

A Climatology-Relative Framework for Evaluating Rainfall-Condition Categories Using Observed and Random Forest-Predicted Dasarian Rainfall

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Abstract—Rainfall variability strongly influences rain-fed agricultural activities in monsoonal regions, particularly across seasonal and spatially varying rainfall regimes. This study develops and applies a climatology-relative framework for evaluating rainfall-condition categories derived from observed and Random Forest (RF)-predicted dasarian rainfall for Besuki Na-Oogst tobacco in ZOM 45–49, Jember, East Java. A 30-year historical rainfall dataset (1993–2022) was used to derive ZOM- and dasarian-specific P25 and P75 relative rainfall-condition thresholds. The same fixed thresholds were then applied to observed and RF-predicted rainfall throughout January–December 2024 to classify rainfall into Dry, Normal, and Wet categories. Categorical correspondence was evaluated using percentage agreement, Cohen's kappa, and a 3×3 confusion matrix at the ZOM $\times$ dasarian level. Across 180 ZOM $\times$ dasarian pairs, observed rainfall produced 50 Dry, 84 Normal, and 46 Wet classifications, whereas RF-predicted rainfall produced 7 Dry, 68 Normal, and 105 Wet classifications. Overall categorical agreement was 38.33% ($\kappa = 0.071$), with variation among the five ZOMs. The most pronounced discrepancy occurred in the Dry category: none of the 50 observed Dry cases were reproduced as Dry by the RF predictions, while 36 were classified as Wet. Conversely, all seven RF-predicted Dry cases corresponded to observed Wet conditions. The continuous comparison indicated that the RF predictions generally reproduced the broad seasonal rainfall pattern but tended to exhibit smoother variations and, in several periods, lower rainfall magnitudes than observed. These differences can lead to categorical reversals when predicted values fall across fixed climatological P25 and P75 boundaries. The findings indicate that RF-derived rainfall-condition patterns may provide complementary information for climatology-relative assessment, but should not be interpreted as direct substitutes for observed rainfall conditions or as standalone planting recommendations. The proposed framework complements conventional numerical rainfall-prediction evaluation by assessing the categorical representation of predicted rainfall within a common local historical climatology at the ZOM $\times$ dasarian scale.

Keywords: Agricultural Climatology; Dasarian Rainfall; Rainfall Prediction; Random Forest; Climatological Thresholds; Besuki Na-Oogst Tobacco; Jember, East Java

1. INTRODUCTION

Rainfall variability is a major source of uncertainty in rain-fed agricultural production, particularly in monsoonal regions where rainfall changes substantially across seasons and locations [1]. In Indonesia, rainfall regimes are represented by Seasonal Zones (Zona Musim; ZOM), which delineate areas with relatively similar seasonal rainfall characteristics. Rainfall assessment within these zones is also commonly represented at the dasarian (10-day) scale, allowing seasonal rainfall changes to be examined at a finer temporal resolution than monthly or annual aggregates. Therefore, rainfall-condition assessment at the ZOM $\times$ dasarian scale provides a more locally relevant representation of rainfall variability than the use of a single threshold across broad administrative areas [2], [3], [4].

This issue is particularly relevant to Besuki Na-Oogst tobacco cultivation in Jember, East Java, which is associated with the transition from relatively dry to wetter conditions. Previous studies have reported relationships between rainfall and tobacco production in Jember and have highlighted the sensitivity of Na-Oogst tobacco production to climatic conditions [5]. However, the available literature does not establish a validated absolute dasarian rainfall threshold that can directly distinguish suitable and unsuitable rainfall conditions for Besuki Na-Oogst tobacco. The available agronomic information therefore does not provide sufficient basis for imposing a single millimetre-based rainfall threshold across different locations and periods [6].

The interpretation of rainfall conditions is inherently dependent on the reference used to define category boundaries. An identical rainfall amount may represent substantially different climatological conditions when it occurs in different seasons or locations because the underlying precipitation distributions are not homogeneous [7], [8]. Operational climate prediction systems can express precipitation forecasts relative to a climatological reference, using categories such as below-normal, near-normal, and above-normal conditions. The World Meteorological Organization (WMO), for example, presents seasonal precipitation forecasts relative to local climatology using these three categories [9]. Similarly, the European Centre for Medium-Range Weather Forecasts (ECMWF) defines seasonal forecast categories using terciles derived from the corresponding model climatological distribution [10]. This climatology-relative approach provides a consistent basis for interpreting whether predicted precipitation is unusually low, near the climatological middle, or unusually high for a given location and forecast period [11].

This climatology-relative approach is important because a common absolute threshold may obscure differences among local rainfall regimes. The same absolute rainfall amount may correspond to different climatological conditions

across locations or seasons because the underlying precipitation distributions differ. Percentile-based approaches provide a statistical means of addressing this issue by relating an observation to its position within the historical distribution of precipitation [12]. Such approaches have been applied in precipitation and drought analyses to characterize hydroclimatic conditions relative to historical climatology [13]. In addition, precipitation forecast verification can explicitly incorporate station climatology into categorical evaluation. For example, the ECMWF Stable Equitable Error in Probability Space (SEEPS) approach uses station climatology to determine precipitation-category boundaries so that forecast evaluation accounts for differences in local climate between observation locations [14].

However, climatology-relative thresholds are not free from uncertainty. Their estimated values depend partly on the length and representativeness of the historical record and on the selected percentile used to define the categories [15]. This consideration is particularly important for rainfall because precipitation distributions often exhibit a wet–dry structure and a long right tail, making their statistical representation challenging [16]. Percentile-based rainfall indicators should also be interpreted within their climatological context, particularly during dry seasons when even a relatively extreme percentile may correspond to a small absolute rainfall anomaly [17]. Consequently, percentile thresholds should be interpreted as statistical references to the historical precipitation distribution rather than as absolute physical or agronomic boundaries. In the present study, this distinction is important because the P25 and P75 thresholds are intended to represent relative climatological rainfall conditions, not crop-specific rainfall requirements.

The threshold issue becomes particularly relevant when continuous rainfall predictions are translated into categorical rainfall conditions. Machine-learning models, including Random Forest (RF), have been widely applied to rainfall prediction and classification because of their ability to represent nonlinear relationships between predictor variables and rainfall outcomes [18]. Previous studies have generally emphasized numerical prediction performance using metrics such as RMSE, MAE, correlation, or related measures. These measures quantify the magnitude of prediction error, but they do not directly indicate whether a predicted rainfall value represents the same climatological condition category as the observed rainfall [19].

Categorical interpretation provides a complementary perspective to continuous prediction accuracy. A relatively small numerical prediction error may cause a predicted value to cross a climatological category boundary, whereas a larger numerical difference may leave both observed and predicted values within the same category. Consequently, numerical prediction accuracy and categorical climatological correspondence represent related but distinct aspects of rainfall prediction. Consistent categorical evaluation therefore requires observed and predicted rainfall to be classified using the same climatological reference rather than separately estimated thresholds. This principle is consistent with established precipitation forecast verification approaches, such as SEEPS, in which forecast and observed precipitation are assigned to the same climatology-based categories for categorical evaluation [7], [8], [20].

Previous rainfall-prediction studies in Indonesia have demonstrated the application of Random Forest and other machine-learning methods to rainfall prediction, classification, and related climate applications [21]. However, these studies have generally focused on numerical prediction performance or direct rainfall classification, rather than examining whether continuous rainfall predictions correspond to the same local climatological condition as the observations. The scientific issue is therefore not simply the absence of previous comparisons, but the need for a consistent methodological reference for translating continuous rainfall predictions into locally meaningful categorical conditions [22].

