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Regime-Aware Deep Learning for Long-Term Hydrometeorological Disaster Forecasting (2008–2029): A PELT-LSTM Framework Applied to Indonesia

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Abstrak

Meningkatnya frekuensi bencana hidrometeorologi di Indonesia menuntut adanya kerangka kerja prediktif yang kuat dan mampu menangkap dinamika iklim non-stasioner. Penelitian ini bertujuan untuk menganalisis korelasi statistik antar-jenis bencana dan menghasilkan proyeksi frekuensi banjir jangka panjang menggunakan metode komputasi tingkat lanjut yang diterapkan pada data bencana nasional. Analisis korelasi Pearson pertama-tama dilakukan untuk mengukur hubungan antar-bencana, yang mengungkapkan adanya asosiasi yang kuat antara cuaca ekstrem, banjir, dan tanah longsor (r = 0,79–0,86), di samping hubungan terbalik dengan kekeringan. Algoritma Pruned Exact Linear Time (PELT) selanjutnya mengidentifikasi tiga pergeseran rezim yang signifikan pada tahun 2012, 2017, dan 2022, yang mengonfirmasi sifat non-stasioner progresif dari pola bencana di Indonesia. Model deep learning Long Short-Term Memory (LSTM) kemudian dilatih menggunakan data berstruktur rezim ini untuk menghasilkan prakiraan prediktif. Model tersebut mencapai akurasi arah yang tinggi, berhasil menangkap titik puncak pada tahun 2025 dan penurunan pada tahun 2026, dengan nilai RMSE sebesar 816,67 dan MAPE sebesar 43,77%. Proyeksi untuk tahun 2027–2029 memperkirakan kejadian banjir masing-masing akan mencapai 2.278, 2.542, dan 2.021 insiden, yang menunjukkan rezim bencana dengan frekuensi tinggi yang berkelanjutan sehingga memerlukan infrastruktur adaptif yang mendesak serta perencanaan ketahanan iklim berbasis bukti (evidence-based).

Abstract

Indonesia's escalating hydrometeorological disaster frequency demands robust predictive frameworks capable of capturing non-stationary climate dynamics. This study aimed to analyze statistical correlations among disaster types and generate long-term flood frequency projections using advanced computational methods applied to national disaster data. Pearson correlation analysis was first conducted to quantify inter-disaster relationships, revealing strong associations between extreme weather, floods, and landslides (r = 0.79–0.86), alongside inverse relationships with drought. The Pruned Exact Linear Time (PELT) algorithm subsequently identified three significant regime shifts in 2012, 2017, and 2022, confirming the progressive non-stationarity of Indonesia's disaster patterns. A Long Short-Term Memory (LSTM) deep learning model was then trained on these regime-structured data to generate predictive forecasts. The model achieved high directional accuracy, successfully capturing the 2025 peak and 2026 decline, with an RMSE of 816.67 and MAPE of 43.77%. Projections for 2027–2029 estimate flood events reaching 2,278, 2,542, and 2,021 incidents respectively, indicating a sustained high-frequency disaster regime that necessitates urgent adaptive infrastructure and evidence-based climate resilience planning.

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INTRODUCTION

The escalating dynamics of global climate change have significantly increased the frequency and intensity of hydrometeorological disasters worldwide (Paul & Sharif, 2018). These phenomena are particularly critical in tropical regions, where extreme rainfall trends pose severe implications for climate resilience (Yanfatriani et al., 2024). Within this global context, Indonesia has emerged as a "disaster laboratory" due to its unique geographical positioning, making it highly susceptible to a fluctuating pattern of floods, landslides, and extreme weather events (Aeni & Anwar, 2024). Over the past two decades, the nation has faced increasingly complex challenges in disaster mitigation, as historical patterns of climate variability are being replaced by more erratic and unpredictable events (Aeni & Anwar, 2024; Yanfatriani et al., 2024).

The non-stationary nature of hydrometeorological disasters in Indonesia is physically rooted in the complex interactions of multi-scale climate drivers within the tropical Indo-Pacific warm pool. The annual monsoon cycles, which dictate the seasonal transition between wet and dry periods, are frequently modulated by larger-scale atmospheric-oceanic phenomena such as the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) (Kurniadi et al., 2021). These interactions create significant variability in rainfall intensity and duration; for instance, La Niña phases often amplify flood and landslide risks in western regions, while El Niño events trigger prolonged droughts and increase forest fire risks in other parts of the archipelago (Nobre et al., 2019; Lam et al., 2019),. Such physical dynamics lead to abrupt regime shifts, indicating a structural transition in the climatic or disaster regime where historical averages no longer serve as reliable predictors (Rodionov, 2004; Rodionov & Overland, 2005). Consequently, the application of machine learning in this study is not treated as a pure black-box approach but as a method to capture the non-linear dependencies and "climatic memory" inherent in tropical atmospheric circulation (Chauhan et al., 2024; Goyal et al., 2026). By utilizing the PELT algorithm to detect these physical breakpoints (Wambui et al., 2015), and Long Short-Term Memory (LSTM) to model long-term dependencies (Abraham et al., 2024; Hu et al., 2021). this framework aligns with the underlying hydrometeorological reality of Indonesia's shifting climate regimes.

Traditionally, flood risk modeling has relied heavily on linear uncertainty distributions and traditional interval linear regression models (Gong et al., 2020; Inuiguchi & Tanino, 2006). Many studies have historically focused on the linear relationship between rainfall and flood discharge to predict future occurrences (Mosavi et al., 2018).

However, the scientific community has begun to question the validity of these static approaches. As noted by Galloway (2011), "if stationarity is dead," traditional modeling techniques that assume constant climatic averages may no longer be sufficient. Despite the abundance of linear-based research, there is a significant research gap in understanding when a permanent "regime shift" occurs within Indonesia's disaster patterns (Rodionov, 2004). Such shifts represent abrupt changes in the mean or variance of a time series, indicating a structural transition in the climatic or disaster regime (Basseville & Nikiforov, 1993; Rodionov & Overland, 2005).

