G-Tech : Jurnal Teknologi Terapan

Vol. 10, No. 3, July 2026, p. 1202-1215
E-ISSN: 2623-064X | P-ISSN: 2580-8737

Comparison of Boolean OR, AND, and OR–AND Models for Monthly Rainfall Classification in Bawean Island

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Article Information

Article History

Received : June 12, 2026
Revised : June 29, 2026
Published : July 10, 2026

***Keywords*:**

Boolean logic;
Rainfall classification;
Rainfall;
Rainy days;
Temperature.

ABSTRACT

Rainfall classification plays an important role in climate monitoring, water resource management, agricultural planning, and hydrometeorological disaster mitigation. While machine learning techniques have been widely used for rainfall classification, they often require substantial computational resources and complex training processes. This study proposes a simple, interpretable, and computationally efficient Boolean-based framework for monthly rainfall classification on Bawean Island, East Java, Indonesia. Monthly climatological data from 1972–2023, including rainfall, rainy days, mean temperature, and minimum temperature, were analyzed, yielding 624 observations. Rainfall was classified into three categories: low (<100 mm), moderate (100–299 mm), and high (≥300 mm). Rainy days were converted into ordinal scores, while mean and minimum temperatures were transformed into binary scores. Three Boolean-based rainfall classification models were developed and evaluated using confusion matrices, accuracy, precision, recall, and F1-score. Correlation analysis showed that rainy days had the strongest relationship with rainfall ($r = 0.858$), followed by minimum temperature ($r = -0.592$) and mean temperature ($r = -0.463$). The hybrid OR–AND model achieved the best overall performance, with 66% accuracy, 71% precision, 62% recall, and 61% F1-score, outperforming both the OR and AND models. These results demonstrate that the proposed Boolean-based framework provides an effective, transparent, and computationally efficient approach for monthly rainfall classification.

INTRODUCTION

Rainfall is a fundamental climatic variable that influences agricultural productivity, water resource management, ecosystem sustainability, and hydrometeorological disaster mitigation (Asdak, 2010; Tjasyono, 2004). Rainfall variability is controlled by atmospheric processes, geographical conditions, and large-scale climate phenomena such as monsoon circulation and climate oscillations (Aldrian & Susanto, 2003; Nuridhati et al., 2025). Therefore, accurate rainfall classification is essential for supporting climate monitoring and environmental management.

Indonesia experiences substantial rainfall variability due to the influence of monsoon systems, the El Niño–Southern Oscillation (ENSO), and regional atmospheric circulation patterns (G. Chen et al., 2024; Vidyarthi & Jain, 2020). Bawean Island, located in the Java Sea, exhibits distinct seasonal rainfall fluctuations that affect local water resources and environmental conditions. Understanding rainfall characteristics in this region is important for climate-related planning and resource management (Badan Meteorologi Klimatologi dan Geofisika, 2025).

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Recent advances in climate science have encouraged the use of machine learning techniques for rainfall estimation and classification because of their ability to improve predictive performance (Anand & Kannan, 2022; Lazri et al., 2020). Several studies have successfully applied artificial neural networks and other machine learning algorithms to rainfall prediction and classification using meteorological variables such as temperature, humidity, pressure, and historical rainfall observations (Damanik et al., 2026; Hudnurkar & Rayavarapu, 2022; Rajkumar & Subrahmanyam, 2021). Furthermore, the integration of meteorological observations, remote sensing products, and neural network models has improved precipitation monitoring and forecasting capabilities across different climatic regions (Benevides et al., 2019; C. Chen et al., 2025; Xia & Wang, 2025). Recent studies have also demonstrated the effectiveness of machine learning for classifying precipitation-related meteorological conditions and supporting weather-based decision-making in environmental applications (Kovalnogov et al., 2024). However, machine learning methods often require large datasets, substantial computational resources, and complex optimization processes, limiting their operational use in some regions (Chakraborty et al., 2024; El-Mahdy et al., 2024).

