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Performance Comparison of Recursive and Semi-Recursive Random Forest Models for Monthly Rainfall Prediction in the Bogowonto Watershed

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ABSTRACT

Unpredictable rainfall is considered a major challenge for agricultural systems in Indonesia, especially in the preparation of planting calendars. Therefore, accurate rainfall predictions are essential for agricultural systems to be more adaptive to climate change. The aim of this study is to analyse and compare the accuracy of two monthly rainfall prediction schemes, namely recursive and semi-recursive approaches, by using the Random Forest algorithm. Climatological data from four stations in the Bogowonto Watershed were used, and the modelling process included data pre-processing, feature engineering (lag, rolling window, and seasonal transformation), and grid search with cross-validation to obtain the optimal parameter combinations. Model performance was evaluated on out-of-sample test and validation data by using RMSE, MAE, NSE, and R^2. The semi-recursive approach improved NSE from 0.20–0.33 to 0.53–0.61 and reduced RMSE from 210.68–255.75 mm to 150.79–211.31 mm, while R^2 values increased from 0.23–0.50 to 0.72–0.82 across the four stations. These results indicate that the semi-recursive approach is more stable in predicting monthly rainfall and thus is recommended for planning a planting calendar in Bogowonto Watershed.

1. INTRODUCTION

Rainfall is a highly influential factor in agricultural systems; especially, in tropical regions like Indonesia. Unpredictable rainfall fluctuations complicate planting schedules, indirectly increasing the risk of crop failure and reducing the efficiency of water resource use (Zaveri *et al*., 2020). Adaptive agricultural systems to climate change need to be implemented, but it is difficult without information such as accurate weather predictions. Planting calendars based on monthly rainfall predictions can be used to adjust planting schedules and minimize the risk of losses because of changing weather patterns (Mondo *et al*., 2024). Therefore, developing rainfall prediction methods is crucial to support agricultural systems which are adaptive to climate change.

Rainfall prediction methods have undergone significant development, ranging from simple statistical models to the use of machine learning algorithms. One of widely used algorithm for rainfall prediction is Random Forest. Random Forest has proven effective in predicting rainfall and demonstrated superior performance in handling nonlinear relationships in climatological data containing many variables (Che Rose *et al*., 2025). Furthermore, Random Forest is capable of producing consistent and accurate predictions across various climate regions (Ogunniyi *et al*., 2024). This algorithm has the advantage of overcoming overfitting and it is robust to noise which makes it widely used for predictions based on long historical data that is difficult to model with conventional methods (Gunawan *et al*., 2024).

In the rainfall prediction process, Random Forest relies heavily on the design of the predictor variables used. One important step in developing this model is feature engineering. Commonly used features include the use of lag variables and rolling windows in climatological data (Mbenza & Sho, 2023). The uses of rolling windows as predictor variables can strengthen the main pattern, reduce short-term fluctuations, and increase the consistency of prediction results; especially, in data with extreme patterns or high noise (El Hafyani *et al*., 2024). Research which had been conducted by Permata *et al*. (2024) shows that the application of rolling windows combined with machine learning models can improve the model's ability to recognize seasonal patterns and predict extreme monthly rainfall events. Meanwhile, research of Rakhmat & Mutohar (2023) demonstrated that optimizing feature engineering techniques significantly determines model accuracy in rainfall prediction.

Despite the widespread use of recursive forecasting in time-series prediction, this approach is known to suffer from error accumulation, particularly in multi-step-ahead forecasting scenarios where each prediction error is propagated forward and compounded in subsequent time steps. In monthly rainfall prediction, this issue is exacerbated by the relatively small sample size and high inter-monthly variability, which can cause the model to drift away from actual patterns when extreme events or anomalies occur. Semi-recursive forecasting offers a potential solution by maintaining predictor variables at their historical average values while applying recursion only to the target variable (rainfall). This strategy reduces the exposure of the model to compounding errors in non-target predictors and preserves the underlying seasonal and climatic patterns, potentially leading to more stable and reliable predictions. However, the trade-off is that semi-recursive forecasting may produce smoother predictions that under-represent extreme values. Therefore, a systematic comparison of these two strategies under real-world conditions is essential to determine their relative strengths and weaknesses for operational monthly rainfall forecasting.

The implementation of decision-making systems and planting calendars based on rainfall prediction has been growing in various countries. In research which had been conducted by Boult *et al*. (2020) showed that the TAMSAT-ALERT system in Africa successfully integrated monthly rainfall predictions and machine learning-based soil moisture data for adaptive planting timing, enabling farmers to more effectively anticipate agricultural disaster risks. Furthermore, the Decision Support System for Agrotechnology Transfer (DSSAT), which has been widely implemented in various countries, has been able to improve agricultural efficiency and food security by providing planting time recommendations based on medium-term weather predictions (Hoogenboom *et al*., 2019). In Indonesia, the implementation of digital planting calendar integrated with rainfall prediction from the BMKG (Meteorology, Climatology, and Geophysics Agency) is able to increase farm adaptation and productivity (Arafat *et al.*, 2025).

To date, research comparing the performance of recursive and semi-recursive approaches in the Random Forest model for monthly rainfall prediction at the watershed scale remains scarce, particularly in tropical regions with high climate variability. Most existing studies focus on daily or weekly forecasting, where larger sample sizes help mitigate error accumulation (Oliveira *et al*., 2025). However, monthly data presents a greater challenge due to limited sample size and the compounded effect of errors over longer prediction horizons. Furthermore, previous studies have not systematically evaluated how different input strategies such as using historical averages versus recursive predictions for predictor variables affect model stability and accuracy in the context of operational planting calendar development. This gap is critical because the reliability of monthly rainfall predictions directly influences the feasibility and effectiveness of adaptive agricultural planning in tropical watersheds. Therefore, a rigorous comparison of recursive and semi-recursive forecasting strategies is necessary to establish which approach is more robust under the complex seasonal and inter-annual climate dynamics typical of regions such as the Bogowonto Watershed.