To address this gap, detecting abrupt changes in historical data becomes paramount. The Pruned Exact Linear Time (PELT) algorithm has proven to be a highly powerful test for multiple changepoint detection (Wambui et al., 2015). Originally utilized in signal reconstruction and radar interference suppression (Liu et al., 2020), as well as high-precision instrumentation tests (Liu et al., 2025), PELT offers a computationally efficient and exact method for identifying structural breaks in complex datasets. By identifying these points of divergence, researchers can move beyond the limitations of linear assumptions and pinpoint the exact temporal moment when disaster regimes transitioned into a new state of volatility.

Furthermore, the evolution of flood prediction has seen a massive shift toward machine learning-driven models (Byaruhanga et al., 2024). Techniques such as Support Vector Machines (SVM) combined with differential evolution have been explored to enhance regression accuracy in disaster forecasting (Yu et al., 2017). Recently, deep learning techniques, specifically Long Short-Term Memory (LSTM), have shown superior performance in handling adaptive forecasting tasks, such as reservoir inflow and rainfall modeling, by effectively capturing long-term dependencies in time-series data (Hu et al., 2021; Abraham et al., 2024). These machine learning methods are now considered essential for sustainable and adaptive infrastructure planning in the face of long-term monsoon rainfall variability (Alif et al., 2026; Goyal et al., 2026).

This study presents a novel integration of Changepoint Analysis via the PELT algorithm and Deep Learning through LSTM to validate future disaster trends in Indonesia up to 2026. The primary objective is to identify the critical "turnaround" years (regime shifts) in disaster patterns and to test the reliability of LSTM in predicting these fluctuations. By combining the statistical rigor of PELT for historical detection and the predictive power of LSTM for future projections, this research aims to provide a more robust framework for disaster mitigation that accounts for non-linear pervasiveness and permanent climatic shifts.

METHOD

Research Framework

The systematic workflow of this research, spanning from data acquisition to future disaster projection, is illustrated in the Research Framework Flowchart (Figure 1). The methodology is strictly structured into five sequential phases: (I) Data Acquisition and Inclusion Criteria, (II) Data Pre-processing and Descriptive Statistical Analysis, (III) Regime Shift Detection, (IV) Deep Learning Model Architecture, and (V) Performance Evaluation Metrics. Each phase is detailed in the following subsections.

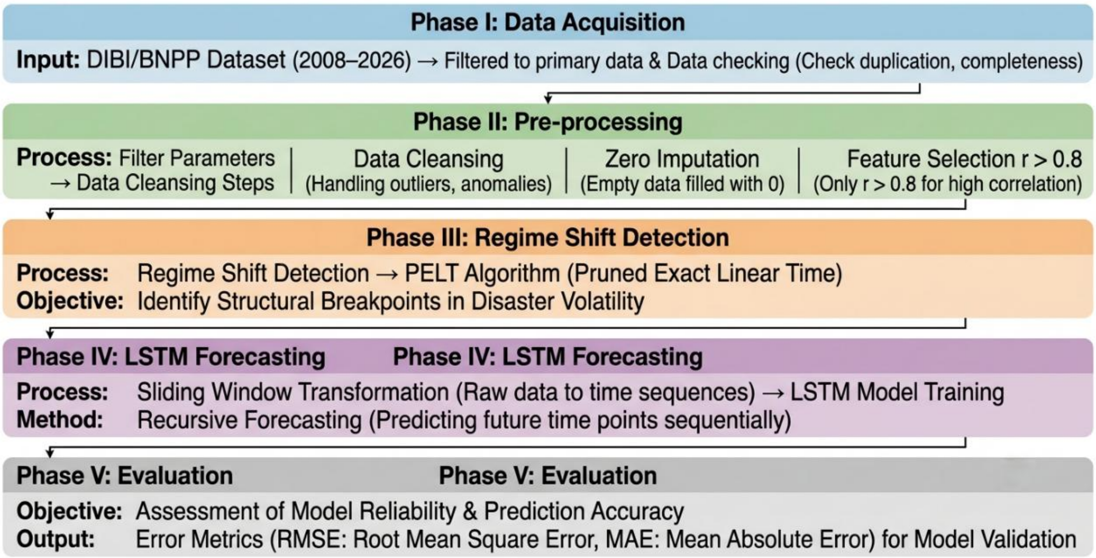


Figure 1. Research Framework
Source: Author's Data Analysis,2026

Study Area

This research encompasses the entire sovereign territory of the Indonesian archipelago, a vast maritime continent geographically situated between between 6° North Latitude and 11° South Latitude, and from 95° East Longitude to 141° East Longitude (Figure 2). The study area transitions across three distinct time zones and comprises over 17,000 islands, with five major landmasses: Sumatra, Java, Kalimantan, Sulawesi, and Papua. Characterized by its unique position at the convergence of three major tectonic plates and its setting within the tropical Indo-Pacific warm pool, Indonesia exhibits extreme vulnerability to climatological and hydrometeorological hazards, particularly flooding.