Boolean logic offers a simple and interpretable alternative for integrating meteorological variables into explicit classification rules (Boolean, 1854). Through OR and AND operators, rainfall categories can be determined using transparent decision structures that are easy to implement and understand. Recent studies have highlighted the growing importance of interpretable classification models and rule-based decision systems that maintain transparency while preserving classification performance (Tuo et al., 2025). Nevertheless, studies comparing Boolean OR, AND, and hybrid OR–AND approaches for rainfall classification remain limited, especially in tropical island environments. Therefore, this study evaluates the performance of these three Boolean logic models using rainy days, mean temperature, and minimum temperature data from Bawean Island to provide a computationally efficient and interpretable rainfall classification approach.

RESEARCH METHODS

This study employed a quantitative classification approach to evaluate the performance of three Boolean-based classification models, namely OR, AND, and OR–AND, for monthly rainfall classification on Bawean Island, East Java, Indonesia. The study area is located in the Java Sea and is influenced by the Asian–Australian monsoon system, resulting in distinct seasonal rainfall variability.

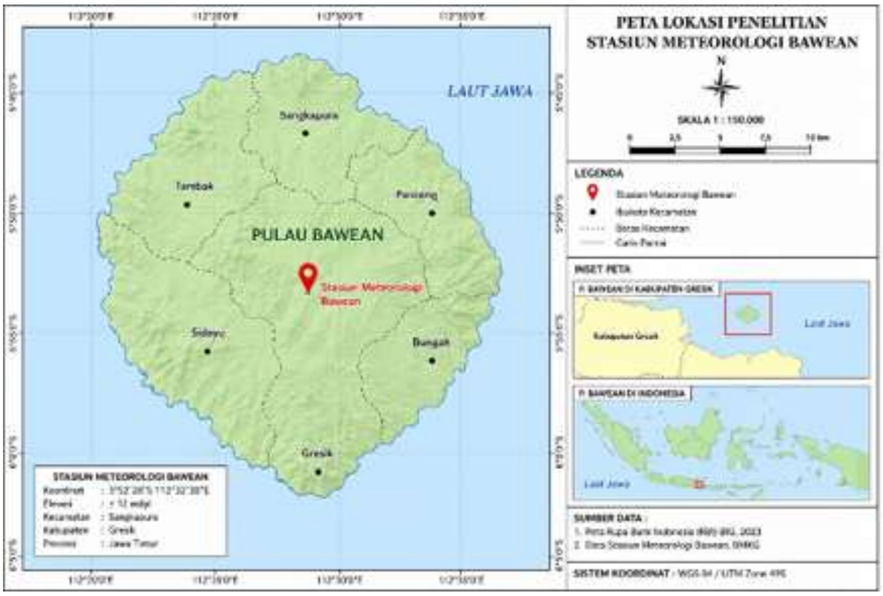

Figure 1. Study Area Location of Bawean Island, East Java, Indonesia

Monthly climatological data from January 1972 to December 2023 were obtained from the Bawean Meteorological Station, yielding 624 observations. The variables analyzed consisted of monthly rainfall, rainy days, mean temperature, and minimum temperature. Rainfall was used as the target variable, while rainy days, mean temperature, and minimum temperature served as predictor variables. The overall research procedure, including data collection, preprocessing, variable transformation, Boolean model development, and performance evaluation, is presented in Figure 2.

