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Tidal flood prediction in Indonesian coastal areas using long short-term memory for enhanced early warning systems

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ABSTRACT

Coastal flooding, locally known as banjir rob, persists as a recurring hazard in Indonesia's low-lying coastal zones, driven by tidal variation, river discharge, and meteorological dynamics. This study applies a Long Short-Term Memory (LSTM) neural network for short-term flood prediction using a multivariate dataset covering 2020–2024. The dataset integrates daily records of water levels from six monitoring stations (Katulampa, Pos Depok, Manggarai, Istiqlal, Jembatan Merah, Flusing Ancol), sea-level observations from Marina Ancol, and meteorological parameters including wind speed, wind direction, rainfall, atmospheric pressure, and sea surface temperature. Flood status was encoded as a binary target (0 = non-flood, 1 = flood) with balanced distribution, enabling robust model generalization. Preprocessing involved data cleaning, normalization, and sliding-window sequencing to capture temporal dependencies. The LSTM architecture combined stacked recurrent layers, dropout regularization, and a dense output layer, trained in TensorFlow with tuned hyperparameters. Evaluation indicated strong predictive skill, with Mean Absolute Error (MAE) below 3 cm, Mean Absolute Percentage Error (MAPE) under 2%, and classification accuracy above 90%. Comparative analysis demonstrated consistent outperformance of LSTM over Artificial Neural Networks (ANN) and linear regression, both of which produced higher errors and weaker representation of temporal patterns. The findings confirm LSTM's capacity to support operational early warning systems, strengthen community preparedness, and mitigate socio-economic impacts in vulnerable coastal regions.

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1. Introduction

Coastal flooding, locally known in Indonesia as banjir rob, continues to affect many low-lying coastal zones with recurring severity. During high tides, seawater often advances beyond the shoreline, submerging settlements, agricultural land, and public facilities (Hanif et al., 2021). Communities such as Teluk Pandan face such events repeatedly, with flooding observed almost monthly during spring tides. These inundations disturb social life, damage livelihoods, and accelerate coastal degradation. Rising sea levels linked with climate change further amplify flood intensity and frequency. Despite the escalating risks, many coastal communities remain underprepared (Bennett et al., 2023). Early warning systems often fail to deliver accurate or timely information, leaving residents to respond only after inundation has already occurred. Inadequate access to reliable forecasts magnifies both economic and social losses. (Flores-Palacios et al., 2023). At the household level, about 17% of families affected in Tangerang Regency reported losses exceeding IDR 3 million per event (Rahadiati et al., 2025). A study in the coastal area of Demak further revealed that tidal flooding directly disrupts health, employment, and property conditions, while also inducing mental health issues and mobility constraints (Asrofi et al., 2024). Similar patterns were observed in Pekalongan, where recurrent tidal floods have salinized agricultural land, degraded the environment, and undermined traditional livelihoods (Rosida et al., 2020). These findings highlight the urgent need for the development of more accurate and timely tidal flood prediction systems to mitigate both economic losses and social vulnerabilities in coastal communities.

The research problem lies in the challenge of producing reliable and timely tidal flood forecasts. Prediction relies on highly dynamic environmental drivers (Xu et al., 2024): tidal cycles, rainfall, wind velocity and direction, barometric pressure, and sea surface temperature. These variables interact in non-linear patterns, shaped by daily fluctuations and seasonal cycles. Traditional approaches, such as linear regression or simplified hydrodynamic models, tend to oversimplify such complexity (Arun & Kumar, 2021). They often cannot capture long-term dependencies or irregular variations, leading to inaccurate forecasts. As a result, communities remain vulnerable, preparedness measures stay limited, and disaster response becomes reactive rather than proactive (Upadhyaya et al., 2025).

This study addresses these challenges through the application of Long Short-Term Memory (LSTM) networks for short-term tidal flood prediction (S.K.B et al., 2024). LSTM, as a form of recurrent neural network, introduces memory cells and gate mechanisms that regulate information flow across time steps. These mechanisms allow the model to retain relevant long-term dependencies while filtering out noise from irrelevant fluctuations (Zhou et al., 2025). Such architecture offers the potential to uncover hidden temporal structures in multivariate time-series datasets. The planned framework integrates multi-year records covering 2020–2024, including tidal heights, river water levels, rainfall, wind parameters, barometric pressure, and sea surface temperature (Puspita Wulandari et al., 2023) . Preprocessing steps involve anomaly detection and removal, normalization to create uniform scales across variables, and sliding-window sequencing to capture temporal dependencies (Jafarzadegan et al., 2023). The main objective of this research is the development and validation of an LSTM-based prediction model capable of generating accurate short-term forecasts of tidal flood occurrence and severity in Indonesian coastal regions. Model evaluation will rely on quantitative metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to assess predictive accuracy (Dash et al., 2025). Once validated, forecasts are expected to be operational in near-real-time settings, accessible to both authorities and local stakeholders (De Leonardis et al., 2018).