The aim of this study is to analyze and compare the accuracy of two monthly rainfall prediction schemes, recursive and semi-recursive, in the Random Forest algorithm by using data from four rainfall stations in the Bogowonto Watershed. The Bogowonto Watershed area has complex seasonal rainfall characteristics, which makes it an ideal location to test the stability of both approaches. We hypothesize that the semi-recursive forecasting approach will provide more stable and accurate monthly rainfall predictions than the recursive approach due to reduced error accumulation in predictor variables, and that this stability will translate into more reliable inputs for developing an adaptive planting calendar. The results are expected to provide empirical evidence and practical recommendations for selecting the most robust forecasting strategy to optimize agricultural systems in tropical watersheds.

2. MATERIALS AND METHODS

2.1. Research Location

This study was conducted in the Bogowonto Watershed area, an agricultural region with diverse climatological and topographic characteristics. The Bogowonto watershed is located across several administrative areas: Wonosobo, Purworejo, Magelang, and parts of Kulon Progo Regency. The Bogowonto watershed covers an area of approximately 612 km² with elevations ranging from 0 to 3,307 meters above sea level. Four rainfall stations were used as observation points: Kradenan, Penungkulan, Bener, and Sapuran Stations. These four stations were selected based on three main criteria: (1) data availability and continuity during the 2002–2024 period, (2) data completeness and quality, and (3) geographic distribution within the watershed. The percentages of data completeness for each station were Kradenan (92%), Sapuran (84%), Penungkulan (76%), and Bener (70%). Although additional stations exist in the surrounding area, they were not used due to inconsistent observation periods, substantial amounts of missing data (>30%), or locations outside the Bogowonto watershed boundary. Previous rainfall studies in tropical regions have shown that missing rainfall records can be handled through data completion and quality control procedures prior to analysis (Mair & Fares, 2011). Therefore, only stations with relatively continuous and sufficiently complete records were selected to maintain model reliability. All data from the four selected stations underwent validation, quality control, and missing data handling procedures according to standard procedures before being used in the analysis. Although the number of stations is limited, the four stations are distributed across the watershed, allowing the capture of rainfall variations in the study area. This station selection supports the training and validation processes of the monthly rainfall prediction model. Geographically, the Bogowonto watershed is located at coordinates 7°28'–7°55' South Latitude and 109°55'–110°15' East Longitude. This study used daily observation data from January 1, 2002, to December 31, 2024, for monthly rainfall prediction. The location of the observation station can be seen in Figure 1.

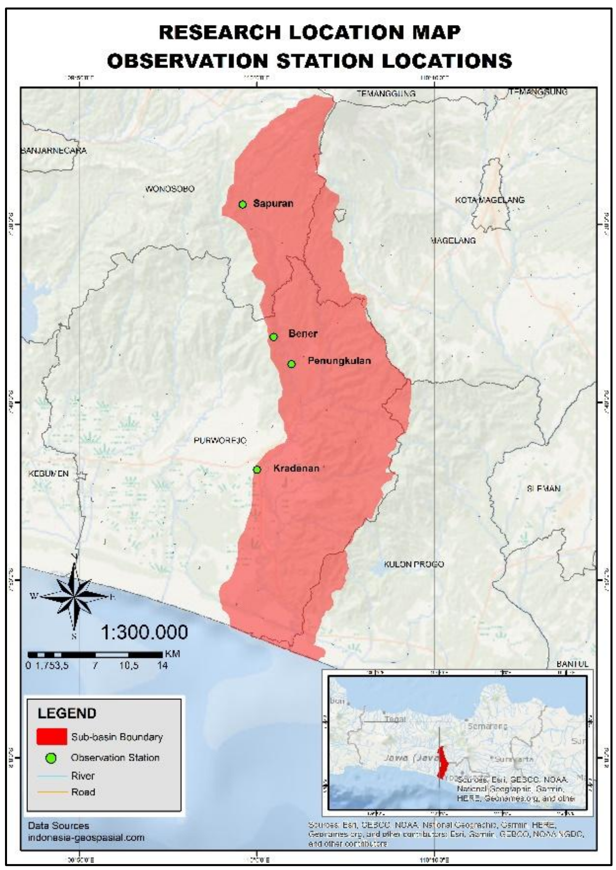

Figure 1. Research location

2.2. Tools and Materials

The materials used in this study include daily rainfall data from four observation stations (Kradenan, Penungkulan, Bener, and Sapuran) in the Bogowonto Watershed for the period January 1, 2002, to December 31, 2024. In addition, daily records of maximum temperature, minimum temperature, average temperature, air humidity, and wind speed, obtained from the Kradenan station, were incorporated as auxiliary climate predictor variables in the Random Forest model for all four target stations. These climatological data were obtained from the archives of the Serayu Opak River Area Center (BBWSSO). It should be noted that the Kradenan station was the only station within the watershed with complete multi-variable records (rainfall, temperature, humidity, and wind speed) for the study period. As such, the auxiliary climate variables for all four target stations were drawn from this single reference station. This is a common practice in watershed-scale rainfall modeling when auxiliary climate data are available from only a subset of stations (Chinasho *et al*., 2021). The limitation is acknowledged, and multi-station climate data integration is recommended for future studies. Data analysis and modeling were conducted by using a laptop with R software and supporting packages consisting of tidyverse, dplyr, lubridate, randomForest, caret, Metrics, tidyr, zoo, readxl, and openxlsx for data processing, machine learning modeling, feature engineering, and model evaluation. Microsoft Excel was used for pre-processing and descriptive analysis of data and validation of prediction results while ArcGIS was used for mapping and spatial visualization of the research location.