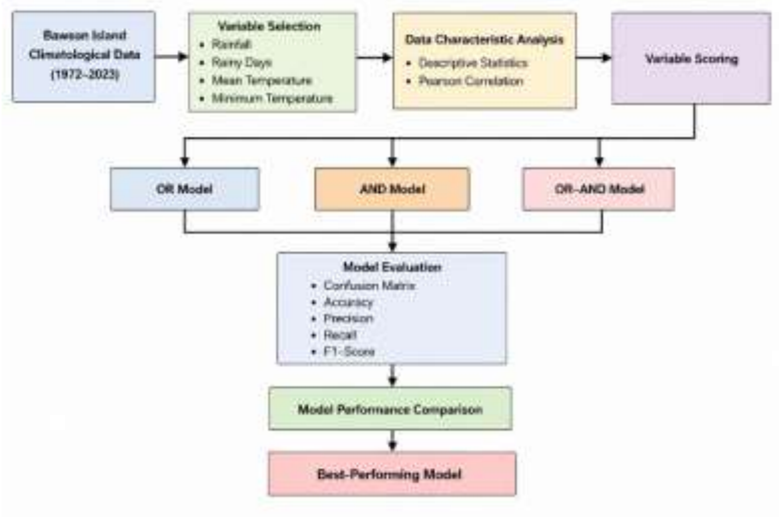

Figure 2. Research Framework

Figure 2 illustrates the research workflow used in this study. The process begins with the collection of climatological data, followed by variable selection, data characteristic analysis, and variable scoring. Three Boolean-based classification models (OR, AND, and OR–AND) were then developed and evaluated using confusion matrices, accuracy, precision, recall, and F1-score. Finally, the performance of the three models was compared to identify the best-performing rainfall classification model.

Monthly rainfall was classified into three categories following the BMKG classification system: low rainfall (<100 mm), moderate rainfall (100–299 mm), and high rainfall (≥300 mm) (Badan Meteorologi Klimatologi dan Geofisika, 2025), as shown in Table 1.

Table 1. Rainfall Classification

Rainfall (mm)	Category
< 100	Low
100 – 299	Moderate
≥ 300	High

Rainy days were transformed into ordinal scores to represent rainfall frequency in the Boolean classification models. The corresponding scoring criteria are presented in Table 2.

Table 2. Rainy Days Classification

Rainy Days	Score
1 – 10	1
11 – 20	2
21 – 31	3

Mean temperature values were transformed into binary scores using the long-term average as the classification threshold. The scoring criteria are presented in Table 3.

Table 3. Mean Temperature Classification

Condition	Score
Below Mean	1
Above Mean	0

Minimum temperature values were transformed into binary scores based on the long-term average minimum temperature. The corresponding classification criteria are presented in Table 4.

Table 4. Minimum Temperature Classification

Condition	Score
Below Mean	1
Above Mean	0

Three Boolean-based classification models were developed for rainfall classification. The OR model assumes that rainfall conditions occur when at least one meteorological indicator supports rainfall occurrence and is expressed as:

$$ORScore = RD + Tavg + Tmin \quad (1)$$

The AND model assumes that rainfall conditions occur when all indicators simultaneously support rainfall occurrence and is calculated as:

$$ANDScore = RD \times (Tavg + 1) \times (Tmin + 1) \quad (2)$$

Meanwhile, the hybrid OR–AND model combines the flexibility of the OR operator with the selectivity of the AND operator and is formulated as:

$$\boldsymbol{OR - ANDScore = RD + (Tavg\ OR\ Tmin)} \quad (3)$$

Pearson correlation analysis was applied to examine the relationships between rainfall and predictor variables. The Pearson correlation coefficient was calculated using:

$$\boldsymbol{r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}}} \quad (4)$$

where coefficient values range from -1 to $+1$, indicating the strength and direction of the relationship between variables (Pearson, 1895).

Model performance was evaluated using confusion matrices and four classification metrics, namely accuracy, precision, recall, and F1-score. These metrics were calculated using Equations (5)–(8) and were used to compare the effectiveness of the OR, AND, and OR–AND models in classifying monthly rainfall categories.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$\boldsymbol{Precision = \frac{TP}{TP+FP}} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$\boldsymbol{F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}} \quad (8)$$

RESULTS AND DISCUSSION

Descriptive Statistics and Correlation Analysis

Descriptive statistics were used to summarize the characteristics of rainfall, rainy days, mean temperature, and minimum temperature during the observation period from 1972 to 2023. The dataset consisted of 624 monthly observations.