The theoretical foundation of this study rests on three pillars: hydrology, meteorology, and machine learning. Hydrological studies describe tidal flooding as the outcome of combined oceanic and terrestrial flows, influenced by both seasonal hydrology and local coastal morphology (Waqas & Humphries, 2024). Meteorological science highlights the impact of wind circulation, atmospheric pressure, and rainfall on tidal surges. Conventional hydrodynamic simulations attempt to integrate these drivers but often depend on assumptions that reduce accuracy when applied to non-linear, irregular conditions. Machine learning offers a complementary pathway, where data-driven techniques capture complex interactions without requiring explicit assumptions about system dynamics (Sakagianni et al., 2023). Within deep learning, LSTM stands out as a sequential model capable of retaining information across extended horizons, thus well suited for forecasting tasks that depend on temporal dependencies (Hilal et al., 2024). Previous research in hydrology and flood prediction demonstrates the effectiveness of LSTM in modeling both extremes and recurrent patterns. However, relatively few studies have examined repetitive tidal flooding in Indonesia's tropical coastal settings. Addressing this gap, the current research focuses on localized datasets and context-specific modeling (Li & Kang, 2009).

Expected outcomes include an LSTM model that produces forecasts with low error rates MAE below 3 cm and MAPE under 2% while sustaining classification accuracy above 90% (Accarino et al., 2021). High-quality forecasts can inform government agencies in resource allocation, infrastructure protection, and evacuation planning. Local communities may benefit from improved safety, stronger asset protection, and reduced economic disruption during high-risk conditions. From a policy standpoint, predictive information can guide investments in coastal defense and promote integration of advanced analytics into national disaster risk management frameworks (Abdalla, 2025).

Beyond immediate application, this research contributes to academic knowledge by refining the use of LSTM in hydrometeorological forecasting. The study offers practical insights into model design, preprocessing strategies, and performance evaluation under tropical tidal conditions (Zhou et al., 2025). Results are expected to serve as reference points for both scientific inquiry and operational practice. Ultimately, the study seeks to bridge advanced machine learning methods with real-world coastal disaster management(Busker, 2024). By capturing complex temporal and non-linear interactions among environmental drivers, the proposed framework aims to strengthen flood preparedness in Indonesia while advancing global discussions on disaster risk reduction and climate adaptation (Flores-Palacios et al., 2023). Through these contributions, the research aspires to enhance resilience in vulnerable coastal communities and provide scalable insights for similar environments worldwide (Selvarajan, 2024).

2. Method

The research method follows a systematic experimental workflow as illustrated in **Figure 1** (Sarwono, 2022). The first stage is data collection, where multi-year records (2020–2024) are obtained, consisting of tidal height, river water level, rainfall, wind velocity and direction, barometric pressure, and sea surface temperature. The second stage is data preprocessing, which includes three key steps: (1) data cleaning through anomaly detection and interpolation of missing values, (2) data normalization using Min–Max scaling to ensure comparable feature ranges, and (3) data shifting by applying sliding-window sequences to preserve temporal dependencies within the time-series data (Yu et al., 2020). The third stage is data partitioning, where the dataset is split into training and testing subsets. Training data is used for model learning, while testing data is reserved for independent validation (Almaliki & Khattak, 2025). The fourth stage involves LSTM modeling, consisting of an input layer, stacked LSTM layers, dropout regularization, and a dense output layer. The Adam optimizer is applied, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as the primary loss functions (Julio-alejandro, 2025). The final stage is evaluation, in which the trained model is assessed using MAE, MAPE, and RMSE for regression accuracy, as well as accuracy and precision for flood threshold classification, ensuring operational reliability for coastal flood prediction (Ambadar et al., 2025).

