RAINFALL ANALYSIS AND FORECASTING USING THE PROPHET METHOD ON TIME SERIES DATA

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Abstract

Climate change has increased rainfall variability, making it more difficult to predict rainfall patterns in terms of intensity, duration, and spatial distribution. This study aims to develop a daily rainfall forecasting model using the Prophet method, which is capable of handling seasonal patterns and long-term trends in time series data. The data used consist of daily rainfall records from 2015 to 2025 across nine regions in Bali Province, obtained from the NASA POWER platform. The research methodology includes data collection, data preprocessing, exploratory data analysis (EDA), Prophet model development with parameter optimization, cross-validation, and forecasting. Model performance is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics on test data. The results indicate that the Prophet method is capable of effectively modeling seasonal patterns and rainfall trends, producing stable predictions for future periods. This forecasting system is expected to serve as a decision-support tool in agriculture, water resource management, and hydrometeorological disaster mitigation.

Keywords: Rainfall, Prophet, Time Series, Forecasting, Bali

INTRODUCTION

Global climate change over recent decades has significantly increased rainfall variability in terms of intensity, duration, and spatial distribution [1]. This dynamic not only affects hydrological systems but also has direct implications for critical sectors such as food security and disaster management [2]. Tropical countries that heavily rely on seasonal rainfall cycles are now facing major challenges in accurately predicting water availability [3]. This uncertainty increases the risk of extreme events such as floods and droughts, which can damage infrastructure and disrupt economic activities [4]. Therefore, the development of adaptive and reliable prediction systems has become essential to mitigate the increasingly severe impacts of climate change [5]. In Indonesia, precipitation patterns have shown increasingly unpredictable fluctuations due to unstable equatorial atmospheric dynamics [6]. Global climate phenomena such as El Niño and La Niña frequently trigger anomalies in the rainy season, disrupting the natural balance between wet and dry seasons [7]. These disruptions affect agricultural planting cycles and increase the risk of hydrometeorological disasters in vulnerable areas [8].

Conventional forecasting methods often fail to capture sudden and highly dynamic seasonal shifts [9]. As a result, the limited availability of accessible prediction tools further weakens local adaptation efforts to climate change [10]. To improve forecasting accuracy, various machine learning approaches have been widely applied, including Naïve Bayes, K-Means, and artificial neural network algorithms [11]. Artificial intelligence approaches have also been extensively adapted for related hydrological variables, such as river discharge forecasting using Deep Learning methods based on Multi-Layer Perceptrons (MLP) [12]. These methods demonstrate strong capability in capturing nonlinear relationships in complex rainfall data [13].

However, most of these approaches require large datasets and involve complex and time-consuming parameter optimization processes [3]. This complexity often becomes a limitation when implementing models in information systems that demand high efficiency and speed [14]. Furthermore, neural network-based approaches are often difficult to interpret for non-technical users due to their "black-box" nature [14]. As an alternative solution, the Prophet method offers an effective and interpreable time series forecasting approach [2]. This method employs an additive model that separates trend, seasonal, and error components independently, enabling it to handle data with strong seasonal patterns [15]. One of Prophet's main advantages is its robustness to missing data and its ability to automatically adjust to trend changes (changepoints) [16].

Its relatively simple structure allows easier integration into information systems compared to more computationally intensive deep learning models [17]. Additionally, Prophet's capability to generate uncertainty intervals provides added value for policymakers in designing more measurable mitigation strategies [18]. Based on this background, this study aims to develop a rainfall forecasting model using the Prophet method, utilizing historical data from 2015 to 2025 in Bali Province. Bali was selected due to its tropical climate characteristics, which exhibit distinct and variable wet and dry seasonal patterns. This research focuses on analyzing the model's performance in capturing long-term trends and seasonal variations from satellite observation data [13]. The forecasting results are expected to provide accurate and stable information to support decision-making in agriculture and water resource management [19]. Thus, this study contributes to the development of practical and accessible predictive technology to support regional climate resilience [20].

LITERATURE REVIEW

Climate change has significantly influenced rainfall variability, resulting in increasing challenges in accurately predicting precipitation patterns. Variations in rainfall intensity, duration, and spatial distribution are widely recognized as key impacts of global climate change, particularly in tropical regions [1]. These changes not only affect hydrological systems but also have serious implications for food security, water resource management, and disaster mitigation [2]. In Indonesia, rainfall patterns are strongly influenced by equatorial atmospheric dynamics and global climate phenomena such as El Niño and La Niña, which often cause irregular seasonal shifts and increase the risk of hydrometeorological disasters [6], [7]. Consequently, the development of accurate and adaptive rainfall forecasting models has become increasingly important.

Traditional statistical forecasting methods often struggle to capture nonlinear relationships and abrupt seasonal changes in rainfall data [9]. To address these limitations, various machine learning approaches have been widely applied, including Naïve Bayes, K-Means, and artificial neural networks [11]. These methods demonstrate strong capabilities in modeling complex rainfall patterns; however, they generally require large datasets and involve complex parameter optimization processes, which can limit their practical implementation [3]. Deep learning techniques, such as Multi-Layer Perceptrons (MLP), have also been utilized in hydrological forecasting and have shown promising results in capturing nonlinear dynamics [12]. Nevertheless, these models are often considered "black-box" systems, making them difficult to interpret for non-technical users and decision-makers [14].