2.3. Research Method

This study used the Random Forest algorithm statistical model in order to predict monthly rainfall in the Bogowonto Watershed. This model was specifically chosen to address the challenges of predicting dynamic, complex climate variables which were influenced by various factors. Data pre-processing was conducted through data cleaning, consistency testing, and monthly aggregation. Daily rainfall data tends to be challenged by large amounts of missing data, either due to recording errors or equipment failure. In order to address this matter, the normal ratio method was used to fill in missing rainfall data (Amin Burhanuddin *et al*., 2016), by using the formula:

$$P_x = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{N_x}{N_i}P_i\right) \quad (1)$$

In Equation (1), the subscript x denotes the target station with missing rainfall data, and the subscript i denotes the i-th comparison station (i = 1, 2, 3, ..., n). P_x is the estimated monthly rainfall at target station x (mm), P_i is the observed monthly rainfall at the i-th comparison station (mm), N_x and N_i are the long-term annual average rainfall at stations x and i, respectively (mm), and n is the number of comparison stations used in the estimation.

Furthermore, in order to ensure data homogeneity and consistency, the RAPS (Rescaled Adjusted Partial Sums) test (Đurin *et al*., 2022) and the Pettitt test (Pettitt, 1979). This stage is used to detect change points (inhomogeneities) which can be caused by changes in equipment, location, or recording errors. The RAPS formula is as follows:

$$Y_t = \frac{S_t - E(S_t)}{\sqrt{Var(S_t)}} \quad (2)$$

where Y_t is the standard value at time t, S_t is the original data value at time t, $E(S_t)$ is the mean of S_t in a certain period, dan $Var(S_t)$ is the variance of S_t in the same period.

When the Pettitt and SNHT tests indicated statistically significant inhomogeneities (p-value < 0.05), a simple mean shift homogenization was applied to the affected series. In this procedure, the detected breakpoints are treated as change points in the mean level of the series. For each segment defined by these breakpoints, the segment mean is computed, and the data in the subsequent segment are adjusted by adding or subtracting the difference between its mean and the mean of a selected reference segment. This adjustment removes artificial shifts in the mean while preserving the temporal variability of the series, in line with established climate data homogenization practices (Ribeiro *et al*., 2016).

After the data was declared clean and homogeneous, monthly aggregation was conducted for rainfall, temperature, humidity, and wind speed. This process aims to facilitate trend analysis and predictive model development. Next, feature engineering was conducted by using two main approaches: recursive and semi-recursive. In the recursive approach, the predicted results are reused as input for the following month's predictions for all variables. This approach is in line with the characteristics of climatological data, which generally exhibits temporal relationships or autoregressive effects. Meanwhile, the semi-recursive approach in this study used historical average values as input for the predictor variables, but recursive predictions were still performed for the main variable, rainfall. This approach used the average patterns of rainfall, temperature, humidity, and wind speed in the same month in previous years as the basis for predictions. The key difference lies in which variables are updated with predicted values at each forecasting step. In the recursive approach, all variables (rainfall, temperature, humidity, and wind speed) are predicted recursively, while in the semi-recursive approach, only rainfall is predicted recursively and non-target variables are fixed at their historical monthly averages. The complete workflow and the divergence in variable update mechanisms between the two approaches are illustrated in Figure 2.

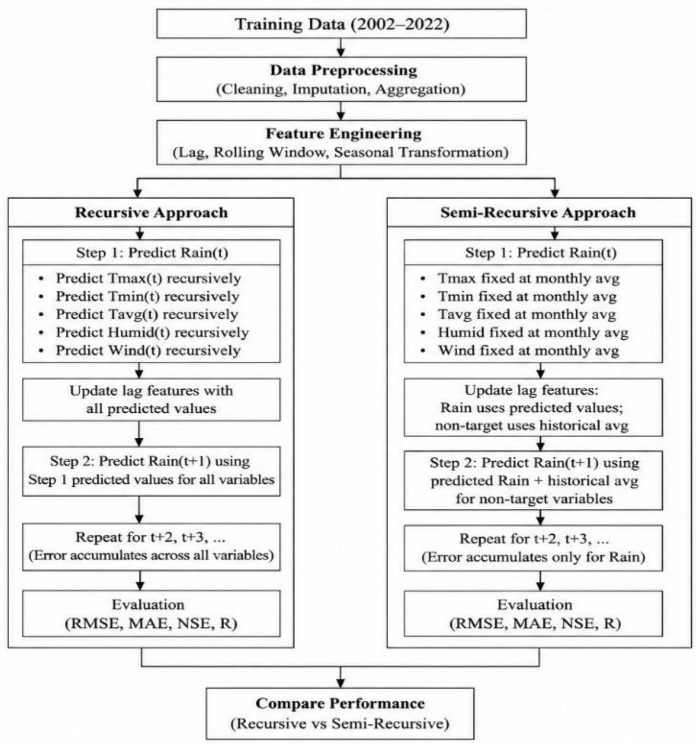

Figure 2. Research flowchart

The additional rolling window feature is used to capture short-term variations and seasonal trends as the following:

$$RM_t = \frac{1}{w}\sum_{i=t-w+1}^{t} x_i \tag{3}$$

where RM_t is the moving average at time t, w is the window size and x_i is the monthly data in order i.

Random Forest model was conducted by using R software with several main stages. It began with determining the best parameters; such as, the number of trees, maximum depth, and the number of variables used in data division. Parameter selection was conducted through a grid search and k-fold cross-validation process in order to ensure the resulting model was more accurate and stable. Data was divided into training and testing data in order to prevent information leakage and avoid overfitting. Furthermore, model performance was evaluated by using four main metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Nash–Sutcliffe Efficiency (NSE), and coefficient of determination (R^2). The formula for each metric is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{5}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}} \right)^2 \quad (7)$$

where y_i is the actual observed value, $\hat{y}_i$ is model prediction results, $\bar{y}$ the average value of observations, and $\bar{\hat{y}}$ the average predicted value.