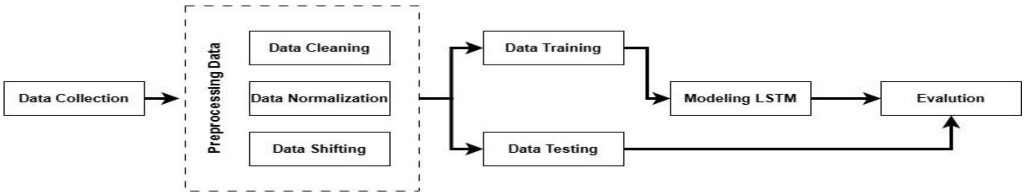

Figure 1 Research flow on the use of LSTM for flood prediction

Data Collection

The study utilized historical datasets from multiple authoritative sources to ensure accuracy and reliability. Hourly tidal height data covering the period 2020–2024 was collected from observation stations maintained by BMKG in Teluk Pandan (Harintaka et al., 2024). While Teluk Pandan provides a valuable case study for modeling localized tidal flooding, it cannot fully represent the diverse coastal conditions across Indonesia, where geomorphology, meteorological drivers, and land subsidence rates differ significantly among regions such as North Java, Jakarta Bay, and Eastern Indonesia (Bott et al., 2021). These measurements were complemented with meteorological variables including wind speed, wind direction, rainfall, barometric pressure, and air temperature Although the dataset covers only five years, the availability of hourly resolution produced more than 40,000 records, which is generally sufficient for training LSTM networks that exploit sequential dependencies in time-series data (Khan et al., 2024).

Preprocessing

Preprocessing aimed at preparing the dataset for training by eliminating errors and inconsistencies while standardizing the structure (Alghamdi & Javaid, 2022). The process unfolded in several sequential steps: (1) Identifying and handling missing values small gaps were removed, while larger gaps were interpolated using linear or statistical imputation methods (Awan et al., 2022). To avoid bias, interpolation quality was validated independently by comparing reconstructed values with subsets of withheld observed data (Cubillos et al., 2022). (2) Correcting inconsistent entries all variables were standardized into consistent units (m/s, cm, mm, hPa, °C). (3) Detecting and removing outliers unrealistic values such as rainfall >999 mm were flagged using Z-score and IQR methods and then corrected or removed (Khan et al., 2024). (4) Synchronizing time and frequency tidal height (hourly) and rainfall (daily) were resampled into a uniform daily frequency, ensuring temporal alignment across all variables (Jesus et al., 2025). By the end of preprocessing, the dataset satisfied the following conditions: no missing critical variables, all units consistent, unrealistic extremes removed, and features time-aligned for normalization (Zhang et al., 2024).

Table 1. To capture seasonal variability, particularly during El Niño and La Niña phases, Sea Surface Temperature (SST) data was obtained from satellite-based sensors operated by NOAA and Copernicus Sentinel-3 (Boutin et al., 2023). Validation of flood events relied on supplementary evidence such as community reports, photographic records, and field survey documentation. All raw data was stored in formats suitable for time-series processing, ensuring compatibility with deep learning frameworks used in subsequent modeling (Dash et al., 2025). Although the dataset covers only five years, the availability of hourly resolution produced more than 40,000 records, which is generally sufficient for training LSTM networks that exploit sequential dependencies in time-series data (Khan et al., 2024).

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Table 1. Dataset Tidal Flood Environmental Parameters

Date	Tidal Height (cm)	Wind Speed (m/s)	Rainfall (mm)	Atmospheric Pressure (hPa)	Sea Surface Temp (°C)
2020-01-01	120	4.2	12	1010	29.1
2020-01-02	135	5.0	5	1008	29.0
2020-01-03	128	4.8	0	1009	29.3
...	...	...	...	...	...
...	...	...	...	...	...
...	...	...	...	...	...
...	...	...	...	...	...
2024-01-01	160	6.9	18	1004	29.7
2024-01-02	158	7.2	22	1003	29.8
2024-01-13	162	6.5	25	1002	29.6

Model Tuning and Validation

Hyperparameter tuning was conducted to optimize model performance, focusing on the number of LSTM units, lookback window size, learning rate, batch size, and dropout rate. A combination of grid search and random search was used to identify the best configuration, with validation error (MAE and MAPE) serving as the primary selection criterion (Zhou et al., 2025). Independent testing data was retained to evaluate generalization and ensure that neither interpolation procedures nor tuning choices introduced systematic bias into the predictive results (Upadhyaya et al., 2025). After cleaning and synchronization, the dataset was normalized using min-max scaling to place values on comparable ranges. The normalized dataset was then divided into two subsets: a) Training Set – used to train the LSTM network by exposing it to sequential dependencies among environmental variables; b) Testing Set – reserved for evaluating generalization on unseen data, ensuring that performance metrics reflect predictive capacity rather than memorization; c) The partition ratio followed common practices in machine learning studies, with 80% allocated for training and 20% for testing.