As an alternative, the Prophet method has emerged as an effective and interpretable time series forecasting approach. Prophet employs an additive regression model that decomposes data into trend, seasonal, and residual components, allowing it to effectively handle strong seasonal patterns [15]. One of its main advantages is its robustness to missing data and its ability to automatically detect trend changes (changepoints), making it suitable for real-world datasets with irregularities [16]. Moreover, Prophet is computationally efficient and easier to implement compared to complex deep learning models, making it suitable for integration into decision-support systems [17]. Its capability to generate uncertainty intervals also provides additional value for risk assessment and policy-making [18].

Previous studies have demonstrated the effectiveness of Prophet in rainfall and hydrological forecasting. For instance, Prophet has been successfully applied to rainfall prediction at the catchment level, showing reliable performance in capturing seasonal variability [2]. Hybrid approaches that combine Prophet with other methods such as Support Vector Regression (SVR) and wavelet transforms have also been shown to improve prediction accuracy [18]. Additionally, time series evaluation techniques such as cross-validation with rolling windows are commonly used to assess model stability and generalization performance [19]. Data preprocessing techniques, including outlier detection and handling missing values, also play a crucial role in improving model accuracy and reliability [21], [22]. Based on these studies, the Prophet method offers a balance between accuracy, interpretability, and computational efficiency, making it a suitable approach for rainfall forecasting, particularly in tropical regions with strong seasonal characteristics.

METHOD

Data Source and Description

This study utilizes secondary data in the form of daily rainfall records from 2015 to 2025, obtained from the NASA POWER platform, covering nine administrative regions in Bali Province. The data serve as the primary foundation for developing a time series forecasting model using the Prophet method. The research workflow is systematically designed and fully focused on model development and evaluation, without involving the development of an information system or dashboard.

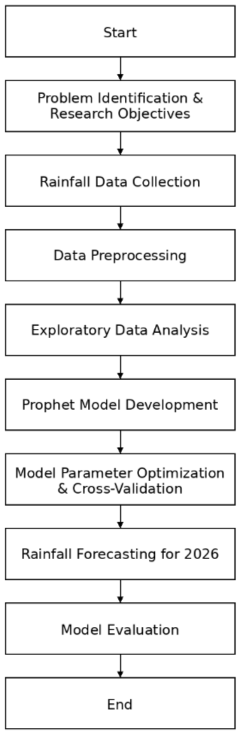


Figure 1. Research Flow Diagram

Based on the research flow diagram, the process is conducted sequentially, starting from problem identification and research objectives, rainfall data collection (2015–2025), data preprocessing, and ending with the final evaluation stage. The data preprocessing stage includes data cleaning, selective outlier handling using the Interquartile Range (IQR) method, format transformation, and splitting the dataset into training and testing sets. Subsequently, Exploratory Data Analysis (EDA) is performed to identify trend patterns, distributions, and seasonal characteristics both visually and statistically. The results of EDA serve as the basis for Prophet model development, model parameter optimization (changepoint_prior_scale and seasonality_prior_scale), and cross-validation using a rolling window approach. The final stage involves rainfall forecasting for the year 2026, followed by model evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and visualization of prediction results.

Data Preprocessing

The data preprocessing stage is conducted to ensure that the dataset is in optimal condition before entering the modeling process. The initial step involves data cleaning by removing missing values and duplicate records that may disrupt the temporal continuity of the time series. A deletion approach is adopted to preserve the integrity of the original patterns without introducing artificial estimates that could bias the data distribution [21]. Additionally, outlier detection is performed using the Interquartile Range (IQR) method to identify values that deviate significantly from the general distribution. Extreme values identified as technical errors are removed, while values that remain within climatologically reasonable limits are retained to preserve the natural variability of the data.

After cleaning, the dataset structure is transformed to meet the model input requirements. The date column is converted into the ISO 8601 standard format, and the rainfall column is ensured to be numeric. The data are then reformatted into two main columns: the time indicator (ds) and the target value (y). The final step in preprocessing is splitting the data chronologically into 80% training data and 20% testing data. This non-random split is crucial in time series analysis to prevent data leakage and to ensure that the model learns only from historical patterns before being evaluated on unseen future periods.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is conducted to understand the fundamental structure, statistical distribution, and temporal characteristics of rainfall data before modeling. The process begins with the calculation of descriptive statistics, including mean, minimum, maximum, and variance, to provide an overview of data distribution. Histogram visualization is used to observe the shape of the data distribution and identify skewness or the presence of extreme values commonly found in climatological datasets. This stage also serves as an initial validation to ensure that the data have been properly preprocessed and are free from technical anomalies that could interfere with the model learning process [6]. Since the data are time series in nature, the analysis focuses on identifying long-term trends and dominant seasonal cycles. Daily time series plots are visualized to observe changes in rainfall intensity over time and detect inter-period fluctuations. Monthly aggregation is performed to highlight wet and dry season patterns characteristic of tropical regions such as Bali.

These visualizations help researchers understand the annual rhythm of rainfall and ensure the consistency of the dataset's temporal structure. Findings from the EDA stage serve as an important foundation for configuring the forecasting model according to data characteristics. The identification of strong seasonal patterns and nonlinear trends confirms the suitability of an additive decomposition approach. Moreover, a comprehensive understanding of data variability enables more targeted and efficient modeling strategies. Thus, EDA acts as an analytical bridge connecting raw data with the development of a robust forecasting model.

Modeling Using the Prophet Method

The Prophet method is selected as the primary forecasting algorithm due to its ability to handle time series data with clear seasonal patterns and dynamic trend changes. This model operates based on an additive regression approach that separates the main components of the data into independent structures.

$$y(t) = g(t) + s(t) + \varepsilon_t$$

In this equation, $y(t)$represents the rainfall value at time t, $g(t)$denotes the trend component capturing long-term movement, $s(t)$represents the seasonal component modeling periodic patterns, and $\varepsilon_t$is the error term or random noise. The trend component $g(t)$is modeled using a piecewise linear function that allows slope changes at specific points to adapt to historical data dynamics. Meanwhile, the seasonal component $s(t)$is represented using a Fourier series with an annual period to capture recurring wet and dry cycles. This separation enables the model to remain stable even when dealing with highly fluctuating or incomplete data. The additive structure also provides flexibility, as it does not require strict stationarity assumptions like conventional statistical methods.