To address this issue, this study develops and applies a climatology-relative categorical evaluation framework at the ZOM $\times$ dasarian scale. The framework derives ZOM- and dasarian-specific P25 and P75 thresholds from a 30-year historical rainfall baseline and keeps these thresholds fixed when classifying both observed and Random Forest-predicted rainfall during the evaluation period. The resulting Dry, Normal, and Wet categories are evaluated using percentage agreement, Cohen's kappa, and a 3×3 confusion matrix. This design provides a common local climatological reference for both datasets and enables the evaluation of whether predicted rainfall reproduces the same rainfall-condition category as observed rainfall. The framework therefore complements conventional numerical rainfall-prediction evaluation by assessing whether continuous predictions reproduce rainfall-condition categories defined within the same local historical climatology.

Accordingly, this study addresses three research questions: (1) What are the historical dasarian rainfall characteristics and ZOM $\times$ dasarian-specific P25 and P75 thresholds for ZOM 45–49? (2) How does the proposed climatology-relative framework classify observed and RF-predicted rainfall into Dry, Normal, and Wet categories? and (3) What is the categorical agreement and spatial-temporal correspondence between observed and RF-predicted rainfall classifications?

2. RESEARCH METHODOLOGY

2.1 Study Area and Data Sources

This study focuses on five Seasonal Zones (ZOM 45–49) covering Jember, East Java, as officially delineated by BMKG. Two rainfall datasets were used. The first is a 30-year historical dasarian rainfall dataset covering 1993–2022 for the five ZOMs, which was used to construct the climatological baseline. The second consists of January–December

2024 dasarian rainfall series for the same five ZOMs, comprising observed rainfall and rainfall predictions generated using a Random Forest (RF) model developed by the authors as part of the present research. The RF prediction results represent the authors' original modelling output and were subsequently used in this study for climatology-relative rainfall-condition classification.

The analysis was conducted at the ZOM $\times$ dasarian level. Historical rainfall was organized according to the 36 calendar-dasarian positions from January Dasarian I to December Dasarian III. The 2024 observed and RF-predicted rainfall series were subsequently classified using the same historical climatological thresholds, and the resulting categorical patterns were compared using percentage agreement, Cohen's kappa, and a confusion matrix.

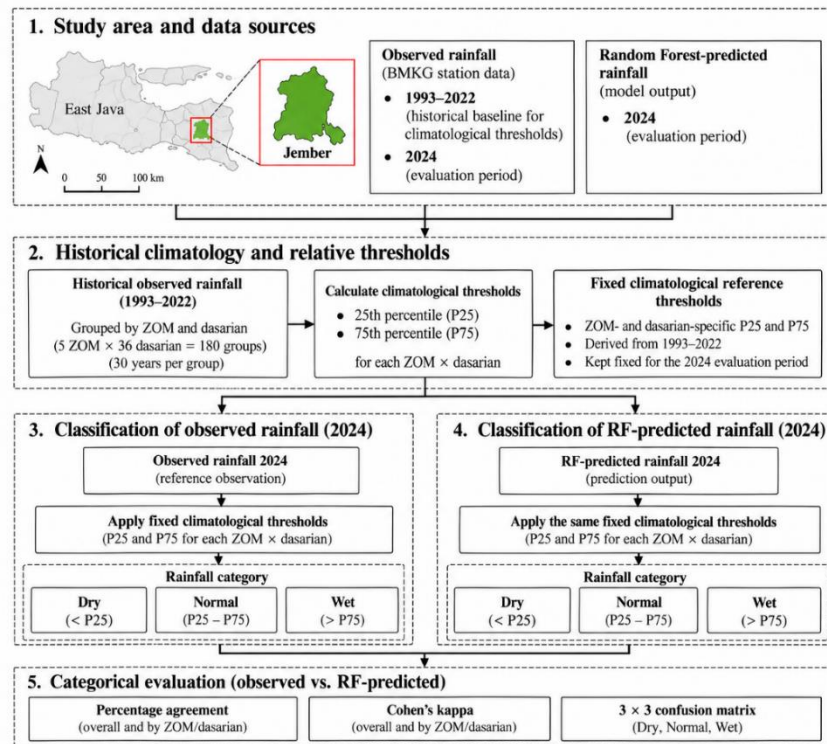


Figure 1. Research methodology flowchart.

Figure 1. Research methodology flowchart

Figure 1 illustrates the overall research framework. Historical observed rainfall from 1993–2022 was used to establish ZOM- and dasarian-specific P25 and P75 thresholds. These thresholds were kept fixed and applied to both observed and Random Forest-predicted rainfall during the 2024 evaluation period. The resulting Dry, Normal, and Wet categories were then compared using percentage agreement, Cohen's kappa, and a 3×3 confusion matrix.

2.2 Random Forest Rainfall Prediction

Random Forest (RF) regression was used to generate the dasarian rainfall predictions evaluated in this study. The RF predictions were obtained from the direct multi-step rainfall forecasting framework developed by the authors for dasarian rainfall prediction in East Java. The predictor variables consisted of lagged rainfall, rolling rainfall statistics, seasonal encoding, Oceanic Niño Index (ONI), Dipole Mode Index (DMI), and Sea Surface Temperature Anomaly (SSTA). The rainfall-related predictors were designed to represent recent rainfall persistence and short-term variability, while the climate indices represented broader seasonal and ocean–atmosphere variability associated with rainfall conditions.

The forecasting framework employed a direct multi-step strategy, in which an independent RF model was developed for each forecast horizon. For each ZOM and forecast horizon, the target rainfall was generated by shifting the observed dasarian rainfall series to the corresponding future period. This approach allowed each forecast horizon to be modelled independently rather than using previous predictions as inputs for subsequent forecasts, thereby avoiding the accumulation of errors associated with recursive forecasting. The resulting RF predictions for ZOM 45–49 were used as the model-generated rainfall inputs in the present study.

The RF regression model consists of an ensemble of decision trees constructed from bootstrap samples of the training data. At each tree split, a randomly selected subset of predictor variables is considered, thereby introducing diversity among the individual trees. For regression, the final prediction is obtained by averaging the predictions generated by the individual trees. This ensemble structure enables RF to represent nonlinear relationships between rainfall and its predictor variables while reducing the variance associated with individual decision trees. The RF implementation used a fixed random state of 42, with a consistent model configuration across ZOMs and forecast horizons.

For the present study, the RF outputs corresponding to ZOM 45–49 were organized according to the ZOM $\times$ dasarian structure of the observed rainfall series for January–December 2024. These RF outputs were retained as model-generated predictions and were not used to calculate or modify the historical climatological thresholds. The predicted rainfall values were subsequently classified using the fixed P25 and P75 thresholds derived independently from the 1993–2022 observed rainfall baseline.

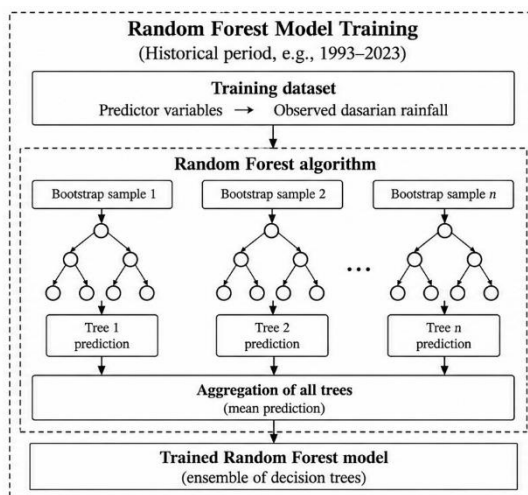


Figure 2. Random Forest (RF) model training process for dasarian rainfall prediction.