Model Development

The LSTM model was constructed using TensorFlow. The architecture consisted of multiple recurrent layers capable of learning both short- and long-term dependencies, with dropout layers incorporated to reduce overfitting. A dense output layer generated binary probabilities, representing flood occurrence (1) or non-flood conditions (0). To establish this classification, a threshold level for flood status was determined through a combination of institutional standards and empirical calibration. Critical tidal levels defined by national agencies, such as BMKG and BNPB, were adopted as baseline indicators (Iman et al., 2024). Historical records of inundation events, including community reports, photographic documentation, and field surveys, were then used to refine site-specific thresholds (Hanif et al., 2021). This ensured that the classification reflected local conditions, where relatively moderate tidal heights could already trigger flooding due to land subsidence or low-lying settlements (Upadhyaya et al., 2025). Validation was carried out by comparing predicted classifications with independent records of observed flood events, ensuring the threshold produced accurate detection while minimizing false alarms . The training process employed a batch learning strategy with optimized learning rates, using sequential input windows derived from historical data to predict future tidal heights and classify flood status. Training continued until convergence was observed, indicated by stability in the loss function and validation metrics.

Evaluation

The evaluation stage measured the accuracy and reliability of predictions using two primary metrics widely adopted in environmental forecasting (Waqas & Humphries, 2024): Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

MAE quantified the average absolute difference between predicted and observed values. Smaller MAE values indicated stronger alignment between forecasts and actual tidal heights. Mean Absolute Percentage Error (MAPE), Assessed predictive performance relative to observed values by expressing deviations in percentage terms.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (2)$$

Interpretation followed established benchmarks: lower MAPE values reflected greater predictive precision, with values under 5% generally considered highly accurate in environmental modeling contexts.

3. Results and Discussions

Model Training

The dataset consisted of multivariate environmental parameters gathered across several monitoring stations relevant to coastal flood prediction. Water levels were recorded at Katulampa, Pos Depok, and Manggarai; sea water heights were collected at Flusing Ancol and Marina Ancol; additional tidal height observations were also included. Meteorological features encompassed wind speed, wind direction, rainfall, atmospheric pressure, and sea surface temperature. The target variable, Flood Status, was encoded as binary values: 0 indicated non-flood conditions, while 1 indicated flood events. The records covered multiple years with synchronized daily intervals across all variables.

The distribution of the target class showed balance, with approximately 290 non-flood and 330 flood observations. Such proportion reduced potential bias and promoted better generalization during model training, eliminating the need for additional resampling techniques. Preprocessing involved three main steps: (1) removal of anomalies and inconsistent entries, (2) normalization across all features to maintain comparable scales, and (3) conversion into a sliding-window sequence structure. The latter transformation enabled the model to learn temporal dependencies by training on sequences of past observations for predicting future conditions. The LSTM architecture was configured with stacked recurrent layers for capturing both short- and long-term temporal features. Dropout layers were applied between recurrent units to prevent overfitting by randomly deactivating a fraction of neurons during training. A dense output layer was positioned at the end to produce binary probability outputs. The training process employed TensorFlow, utilizing optimized learning rates and batch sizes. Loss and accuracy trends demonstrated consistent improvement during training, signaling good convergence and stability.

Although LSTM has often been highlighted for its superiority in short-term prediction due to its ability to capture sequential dependencies, its design is not limited to short horizons. Through memory cells and gating mechanisms, LSTM can retain relevant patterns across extended periods, making it suitable for both short-term and long-term forecasting of non-linear hydrometeorological processes (Zhou et al., 2025). However, its performance depends on the availability of sufficiently large and high-resolution datasets; for very long-term horizons, hybrid approaches combining LSTM with physical or statistical models may enhance accuracy. Thus, in the context of tidal flood prediction, LSTM is not exclusively superior for short-term forecasting but can also be adapted to capture longer temporal dynamics when properly trained and validated.