During training, the model utilizes historical data from 2015 to 2025 to optimally estimate each component's parameters. The configuration is adjusted through hyperparameter optimization to balance trend flexibility and seasonal strength. After training, the model generates future predictions along with uncertainty intervals that reflect data variability. This output provides a comprehensive projection of rainfall for further analysis.

Evaluation

Model performance evaluation is conducted to measure how closely the predicted values match the actual historical data. The evaluation uses two main statistical error metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). MAE provides the average absolute difference between predicted and actual values in millimeters, making it easy to interpret. RMSE places greater emphasis on larger errors, making it suitable for assessing model performance under highly variable weather conditions. The combination of these metrics enables a quantitative and objective assessment of model accuracy. In addition to metric-based evaluation, cross-validation is performed using a rolling window approach to test model stability across different time periods. In each iteration, the model is trained on data up to a certain point and then tested on subsequent periods sequentially.

This approach preserves the chronological structure of time series data, making the evaluation more representative of real forecasting scenarios [19]. Cross-validation results are analyzed to assess consistency in prediction errors across iterations, indicating the model's generalization capability. A stable model will exhibit relatively small variations in error across all testing periods. The evaluation stage also includes visual analysis by comparing actual data plots with predicted results to assess the alignment of trend and seasonal patterns. Discrepancies such as shifted rainfall peaks or amplitude differences indicate limitations in capturing specific data characteristics. Additionally, uncertainty intervals produced by the model are analyzed to understand the confidence level of future predictions. These evaluation results serve as the basis for determining the feasibility of the Prophet model for operational forecasting and interpretation.

RESULTS AND DISCUSSION

Data Characteristics After Preprocessing

After undergoing preprocessing, the daily rainfall dataset for the period 2015–2025 from nine regions in Bali Province is ready for further analysis. The data cleaning process successfully removed missing values and duplicate records without disrupting the temporal continuity of the time series, ensuring consistency for modeling [22]. The final number of observations reflects sufficient data quality to capture trend and seasonal patterns representatively. This clean dataset serves as the primary foundation for developing a reliable and stable forecasting model.

Figure 2. Boxplot of Data Before Outlier Treatment

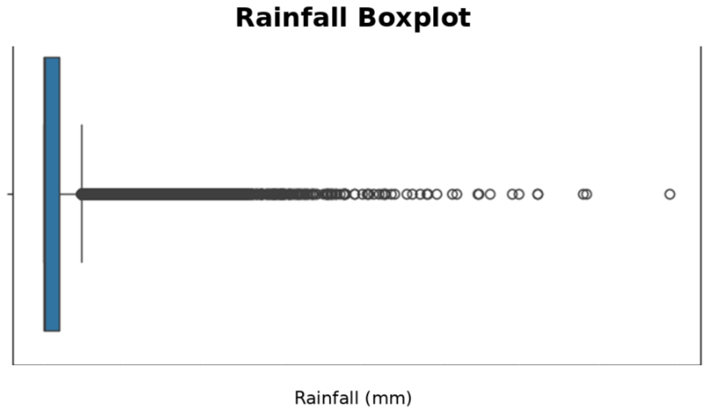
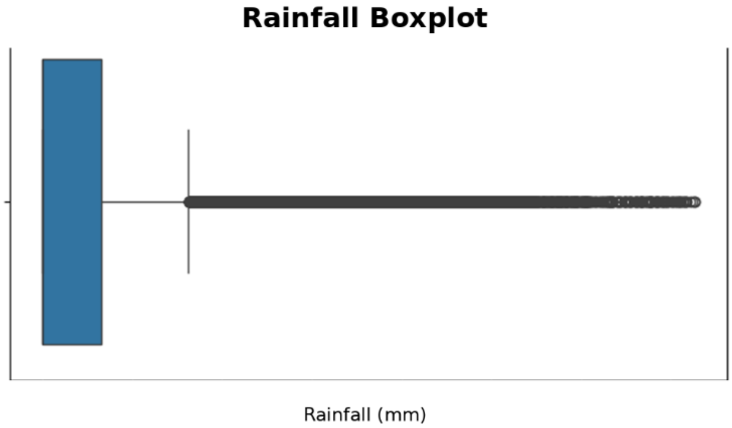


Figure 3. Boxplot After Outlier Handling



The boxplot visualization before and after outlier handling shows a significant change in the data distribution. Previously, several extreme values were observed beyond climatologically reasonable limits, which were likely caused by recording errors or sensor disturbances. After applying outlier treatment using the Interquartile Range (IQR) method, the data distribution becomes more concentrated within a rational range without eliminating the natural variability of rainfall. These results confirm that the applied data cleaning approach effectively improves dataset quality while preserving the essential statistical characteristics required for modeling. The descriptive statistical profile of the dataset after preprocessing indicates that rainfall in Bali exhibits a highly skewed distribution, with a dominance of low or zero values on days without rainfall. The average daily rainfall varies across regions, reflecting the influence of topography and geographical location of each district or city. Regions with higher elevation tend to show greater rainfall intensity compared to coastal areas. Understanding these distribution characteristics is crucial for configuring the Prophet model to effectively handle non-symmetric and highly variable data patterns.