Figure 2 illustrates the general workflow of the Random Forest (RF) model used for dasarian rainfall prediction. The training dataset consists of predictor variables and observed dasarian rainfall as the response variable. In the RF algorithm, multiple decision trees are constructed from bootstrap samples of the training data, and each tree generates an individual prediction. The predictions from all trees are then aggregated to obtain the final RF prediction. The resulting trained RF model was subsequently used to generate dasarian rainfall predictions for the 2024 evaluation period.

2.3 Evaluation Framework and Reference Data

The present study evaluates the Random Forest (RF) predictions using observed rainfall as the observational reference for the 2024 evaluation period. The RF-predicted rainfall is treated as model-generated output and is not considered ground truth. To provide a common climatological reference for both datasets, rainfall-condition thresholds were established independently from the 30-year historical observed rainfall baseline for 1993–2022.

For each ZOM and dasarian position, the 25th percentile (P25) and 75th percentile (P75) were calculated from the corresponding historical rainfall observations. These climatological thresholds were fixed before the evaluation and were not recalculated, adjusted, or derived from either the observed or RF-predicted rainfall during 2024. Consequently, the same ZOM- and dasarian-specific thresholds were applied to both datasets throughout the evaluation period.

The observed and RF-predicted rainfall values for January–December 2024 were then classified into three climatology-relative rainfall conditions: Dry, Normal, and Wet. A rainfall value was classified as Dry when it was less than or equal to P25, Normal when it was greater than P25 but less than P75, and Wet when it was greater than or equal to P75. This classification provides a common basis for comparing the rainfall-condition categories represented by the observations and the RF predictions.

Accordingly, the evaluation does not compare RF predictions against thresholds derived from the RF output, nor does it use RF predictions to establish the reference distribution. Instead, it examines the categorical correspondence between observed and RF-predicted rainfall under an external historical climatological reference. This framework allows the study to assess whether the RF predictions reproduce the climatology-relative rainfall conditions observed during 2024 across the evaluated ZOMs and dasarian periods.

2.4 Historical Climatology and Relative Thresholds

The historical dataset consisted of 150 Year $\times$ ZOM records covering five ZOMs (45, 46, 47, 48, and 49) over the 30-year period from 1993 to 2022. Each year contained 36 calendar-dasarian positions, from January Dasarian I to December Dasarian III, resulting in a total of 5,400 rainfall observations. Data-quality verification confirmed that the dataset contained no missing values, no duplicated Year–ZOM combinations, and no negative rainfall values.

For climatological analysis, rainfall observations were grouped according to ZOM and calendar-dasarian position. This produced 180 climatological groups (5 ZOMs $\times$ 36 dasarian positions), with 30 historical observations in each group. Thus, each rainfall value in the 2024 evaluation period was compared with the historical rainfall distribution corresponding to the same ZOM and dasarian position, rather than with a pooled rainfall distribution across different locations or periods.

For each climatological group, the 25th percentile (P25), 50th percentile (P50), and 75th percentile (P75) were calculated using linear percentile interpolation. The percentile calculation was based on the 30 historical observations within each ZOM × dasarian group. P25 and P75 were subsequently used as the lower and upper boundaries for defining climatology-relative rainfall conditions, while P50 was retained as a measure of the historical central tendency.

The rainfall-condition categories were defined consistently for both observed and RF-predicted rainfall. A rainfall value less than or equal to P25 was classified as Dry, a value greater than P25 but less than P75 was classified as Normal, and a value greater than or equal to P75 was classified as Wet. The classification rule was applied independently to each ZOM and dasarian position using its corresponding fixed historical thresholds.

These thresholds represent the relative position of rainfall within the historical climatological distribution of each ZOM and dasarian period. They are therefore intended as climatological reference thresholds rather than absolute rainfall limits. In particular, the P25 and P75 thresholds do not represent agronomic or biological requirements for Besuki Na-Oogst tobacco. The historical observed rainfall data were used solely to establish the climatological reference distribution, and the resulting thresholds were fixed before being applied to the 2024 observed and RF-predicted rainfall.

2.5 Relative Rainfall-Condition Thresholds

For each of the 180 climatological groups, the 25th percentile (P25), 50th percentile (P50), and 75th percentile (P75) were calculated from the 30 historical rainfall observations corresponding to the same ZOM and calendar-dasarian position. Linear percentile interpolation was used to estimate the percentile values. For a climatological group containing ($n = 30$) observations, the interpolated rank position for percentile (p) was calculated as:

$$h = 1 + p(n - 1) \quad (1)$$

where (p) represents the desired percentile (0.25, 0.50, or 0.75) and (n) is the number of observations in the climatological group. If (h) was not an integer, the percentile value was obtained by linear interpolation between the observations at the lower and upper rank positions.

$$Q_p = x_{[h]} + (h - [h])(x_{[h]} - x_{[h]}) \quad (2)$$

where Q_p is the estimated percentile value, $x_{[h]}$ and $x_{[h]}$ are the observations at the lower and upper rank positions, respectively, and h is the interpolated rank position.

The resulting P25 and P75 values were used as the climatological boundaries for the rainfall-condition categories. For each ZOM and dasarian position, rainfall values satisfying ($R \leq P25$) were classified as Dry, values satisfying ($P25 < R < P75$) were classified as Normal, and values satisfying ($R \geq P75$) were classified as Wet, where (R) denotes the rainfall value being classified. Thus, the classification boundaries were specific to both location and calendar-dasarian position. where the $n = 30$ values in a climatological group are sorted in ascending order $x(1) \leq x(2) \leq \dots \leq x(30)$, $h = 1 + p(n - 1)$ is the interpolated rank position for percentile p (e.g., $p = 0.25$ for P25), and $[h]$ and $[h]$ denote the floor and ceiling of h .

Rainfall values were then classified as: Dry when rainfall $\leq P25$; Normal when $P25 < \text{rainfall} < P75$; and Wet when rainfall $\geq P75$. These thresholds are climatological-relative thresholds, describing a rainfall value's position within its own local 30-year historical distribution, conceptually related to percentile-based drought/wet classification frameworks used internationally. They are explicitly not agronomic or biological thresholds for tobacco cultivation.

2.6 Classification of 2024 Rainfall

The observed and RF-predicted rainfall data for January–December 2024 were classified using the fixed P25 and P75 thresholds derived from the 1993–2022 historical climatological baseline. The classification was performed independently for each ZOM and calendar-dasarian position, resulting in 36 dasarian positions for each of the five ZOMs and a total of 180 paired ZOM × dasarian observations for the evaluation period.

For each ZOM × dasarian pair, the observed 2024 rainfall and the corresponding RF-predicted rainfall were evaluated against the same historical P25 and P75 thresholds. Observed rainfall was first assigned to the Dry, Normal, or Wet category, and the corresponding RF-predicted rainfall was then classified using the identical threshold for that ZOM and dasarian position. This procedure ensured that differences between the two categorical patterns reflected differences in the observed and predicted rainfall values rather than differences in the reference thresholds.

The classification results were organized as paired observations, with each pair consisting of one observed rainfall category and its corresponding RF-predicted category for the same ZOM and dasarian period. The resulting categorical pairs were subsequently used to calculate the overall percentage agreement, Cohen's kappa, and the 3×3 confusion matrix described in Section 2.7.

The classification was applied consistently across the full January–December 2024 period. No threshold was recalculated or modified during the classification process, and the RF predictions were not used to redefine the climatological categories. Therefore, the resulting Dry, Normal, and Wet patterns represent the correspondence between observed and RF-predicted rainfall under a common fixed historical climatological reference.