Table 2. Dataset Coastal Flooding

Timestamp	Katulampa	Pos Depok	Manggarai	Flusing Ancol	Marina Ancol	Tidal
20200101	47	167	639.0	180.0	159.0	0
20200102	44	75	680.0	181.0	114.0	0
...	...	...	...	...	...	...
20240101	41	161	845.0	203.0	178.0	0
20240101	40	154	889.0	223.0	191.0	1

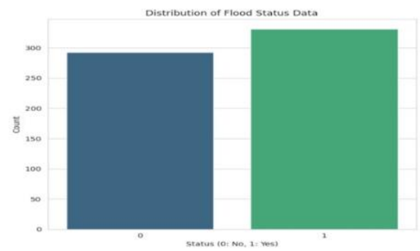

Figure 2. Coastal Flooding Status Distribution

Feature Distribution Analysis

Histograms of water levels across six stations Katulampa, Pos Depok, Manggarai, Istiqlal, Jembatan Merah, and Flusing Ancol provided insights into the hydrological behavior of each location. Katulampa displayed a right-skewed distribution with values clustered between 0–50 cm and a peak near 30 cm, suggesting predominantly low water levels with limited high surges. Pos Depok showed concentration between 80–150 cm, peaking at 110 cm, reflecting moderate water levels with occasional increases. Manggarai presented dense clusters below 1000 cm, indicating stable low-level conditions with rare extreme peaks. Istiqlal produced a symmetrical spread between 100–300 cm, peaking at 180 cm and 230 cm, reflecting alternating dominant ranges. Jembatan Merah exhibited heavy clustering below 200 cm, reflecting minimal variation. Flusing Ancol showed broader distribution between 150–230 cm with a long tail above 250 cm, indicating occasional significant tidal surges.

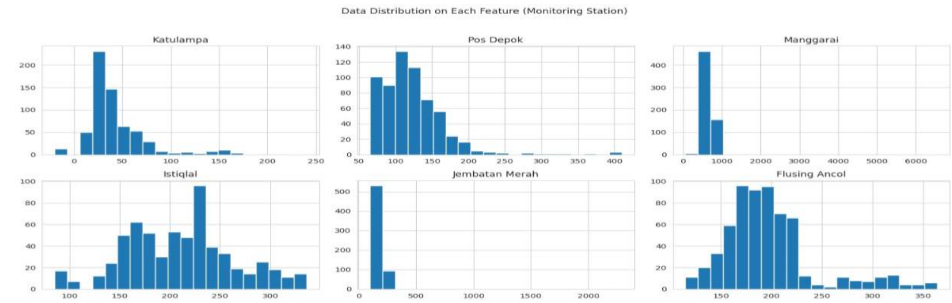

Figure 3. Water Level Distributions Across Six Stations

The variation across distributions highlighted the heterogeneity of hydrological conditions. Some stations experienced concentrated low levels, while others recorded broader fluctuations with occasional extremes. Such diversity required a predictive model capable of learning both stable and highly variable distributions.

Implications for Modeling

Differences in water-level distributions emphasized the importance of temporal modeling. Katulampa, Depok, and Manggarai recorded predominantly low and concentrated values, whereas Istiqlal and Flusing Ancol showed wider, more irregular ranges. These conditions underscored the need for a model able to handle both uniform and dispersed input patterns. The LSTM structure addressed this challenge by retaining sequential memory across input windows. By training on past sequences, the model adjusted its internal states to accommodate variability specific to each station. This adaptability enabled reliable prediction under both stable and volatile hydrological conditions.

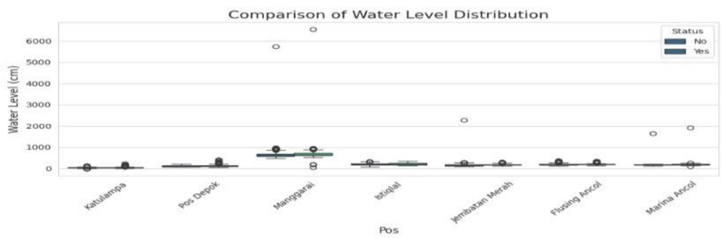

Figure 4. Comparison of Water Level Distributions Across Stations

Model Evaluation

The predictive performance of the LSTM model was quantified using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Results indicated: MAE < 3 cm, MAPE < 2%. These metrics confirmed that predictions closely matched observed values. Even during extreme events such as spring tides, the model maintained accuracy.