Exploratory Data Analysis (EDA) Results

The results of descriptive statistical analysis indicate significant variation in rainfall characteristics across the nine regions in Bali Province. High-elevation areas such as Buleleng and Tabanan tend to record higher average and maximum rainfall values compared to coastal regions such as Denpasar and Badung. This understanding of spatial variation serves as an important basis for configuring the forecasting model, as supported by regional precipitation studies that emphasize the influence of topography on rainfall distribution [7]

Figure 4. Histogram of Rainfall Distribution Data

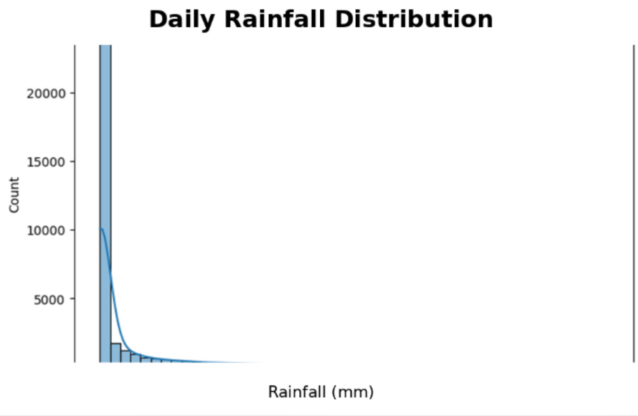
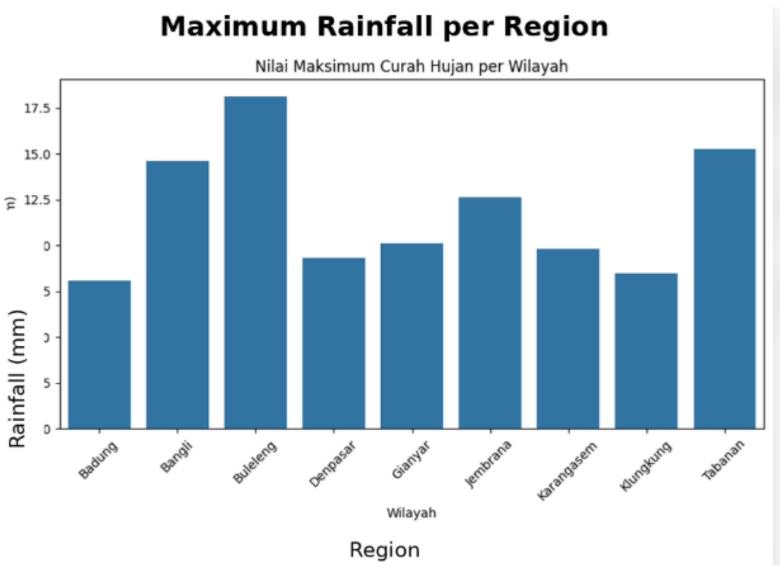
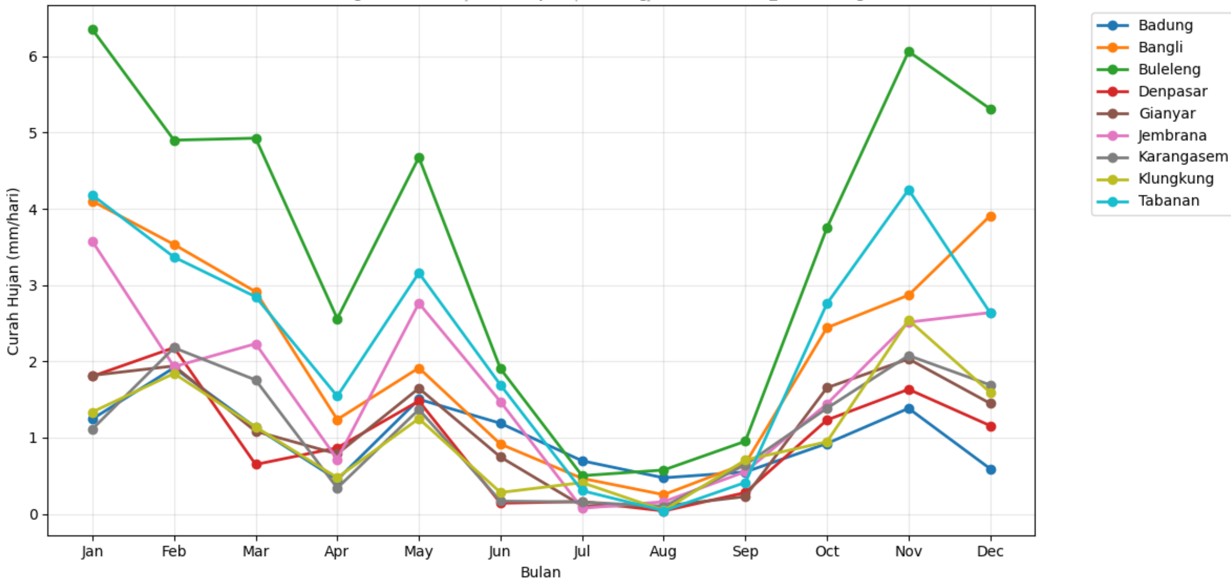


Figure 5. Bar Chart of Maximum Rainfall per Region



The histogram visualization of rainfall distribution confirms that the data exhibit a highly skewed pattern, with a dominance of low or zero values on days without rainfall. The right-skewed tail indicates the presence of extreme values representing heavy rainfall events, which are a natural phenomenon in tropical climates. Meanwhile, the bar chart of maximum rainfall values across regions shows that Buleleng records the highest daily rainfall intensity, followed by Tabanan and Bangli, whereas Badung and Klungkung exhibit relatively lower daily averages. These findings indicate that rainfall intensity varies across regions, although overall rainfall is still dominated by lower levels, as observed in each area.