2.7 Categorical Comparison Metrics

The correspondence between observed and RF-predicted rainfall-condition categories was evaluated using percentage agreement, Cohen's kappa, and a 3×3 confusion matrix. These metrics were calculated from the paired categorical observations obtained for the same ZOM and dasarian period during January–December 2024. A total of 180 paired ZOM $\times$ dasarian observations were evaluated, consisting of 36 pairs for each of the five ZOMs.

Percentage agreement was calculated as the proportion of paired observations in which the observed and RF-predicted categories were identical. It was expressed as a percentage using:

$$\text{Agreement (\%)} = \left(\frac{N_{\text{agree}}}{N_{\text{total}}} \right) \times 100 \quad (3)$$

Where N_{agree} is the number of ZOM $\times$ dasarian pairs for which the observed and RF-predicted classifications matched, and $N_{\text{total}} = 180$ is the total number of paired comparisons. Cohen's Kappa. Categorical agreement beyond the level expected by chance was quantified using Cohen's kappa :

$$\kappa = \frac{(P_o - P_e)}{(1 - P_e)} \quad (4)$$

Where P_o represents the observed proportion of agreement and P_e represents the expected proportion of agreement based on the marginal category frequencies. Cohen's kappa was calculated for the complete set of 180 paired observations and separately for each ZOM using its 36 paired observations.

Confusion Matrix. A 3×3 confusion matrix was also constructed to examine the direction of categorical correspondence between the observed and RF-predicted rainfall conditions. The three categories Dry, Normal, and Wet were used for both dimensions of the matrix. Rows represented the observed rainfall categories, while columns represented the RF-predicted categories. The diagonal elements represented exact categorical agreement, whereas the off-diagonal elements represented categorical discrepancies between the observed and predicted rainfall conditions.

The three metrics were interpreted together to distinguish the overall level of categorical correspondence from the direction and distribution of individual classification discrepancies. Percentage agreement describes the proportion of exact matches, Cohen's kappa accounts for chance agreement, and the confusion matrix identifies the specific transitions between Dry, Normal, and Wet categories.

2.8 Temporal and Spatial Analysis

The spatial and temporal patterns of the rainfall-condition classifications were examined at the ZOM $\times$ dasarian level to identify differences in categorical correspondence across locations and periods. The analysis covered five ZOMs (45–49) and 36 calendar-dasarian positions from January to December 2024. For each ZOM, the observed and RF-predicted rainfall-condition sequences were arranged chronologically from January Dasarian I to December Dasarian III.

Temporal analysis focused on the distribution and sequence of Dry, Normal, and Wet classifications throughout the 2024 evaluation period. The observed and RF-predicted classifications were compared for corresponding dasarian periods to identify periods in which the two datasets produced the same category or different categories. Particular attention was given to transitions across the P25 and P75 climatological boundaries because differences in rainfall magnitude around these fixed thresholds can result in different categorical assignments.

Spatial analysis was conducted by comparing the categorical patterns among ZOM 45–49. The number and distribution of Dry, Normal, and Wet classifications were examined separately for each ZOM, together with the corresponding agreement between observed and RF-predicted categories. This analysis was used to identify whether categorical discrepancies were distributed consistently across the study area or varied among individual ZOMs.

The temporal and spatial patterns were visualized using the observed and RF-predicted rainfall series relative to the historical P25–P75 climatological range and using a rainfall-condition classification heatmap. The continuous rainfall comparison provides the magnitude and seasonal context of the predictions, whereas the categorical heatmap illustrates the spatial-temporal distribution of Dry, Normal, and Wet conditions. These complementary analyses were used to interpret the categorical agreement results without treating the RF predictions as an observational reference.

2.9 Scope and Limitations

The scope of this study is limited to the climatology-relative categorical evaluation of observed and Random Forest (RF)-predicted dasarian rainfall across ZOM 45–49 in Jember, East Java. The climatological reference was constructed from observed rainfall during 1993–2022, while the categorical evaluation was conducted for the January–December 2024 period. The analysis focuses on the correspondence of Dry, Normal, and Wet rainfall-condition categories at the ZOM $\times$ dasarian level.

Several limitations should be considered when interpreting the results. First, the categorical evaluation covers only one independent evaluation year, namely 2024. Therefore, the observed categorical correspondence and discrepancies identified in this study should not be generalized to other years without further multi-year evaluation. Second, the present framework evaluates the categorical representation of RF-predicted rainfall relative to historical climatology and does not constitute a comprehensive independent validation of the numerical RF prediction

performance. Continuous prediction errors, prediction bias, and predictor-specific contributions are beyond the primary scope of this analysis.

Third, the P25 and P75 thresholds represent statistical positions within the historical rainfall distribution for each ZOM and dasarian period. They are not absolute rainfall thresholds and should not be interpreted as crop-specific agronomic requirements or direct indicators of tobacco planting suitability. Consequently, the resulting Dry, Normal, and Wet categories describe relative climatological conditions rather than definitive agricultural suitability.

Finally, the interpretation of categorical discrepancies is limited to the common historical climatological reference established in this study. Further research involving multiple independent evaluation years, comprehensive numerical prediction verification, analysis of prediction errors and predictor contributions, and integration with agronomic and environmental indicators would be required to assess the persistence and practical applicability of the identified rainfall-condition patterns.

3. RESULTS AND DISCUSSION

3.1 Historical Climatology of ZOM 45–49

The 30-year historical rainfall dataset (1993–2022) comprised 5,400 observations across five ZOMs and 36 calendar-dasarian positions. The resulting climatological distributions showed substantial temporal and spatial variability across ZOM 45–49. Rainfall was generally lower during the August–September period and increased toward the later part of the year, particularly during November–December. These variations support the use of ZOM- and dasarian-specific climatological thresholds rather than a single threshold applied across all locations and periods.

The historical rainfall distributions also showed differences in their central tendency and spread among the ZOM × dasarian groups. Across the 180 climatological groups, 35 groups had mean and median rainfall values greater than 3 mm. These groups were concentrated primarily during the relatively dry August–September period, particularly in ZOM 45 and ZOM 46. The presence of very low rainfall values in some climatological groups illustrates the substantial variation in the absolute rainfall amounts associated with the same relative rainfall condition across different dasarian periods.

The percentile-based analysis further demonstrated substantial differences in the climatological rainfall ranges among ZOMs and dasarian positions. For example, the P25 value for September Dasarian I in ZOM 48 was approximately 0.03 mm, indicating that the lower quartile of the historical rainfall distribution for this period was very small. In contrast, the P75 value for December Dasarian III in ZOM 48 reached approximately 187.9 mm. These results demonstrate that the absolute rainfall amounts associated with the P25 and P75 boundaries can differ considerably depending on the ZOM and dasarian position.