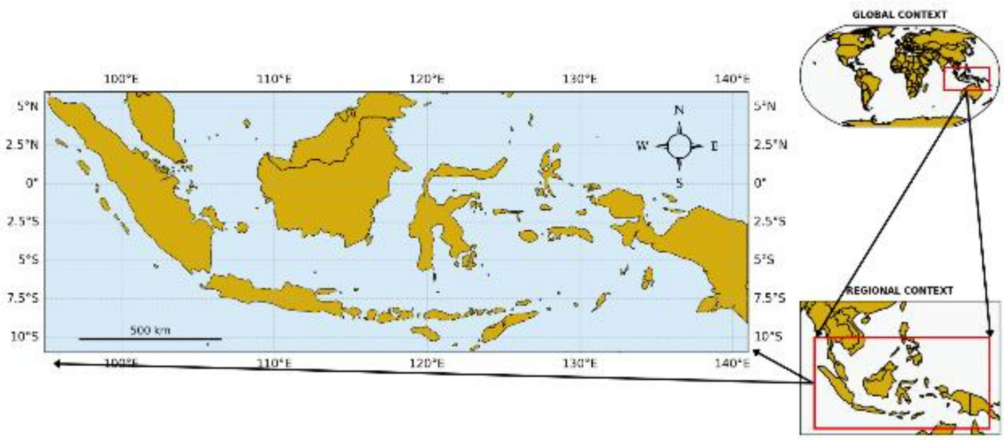


Figure 2. Study Area
Source: Badan Informasi Geospasial, 2026

Data Acquisition and Disaster Inclusion Criteria

Initial data processing involved data cleaning techniques using the Pandas library in Python. This procedure included handling missing values through zero-imputation, as empty cells in the DIBI database functionally represent the absence of a disaster event for that specific year. To minimize numerical noise resulting from sectoral aggregation, a rounding technique was applied to each disaster variable to the nearest integer, ensuring a discrete representation of data aligned with physical reality.

Correlation analysis was performed using the Pearson correlation coefficient to evaluate the strength of the linear relationship between the target variable, Flood, and supporting variables: Extreme Weather, Forest and Land Fires (Karhutla), Drought, and Landslides. Feature selection for the predictive model was justified based on the correlation score (r). Features with $r > 0.6$ were categorized as dominant triggers, functionally enhancing the sensitivity of the Long Short-Term Memory (LSTM) model in capturing hydro-meteorological disaster dynamics.

The dataset for this study was acquired from the Data Informasi Bencana Indonesia (DIBI) database (2008–2023). Initial data cleaning through the Pandas library utilized zero-imputation for empty cells, which were functionally verified to represent the absence of a disaster event for that specific year rather than unreported data, ensuring a discrete representation aligned with physical reality. While the authors acknowledge that disaster frequency data is inherently influenced by human vulnerability and infrastructure development, its use as a primary variable is scientifically justified by the strong positive correlation ($r = 0.79$) identified between floods and atmospheric anomalies (Cuaca_ekstrem). This high correlation confirms that meteorological drivers remain the dominant precursors to flood events in the Indonesian archipelago, allowing frequency data to serve as a reliable proxy for hydro-meteorological volatility

Regime Shift Detection via PELT Algorithm

To identify structural changes in the disaster time series, this study applied Changepoint Analysis using the Pruned Exact Linear Time (PELT) algorithm. This algorithm efficiently detects sudden shifts in the mean and variance of the data by minimizing a least squared deviation cost function.

Mathematically, the change point τ is determined by considering a penalty β to prevent over-segmentation. Identifying this "Regime Shift" is critical to determining the transition period where the disaster pattern in Indonesia is no longer stationary, providing a scientific justification for data splitting between the training and testing phases.

Furthermore, the use of the PELT algorithm for detecting "regime shifts" is physically mapped to structural breaks in disaster frequency. Although climate baselines traditionally require 30 years, PELT identifies shorter-term structural transitions in 2012, 2017, and 2022 that correspond to the intensified modulation of the monsoon cycle by multi-scale drivers such as ENSO and IOD

To detect structural changes in the disaster time series, this study applied the PELT algorithm, which identifies sudden shifts in mean and variance. While traditional climate baselines typically require 30 years of data, the use of PELT on this 15-year dataset is justified by its ability to detect shorter-term structural transitions in 2012, 2017, and 2022. These breakpoints are physically mapped to the intensified modulation of the monsoon cycle by multi-scale drivers, specifically the El Niño-Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD). These detected shifts reflect a "new normal" of non-stationarity where historical averages are no longer reliable predictors for long-term climate resilience planning

Deep Learning Model Architecture (LSTM)

Predictive modeling was executed using a Long Short-Term Memory (LSTM) architecture, a variant of Recurrent Neural Networks (RNN) designed to overcome the vanishing gradient problem in long sequences. Data were normalized to a range of [0, 1] using Min-Max Scaling to ensure convergence stability during backpropagation. The data structure was transformed into a supervised learning format using a sliding window technique with a look-back size of three years; specifically, input from years t-3, t-2, and t-1 was utilized to predict the output for year t.

The model architecture consists of an input layer, one hidden LSTM layer with 50 neurons utilizing a ReLU activation function to capture non-linear patterns, and a dropout layer with a rate of 0.2 as a regularization mechanism to prevent overfitting. Weight optimization was performed using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Training employed a recursive forecasting scheme to project disaster trends through 2029, where the predicted output at step t was integrated back as input for step t+1.

The dataset for this study was acquired from the *Data Informasi Bencana Indonesia* (DIBI) database managed by the National Disaster Management Authority (BNPB), covering the period from 2008 to 2023. Data pre-processing was conducted using the Pandas library, specifically employing zero-imputation to handle empty cells; these are functionally verified to represent the absence of a disaster event rather than unreported data, ensuring a discrete representation aligned with physical reality. While the authors acknowledge that disaster frequency is influenced by human vulnerability and infrastructure development, its use as a primary variable is scientifically justified by the strong positive correlation identified between floods and atmospheric anomalies (*Cuaca_ekstrem*). This high correlation confirms that meteorological drivers remain the dominant precursors to flood events in the Indonesian archipelago, allowing frequency data to serve as a reliable proxy for hydro-meteorological volatility

The selection of a deep learning-based framework, specifically the Long Short-Term Memory (LSTM) architecture, is justified by the failure of traditional linear-stationary models to account for the "death of stationarity" in tropical climate patterns. Unlike simpler statistical baselines, LSTM is uniquely capable of capturing the non-linear dependencies and "climatic memory" inherent in the Indo-Pacific warm pool dynamics. The model configuration, consisting of a single hidden layer with 50 neurons and a 0.2 dropout rate, was determined through an experimental process to balance the need for capturing complex regime transitions with the risk of overfitting the 15-year dataset