Figure 6. Monthly Average in 2025 per Region



The analysis of seasonal patterns based on monthly average aggregation in 2025 indicates a consistent rainfall and dry season cycle characteristic of Bali. Months with the highest rainfall intensity generally occur during January–February and November–December, corresponding to the regional rainy season pattern. In contrast, the period from June to August shows the lowest values, representing the dry season with minimal precipitation. This clear and recurring seasonal pattern provides strong justification for the use of the Prophet method, which is specifically designed to model periodic components in time series data.

Prophet Model Performance

The baseline evaluation results of the Prophet model indicate variations in performance across regions, as reflected by the MAE and RMSE values presented in Table 1. Denpasar and Badung exhibit relatively low error values, with RMSE values of 1.70 mm and 1.69 mm, respectively, indicating good predictive performance. In contrast, Buleleng and Tabanan show higher error values, with RMSE reaching 4.33 mm and 3.55 mm, reflecting the high variability of rainfall that is not yet fully captured by the baseline model. Overall, the average MAE and RMSE values fall within an acceptable range for daily rainfall forecasting applications, with error levels consistent with hydrometeorological model evaluation standards [18]. In general, these baseline results suggest that the model performance can still be improved through parameter optimization.

Table 1. Model Performance (MAE/RMSE)

Region	MAE (Baseline)	RMSE (Baseline)
Badung	1.15	1.69
Bangli	2.09	3.55
Buleleng	2.94	4.33
Denpasar	1.07	1.70
Gianyar	1.27	2.04
Jembrana	1.79	2.76
Karangasem	1.30	2.01
Klungkung	1.10	1.77
Tabanan	2.35	3.55

Cross-Validation Evaluation

The cross-validation evaluation indicates that the model performance is more stable compared to the baseline scenario, as reflected by the RMSE values in Table 2. Klungkung and Badung exhibit the lowest error values, at 1.53 mm and 1.62 mm, respectively, indicating strong prediction consistency.

In contrast, Buleleng and Tabanan show higher RMSE values of 3.78 mm and 3.18 mm, respectively, suggesting greater complexity in rainfall patterns that are more difficult to model. This indicates the need for parameter optimization to achieve more optimal performance.

Table 2. Cross-Validation Evaluation Results

Region	RMSE (CV)
Badung	1.62
Bangli	2.91
Buleleng	3.78
Denpasar	1.64
Gianyar	1.80
Jembrana	2.58
Karangasem	1.86
Klungkung	1.53
Tabanan	3.18

The parameter optimization results indicate that the combination of a changepoint_prior_scale value of 0.01 and a seasonality_prior_scale value of 1 yields the best performance across all study regions. The consistency of these parameters suggests that rainfall patterns across regions share similar temporal dynamics, allowing them to be effectively represented using a model with relatively low complexity. The small value of changepoint_prior_scale indicates that trend changes occur gradually, thus not requiring high flexibility in trend modeling. Meanwhile, the low value of seasonality_prior_scale suggests that the annual seasonal component is already well captured without the need for excessive amplification. These findings imply that the seasonal structure of rainfall data is relatively stable, enabling a simpler model to produce consistent predictions with good generalization performance.

Table 3. Best Hyperparameters of the Prophet Model

Region	Best CPS (changepoint_prior_scale)	Best SPS (seasonality_prior_scale)
Badung	0.01	1
Bangli	0.01	1
Buleleng	0.01	1
Denpasar	0.01	1
Gianyar	0.01	1
Jembrana	0.01	1
Karangasem	0.01	1
Klungkung	0.01	1
Tabanan	0.01	1

The model decomposition analysis for the Buleleng region shows that rainfall variability is predominantly influenced by the annual seasonal component, with relatively contrasting fluctuations between the beginning, middle, and end of the year. The highest seasonal values occur at the beginning and end of the year, while a significant decrease is observed during the mid-year period. The long-term trend component remains relatively stable without notable changes. This pattern reflects the rainfall characteristics of northern Bali, which exhibits more distinct seasonal variations throughout the year compared to urban areas.

Figure 7. Decomposition of Prophet Components (Trend and Yearly Seasonality) in the Buleleng Region

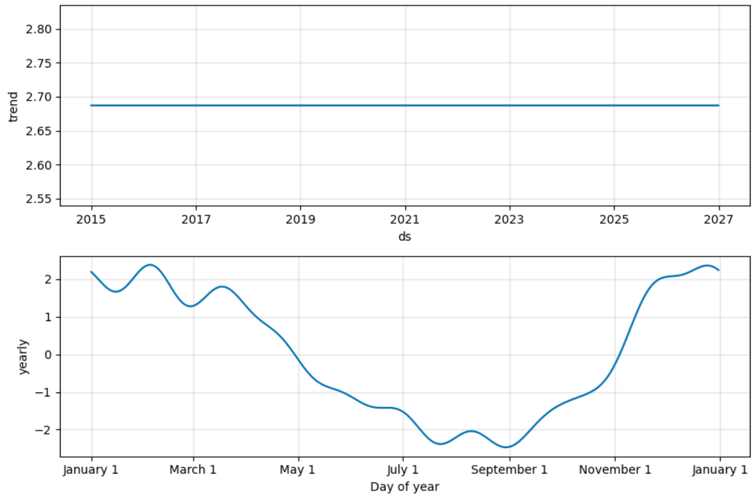
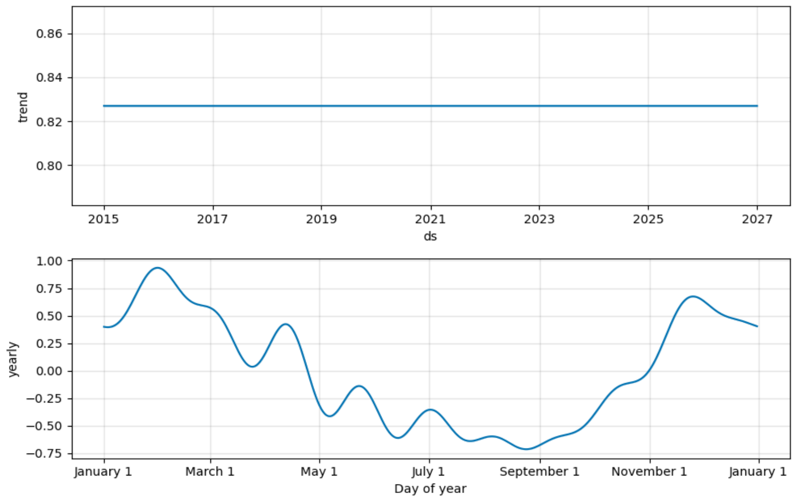