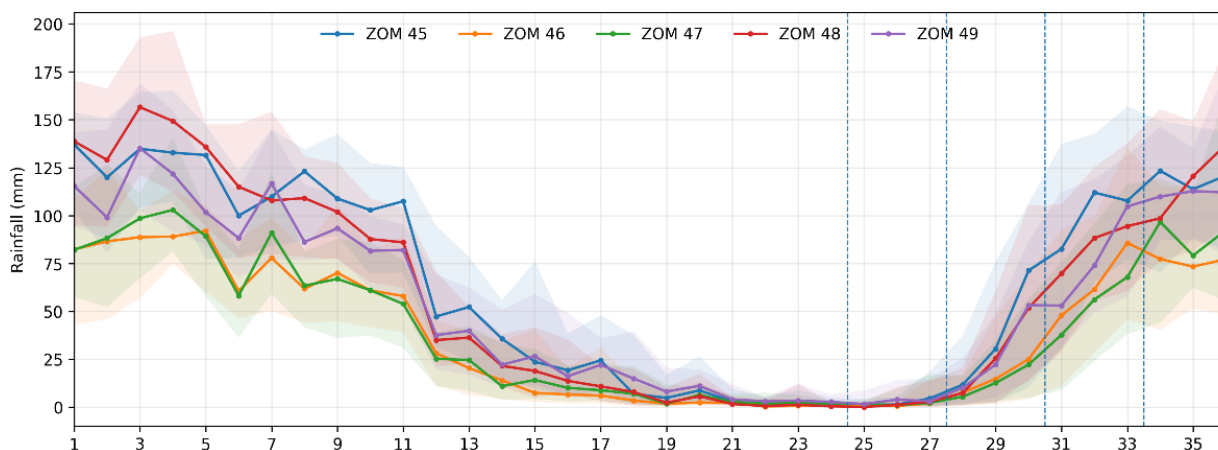


Figure 3. Historical Climatological Rainfall and P25–P75 Ranges across ZOM 45–49, 1993–2022.

As shown in Figure 3, August and September are characterized by relatively low dasarian rainfall and pronounced right-skewness. Among the 180 ZOM × dasarian groups, 35 have a mean-to-median ratio exceeding 3, concentrated primarily in August–September for ZOM 45 and ZOM 46. ZOM 48 September Dasarian I has a P25 of only 0.03 mm, indicating that the lower quartile of historical rainfall for this period is effectively rainless. From October onward, median rainfall and the P25–P75 range generally increase, reaching higher values during November and December. For example, ZOM 48 December Dasarian III has a P75 of 187.9 mm.

Figure 4 shows the interquartile rainfall range (P75–P25) for each ZOM × dasarian combination based on the 1993–2022 climatological baseline. The range is generally narrower during the dry-season dasarians, particularly around August–September, indicating relatively limited variability in rainfall within these periods. From October onward, the interquartile range generally expands as rainfall increases toward November and December. The spatial distribution of the ranges also differs among ZOMs, indicating that the magnitude of rainfall variability is not uniform

across the seasonal zones. These differences further support the use of ZOM- and dasarian-specific percentile thresholds rather than a single pooled threshold for the entire study area.

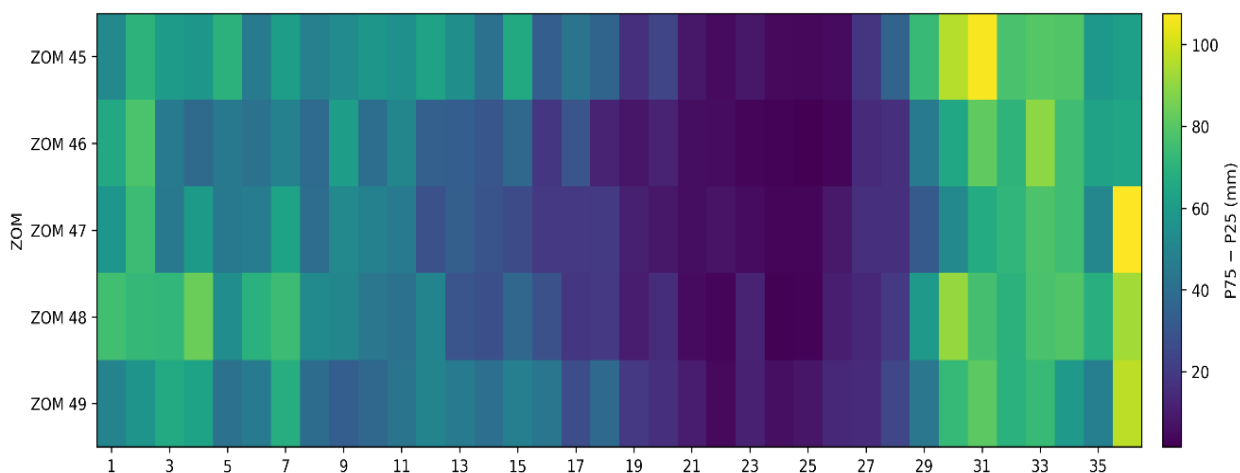


Figure 4. Interquartile Rainfall Range (P75–P25) across ZOM 45–49 and Dasarian Positions, 1993–2022.

These characteristics support the use of independent thresholds for each ZOM × dasarian combination rather than pooling rainfall observations across zones or calendar positions. A single province-wide or ZOM-wide threshold could combine rainfall distributions that differ substantially between the dry-season and wet-season periods. The percentile-based approach used here follows established distribution-relative approaches for characterizing precipitation conditions, adapted to the ZOM × dasarian resolution of the BMKG seasonal-zone framework. The spatial differences among ZOMs, particularly the contrasting late-season rainfall variability across the zones, further support the use of zone- and dasarian-specific thresholds. Dry, Normal, and Wet therefore represent the relative position of rainfall within the local 30-year climatological distribution and are not interpreted as agronomic suitability classes.

3.2 Observed and RF-Predicted Rainfall-Condition Patterns

Across the 180 ZOM × dasarian pairs covering January–December 2024, observed rainfall produced 50 Dry, 84 Normal, and 46 Wet classifications, whereas RF-predicted rainfall produced 7 Dry, 68 Normal, and 105 Wet classifications after applying the same fixed climatological thresholds described in Section 2.3. The RF predictions therefore produced substantially fewer Dry classifications and more Wet classifications than the observed rainfall. Notably, none of the 50 observed Dry cases were reproduced as Dry by the RF predictions: 14 were classified as Normal and 36 as Wet. Conversely, all 7 RF-predicted Dry cases corresponded to observed Wet conditions. These results indicate a clear difference in the categorical distribution of the two datasets, which is further examined using the confusion matrix and ZOM-specific agreement patterns in Section 3.3.

At the continuous rainfall level, Figure 4 shows the observed and RF-predicted rainfall series for January–December 2024 in relation to the historical P25–P75 climatological range. Across the five ZOMs, both series generally reflect the seasonal transition from relatively higher rainfall at the beginning of the year toward lower rainfall during the middle of the year, followed by an increase toward November and December. However, substantial differences in magnitude and short-term variability are evident between the observed and RF-predicted series. The observed rainfall generally exhibits sharper fluctuations between consecutive dasarians, particularly during the transition toward the wetter period, whereas the RF predictions tend to produce smoother trajectories. In several late-year dasarians, observed rainfall rises above the climatological P75, while the RF predictions remain closer to or below the upper climatological range. These differences are relevant to the categorical evaluation because rainfall values crossing the fixed P25 or P75 boundaries can result in different Dry, Normal, or Wet classifications even when the broader seasonal pattern is similar.

Figure 5 shows the observed and Random Forest-predicted rainfall for January–December 2024 across ZOM 45–49 in relation to the historical climatological rainfall distribution. The shaded area represents the P25–P75 range derived from the 1993–2022 historical baseline, while the P50 line indicates the historical median for each dasarian position. The observed and RF-predicted series represent the 2024 evaluation data. Across the five ZOMs, both series generally follow the seasonal transition from relatively lower rainfall during the dry-season period toward higher rainfall during the later months, although substantial differences in magnitude and short-term variability are evident. Several observed values exceed the historical P75, particularly during the later dasarians, whereas RF predictions tend to remain closer to the climatological range in several periods. These differences provide the continuous-rainfall context for the subsequent categorical evaluation using the fixed P25 and P75 thresholds.