The descriptive statistics of the meteorological variables are summarized in Table 5. The results indicate substantial variability in rainfall, with values ranging from 0 to 889.4 mm and an average monthly rainfall of 197.33 mm. The high standard deviation (183.41 mm) reflects considerable seasonal variability. Rainy days averaged 10.94 days per month, whereas mean and minimum temperatures remained relatively stable throughout the observation period.

Table 5. Descriptive Statistics of Meteorological Variables

	Rainfall	Rainy Days	Mean Temperature	Minimum Temperature
count	624	624	624	624
mean	197.33	10.94	27.86	25.12
std	183.41	7.93	0.72	0.89
min	0	0	26.05	22.75
25%	36.6	3	27.33	24.46
50%	163.05	11	27.82	25.12
75%	312.175	17	28.32	25.78
max	889.4	31	30.10	27.30

Pearson correlation analysis was performed to evaluate the relationships between rainfall and the predictor variables. As shown in Figure 3, rainy days exhibited the strongest positive correlation with rainfall (r = 0.858), indicating that months with more rainy days generally experienced higher rainfall totals. In contrast, mean temperature (r = −0.463) and minimum temperature (r = −0.592) showed moderate negative correlations with rainfall. These findings indicate that rainfall variability in Bawean Island is strongly associated with precipitation frequency and lower air temperatures. Therefore, all three variables were considered suitable predictors for Boolean-based rainfall classification. It should be noted that the correlation analysis was conducted using the complete dataset from 1972 to 2023 without separating the observations into different climatic periods. Consequently, this study did not evaluate whether the relationships among the variables changed over time due to global warming. Future studies may compare different climatic periods to investigate the long-term effects of climate change on rainfall variability.

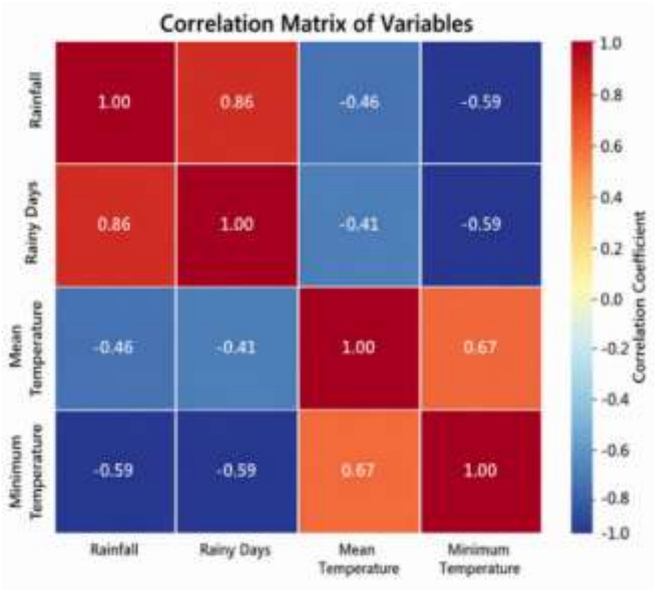

Figure 3. Pearson Correlation Matrix

Figure 3 presents the Pearson correlation matrix among rainfall, rainy days, mean temperature, and minimum temperature. Rainy days showed the strongest positive correlation with rainfall (r = 0.86), whereas minimum temperature (r = −0.59) and mean temperature (r = −0.46) exhibited moderate negative correlations. In addition, mean and minimum temperatures were positively correlated (r = 0.67), indicating a consistent relationship between the two temperature variables. Overall, these results support the use of the selected variables as predictors for Boolean-based rainfall classification.

Performance of Boolean OR and AND Models

The OR and AND models were developed using rainy days, mean temperature, and minimum temperature scores. The OR model assumes that rainfall conditions can be represented when at least one meteorological indicator supports rainfall occurrence, whereas the AND model requires all indicators to simultaneously satisfy rainfall conditions.

The distribution of OR scores is presented in Figure 4. The model achieved an overall accuracy of 64%, with precision, recall, and F1-score values of 0.60, 0.63, and 0.59, respectively (Tables 6 and 7). The model performed relatively well in identifying low and high rainfall categories but showed limited capability in classifying moderate rainfall conditions.