Figure 8. Prophet Components (Trend & Yearly) for the Denpasar Region

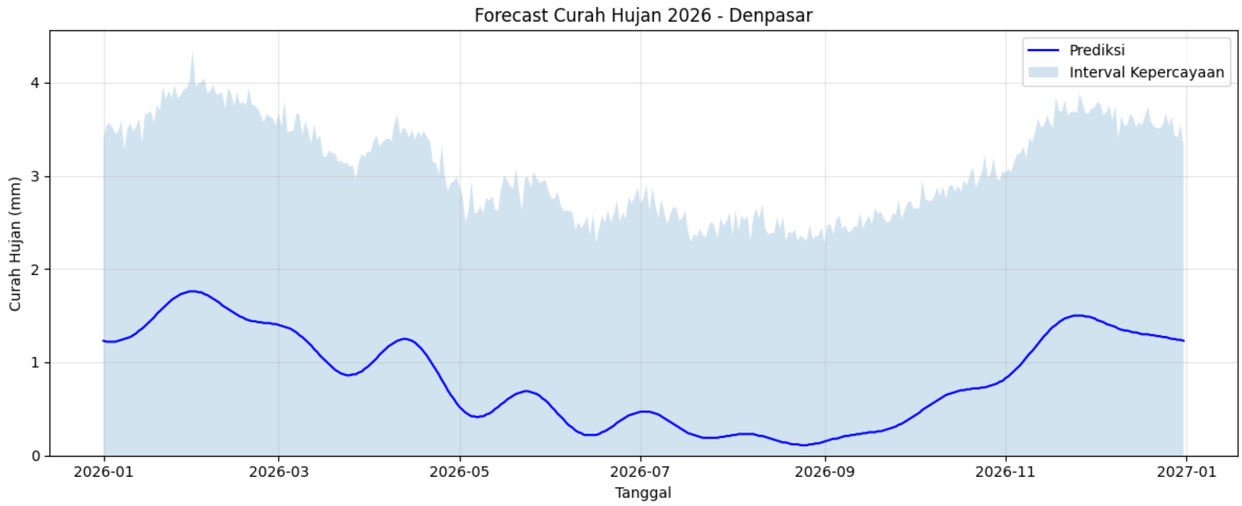


The model decomposition for the Denpasar region shows that the annual seasonal component remains the dominant factor in shaping rainfall patterns, but with relatively smoother fluctuations compared to the Buleleng region. Peak rainfall occurs at the beginning and end of the year, while a decline is observed during the mid-year period. The long-term trend component tends to remain stable without significant changes.
This pattern reflects a more evenly distributed rainfall throughout the year, which is commonly observed in urban areas.

Rainfall Forecast Results for 2026

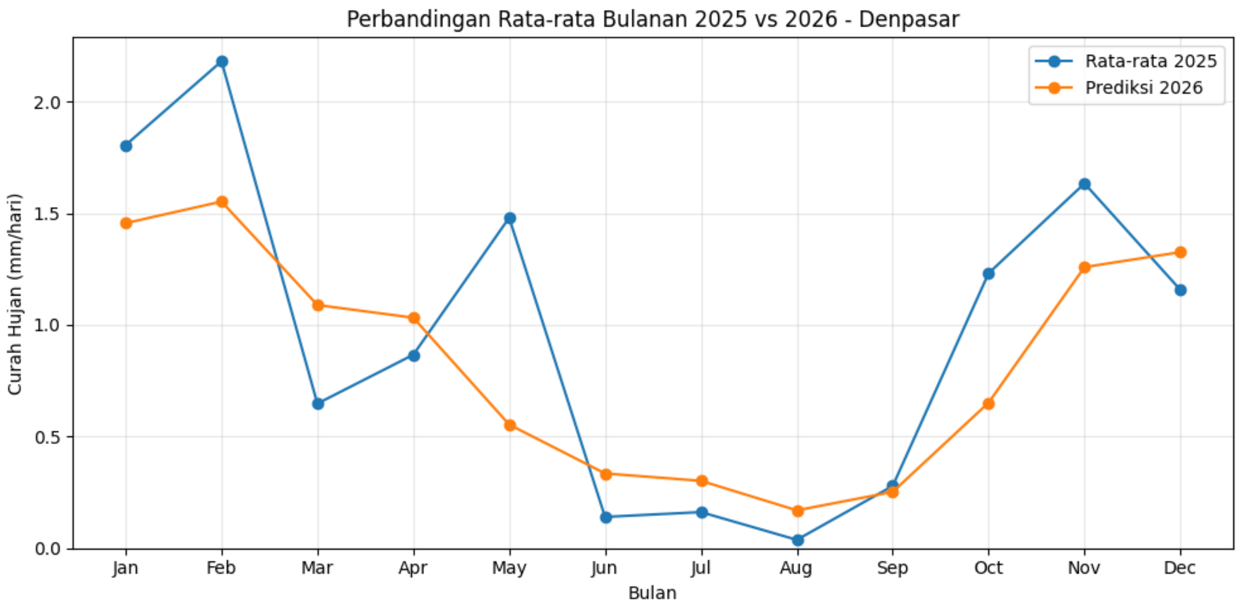
The visualization of daily rainfall forecasting results for 2026 indicates a consistent annual seasonal pattern aligned with the historical rainfall distribution in Bali. Peak rainfall intensity is observed at the beginning and end of the year, particularly in January, February, November, and December, corresponding to the rainy season period. In contrast, the mid-year period, especially from June to August, shows relatively low rainfall intensity, reflecting the dry season phase. Additionally, differences in dynamics across regions are evident from the smoothness of prediction variations, where coastal areas such as Denpasar and Badung exhibit more gradual patterns compared to other regions.