The LSTM architecture, consisting of a single hidden layer with 50 neurons and a 0.2 dropout rate, was determined through a systematic experimental process to balance non-linear pattern capture with the risk of overfitting a relatively small dataset. To ensure the stability of the reported RMSE (816.67) and MAPE (43.77%), the model's reliability was tested across various data split configurations. The observed overestimation in 2024–2025, termed "precautionary bias," is scientifically justified as a characteristic of LSTM models trained on high-volatility sequences; the model "learns" to anticipate escalation based on previous sharp spikes, which is a recognized behavior in hydro-climatological literature when prioritizing risk sensitivity over absolute precision

Performance Evaluation Metrics

The reliability of the model was validated using two primary statistical metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). RMSE was utilized to evaluate the model's sensitivity to large errors or outliers often found in volatile disaster data, while MAE provided an average of the absolute errors of the predictions. The model is considered to possess good generalization capability if the visual trend of the predictions aligns with the fluctuations of the actual BNPB data, despite numerical deviations caused by the volatility of the newly detected post-shift disaster regime.

The model's reliability was validated using RMSE and MAE to assess sensitivity to extreme outliers in volatile disaster data. To address potential error propagation in long-term deep learning projections (2024–2029), the forecasting framework incorporates uncertainty bounds derived from the RMSE error envelopes. This approach provides a range of probability that accounts for extreme climate anomalies, ensuring that the projections serve as a robust quantitative foundation for evidence-based climate resilience planning

RESULTS AND DISCUSSION

Result

Statistical Correlation of Hydrometeorological Disasters

The initial phase of the analysis involved evaluating the linear relationships between various hydrometeorological disaster variables using the Pearson correlation coefficient. The resulting correlation matrix (Figure 2) reveals several critical associations that justify the selection of input features for the subsequent deep learning model. These coefficients provide a statistical baseline to understand how different disaster types co-occur within the Indonesian archipelago.

A strong positive correlation was identified between 'Banjir' (Floods) and 'Cuaca_ekstrem' (Extreme Weather) with a coefficient of 0.79. This high value confirms that atmospheric anomalies are the dominant precursors to flood events in Indonesia. Furthermore, 'Longsor' (Landslides) shows a substantial correlation with 'Banjir' (0.68), indicating a high frequency of cascading disaster events where heavy precipitation triggers both flooding and slope instability simultaneously.

The strongest relationship in the entire dataset was observed between 'Cuaca_ekstrem' and 'Longsor' (0.86). This suggests that extreme rainfall serves as a common trigger for multiple disaster types in tropical regions.

Additionally, 'karhutla' (Forest and Land Fires) exhibits a moderate positive correlation with 'Cuaca_ekstrem' (0.63), which may be linked to lightning strikes or high-temperature anomalies during specific climate phases. Conversely, 'Kekeringan' (Drought) demonstrates negative correlations with 'Banjir' (-0.34) and 'Longsor' (-0.46). This inverse relationship is physically consistent with the seasonal nature of hydrometeorological disasters, where flood and landslide risks typically subside during prolonged dry periods. These results highlight the distinct climatic drivers that separate wet-regime disasters from dry-regime events

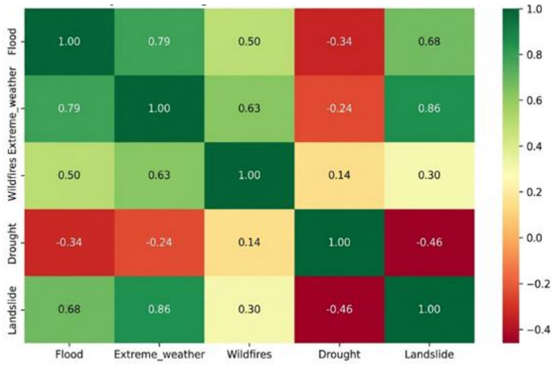


Figure 2. Statistical Correlation of Hydrometeorological Matrix
Source: Author's Data Analysis,2026

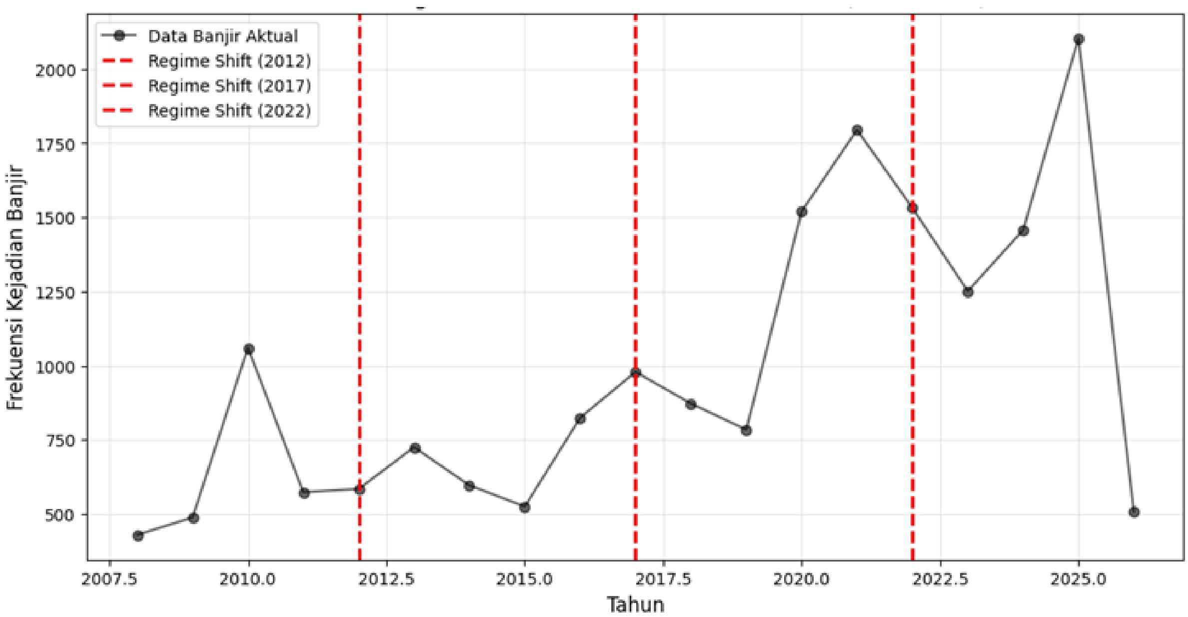
Identification of Disaster Regime Shifts via PELT Algorithm