3. RESULTS AND DISCUSSION

3.1. Data Pre-processing

Climatological data generally suffers from issues with the completeness and accuracy of recording, particularly daily data. Therefore, preprocessing of the data is necessary before it is used as input to the Random Forest model. It ensures completeness and consistency of the data so that it prevents errors in the prediction process. The method used to address missing data in this study is the normal ratio. This method used the ratio of the average annual rainfall from several stations surrounding the target station to estimate missing values. Imputation results using this method maintain the spatial pattern of rainfall between stations without causing excessive bias so that it maintains data trends. The normal ratio is considered effective in maintaining spatial and temporal homogeneity and it has been widely used in various studies in order to estimate missing rainfall (Amin Burhanuddin *et al*., 2016). In order to address missing values in maximum temperature, minimum temperature, average temperature, humidity, and wind speed data, the mean imputation method, commonly used in meteorological data, was used (Hadeed *et al*., 2020).

The next step was to aggregate the daily data into monthly data for all variables. This monthly aggregation aims to mitigate the risk of short-term fluctuations which frequently occur in daily data. Furthermore, this aggregation can clarify seasonal patterns which make them more relevant for developing planting calendars. For rainfall data, aggregation was conducted by summing the total daily rainfall for each month. Meanwhile, other variables, including maximum temperature, minimum temperature, average temperature, humidity, and wind speed, were aggregated by using the average value for each month. After aggregation, the data spanned 276 months.