Figure 9. Rainfall Forecast for 2026 in Denpasar



The comparison of monthly averages between the actual data in 2025 and the forecast for 2026 in the Denpasar region shows a consistent seasonal pattern, with peak rainfall occurring at the beginning and end of the year, and a decline during the mid-year period. Although there are slight differences in intensity levels in several months, the overall pattern remains consistent. This indicates that the model is able to effectively capture the seasonal dynamics of rainfall.

Figure 10. Comparison of Monthly Averages: 2025 vs 2026



The rainfall forecast results for 2026 in the Buleleng region show a clear seasonal pattern, with high intensity at the beginning and end of the year and a significant decline during the mid-year period.

The minimum period occurs from July to September, representing the dry season phase. Compared to coastal regions, rainfall variation in Buleleng appears more pronounced throughout the year.

Additionally, the relatively wide confidence interval range indicates a higher level of uncertainty in this region.

Figure 11. Forecasted Rainfall for 2026 in the Buleleng Region

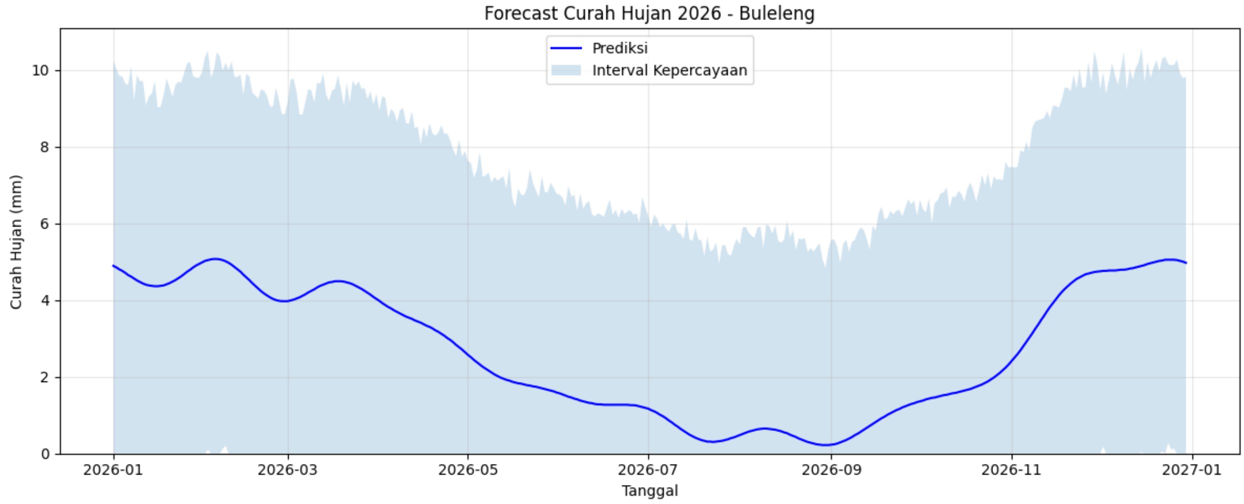
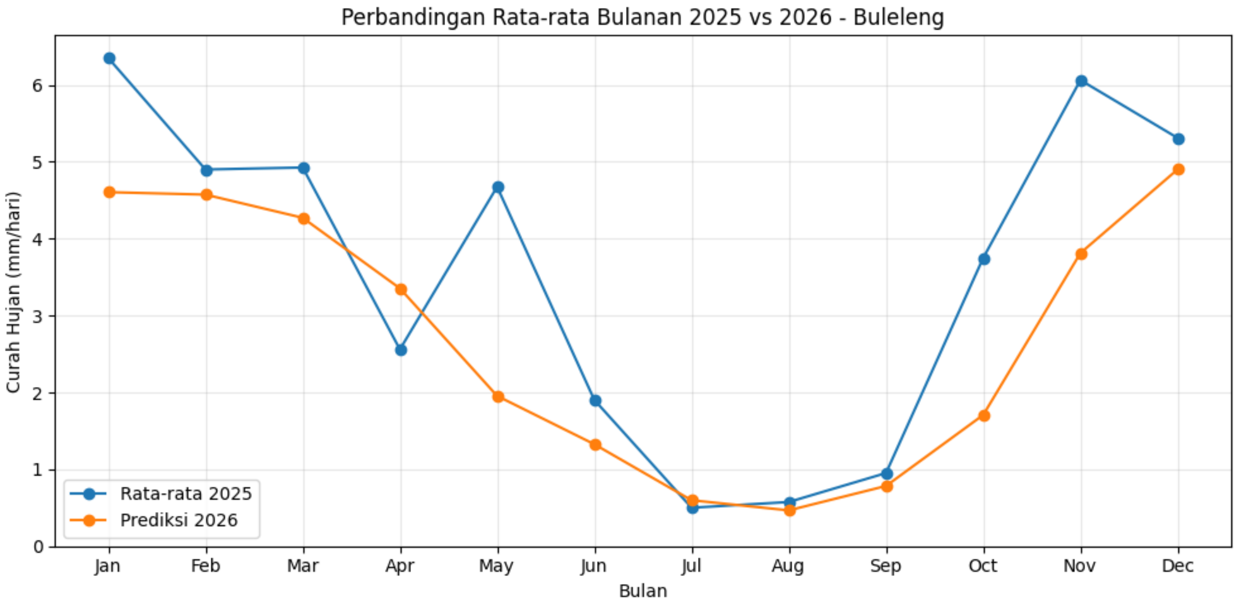