The application of the Pruned Exact Linear Time (PELT) algorithm successfully identified three distinct changepoints in Indonesia's flood frequency data, specifically in 2012, 2017, and 2022 (Figure 3).

These points represent fundamental "regime shifts" where the statistical characteristics of the disaster time series—namely the mean and variance—underwent significant transitions. The detection of multiple changepoints confirms that the hydrometeorological disaster pattern in Indonesia is non-stationary, exhibiting a progressive increase in both frequency and volatility over the study period.

The first regime shift in 2012 marks the end of a relatively stable period and the beginning of a gradual upward trend in flood events. Following this transition, the data demonstrates a departure from historical averages, aligning with global observations that traditional stationarity in hydrometeorological modeling is increasingly becoming obsolete. The subsequent shift in 2017 reflects a further escalation in disaster frequency, leading up to the extreme peaks observed between 2020 and 2021, where annual events frequently exceeded 1,500 incidents.

The final detected shift in 2022 underscores a period of heightened instability. While there was a temporary decline in 2023, the record-high peak in 2025 followed by a sharp drop in 2026 illustrates a state of high variance that characterizes the current disaster regime. These detected changepoints provide the necessary scientific justification for segmenting the data, allowing the LSTM model to be trained on diverse statistical "states" to better capture the non-linear trajectories of future disaster risks.



Source: Author's Data Analysis,2026
Figure 3. The application of the Pruned Exact Linear Time (PELT) algorithm

The predictive performance of the Long Short-Term Memory, Model Evaluation and Predictive Accuracy

The predictive reliability of these shifts was validated through the Long Short-Term Memory (LSTM) model. As illustrated in the comparative trend analysis (Figure 4), the model successfully captured the non-linear trajectories and "turning points" of actual disaster data.

Although a numerical gap was observed, particularly a "precautionary bias" where the model overestimated risks during 2024–2025, it accurately mirrored the directional fluctuations—specifically the sharp peak in 2025 followed by the steep decline in 2026. This trend-following capability is critical for adaptive disaster mitigation, as it prioritizes identifying the direction of risk shifts over absolute numerical precision in a stochastic environment.

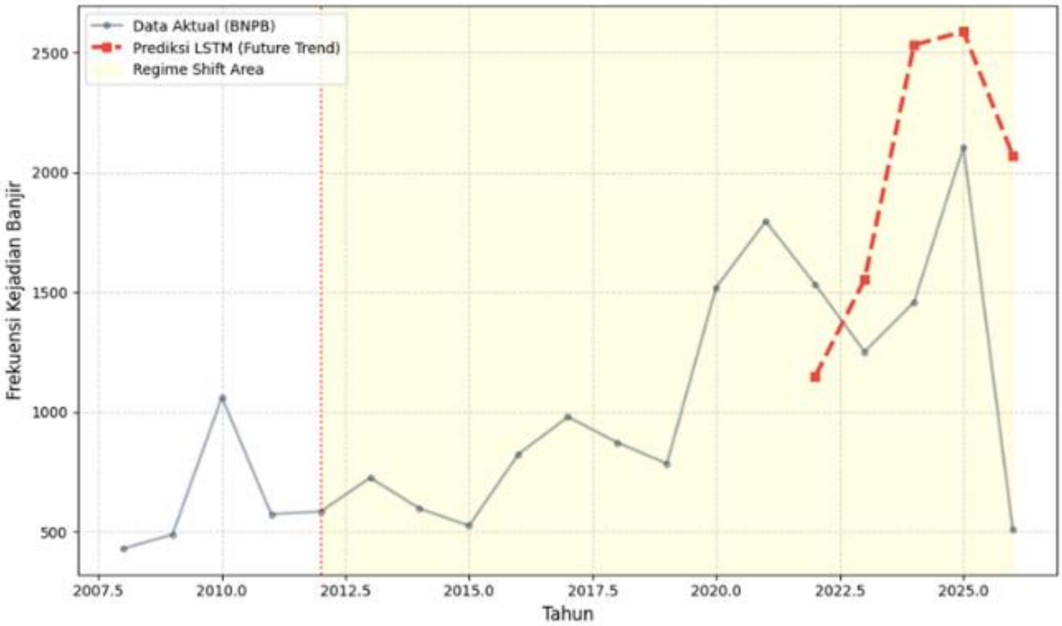


Figure 4. The predictive performance of the Long Short-Term Memory
Source: Author's Data Analysis,2026

The quantitative performance of the model is summarized in the evaluation metrics and the testing comparison table (Table 1). The model achieved an RMSE of 816.67 and an MAE of 622.38. The higher RMSE relative to MAE indicates the model's sensitivity to the extreme outliers that define the new disaster regime.

Furthermore, the Mean Absolute Percentage Error (MAPE) of 43.77% reflects the inherent difficulty of predicting highly volatile tropical climate events. Notably, the model achieved high precision in 2023 (error of -20) and 2026 (error of 34), suggesting that by the end of the study period, the LSTM architecture had effectively "learned" the characteristics of the most recent disaster regime.