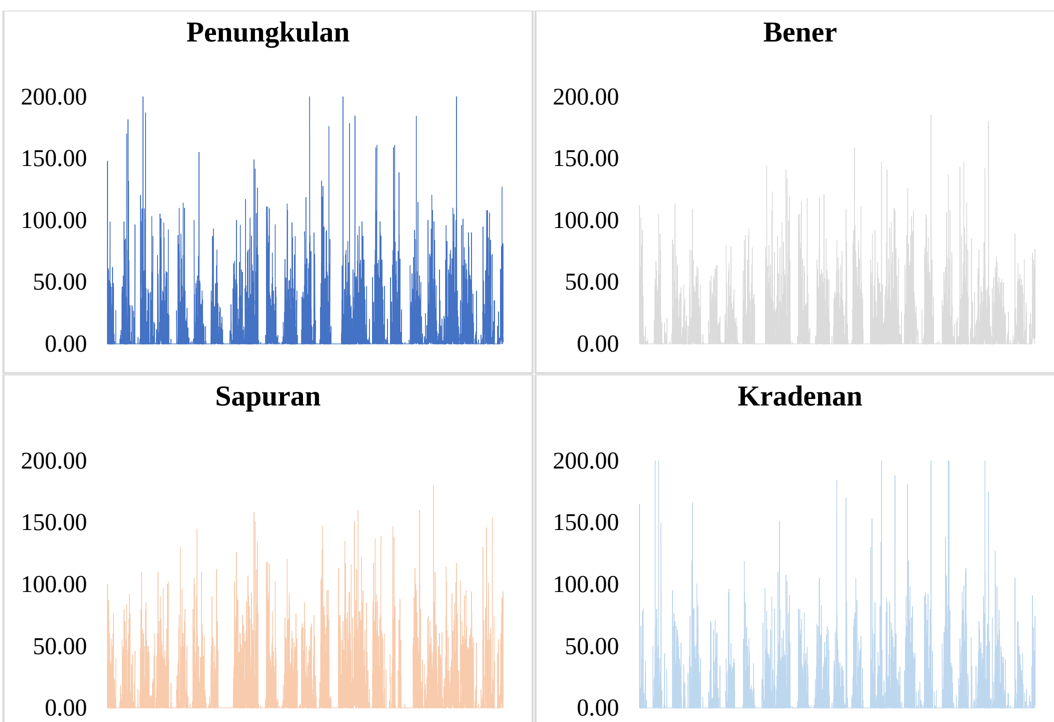

Figure 3. Daily rainfall data from four stations after imputation

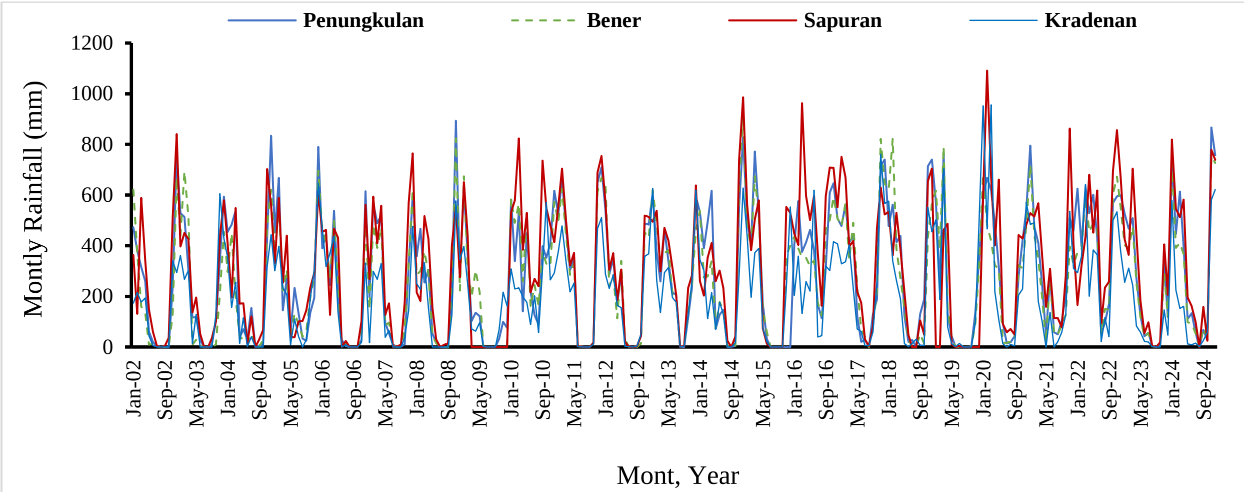

Figure 4. Monthly rainfall data from 4 stations

After the missing value imputation process and monthly aggregation, a consistency test was conducted using the Rescaled Adjusted Partial Sums (RAPS) method to identify potential data anomalies arising from recording errors or equipment replacement. The RAPS test results for the four stations are as follows: Penungkulan (Q/√n = 1.29; R/√n = 1.43), Bener (Q/√n = 1.46; R/√n = 1.67), Sapuran (Q/√n = 1.60; R/√n = 1.71), and Kradenan (Q/√n = 1.25; R/√n = 1.66). The critical values of the RAPS test are presented in Table 1. At the α = 5% significance level, the data from Penungkulan and Kradenan stations are consistent, while Bener and Sapuran stations show values exceeding the critical thresholds, indicating potential inhomogeneity. Based on the position of the maximum cumulative deviation in the RAPS calculation, this change point is estimated to occur around 2016, which coincides with the 2015 - 2016 El Niño event (ENSO index > 2). During this event, localized weather anomalies including increased rainfall in parts of Indonesia during the December - February period were documented despite the overall drying tendency of El Niño. It is also possible that equipment replacement or maintenance at the rain gauge stations could have contributed to the observed change. Without station level metadata, the relative contribution of climatic versus instrumental factors cannot be definitively determined. Nevertheless, in the absence of extreme outliers in the resulting time series and given the practical requirements of the machine learning based prediction model, the rainfall data from all four stations are retained for the prediction analysis.

Table 1. Critical values of the RAPS test (Buishand, 1982)

n	Q/√n (90%)	Q/√n (95%)	Q/√n (99%)	R/√n (90%)	R/√n (95%)	R/√n (99%)
10	1.05	1.14	1.29	1.21	1.28	1.38
20	1.1	1.22	1.42	1.34	1.43	1.6
30	1.12	1.24	1.46	1.4	1.5	1.7
40	1.13	1.26	1.5	1.42	1.53	1.74
50	1.14	1.27	1.52	1.44	1.55	1.78
100	1.17	1.29	1.55	1.5	1.62	1.86
∞	1.22	1.36	1.63	1.62	1.75	2

Furthermore, for the maximum temperature, minimum temperature, average temperature, humidity, and wind speed series, the RAPS consistency test indicated that these data were not consistent, as the calculated Q/n^0.5 and R/n^0.5 values exceeded the corresponding critical values at the 5% significance level. This result suggests the presence of inhomogeneities in the supporting climatological variables, which is consistent with the outcomes of the Pettitt and SNHT tests that yielded *p*-values below 0.05 for most of these series (Ahmed *et al*., 2018). Nevertheless, given the data limitations and the role of these variables as predictors rather than primary targets, they were retained in the modelling framework, and the potential impact of their inhomogeneities was mitigated through cross-validation and comprehensive model performance assessment. Homogenization was attempted using the mean shift method, which improved the homogeneity of wind speed (p-value = 0.26) and humidity data after three iterations (p-value = 0.09). However, temperature variables (maximum, minimum, and average) remained non-homogeneous even after multiple homogenization attempts. This persistent inhomogeneity is consistent with information obtained from BBWSSO indicating that measuring instruments at the station were repaired and replaced on several occasions, resulting in systematic shifts in the time series. Given the limited number of instrumented weather stations in the study area, excluding non-homogeneous temperature variables entirely would preclude their use as auxiliary predictors in the machine learning model. Therefore, these variables were retained with the explicit acknowledgement that their non-homogeneity represents a limitation of this study. The potential impact on model reliability is addressed through the use of cross-validation and comprehensive model performance assessment during the prediction process.

In this study, the data was divided into three parts: training data from January 2002 to December 2022, which was used to train the model. Testing data from January 2023 to December 2023 was used to evaluate model performance. Data from January 2024 to December 2024 was used for model validation. The training and testing processes were conducted in R software while model validation was conducted manually by using Excel by comparing the predicted and actual data.

3.2. Random Forest Prediction Model

The process of predicting monthly rainfall by using the Random Forest algorithm was conducted by using R software. This algorithm works by combining multiple decision trees generated from random subsets of training data using bootstrap sampling, where observations are drawn with replacement to increase model diversity and robustness. The decisions from each tree were aggregated and the final decision was then taken from the resulting average value. This ensemble approach has proven effective in handling complex and nonlinear climatological data in rainfall prediction applications. Primajaya & Sari (2018) demonstrated that a Random Forest model for precipitation prediction in Indonesia using multiple meteorological predictors achieved good classification performance with relatively low MAE and RMSE values. Furthermore, Ejike *et al*. (2025) showed that Random Forest was able to capture nonlinear relationships between rainfall and atmospheric variables such as humidity, temperature, pressure, and wind. These findings support the suitability of Random Forest for modelling complex climatological relationships. Furthermore, Random Forest is able to address interdependencies between variables and minimize the risk of overfitting (Breiman, 2001).

Recent research has also shown that Random Forest performs quite well for predicting monthly rainfall in Indonesia. Appropriately applied feature selection and data preprocessing can support prediction results. Research conducted by Sulistyowati *et al*. (2025) showed that the use of Recursive Feature Elimination (RFE) and rolling mean techniques significantly improved Random Forest's ability to differentiate rainfall events by season in Jakarta. In that study, the Random Forest model achieved a classification accuracy of 0.7622, indicating that approximately 76.22% of rainfall events in the testing dataset were correctly classified. These results can be a strong foundation for rainfall prediction in areas with similar conditions, namely tropical environments with complex climate dynamics. Sulistyowati *et al*. (2025) also showed that temperature and relative humidity consistently appeared among the most influential variables for distinguishing rainfall events across several classification models. This finding supports the selection of temperature and humidity variables in this study because these variables are closely related to atmospheric conditions that influence rainfall formation and seasonal variability in tropical regions.

Validating model selection through comparisons of various methods remains a crucial step in developing rainfall prediction systems. A study on monthly rainfall prediction in West Sumatra, a comparison was conducted between SARIMA, ETS, LSTM, and XGBoosting models (Aslam & Afghani, 2024). The results showed that deep learning and machine learning-based models such as LSTM and XGBoosting provided better NSE values (0.61 and 0.54) than SARIMA, which had an NSE of 0.18. These results indicate that machine learning models are more suitable for monthly rainfall prediction, especially in areas with large datasets and clear seasonal patterns.

