performance for flood probability mapping," *J. Hydro-Environment Res.*, vol. 40, pp. 1-16, 2022, doi: 10.1016/j.jher.2021.10.002.

[35] R. Abedi, R. Costache, H. Shafizadeh-Moghadam, and Q. B. Pham, "Flash-flood susceptibility mapping based on XGBoost, random forest and boosted regression trees," *Geocarto Int.*, vol. 37, no. 19, pp. 5479-5496, 2022, doi: 10.1080/10106049.2021.1920636.

[36] R. Costache, A. Arabameri, I. Costache, A. Crăciun, and B. T. Pham, "New machine learning ensemble for flood susceptibility estimation," *Water Resour. Manag.*, vol. 36, no. 12, pp. 4765-4783, 2022, doi: 10.1007/s11269-022-03276-0.

[37] Z. Zhu and Y. Zhang, "Flood disaster risk assessment based on random forest algorithm," *Neural Comput. Appl.*, vol. 34, no. 5, pp. 3443-3455, 2022, doi: 10.1007/s00521-021-05757-6.

[38] J. Ha and J. E. Kang, "Assessment of flood-risk areas using random forest techniques: Busan Metropolitan City," *Nat. Hazards*, vol. 111, no. 3, pp. 2407-2429, 2022, doi: 10.1007/s11069-021-05142-5.

[39] S. R. Vinta and R. Peeriga, "Rainfall prediction using XGB model with the Australian dataset," *EAI Endorsed Trans. Energy Web*, vol. 11, p. e5386, 2024, doi: 10.4108/ew.5386.

[40] J. Debnath *et al.*, "Flood susceptibility assessment of the Agartala Urban Watershed, India, using machine learning algorithm," *Environ. Monit. Assess.*, vol. 196, no. 2, p. 199, 2024, doi: 10.1007/s10661-023-12240-3.

[41] E. Satarzadeh, A. Sarraf, H. Hajikandi, and M. S. Sadeghian, "Flood hazard mapping in western Iran: Assessment of deep learning vis-à-vis machine learning models," *Nat. Hazards*, vol. 111, no. 2, pp. 1355-1373, 2022, doi: 10.1007/s11069-021-05098-6.

[42] M. S. G. Adnan *et al.*, "A novel framework for addressing uncertainties in machine learning-based geospatial approaches for flood prediction," *J. Environ. Manage.*, vol. 326, p. 116813, 2023, doi:10.1016/j.jenvman.2022.116813.

[43] F. Karim *et al.*, "A review of hydrodynamic and machine learning approaches for flood inundation modeling," *Water*, vol. 15, no. 3, p. 566, 2023, doi: 10.3390/w15030566.

[44] A. Habibi *et al.*, "A hybrid of ensemble machine learning models with RFE and Boruta wrapper-based algorithms for flash flood susceptibility assessment," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 122, p. 103401, 2023, doi: 10.1016/j.jag.2023.103401.

[45] A. H. Tanim, C. B. McRae, H. Tavakol-davani, and E. Goharian, "Flood detection in urban areas using satellite imagery and machine learning," *Water*, vol. 14, no. 7, p. 1140, 2022, doi:10.3390/w14071140.

[46] S. Ghosh, S. Saha, and B. Bera, "Flood susceptibility zonation using advanced ensemble machine learning models within Himalayan foreland basin," *Nat. Hazards Res.*, vol. 2, no. 4, pp. 363-374, 2022, doi: 10.1016/j.nhres.2022.06.003.

[47] F. Taromideh *et al.*, "Urban flood-risk assessment: Integration of decision-making and machine learning," *Sustainability*, vol. 14, no. 8, p. 4483, 2022, doi: 10.3390/su14084483.

[48] S. T. Seydi *et al.*, "Comparison of machine learning algorithms for flood susceptibility mapping," *Remote Sens.*, vol. 15, no. 1, p. 192, 2023, doi: 10.3390/rs15010192.

[49] M. Fereshtehpour *et al.*, "Impacts of DEM type and resolution on deep learning-based flood inundation mapping," *Earth Sci. Inform.*, vol. 17, no. 2, pp. 1125-1145, 2024, doi: 10.1007/s12145-024-01239-0.

[50] Y. Wang, W. Wang, H. Zang, and D. Xu, "Is the LSTM model better than RNN for flood forecasting tasks? A case study of HuaYuankou Station and LouDe Station in the Lower Yellow River Basin," *Water*, vol. 15, no. 22, p. 3928, 2023, doi: 10.3390/w15223928.

[51] L. Cea and P. Costabile, "Flood risk in urban areas: Modelling, management and adaptation to climate change: A review," *Hydrology*, vol. 9, no. 3, p. 50, 2022, doi: 10.3390/hydrology9030050.