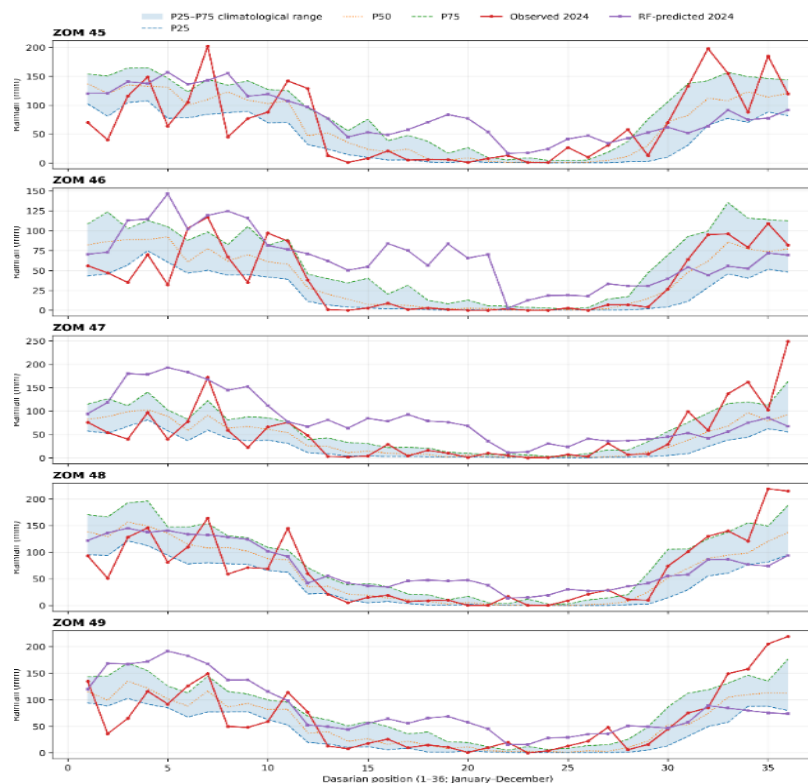


Figure 5. Observed and Random Forest-Predicted Rainfall in 2024 Relative to Historical P25–P75 Climatology across ZOM 45–49.

3.3 Categorical Agreement and Spatial-Temporal Discrepancies

The aggregate categorical agreement between the observed and RF-predicted rainfall-condition patterns across the 180 ZOM $\times$ dasarian pairs was 38.33%, with an aggregate Cohen's kappa of 0.071. Under the Landis and Koch scale, this corresponds to a slight level of chance-corrected agreement. Agreement varied among the five ZOMs, ranging from 44.44% in ZOM 46 ($\kappa = 0.250$) to 30.56% in ZOM 47 ($\kappa = -0.042$). ZOM 45 and ZOM 48 both showed 41.67% agreement ($\kappa = 0.094$), while ZOM 49 showed 33.33% agreement ($\kappa = -0.025$). This variation indicates that the correspondence between observed and RF-predicted rainfall-condition categories was not spatially uniform across the study area. The relatively low overall agreement and the differences among ZOMs indicate that the categorical correspondence of the RF predictions depends on the specific spatial and temporal rainfall conditions represented in the evaluation period.

Table 1. Categorical agreement between observed and RF-predicted rainfall by ZOM, January–December 2024.

ZOM	Agreement	Cohen's k	Observed Dry	RF-Pred Dry
45	41.67	0.094	10	2
46	44.44	0.250	12	0
47	30.56	-0.042	8	0
48	41.67	0.094	11	2
49	33.33	-0.025	9	3

The confusion matrix provides further insight into the direction and asymmetry of the categorical discrepancies. Of the 50 observed Dry cases, none were classified as Dry by the RF predictions; 14 were classified as Normal and 36 as Wet. Among the 84 observed Normal cases, 42 were correctly classified as Normal, while the remaining 42 were classified as Wet. For the 46 observed Wet cases, 27 were correctly classified as Wet, 12 were classified as Normal, and 7 were classified as Dry. Thus, the most pronounced discrepancy occurred in the Dry category, where none of the observed Dry conditions were reproduced by the RF predictions and most were instead represented as Wet.

Table 2. Confusion matrix of observed and Random Forest-predicted rainfall-condition categories, January–December 2024.

Observed \ RF-predicted	Dry	Normal	Wet	Total
Dry	0	14	36	50
Normal	0	42	42	84

Observed \ RF-predicted	Dry	Normal	Wet	Total
Wet	7	12	27	46

The absence of any Dry-to-Dry correspondence should be interpreted in the context of the substantially different category frequencies between the two datasets. Observed rainfall contained 50 Dry classifications, whereas the RF predictions contained only 7 Dry classifications. Therefore, the discrepancy in the Dry category during the full-year evaluation cannot be explained by a simple spatial-temporal displacement of an equal number of Dry classifications. Instead, the RF predictions substantially underrepresented the observed Dry category.

The spatial distribution of this discrepancy also varied among the ZOMs. In ZOM 46, all 12 observed Dry cases were classified as Wet by the RF predictions, with no RF-predicted Dry cases. In ZOM 47, all 8 observed Dry cases were likewise classified as Wet. ZOM 49 contained 9 observed Dry cases, of which 6 were classified as Wet and 3 as Normal. ZOM 45 and ZOM 48 showed somewhat more mixed patterns, although neither reproduced all observed Dry cases. These differences indicate that the underrepresentation of Dry conditions occurred across multiple ZOMs but with different magnitudes and category-transition patterns.

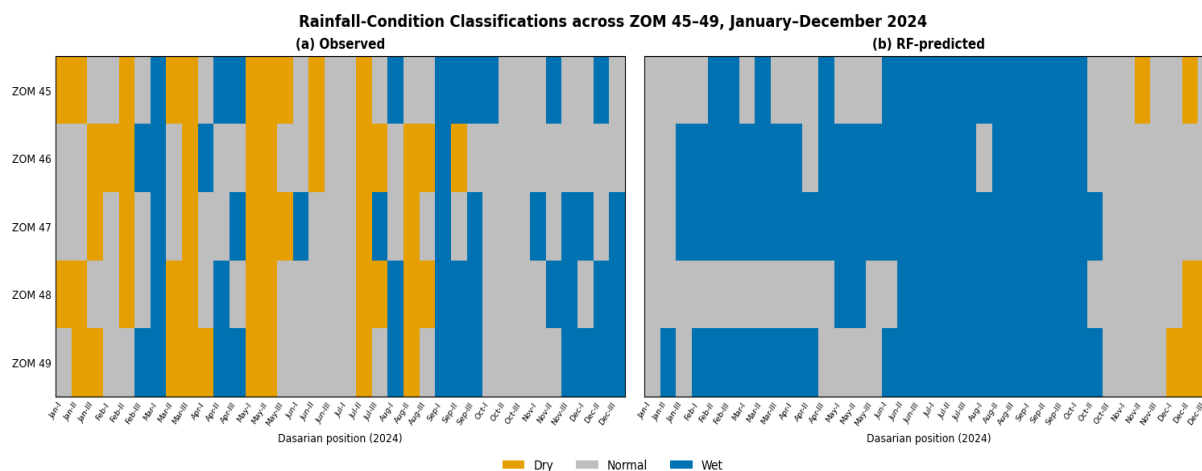


Figure 6. Heatmap of rainfall-condition classifications (Dry/Normal/Wet) for January–December 2024. Panel (a): observed rainfall-condition pattern. Panel (b): RF-predicted rainfall-condition pattern.