In this study, Random Forest was implemented using two different approaches: recursive forecasting and semi-recursive forecasting. Both approaches were evaluated separately in order to compare their prediction performance. The primary target variable was monthly rainfall, while maximum temperature (Tmax), minimum temperature (Tmin), average temperature (Tavg), humidity (RH), and wind speed (Wind) were used as supporting predictor variables. Additional features including lag variables, rolling windows, and seasonal transformations (sin and cos month) were added in order to improve the model's ability to recognize temporal rainfall patterns and seasonal cycles in the Bogowonto Watershed.

Grid search and cross-validation were used in order to identify the best combination of lag, rolling window, and mtry parameters (Putra *et al*., 2024). The lag features tested ranged from 1 to 12 months, rolling window sizes included 3, 6, 9, and 12 months, while mtry values ranged from 5 to 12. The best model for each station was selected based on NSE performance, with optimal parameter combinations varying according to local rainfall characteristics and data quality.

The model results indicate that lag rainfall and rolling mean features contributed substantially to prediction performance. The best-performing model was obtained using six lag features and a three-month rolling window, indicating that monthly rainfall in the Bogowonto Watershed is strongly influenced by temporal persistence and short-term seasonal continuity. These features enabled the Random Forest model to better capture rainfall memory patterns from previous months.

Seasonal transformation features (sin and cos month) also improved the model's ability to recognize recurring monsoonal rainfall cycles commonly observed in tropical regions. Meanwhile, climatological variables such as temperature, humidity, and wind speed contributed as supporting predictors for identifying atmospheric conditions associated with wet and dry periods.

The prediction behavior of the model differed significantly between recursive and semi-recursive approaches. In the recursive scheme, all predictor variables were updated using previous prediction results, causing errors to accumulate over time and reducing model stability. This condition was reflected in the lower NSE values obtained from the recursive approach. In contrast, the semi-recursive approach maintained non-target climatological variables using historical monthly average values, which preserved seasonal data patterns and reduced prediction drift. As a result, the semi-recursive approach produced more stable predictions and better evaluation metrics.

3.2.1. Recursive Approach

Random Forest can be run after optimal parameters are obtained from the grid search process. The prediction process is conducted in stages, with predictions for maximum temperature, minimum temperature, average temperature, humidity, and wind speed being performed separately, and the results are used as input for the main target prediction that is rainfall. Predictions are conducted recursively, with the previous month's prediction results being used as input for the next month's prediction. During model training, time series features; such as, lag and rolling window are structured by using special functions in order to ensure that the values used and stored are the previous prediction results, not the actual data, to prevent future information leakage. Furthermore, predictions are conducted sequentially based on time, and the results are used directly to calculate the next prediction value. This approach does not use actual values so that any error in one prediction will significantly impact subsequent predictions due to the accumulated values. Prediction results are then evaluated by using the RMSE, MAE, NSE, and R^2 metrics. A positive NSE value indicates that the model performs better than predictions using the historical average approach.

Evaluation on the test data (2023 data) showed poor results, with the NSE for all four stations negative, indicating that the model was no better than simply using historical average predictions. The RMSE and MAE values were also high, which indicated a relatively large monthly prediction error, but the R^2 value was considered good, with a value greater than 0.6. The difference between a high R^2 value and a negative NSE value indicates that the model is able to follow the overall data pattern, but it is unable to produce predictions that closely approximate the actual data. The R^2 is used to assess how well the prediction pattern follows the actual data, while the NSE is highly sensitive to error, so excessive bias, whether the model overpredicts or underpredicts, will immediately decrease the NSE value (Onyutha, 2024).

Table 2. Recursive approach test-set evaluation metrics

Stations	RMSE	MAE	NSE	R^2
Penungkulan	200.47	174.35	-0.03	0.63
Bener	166.92	153.85	0.00	0.70
Sapuran	257.41	235.21	-0.43	0.61
Kradenan	183.52	167.35	-1.92	0.62

This condition suggests the presence of systematic bias during extreme climate conditions in 2023. Although the recursive model was able to capture the overall rainfall fluctuation pattern, the predicted values tended to be smoother than the observed rainfall data, resulting in underprediction during extreme wet months and overprediction during extremely dry periods. Consequently, large residual errors were produced despite relatively high R^2 values. The strong El-Niño event occurring from August 2023 to January 2024, with an ENSO index exceeding 1.5, significantly altered rainfall variability during the testing period and caused substantial deviations from historical rainfall patterns used during model training. This condition increased the sensitivity of the recursive approach to accumulated prediction errors, particularly at the Kradenan station, which showed the lowest NSE value (-1.92).

This evaluation revealed the importance of strengthening the prediction model and conducting evaluation beyond standard statistical metrics in order to explain anomalous prediction behavior during extreme climate conditions. Despite the poor evaluation results, the prediction process was continued because the climate anomalies during the testing year provided important information regarding the limitations and stability of the recursive prediction approach under highly variable climatic conditions.

Using the model trained on the training data and tested on the test data, pure predictions were made for the 2024 data. In this stage, predictions were made without incorporating actual values into the model which allowed the Random Forest to truly make pure predictions. The results were validated manually by using Excel. The prediction results using the recursive approach for 2024 can be seen in Figure 5.