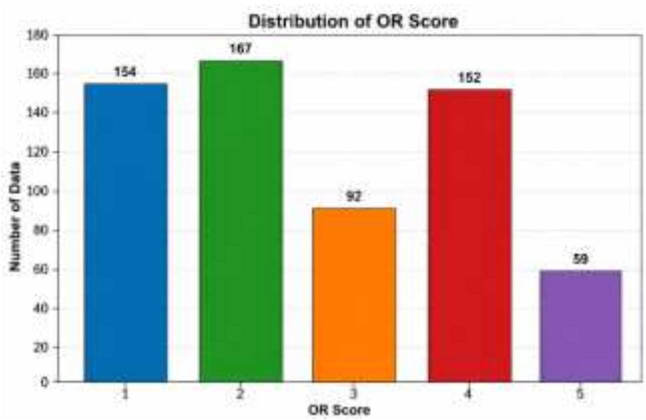

Figure 4. Distribution of OR Scores

Figure 4 shows the distribution of scores produced by the Boolean OR model. Most observations were concentrated at scores 2 and 4, indicating that the OR operator provides a flexible classification by allowing rainfall conditions to be identified when at least one predictor variable satisfies the specified criteria.

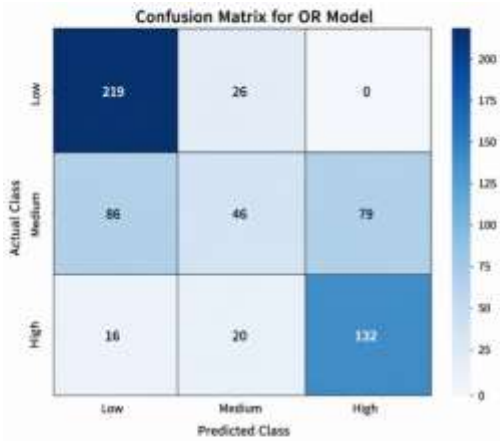

Figure 5. Confusion Matrix of the OR Model

Figure 5 presents the confusion matrix of the OR model. Most low- and high-rainfall observations were correctly classified, whereas moderate rainfall exhibited the highest number of misclassifications. This result indicates that the OR model effectively distinguishes distinct rainfall categories but has limited ability to classify transitional rainfall conditions.

The classification performance of the OR model for each rainfall category is summarized in Table 6. The model achieved the highest precision, recall, and F1-score for the low-rainfall category, whereas the moderate rainfall category showed the lowest classification performance, indicating greater difficulty in identifying transitional rainfall conditions.

Table 6. Performance Metrics of the OR Model

Category	Precision	Recall	F1-Score
Low	0.68	0.89	0.77
Moderate	0.5	0.22	0.3
High	0.63	0.79	0.7

The overall performance of the OR model is presented in Table 7. The model achieved an overall accuracy of 64%, with balanced precision, recall, and F1-score values, indicating moderate classification performance for monthly rainfall classification.

Table 7. Overall Performance

Metric	Value
Accuracy	0.64
Precision	0.6
Recall	0.63
F1-Score	0.59

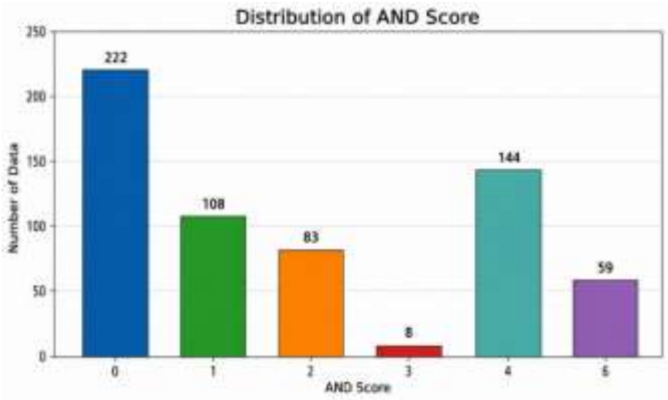

Figure 6. Distribution of AND Scores

Figure 6 shows the distribution of scores produced by the Boolean AND model. Compared with the OR model, the scores are more concentrated, particularly at scores 0 and 4, because the AND operator requires all predictor variables to satisfy the classification criteria simultaneously. As a result, the model is more selective but less flexible in representing rainfall variability.