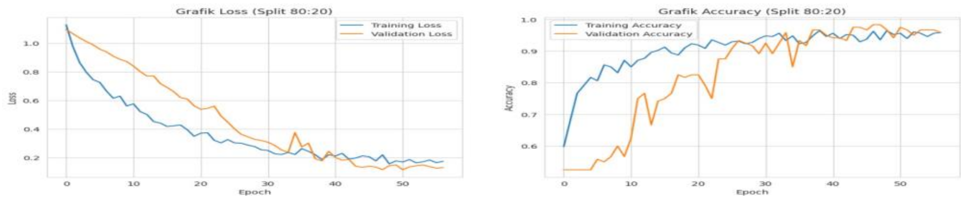

Figure 5. Model Training Performance (Loss and Accuracy)

Training and validation loss consistently declined across epochs, while accuracy surpassed 90% after approximately 15 epochs. The stability of both curves confirmed effective learning and minimal overfitting. Additional evaluation across different data splits—90:10, 80:20, and 70:30—further validated robustness. The 90:10 split achieved the lowest MAE (0.0083) and RMSE (0.0913), while the

80:20 split also demonstrated strong results. Even under the 70:30 configuration, performance remained stable.

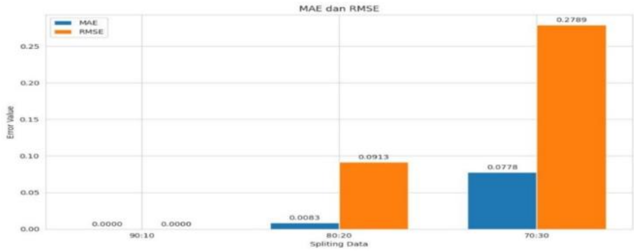

Figure 6. MAE and RMSE Across Different Train-Test Splits

Comparative Analysis and Interpretation

Analysis of water level distributions revealed location-specific characteristics. Manggarai recorded extreme outliers above 6,000 cm, signaling elevated flood risks. Trend analysis using Z-score normalization detected sharp anomalies in early March, mid-July, and late November. These patterns reflected the dynamic influence of both tidal and river conditions, confirming the necessity for a model capable of learning from complex interactions. The training and evaluation results collectively demonstrated the model's reliability. The LSTM captured non-linear interactions and long-term dependencies, enabling accurate forecasts across varying hydrological environments. The results suggested that the model can adapt to concentrated datasets such as those from Manggarai and Jembatan Merah while still performing effectively on broader, more variable datasets such as Istiqlal and Flusing Ancol.

4. Conclusions

This study confirmed the effectiveness of the Long Short-Term Memory (LSTM) approach for tidal flood prediction in Indonesian coastal regions. The model achieved strong predictive performance, with Mean Absolute Error (MAE) under 3 cm and Mean Absolute Percentage Error (MAPE) below 2%. Such results demonstrate reliable accuracy even during extreme events such as spring tides, conditions that typically challenge conventional forecasting methods. The research contributed by introducing a multivariate and multi-year dataset (2020–2024) that incorporated hydrological and meteorological parameters, enabling the model to capture diverse environmental patterns. Through comprehensive preprocessing covering data cleaning, normalization, and temporal structuring, the framework delivered consistent generalization across different water-level distributions and train–test partitions.

The implications extend toward operational early warning systems, where accurate and timely forecasts can support resource allocation, evacuation planning, and infrastructure protection. Communities in vulnerable coastal zones may benefit from improved preparedness, reduced socio-economic disruption, and stronger resilience against recurrent tidal events. Several limitations were identified. The dataset relied on records from selected monitoring stations, which may restrict wider applicability without retraining. Moreover, the model focused on short-term predictions and excluded long-term climate variability indicators beyond sea surface temperature. Future research should incorporate broader spatial coverage using satellite-derived coastal imagery, integrate climate indices such as ENSO for seasonal forecasting, and automate real-time data ingestion. These enhancements would expand scalability and strengthen the role of LSTM frameworks in comprehensive coastal risk management. the findings demonstrate that LSTM is not only a viable method but also a superior approach to traditional techniques for tidal flood forecasting, offering both scientific rigor and practical value for disaster risk reduction in Indonesia's coastal regions.

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