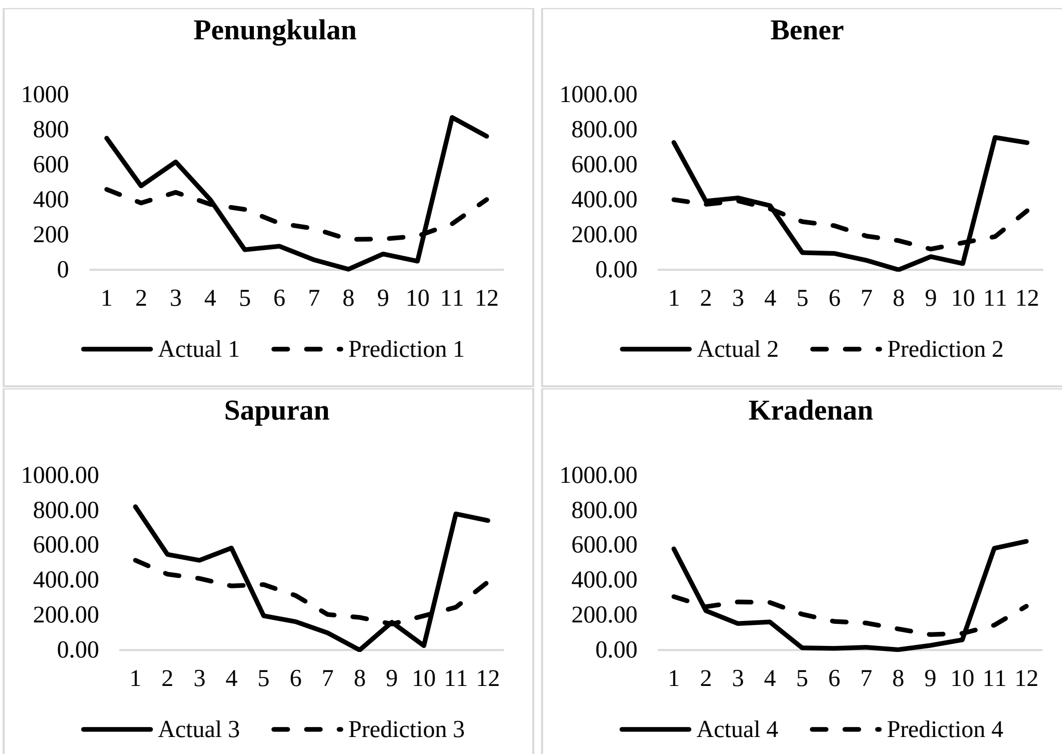

Figure 5. Recursive prediction results for 2024

3.2.2. Semi-Recursive Approach

In this semi-recursive Random Forest approach, the input values for the predictor variables, including maximum temperature, minimum temperature, average temperature, humidity, and wind speed, are input by using monthly averages from previous years. Meanwhile, the main target, rainfall, is input recursively. After the best combination is obtained through the grid search process, the model is run by using a prediction function with mtry, lag, and rolling window parameters. The model works by using the last value from the training data in order to initiate predictions and then storing the results. Once the predicted rainfall value for the first month is obtained, the result is immediately fed back into the model so that this value can be used to predict the next day. This recursive approach, utilizing historical averages on non-target predictor variables, ensures the model maintains data patterns and stability.

Table 3. Semi-recursive approach test-set evaluation metrics

Stations	RMSE	MAE	NSE	R²
Penungkulan	110.52	79.56	0.69	0.79
Bener	112.81	92.91	0.54	0.73
Sapuran	145.78	124.79	0.54	0.58
Kradenan	113.75	86.10	-0.12	0.61

Evaluation on the test data (2023 data) showed better results than the recursive approach. However, one station showed a negative NSE value. The Kradenan station still produced a slightly negative NSE value (-0.12), indicating that the semi-recursive approach was less effective at this location compared to the other stations. This condition may be related to local rainfall characteristics that differ from the general regional pattern represented in the training data. Differences in local topography and microclimatic conditions may have contributed to higher rainfall variability and reduced model generalization capability at the Kradenan station. In addition, local data quality and the presence of anomalous rainfall events during the testing period may also have influenced prediction accuracy at this station.

These improved results occurred since the data patterns and stability, particularly for non-target predictor variables, were better maintained by using monthly average values from the training data so that it eliminates error accumulation. Meanwhile, this approach is more robust to high climate variability, it does have the drawback of tending to produce overly smooth prediction patterns. It can result in under-capturing extreme rainfall variations; especially, when the predicted rainfall values depend on previous predictions. Based on the results of the test data evaluation, the semi-recursive forecasting approach was subsequently applied for monthly rainfall prediction in 2024 using monthly average values for non-target predictor variables, similar to the procedure used during the testing phase.

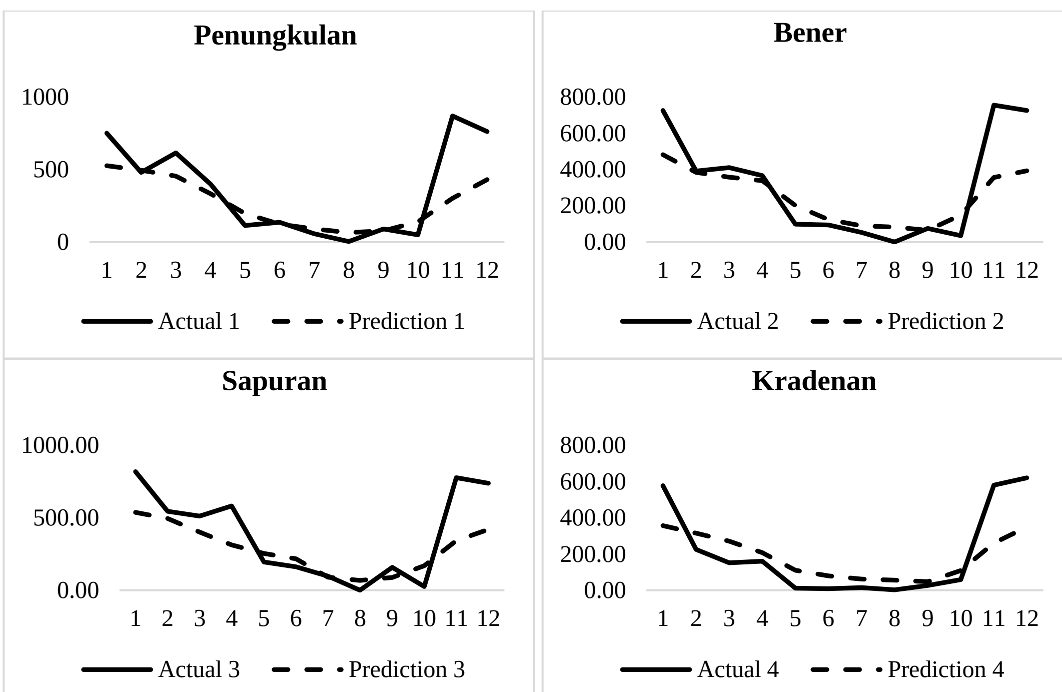

Figure 6. Semi-recursive prediction results for 2024

3.3. Comparison of Results

The main difference between the two approaches lies in the step of updating climatological variables in the prediction process. In the recursive approach, all variables are updated by using previous predictions. In the semi-recursive approach, only the rainfall variable is updated by using previous predictions, while non-target variables are filled in using historical monthly average values. This difference impacts the level of accumulated error. The out-of-sample validation results for the predictions from both approaches are presented in Table 4.