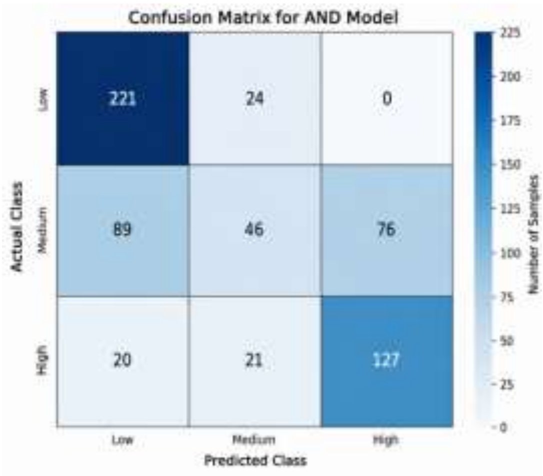

Figure 7. Confusion Matrix of the AND Model

Figure 7 presents the confusion matrix of the AND model. Most low-rainfall observations were correctly classified, whereas moderate rainfall showed the highest number of misclassifications. This result indicates that the stricter decision rules of the AND operator improve classification consistency for clear rainfall conditions but reduce its ability to identify transitional rainfall categories.

The classification performance of the AND model is presented in Tables 8 and 9. Although the AND model achieved an overall accuracy of 63%, its stricter logical constraints reduced classification flexibility, particularly for the moderate rainfall category. These findings suggest that using a single Boolean operator alone may not adequately represent the complexity of rainfall-generating processes.

Table 8. Performance Metrics of the AND Model

Category	Precision	Recall	F1-Score
Low	0.67	0.9	0.77
Moderate	0.51	0.22	0.3
High	0.63	0.76	0.68

Table 9. Overall Performance

Metric	Value
Accuracy	0.63
Precision	0.6
Recall	0.63
F1-Score	0.59

Performance of the Hybrid OR–AND Model

To improve classification performance, a hybrid OR–AND model was developed by combining the flexibility of the OR operator with the selectivity of the AND operator. Figure 8 presents the distribution of OR–AND scores. The hybrid model achieved an overall accuracy of 66%, which was higher than both the OR and AND models. Furthermore, the model produced the highest precision (71%) and F1-score (61%), indicating a more balanced classification performance.

A notable improvement was observed in the moderate rainfall category, where recall increased from 0.22 in both OR and AND models to 0.50 in the OR–AND model. This result demonstrates the ability of the hybrid approach to better capture transitional rainfall conditions. Although recall for the high-rainfall category decreased, the precision value reached 0.93, indicating that high-rainfall predictions generated by the model were highly reliable. Overall, the OR–AND model provided the most balanced classification performance among the three Boolean-based classification approaches.

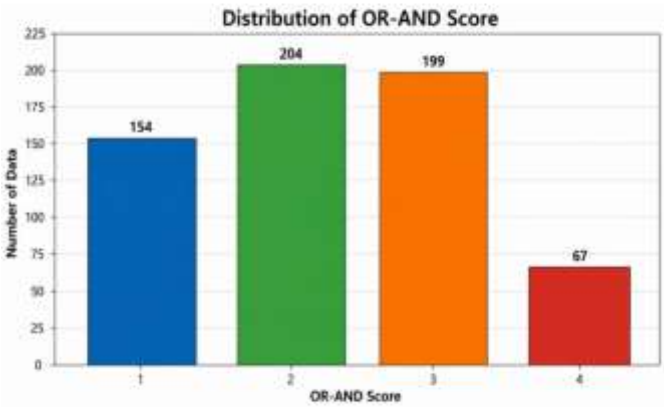

Figure 8. Distribution of OR–AND Scores

Figure 8 illustrates the distribution of scores generated by the hybrid OR–AND model. Most observations were concentrated at scores 2 and 3, while relatively few were assigned to score 4. This distribution indicates that the hybrid model provides a more balanced representation of rainfall conditions by combining the flexibility of the OR operator with the selectivity of the AND operator.