Figure 12. Monthly Averages: 2025 vs 2026 in the Buleleng Region



The comparison of monthly averages between 2025 and the 2026 forecast in the Buleleng region shows a consistent seasonal pattern, with high rainfall intensity at the beginning and end of the year and a decline during the mid-year period. Although differences are observed in several months, particularly during peak periods, the overall trend remains consistent. This indicates that the model is able to effectively represent the seasonal rainfall pattern in the Buleleng region, although variations in intensity are still evident.

Table 4. Comparison of 2025 vs 2026

Region	Average 2025	Forecasted Average 2026
Badung	1.00	0.94
Bangli	2.10	1.77
Buleleng	3.53	2.68
Denpasar	0.96	0.83
Gianyar	1.13	0.92
Jembrana	1.67	1.46
Karangasem	1.07	0.97
Klungkung	1.04	0.81
Tabanan	2.26	1.85

The table comparing monthly averages shows that most regions are predicted to experience a decrease in rainfall intensity in 2026 compared to the 2025 average. Buleleng and Tabanan record the largest decreases, while Denpasar and Klungkung show relatively minor changes. The uncertainty intervals generated by the model provide a range of possible rainfall values, enabling users to estimate risk levels for specific periods [15]. These results offer practical insights that can support agricultural planning, water resource management, and hydrometeorological disaster mitigation.

Discussion

The results of this study indicate that the Prophet method is effective in modeling seasonal patterns and long-term trends of daily rainfall in Bali Province. The model's ability to produce stable predictions along with uncertainty intervals provides an advantage over conventional methods, which often generate only point estimates [14]. However, variations in accuracy across regions are observed, which can be attributed to differences in topographical characteristics and local rainfall variability. Regions with extreme fluctuations tend to exhibit higher prediction errors, indicating the need for additional approaches to better capture extreme weather events.

The main limitation of this study lies in the use of a single data source from a satellite platform without integrating supporting climatological variables such as temperature, humidity, or climate oscillation indices. The inclusion of exogenous variables could enhance the model's ability to respond to atmospheric dynamics affecting rainfall patterns.Furthermore, although Prophet is relatively robust to missing data, the quality of forecasting results still depends on the consistency and completeness of historical data. Future research may integrate hybrid or ensemble approaches to improve accuracy, particularly in regions with high variability.

Practically, the forecasting results can serve as an information base for stakeholders in developing climate adaptation strategies. The predicted patterns can be utilized for crop scheduling, reservoir management, and flood and drought mitigation planning. The availability of accurate climate data also has broader implications for other environmental sectors, including aquatic ecosystem modeling and biodiversity conservation in island regions that are sensitive to precipitation cycles [23]. However, it is important to emphasize that the predictions are probabilistic in nature and should be interpreted alongside other climatological information. Disseminating forecasting information through accessible and user-friendly platforms will enhance its practical benefits for communities and local governments.

CONCLUSION

This study successfully developed a daily rainfall forecasting model using the Prophet method based on historical data from 2015 to 2025 across nine regions in Bali Province. The evaluation results show that the Prophet method effectively captures seasonal patterns and long-term rainfall trends, as reflected by an average MAE of 1.66 mm and an average RMSE of 2.56 mm. Coastal regions such as Badung and Denpasar exhibit the highest prediction accuracy, with RMSE values below 1.8 mm, while regions with more complex topography such as Buleleng and Tabanan show higher errors due to greater rainfall variability. These findings confirm that the Prophet method is effective for tropical rainfall data with clear seasonal patterns, although its performance may vary depending on the spatial and temporal characteristics of the study area. The main contribution of this study lies in the application of an optimized Prophet method within the context of Indonesia's tropical climate, particularly in Bali. The developed model is capable of generating stable predictions along with uncertainty intervals, providing more comprehensive information for users in assessing forecast reliability. Additionally, the data preprocessing approach and cross-validation-based evaluation applied in this study can serve as a methodological reference for similar rainfall forecasting studies in other regions. The limitations of this study include the use of a single satellite data source without incorporating supporting climatological variables such as temperature, humidity, or climate oscillation indices. The inclusion of exogenous variables and hybrid approaches with methods such as LSTM or SARIMA has the potential to improve prediction accuracy, particularly in regions with high variability. Future research may also integrate forecasting results into web-based information systems or mobile applications to enhance accessibility and interactivity for the public and stakeholders. With further development, Prophet-based rainfall forecasting models are expected to become reliable decision-support tools for hydrometeorological disaster mitigation and sustainable water resource management

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