Figure 6 further illustrates the spatial and temporal differences between the observed and RF-predicted rainfall-condition patterns across the five ZOMs. The observed classification pattern contains a substantially larger number of Dry periods distributed across the year, whereas the RF-predicted pattern is dominated more strongly by Normal and Wet classifications and contains relatively few Dry periods. The contrast is particularly evident in ZOM 46 and ZOM 47, where observed Dry conditions are frequently represented as Wet by the RF predictions. In ZOM 49, the discrepancy becomes especially pronounced toward December, when the RF predictions classify all three December dasarians as Dry while the corresponding observed conditions are classified as Wet. Similar Wet-to-Dry reversals also occur in December for ZOM 48 and in December Dasarian II for ZOM 45. These patterns indicate that the categorical differences are distributed across both space and time rather than being confined to a single ZOM or a single period. The continuous rainfall comparison in Figure 3 provides further context for these categorical discrepancies. The RF predictions generally reproduce the broad seasonal evolution of rainfall but tend to exhibit smoother temporal variations than the observed series. Several observed rainfall values during November–December exceed their corresponding climatological P75 thresholds, whereas the RF predictions remain substantially lower and, in some cases, fall below P25. For example, in ZOM 49 during December, the observed rainfall values were 158, 205, and 219 mm, while the corresponding RF predictions were approximately 79.8, 75.6, and 73.6 mm. Because the P25 thresholds for these three periods were approximately 87.3, 87.5, and 79.6 mm, respectively, the observed values were classified as Wet whereas the RF predictions were classified as Dry. This illustrates how differences in continuous prediction magnitude can translate into categorical reversals when predictions are evaluated against fixed climatological boundaries.

3.4 Implications for Agricultural Interpretation

The observed and RF-predicted rainfall-condition patterns provide a climatology-relative perspective for interpreting rainfall conditions relevant to agricultural activities in the study area. The observed 2024 rainfall pattern shows substantial variation in Dry, Normal, and Wet conditions across the five ZOMs and 36 dasarian periods. In contrast, the RF-predicted pattern contains substantially fewer Dry classifications and a greater number of Wet classifications. This difference indicates that the observed and RF-predicted datasets provide different representations of rainfall conditions during the 2024 evaluation year and should therefore be interpreted separately when considering agricultural applications.

Table 3. Observed and RF-predicted rainfall-condition distributions by ZOM, January–December 2024.

ZOM	Observed Dry	Observed Normal	Observed Wet	RF Dry	RF Normal	RF Wet
45	10	14	12	2	16	18
46	12	14	10	0	13	23
47	8	17	11	0	13	23
48	11	19	6	2	14	20
49	9	20	7	3	12	21

The categorical differences are particularly relevant when rainfall conditions are interpreted relative to local climatology. The observed rainfall contains 50 Dry, 84 Normal, and 46 Wet classifications, whereas the RF predictions contain 7 Dry, 68 Normal, and 105 Wet classifications. The confusion matrix further shows that none of the 50 observed Dry cases were reproduced as Dry by the RF predictions, while 36 were classified as Wet. These discrepancies indicate that agricultural interpretations based on the RF-predicted rainfall-condition pattern could differ substantially from those based on the observed rainfall pattern. Therefore, the RF-derived categorical pattern should be treated as a model-based representation of rainfall conditions rather than as a direct substitute for the observed rainfall condition.

From an agricultural perspective, the rainfall-condition categories can be used as preliminary climatological information for identifying periods that may warrant further investigation. However, the Dry, Normal, and Wet categories in this study are defined using ZOM- and dasarian-specific P25 and P75 thresholds derived from the 1993–2022 historical rainfall distribution. These thresholds describe the relative position of rainfall within the local climatology and are not crop-specific agronomic thresholds. Consequently, the categorical results should not be interpreted as definitive recommendations for tobacco planting periods.

A more comprehensive agricultural interpretation would require the integration of rainfall conditions with crop phenology, soil moisture, soil characteristics, water availability, and validated agronomic rainfall requirements for Besuki Na-Oogst tobacco. In addition, the present evaluation covers a single year, January–December 2024, and focuses on categorical correspondence rather than independent validation of the numerical RF prediction performance. The results should therefore be interpreted as a climatology-relative assessment of rainfall-condition representation and as a basis for further agricultural and model-validation analysis rather than as a standalone planting recommendation.

3.5 Limitations and Interpretation

Several limitations should be considered when interpreting the categorical discrepancies identified in this study. First, the evaluation covers only one year (January–December 2024). Although 50 observed Dry cases were identified, none of these cases were reproduced as Dry by the RF predictions. This result should therefore be interpreted as a finding specific to the evaluated 2024 dataset and should not be generalized as evidence of a systematic limitation of Random Forest rainfall prediction.

Second, the present analysis focuses on the climatology-relative categorical representation of RF-predicted rainfall rather than providing a comprehensive independent validation of the numerical RF model. The categorical discrepancies therefore indicate differences between observed and predicted rainfall conditions under a common climatological reference, but they do not by themselves establish the specific cause of the model behaviour. In particular, the analysis does not separately quantify prediction bias, residual characteristics, feature contributions, or model sensitivity around the climatological thresholds.

Third, the P25 and P75 thresholds represent the relative position of rainfall within the historical distribution for each ZOM and dasarian and are not agronomic thresholds for tobacco suitability. Consequently, a Dry, Normal, or Wet classification indicates a relative climatological condition rather than a direct assessment of whether a particular period is suitable for tobacco planting. Differences between observed and predicted rainfall can also result in categorical changes when values fall near or across the fixed P25 and P75 boundaries.

Finally, the historical climatological reference is based on 30 years of observed rainfall (1993–2022), whereas the categorical evaluation is limited to the 2024 period. The findings would therefore benefit from evaluation across multiple independent years and from complementary analysis of continuous prediction errors, predictor contributions, and sensitivity to the P25 and P75 thresholds. Such analyses could help determine whether the observed categorical discrepancies are persistent across years and whether they are associated primarily with the numerical prediction behaviour, the predictor information used by the RF model, or the conversion of continuous rainfall predictions into climatology-relative categories.

3.6 Discussion

The results demonstrate that rainfall-condition classification is strongly influenced by the spatial and temporal characteristics of the climatological reference used for evaluation. The 30-year historical rainfall record showed substantial variation across ZOM 45–49 and calendar-dasarian positions, with relatively low rainfall during August–September and increasing rainfall toward November–December. The large differences in climatological rainfall ranges, such as the P25 of approximately 0.03 mm for September Dasarian I in ZOM 48 and the P75 of approximately

187.9 mm for December Dasarian III in the same ZOM, indicate that a common absolute rainfall threshold would not adequately represent local rainfall conditions. Therefore, the use of ZOM- and dasarian-specific P25 and P75 thresholds provides a more context-sensitive basis for distinguishing Dry, Normal, and Wet conditions. This finding is consistent with previous studies emphasizing the importance of local climatology and temporal rainfall characteristics in precipitation assessment and forecasting [1], [2], [3], [7], [12].

The observed and RF-predicted rainfall produced substantially different categorical distributions despite generally following a similar broad seasonal rainfall pattern. Observed rainfall resulted in 50 Dry, 84 Normal, and 46 Wet classifications, whereas RF predictions resulted in only 7 Dry, 68 Normal, and 105 Wet classifications. This indicates that the RF predictions tended to represent rainfall conditions as Normal or Wet more frequently and substantially underrepresented Dry conditions. At the continuous level, the RF predictions were able to reproduce the general seasonal evolution of rainfall but exhibited smoother temporal variations and, in several periods, lower rainfall magnitudes than the observations. Such behavior is important because Random Forest is designed to represent nonlinear relationships through an ensemble of decision trees, while the resulting predictions may not reproduce all short-term fluctuations in the observed rainfall series [18], [21]. The present findings therefore indicate that reproducing the broad seasonal pattern does not necessarily ensure that the predicted rainfall will reproduce the same climatological condition category.