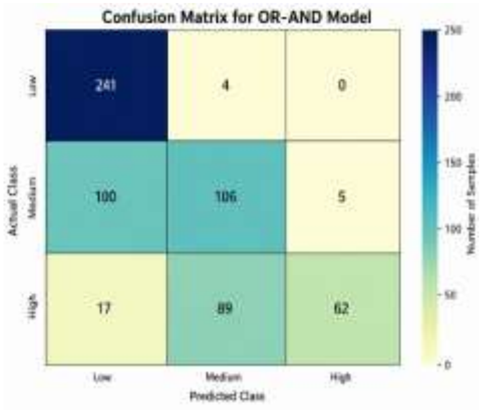

Figure 9. Confusion Matrix of the OR–AND Model

Figure 9 presents the confusion matrix of the OR–AND model. The model correctly classified most low-rainfall observations and showed improved performance in identifying moderate rainfall compared with the OR and AND models. Although some high-rainfall observations were still misclassified, the hybrid approach provided a more balanced classification performance across all rainfall categories.

Tables 10 and 11 summarize the classification performance of the hybrid OR–AND model at both the category and overall levels. The hybrid model achieved excellent recall for the low-rainfall category (0.98) and the highest precision for the high-rainfall category (0.93). Furthermore, the moderate rainfall category showed improved recall compared with the OR and AND models, resulting in the highest overall performance, with an accuracy of 66%, precision of 71%, recall of 62%, and an F1-score of 61%. These results demonstrate that combining OR and AND operators provides a more balanced and effective rainfall classification than using either operator individually.

Table 10. Performance Metrics of the OR–AND Model

Category	Precision	Recall	F1-Score
Low	0.67	0.98	0.8
Moderate	0.53	0.5	0.52
High	0.93	0.37	0.53

Table 11. Overall Performance

Metric	Value
Accuracy	0.66
Precision	0.71
Recall	0.62
F1-Score	0.61

Comparative Analysis and Implications

The findings further demonstrate that simple rule-based approaches can achieve competitive classification performance without requiring large datasets, intensive computation, or complex model training. Compared with conventional machine learning approaches reported in previous studies, the proposed Boolean-based framework offers greater transparency and interpretability while maintaining computational efficiency. Therefore, the OR–AND framework can serve as a practical alternative for rainfall classification and climate-related decision-support applications, particularly in data-limited regions.

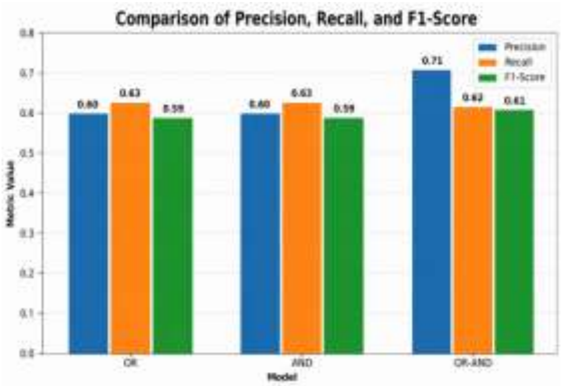

Figure 10. Comparison of Model Performance

A comparative evaluation of the three Boolean classification models is presented in Figure 10 and Table 12. The OR–AND model achieved the highest overall accuracy (66%), precision (71%), and F1-score (61%), outperforming both the OR and AND models while maintaining comparable recall. These results indicate that integrating the flexibility of the OR operator with the selectivity of the AND operator provides a more balanced representation of rainfall variability and improves overall classification performance.