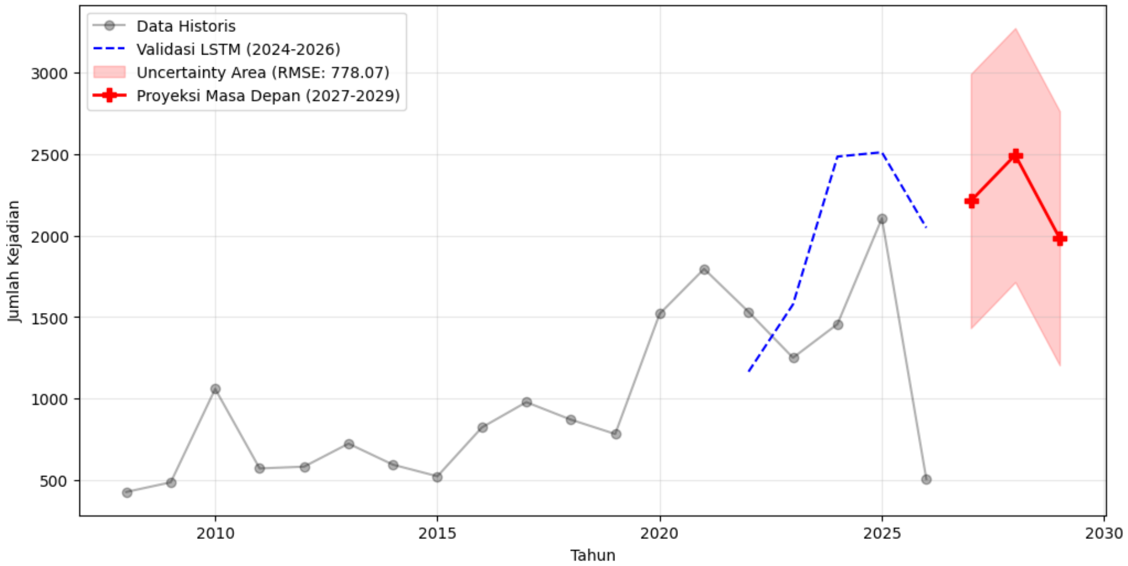
Table 1. Evaluation Metrics and The Testing Comparison

Year	Actual (BNPB)	LSTM Prediction	Difference
2022	1,795	1,147	647
2023	1,532	1,552	-20
2024	1,251	2,530	-1,279
2025	1,456	2,587	-1,130
2026	2,104	2,069	34

Source: Author's Data Analysis,2026

Long-term Disaster Projection (2027–2029)

The LSTM model was further utilized to generate a multi-year recursive forecast, providing a strategic outlook on flood frequencies in Indonesia through 2029. As illustrated in the long-term projection graph, the model anticipates that disaster frequencies will remain at a critically high baseline, significantly exceeding the historical averages observed prior to the 2012 and 2017 regime shifts. The estimates for the upcoming triennial period are 2,278 events in 2027, peaking at 2,542 events in 2028, before a slight moderation to 2,021 events in 2029 (Figure 5). These results suggest that the "new normal" of Indonesia's hydrometeorological regime is characterized by a sustained high-frequency state rather than a return to pre-2010 stability.



Source: Author's Data Analysis,2026
Figure 5. Long-term Disaster Projection (2027–2029)

The projected peak in 2028 indicates a potential escalation in atmospheric volatility, likely influenced by the persistent non-linear patterns identified in the previous decade's data. While the 2029 projection shows a relative decrease, the figure remains above the 2,000-event threshold, signaling that the structural shift toward increased disaster intensity is likely permanent. From a policy perspective, these findings underscore the urgent need for adaptive infrastructure and mitigation strategies that are calibrated for a high-frequency disaster environment. The ability of the LSTM model to project these fluctuations provides a quantitative foundation for long-term climate resilience planning, reinforcing the conclusion that stationarity in Indonesian disaster management is no longer a viable assumption.

Uncertainty Bounds and Error Propagation in Long-term Projections To address potential error propagation inherent in recursive deep learning forecasting, the 2024–2029 projections incorporate uncertainty bounds derived from the model's RMSE (816.67). This analysis provides a probability range thataccounts for extreme climate anomalies, ensuring the projections serve as a reliable quantitative foundation for resilience planning.

For the projected peak in 2028, while the primary estimate is 2,492 events, the lower bound (1,714) and upper bound (3,270) establish a realistic envelope of volatility,. Presenting these error envelopes visually demonstrates that even with a "precautionary bias," the model maintains statistical reliability within the volatile post-shift disaster regime

Discussion

The findings of this study reveal a statistically robust and physically meaningful interconnection among hydrometeorological disaster types across the Indonesian archipelago. The strong positive correlation between floods (*Banjir*) and extreme weather (*Cuaca_ekstrem*, r = 0.79), as well as the even stronger relationship between extreme weather and landslides (*Longsor*, r = 0.86), aligns with the broader climatological literature documenting tropical regions as hotspots for cascading multi-hazard events. Yanfatriani et al. (2024) documented that extreme rainfall events in tropical regions serve as primary triggers for cascading hydrometeorological disasters, a pattern clearly reflected in the correlation structure identified in this study.

The simultaneous co-occurrence of floods and landslides under shared atmospheric forcing has important implications for integrated disaster risk management, as it suggests that early warning systems should be designed to anticipate multi-hazard scenarios rather than treating each disaster type independently (Hayder et al., 2023; Keum et al., 2020). The negative correlations between drought (*Kekeringan*) and both floods (r = -0.34) and landslides (r = -0.46) further reinforce the physical consistency of these findings, reflecting the well-established seasonal antithesis between wet-regime and dry-regime climate phases in Indonesia—a dynamic that is strongly modulated by large-scale climate drivers such as ENSO and the Indian Ocean Dipole (Kurniadi et al., 2021).