A particularly important finding is the strong asymmetry in categorical discrepancies, especially for the Dry category. None of the 50 observed Dry cases were reproduced as Dry by the RF predictions; instead, 14 were classified as Normal and 36 as Wet. Conversely, all seven RF-predicted Dry cases corresponded to observed Wet conditions. This pattern resulted in an overall categorical agreement of only 38.33% and a Cohen's kappa of 0.071, indicating slight chance-corrected agreement. The absence of Dry-to-Dry correspondence should not, however, be interpreted directly as evidence that the RF model systematically fails to predict dry rainfall conditions. The RF output contained only seven Dry classifications compared with 50 Dry classifications in the observations, indicating that the two datasets had substantially different category frequencies. This distinction is important because categorical agreement depends not only on the magnitude of continuous prediction errors but also on whether predictions fall on the same side of fixed climatological boundaries. Similar considerations have been emphasized in climatology-based precipitation verification, where forecast categories are evaluated relative to a common climatological reference [7], [8], [14], [20].

The spatial and temporal analysis further indicates that the categorical correspondence was not uniform across the five ZOMs. Agreement ranged from 44.44% in ZOM 46 ($\kappa = 0.250$) to 30.56% in ZOM 47 ($\kappa = -0.042$), while ZOM 45 and ZOM 48 both achieved 41.67% agreement and ZOM 49 achieved 33.33%. The discrepancies were also expressed differently across locations and periods. In ZOM 46 and ZOM 47, observed Dry conditions were frequently classified as Wet by the RF predictions, whereas ZOM 49 showed particularly strong reversals during December. For example, observed rainfall in ZOM 49 during the three December dasarians reached 158, 205, and 219 mm, while the corresponding RF predictions were approximately 79.8, 75.6, and 73.6 mm. Because the corresponding P25 thresholds were approximately 87.3, 87.5, and 79.6 mm, the observed values were classified as Wet while the RF predictions were classified as Dry. This example demonstrates that categorical reversals can occur even when the model broadly follows the seasonal rainfall cycle, particularly when predicted values are close to or cross the climatological P25 and P75 boundaries. Such spatial and temporal variability is consistent with previous studies showing that rainfall prediction skill can differ across locations and forecast periods because of differences in local rainfall regimes and climate variability [2], [3], [9], [10].

The findings also highlight the importance of distinguishing continuous prediction performance from categorical climatological correspondence. A rainfall prediction may appear reasonable in terms of its general seasonal trajectory but still produce a different Dry, Normal, or Wet category when evaluated against a fixed historical threshold. Conversely, a numerical difference between observed and predicted rainfall does not necessarily lead to a categorical disagreement when both values remain within the same climatological interval. The proposed framework therefore provides information that cannot be obtained from numerical prediction metrics alone. This complements previous rainfall-prediction studies that primarily evaluate model performance using continuous measures or direct rainfall classification [18], [19], [21], [22]. By applying identical ZOM- and dasarian-specific thresholds to both observed and predicted rainfall, the present approach isolates the categorical correspondence under a common historical reference rather than allowing the prediction model to define its own climatological baseline.

Overall, the main contribution of this study is the demonstration that the categorical interpretation of rainfall predictions is highly dependent on the interaction between local climatology, temporal rainfall variability, and prediction magnitude. The use of a 30-year historical baseline and fixed ZOM $\times$ dasarian P25–P75 thresholds provides a consistent framework for evaluating whether RF-predicted rainfall reproduces the climatological condition represented by observations. However, the resulting Dry, Normal, and Wet categories should be interpreted as relative climatological conditions rather than absolute agricultural suitability classes. In particular, the substantial discrepancy in the Dry category indicates that RF-derived categorical patterns should be used as complementary model-based information rather than as substitutes for observed rainfall or standalone planting recommendations. A more comprehensive agricultural application would require integration with crop phenology, soil moisture, soil characteristics, water availability, and validated agronomic rainfall requirements, as also indicated by the scope and limitations of the present study [5], [6], [12], [13].

4. CONCLUSION

This study developed and applied a climatology-relative framework for evaluating rainfall-condition categories derived from observed and Random Forest (RF)-predicted dasarian rainfall in ZOM 45–49, Jember, East Java. Using a 30-year historical rainfall baseline (1993–2022), ZOM and dasarian specific P25 and P75 thresholds were established and kept fixed throughout the January–December 2024 evaluation period. This approach provided a common local climatological reference for classifying both observed and RF-predicted rainfall into Dry, Normal, and Wet conditions. The historical climatology showed a clear seasonal rainfall structure, with relatively low rainfall during August–September and increasing rainfall toward November–December. The historical distributions also differed among ZOMs and dasarian positions, supporting the use of location- and period-specific percentile thresholds rather than a single pooled threshold. The 2024 evaluation produced 50 Dry, 84 Normal, and 46 Wet classifications for observed rainfall, compared with 7 Dry, 68 Normal, and 105 Wet classifications for RF-predicted rainfall. Overall categorical agreement between observed and RF-predicted rainfall conditions was 38.33%, with a Cohen's kappa of 0.071. Agreement varied among the five ZOMs, with values ranging from 30.56% to 44.44%. The most pronounced discrepancy occurred in the Dry category: none of the 50 observed Dry cases were reproduced as Dry by the RF predictions, while 14 were classified as Normal and 36 as Wet. Conversely, all seven RF-predicted Dry cases corresponded to observed Wet conditions. These results demonstrate a substantial difference in the categorical representation of rainfall conditions between the observed and RF-predicted datasets during the 2024 evaluation year. The continuous comparison further showed that the RF predictions generally reproduced the broad seasonal evolution of rainfall but exhibited smoother temporal variations and, in several periods, lower rainfall magnitudes than observed. Differences in prediction magnitude can result in categorical reversals when predicted values fall across the fixed P25 and P75 climatological boundaries. However, the present analysis does not provide sufficient evidence to attribute these discrepancies to a specific modelling mechanism. The proposed framework therefore provides a complementary perspective for evaluating rainfall predictions relative to local historical climatology. The resulting Dry, Normal, and Wet categories represent relative climatological conditions and are not agronomic thresholds for tobacco suitability. Accordingly, the RF-derived categorical patterns should not be interpreted as direct substitutes for observed rainfall conditions or as standalone planting recommendations. Multi-year evaluation, independent numerical validation of RF predictions, analysis of prediction errors and predictor contributions, and integration with agronomic indicators are required to assess the persistence and practical applicability of the identified rainfall-condition patterns.

5. DECLARATIONS

5.1 Author Contributions

Conceptualization: S. A, and Y.M.A;

Methodology: S. A, and Y.M.A;

Software: S. A, and U.P;

Validation: S. A, and F.N;

Formal Analysis: S. A, and Y.M.A;

Investigation: S. A, and U.P;

Resources: S. A, and Y.M.A;

Data Curation: S.A;

Writing Original Draft Preparation: S.A, and F.N;

Writing Review and Editing: S.A, and T.S;

Visualization: S. A, Y.M.A, and T.S;

5.2 Data Availability

The data used in this study were obtained from the East Java Climatology Station (Stasiun Klimatologi Jawa Timur) and are available upon request, subject to the data access policy of the institution.

5.3 Funding

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5.4 Institutional Review Board Statement

Not applicable.

5.5 Informed Consent Statement

Not applicable.

5.6 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.7 Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and took full responsibility for the final publication.

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