Table 4. Validation of 2024 prediction results

Recursive				
Stations	**RMSE**	**MAE**	**NSE**	**R^2**
Penungkulan	255.75	208.22	0.32	0.50
Bener	241.66	178.57	0.26	0.35
Sapuran	241.62	201.85	0.33	0.49
Kradenan	210.68	170.36	0.20	0.23
Semi-recursive				
Stations	**RMSE**	**MAE**	**NSE**	**R^2**
Penungkulan	211.31	138.44	0.54	0.72
Bener	174.80	120.07	0.61	0.82
Sapuran	203.16	155.87	0.53	0.77
Kradenan	150.79	117.55	0.59	0.73

Based on the prediction results from the two approache schemes in this study, relatively high RMSE and MAE values are observed across the four stations. However, the recursive approach consistently has higher values than the semi-recursive approach. It may occur because errors in the recursive scheme accumulate, making the predictions for the following month increasingly distant from actual conditions. In the semi-recursive scheme, the input for non-target variables is the monthly average value from the previous year, which helps maintain data patterns and stability.

The recursive approach continuously reused prediction outputs from previous periods as new inputs for subsequent predictions. Under highly variable rainfall conditions, small prediction deviations propagated recursively and gradually amplified over time, leading to larger cumulative errors. In contrast, the semi-recursive approach maintained stable climatological predictor variables using historical monthly averages, thereby reducing prediction drift and improving model stability. This mechanism explains why the semi-recursive approach consistently produced lower RMSE and MAE values across all observation stations.

Furthermore, the NSE value for the recursive approach ranged from 0.20 to 0.33, significantly lower than the results for the semi-recursive approach, which ranged from 0.53 to 0.61. However, both models performed better than the simple prediction approach, which only used the average value. Based on the guidelines for using NSE values by Moriasi *et al*. (2007), NSE is divided into several categories: very good (NSE > 0.75), good (NSE 0.65-0.75), satisfactory (NSE 0.50-0.65), and unsatisfactory (NSE ≤ 0.50). Based on the results of this study, the recursive approach is categorized into the unsatisfactory category. Meanwhile, the results for the semi-recursive approach is categorized into the satisfactory category.

Although all NSE values in the 2024 validation results were positive, the recursive approach still produced substantially lower NSE values than the semi-recursive approach. Negative NSE values generally occur when prediction errors exceed the variability of the observed data relative to its mean value, indicating that the model performs worse than predictions based on the historical mean. Similar conditions have also been reported in machine learning-based climate prediction studies under anomalous climate variability. Pal *et al*. (2020) reported that Random Forest models were able to capture general ENSO phase patterns but tended to underestimate the magnitude of strong climate events during anomalous conditions. This mechanism is consistent with the findings of this study, where the recursive approach showed higher sensitivity to accumulated prediction errors and extreme rainfall variability, while the semi-recursive approach produced more stable prediction performance by maintaining stable non-target predictor inputs.

In line with the NSE values, the R^2 for the recursive approach ranged from 0.23 to 0.50 which lower than the R^2 for the semi-recursive approach, which ranged from 0.72 to 0.82. Therefore, based on these results, the first approach falls into the poor category while the second approach falls into the good category.

Table 6. R^2 category (Chow *et al*., 1988)

R^2	Category
> 0.8	Very good
$0.6 < R^2 \leq 0.8$	Good
$0.5 < R^2 \leq 0.6$	Satisfactory
≤ 0.5	Unsatisfactory

The results of this study show that the semi-recursive approach produced more stable monthly rainfall predictions than the recursive method in the study area. By maintaining stable non-target climatological inputs, the semi-recursive approach reduced prediction drift and improved temporal consistency under highly variable climate conditions. These findings are consistent with Waqas *et al*. (2024), who emphasized the importance of stable input features in time-series climate prediction models.

4. CONCLUSIONS

This study demonstrates that the semi-recursive forecasting approach produced more stable monthly rainfall predictions than the fully recursive approach in the Bogowonto Watershed. The semi-recursive approach consistently generated lower RMSE and MAE values, while NSE values increased from 0.20–0.33 to 0.53–0.61 and R^2 values increased from 0.23–0.50 to 0.72–0.82. These results indicate that maintaining non-target climatological predictor variables using historical monthly average values can reduce recursive error accumulation and preserve temporal rainfall patterns under highly variable climate conditions. In contrast, the recursive approach was more sensitive to accumulated prediction errors, particularly during extreme climate anomalies such as El Niño and La Niña events.

Scientifically, this study highlights the importance of predictor stability in recursive time-series rainfall forecasting models. Practically, the proposed approach has potential applications in supporting adaptive cropping calendar development and irrigation water management under climate variability conditions. However, the model performance remained sensitive to anomalous rainfall variability and extreme climate conditions. Therefore, future research is recommended to integrate larger climatological datasets, remote sensing information, and hybrid deep learning approaches in order to improve prediction accuracy and representation of extreme rainfall events.

AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
YKAS	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓
HGM	✓			✓	✓					✓		✓	✓	
SSA	✓									✓		✓		

C: Conceptualization	Fo: Formal Analysis	O: Writing - Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing - Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

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