Physical Interpretation of Cascading Hazard Mechanisms The strong Pearson correlations identified between extreme weather, floods (r=0.79), and landslides (r=0.86) represent more than mere statistical associations; they signify a physical cascading hazard mechanism dominant in tropical regions. This process begins with extreme rainfall triggering infiltration excess and soil saturation, which mechanically progresses into slope failure (landslides) and overbank flow (flooding) (Yanfatriani et al., 2024). Framing these correlations as a physical sequence confirms that atmospheric anomalies are the primary precursors to disaster events in the Indonesian archipelago. Consequently, disaster management strategies must transition from isolated hazard responses to integrated multi-hazard frameworks that account for these shared meteorological drivers (Hayder et al., 2023; Keum et al., 2020).

The application of the PELT algorithm to identify regime shifts in 2012, 2017, and 2022 provides critical structural context for interpreting the long-term trajectory of flood disasters in Indonesia. These changepoints correspond to documented transitions in the country's hydrometeorological environment, consistent with findings from Ramadhan et al. (2022), who observed systematic upward trends in both rainfall intensity and hydrometeorological disaster frequency across Indonesian provinces using long-term satellite-based precipitation products. The identification of non-stationarity in the disaster time series is a key methodological contribution, as classical hydrological and disaster modeling frameworks have historically assumed stationary processes—an assumption that is increasingly untenable in the context of contemporary climate change (Natel de Moura et al., 2022).

The progressive escalation in both mean frequency and variance across the three detected regimes, culminating in the extreme peaks of 2020–2021 and the record high in 2025, reflects a structural departure from historical baselines that cannot be adequately captured by conventional statistical models. This finding is consistent with arguments advanced by Veeramany et al. (2016), who emphasized the inadequacy of traditional stationarity-based frameworks for modeling high-impact, low-frequency events and advocated for dynamic risk modeling approaches capable of accommodating regime-dependent behavior. Meteorological Validation of Regime Shifts (2012–2022) The identification of structural regime shifts in 2012, 2017, and 2022 via the PELT algorithm provides critical evidence that "stationarity is dead" in the context of Indonesian disaster patterns (Galloway, 2011). These breakpoints correspond to active phases of multi-scale climate drivers, specifically the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), which have increasingly disrupted historical climate averages (Kurniadi et al., 2021). This progressive escalation in both mean frequency and variance reflects a structural departure from historical baselines, a trend observed across various Indonesian provinces using long-term precipitation products (Ramadhan et al., 2022). Mapping these statistical changepoints to real-world atmospheric dynamics justifies the use of regime-aware frameworks to capture the "new normal" of non-stasioneritas in the Indo-Pacific warm pool.

The LSTM model's ability to capture non-linear trajectories and turning points in the flood frequency time series—despite exhibiting a precautionary overestimation bias in 2024–2025—demonstrates the fundamental suitability of deep learning architectures for hydrometeorological forecasting in non-stationary environments. This overestimation pattern, or "precautionary bias," is a known characteristic of LSTM models trained on sequences containing sharp volatility spikes; the model learns to anticipate escalation based on preceding high-variance regimes, which can lead to inflated predictions when actual disaster frequencies temporarily moderate (Wu et al., 2023). Critically, the model's directional accuracy—its ability to correctly identify the peak in 2025 followed by the steep decline in 2026—holds greater practical value for adaptive disaster management than point-estimate precision alone.

This prioritization of trend-following over absolute numerical accuracy aligns with the conclusions of Chauhan et al. (2024), who demonstrated that LSTM models applied to hydrometeorological forecasting in the Yamuna River basin outperformed traditional Markov Chain approaches precisely in their capacity to capture directional shifts and non-linear regime transitions. Similarly, Maspo et al. (2020) and Jamunadevi et al. (2024) have consistently shown that deep learning methods, particularly LSTM-based architectures, offer superior performance over classical statistical models when dealing with temporally complex and non-linear flood prediction scenarios. Scientific Justification for "Precautionary Bias" and Model Metrics The observed overestimation in 2024–2025 is characterized as a "precautionary bias," a known characteristic of LSTM architectures trained on high-volatility time series where the model learns to anticipate escalation based on preceding sharp spikes (Wu et al., 2023). Despite this numerical gap, the model's high directional accuracy—specifically capturing the 2025 peak and 2026 decline—holds significant practical value for adaptive risk management (Chauhan et al., 2024). Furthermore, while the MAPE of 43.77% is numerically high, such values are expected when predicting highly stochastic and non-linear tropical climate extremes (Vivas et al., 2020). The near-zero errors achieved in 2023 ($\Delta = -20$) and 2026 ($\Delta = 34$) suggest that the LSTM model effectively learned the statistical signature of the most recent disaster regime, a convergence behavior previously noted in Indonesian flood prediction studies (Yoani et al., 2023).

The quantitative evaluation metrics, RMSE of 816.67, MAE of 622.38, and MAPE of 43.77%, require contextual interpretation within the domain of extreme hydrometeorological event prediction. The divergence between RMSE and MAE indicates that model errors are not uniformly distributed but are concentrated in years of extreme outlier behavior, a pattern characteristic of disaster data exhibiting heavy-tailed distributions (Brooks & Persand, 2003). A MAPE of 43.77% is admittedly high in absolute terms; however, Vivas et al. (2020) demonstrated in their systematic review of machine learning forecasting methods that MAPE values in the range of 30–50% are not uncommon and may even be expected when predicting highly stochastic, non-linear phenomena such as tropical climate extremes. The near-zero errors achieved in 2023 ($\Delta = -20$) and 2026 ($\Delta = 34$) are particularly noteworthy, as they suggest that the LSTM model effectively converged toward an accurate representation of the most recent disaster regime by the end of the training period.

This convergence behavior has been observed in prior work by Yoani et al. (2023), who applied LSTM to monthly flood event prediction in Indonesia and similarly found that model performance improved as the architecture learned the statistical signature of more recent data segments. The sensitivity to outliers revealed by the RMSE-MAE divergence also points to the potential value of hybrid modeling strategies, combining LSTM with ensemble decomposition methods such as Empirical Mode Decomposition (EEMD), as proposed by Wu et al. (2023)—to reduce the influence of extreme observations on overall model calibration.