The present findings demonstrate that the proposed Boolean-based framework provides competitive rainfall classification performance without requiring extensive computational resources or complex model training. Owing to its transparent rule-based structure, the proposed approach offers a practical alternative for operational climate monitoring and decision-support applications, particularly in regions with limited computational infrastructure.

Table 12. Comparison of Classification Performance

Model	Accuracy	Precision	Recall	F1-Score
OR	0.64	0.6	0.63	0.59
AND	0.63	0.6	0.63	0.59
OR–AND	0.66	0.71	0.62	0.61

The superior performance of the hybrid OR–AND model can be attributed to its ability to effectively balance the flexibility of the OR operator with the selectivity of the AND operator. The OR model classifies rainfall when at least one predictor satisfies the specified condition, making it more flexible but potentially increasing false positive classifications. In contrast, the AND model requires all predictors to satisfy the classification criteria simultaneously, resulting in stricter decision rules that may increase false negative classifications. By integrating these complementary logical operators, the OR–AND model achieved a better balance between precision and recall, resulting in the highest overall accuracy and F1-score. Although its recall (0.62) was slightly lower than that of the OR and AND models (0.63), the substantial improvement in precision (0.71) reduced false positive classifications and consequently improved the overall classification performance.

In addition, the proposed Boolean-based classification framework aligns well with the principles of Explainable Artificial Intelligence (XAI), which emphasize transparency and interpretability in decision-making. Unlike many machine learning models that operate as black-box systems, the Boolean OR, AND, and OR–AND models classify rainfall using explicit logical rules that can be easily understood and interpreted. This transparency enables users to identify how each meteorological variable contributes to the classification outcome, making the proposed approach suitable for operational climate monitoring and decision-support applications, particularly in regions with limited computational resources.

The present findings are consistent with previous studies demonstrating that rainfall classification can be improved by integrating multiple meteorological variables. Although machine learning approaches generally provide high predictive performance, they often require extensive computational resources and complex model optimization. In contrast, the proposed Boolean-based framework offers a simple, transparent, and computationally efficient alternative while maintaining competitive classification performance, making it suitable for operational climate monitoring in regions with limited computational infrastructure and data availability.

CONCLUSION

This study evaluated the performance of Boolean OR, AND, and hybrid OR–AND models for monthly rainfall classification in Bawean Island using rainy days, mean temperature, and minimum temperature data from 1972–2023. The results revealed that rainy days had the strongest relationship with rainfall ($r = 0.858$), followed by minimum temperature ($r = -0.592$) and mean temperature ($r = -0.463$), indicating that rainfall variability is strongly influenced by precipitation frequency and associated temperature conditions. Among the three classification approaches, the OR–AND model demonstrated the best overall performance, achieving an accuracy of 66%, precision of 71%, recall of 62%, and F1-score of 61%, outperforming both the OR and AND models. These findings suggest that combining OR and AND operators provides a more balanced representation of meteorological conditions and improves rainfall classification performance while maintaining transparency and computational simplicity. Therefore, the proposed OR–AND framework can serve as an interpretable and computationally efficient alternative for rainfall classification and climate monitoring, particularly in regions with limited data availability and computational resources.

This study is limited by the use of climatological data from a single meteorological station and a limited number of predictor variables. Consequently, the proposed framework may not fully represent rainfall characteristics in other climatic regions or under different environmental conditions. Future studies may incorporate additional climatic variables, such as relative humidity, wind speed, and atmospheric pressure, validate the proposed framework using multi-station datasets, and compare Boolean logic approaches with machine learning algorithms to further improve classification performance and operational applicability.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the Bawean Meteorological Station and the Indonesian Agency for Meteorology, Climatology, and Geophysics (Badan Meteorologi, Klimatologi, dan Geofisika) for providing the climatological data used in this study. The authors also acknowledge the Department of Informatics Engineering, Faculty of Science and Technology, Maulana Malik Ibrahim State Islamic University of Malang, for academic support during the research process. Appreciation is extended to all colleagues and reviewers whose valuable suggestions and constructive feedback contributed to the improvement of this manuscript.

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