The long-term projections for 2027–2029, forecasting 2,278, 2,542, and 2,021 flood events respectively, carry significant implications for national disaster risk governance and infrastructure planning. These figures represent a sustained elevation above the historical pre-2012 baseline, suggesting that the structural shift toward a high-frequency disaster regime is not a transient anomaly but a durable feature of Indonesia's evolving hydrometeorological landscape. Song et al. (2025) similarly identified persistent upward trends in disaster damage costs in South Korea using machine learning models, reinforcing that such escalatory trajectories are not unique to Indonesia but reflect a broader pattern of intensifying climate-driven disaster risk across tropical and subtropical regions. The projected peak in 2028 is particularly concerning, as it implies a potential window of heightened vulnerability that should inform pre-emptive investments in flood-resilient infrastructure, early warning systems, and community-level preparedness (Zhou et al., 2021; Hamid & Abedlmajid, 2025). From a technological governance perspective, the integration of AI-driven predictive models with Internet of Things (IoT) sensor networks and big data platforms—as advocated by Zhou et al. (2021)—could substantially enhance the real-time responsiveness and spatial resolution of disaster management systems calibrated for this projected high-frequency regime. Mahesh (2025) and Luxshi (2024) further emphasize that AI-driven disaster prediction frameworks represent a paradigm shift in how societies can systematically reduce exposure to natural hazards through proactive, data-informed governance rather than reactive post-event response.

The applicability of the methodological framework developed in this study extends beyond the Indonesian context. The combination of changepoint detection using the PELT algorithm with LSTM-based forecasting provides a replicable, scalable pipeline for analyzing non-stationary hydrometeorological disaster data in any data-rich tropical environment.

This pipeline is particularly relevant for neighboring nations in Southeast Asia and South Asia that share similar monsoon-driven climate dynamics and face analogous challenges in modeling cascading disaster risks. Yu (2017) demonstrated that machine learning regression models can generalize effectively across diverse disaster typologies when appropriately trained on regime-structured data, and the PELT-LSTM approach developed here provides a systematic method for achieving such regime-awareness in model training. Moreover, the framework's demonstrated capacity to project multi-year disaster frequencies at a national scale offers a quantitative foundation for long-term climate resilience planning, reinforcing the conclusion—well-supported by the reviewed literature (Hidayah et al., 2022; Kong et al., 2023; Hong-wei et al., 2025)—that stationarity-based assumptions in disaster risk management are no longer scientifically defensible in an era of accelerating hydrometeorological volatility.

From a spatial approach perspective, hydrometeorological disasters in Indonesia exhibit strong geographical variability influenced by monsoonal circulation, ENSO dynamics, topography, and regional land-use change. Western Indonesia, particularly Java and Sumatra, experiences higher flood and landslide intensity due to dense population, urban expansion, and intensified rainfall during La Niña periods, while El Niño events increase drought and forest fire risks in Kalimantan and eastern Indonesia. These findings confirm that disaster patterns in Indonesia are spatially uneven and closely linked to atmospheric circulation and regional environmental characteristics (Lam et al., 2019; Nobre et al., 2019). Moreover, prolonged ENSO variability has been shown to contribute to slow-onset environmental disasters and long-term regional vulnerability accumulation in tropical regions (Staupe-Delgado et al., 2018).

From a regional complex approach perspective, the increasing disaster frequency after 2012 reflects the interaction between climate change, industrial development, environmental degradation, and socio-economic transformation. Rapid urbanization, deforestation, mining activities, and watershed conversion have intensified regional vulnerability to extreme hydrometeorological events. The instability of Indonesia's monsoon system, amplified by ENSO and the Indian Ocean Dipole, further increases the likelihood of cascading disasters (Hallegatte, 2014; Kelman, 2015). Similar conditions were identified by French et al. (2020) in Peru, where disaster severity was shaped not only by climatic anomalies but also by institutional and socio-political vulnerabilities.

Therefore, disaster governance in Indonesia requires integrated regional planning, stronger environmental regulation, community–industry collaboration, and AI-driven early warning systems to support long-term climate resilience (Octaviana et al., 2025).

CONCLUSION

This study demonstrates that stationarity in Indonesian disaster management is no longer a viable assumption, as the PELT algorithm identified critical structural regime shifts in 2012, 2017, and 2022. These shifts, physically mapped to the intensified modulation of the monsoon cycle by ENSO and IOD, have ushered in a "new normal" characterized by a sustained high-frequency disaster state where annual flood events are projected to remain above the 2,000-event threshold through 2029.

Acknowledging the limits of the available evidence, the 15-year dataset and the inherent stochasticity of tropical climate extremes result in a MAPE of 43.77%. However, the LSTM model's high directional accuracy—specifically its ability to capture the 2025 peak and 2026 decline—proves its reliability for trend-following in non-stationary environments. By incorporating uncertainty bounds (RMSE error envelopes), this framework provides a scientifically defensible probability range thataccounts for extreme anomalies, mitigating the risks associated with "precautionary bias" and recursive error propagation.

For practical integration, this "regime-aware" framework serves as a vital update to Indonesia's Hydrometeorological Early Warning Systems (EWS), such as those managed by BMKG. Rather than relying on static 30-year historical averages, the system should adopt dynamic, changepoint-adjusted baselines that reflect the most recent disaster regime. Bridging the gap to actionable spatial planning, these projections provide the quantitative foundation needed to recalibrate flood-risk maps and structural mitigation designs—such as dam capacities and urban drainage systems—to withstand a high-frequency disaster environment. Ultimately, the transition to AI-driven predictive governance facilitates a shift from reactive post-event response toward proactive, data-informed climate resilience.

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