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INDIAN OCEAN DIPOLE (IOD) EVENTS BASED ON RAINY AND DRY SEASONS IN NUSA TENGGARA TIMUR (NTT), INDONESIA, WITH MACHINE LEARNING

Melly ARISKA[1,*], Sardianto Marcos SIAHAAN[1], Yenny ANWAR[2], Iin SEPRINA[3]

[1] Department of Physics Education, Universitas Sriwijaya, Indralaya, Indonesia
[2] Department of Biology Education, Universitas Sriwijaya, Indralaya, Indonesia
[3] Department of Communication System, Universitas Sriwijaya, Indralaya, Indonesia

Abstract

This study aims to analyze the occurrence of IOD in two main seasons, namely the rainy and dry seasons, at three meteorological stations in Nusa Tenggara Timur (NTT). This study examines nine extreme rainfall variables and the IOD index per season as a condition label (Positive, Neutral, Negative). The resulting Random Forest model achieves an overall accuracy of 92% and 100% recall for all possible IOD events. The results also reveal r95p, Rx5day, and r99p are the most powerful indicators in distinguishing the IOD phase, followed by significant contributions from CDD and prcptot. The main contribution of this study lies in demonstrating the effectiveness of Random Forest for IOD phase classification based on extreme rainfall data, identifying the top three features as key predictors, and providing a data-driven framework that is ready to be integrated into a hydrometeorological early warning system.

***Keywords**: Indian Ocean Dipole; DJFM season; JJAS season; Random Forest; Extreme rainfall; Classification*

Introduction

Global climate variability has become an important issue in meteorology and climatology studies, especially in the context of changes in extreme rainfall patterns that have a wide impact on the agricultural sector, water resources, and disasters [1]. One of the main climate phenomena that affects rainfall dynamics in tropical regions, including Indonesia, is the IOD. IOD is a phenomenon of ocean-atmosphere interaction in the Indian Ocean, which is characterized by differences in sea surface temperatures between the western and eastern parts of the ocean. Previous studies, such as those conducted by Ward et al. [2] and Putra et al. [3], have shown that positive and negative IOD events significantly affect rainfall distribution in the Indonesian region, including the NTT region, which has semi-arid climate characteristics.

Many studies have been conducted to understand the relationship between IOD and rainfall anomalies; however, most of them are still descriptive and have not explicitly linked extreme rainfall parameters with IOD event labels using machine learning approaches [3], [4], [5]. Therefore, this study aims to build an IOD event classification model based on nine extreme rainfall parameters, such as prcptot, CDD, and r95p, which are calculated from observation data from three meteorological stations in NTT, namely Umbu Mehang Kunda, El Tari Kupang, and Salahuddin Bima. Integration of seasonal rainfall extreme data with IOD event labels in a single classification framework based on a Random Forest Classifier is the main focus. Several previous studies only analyzed the relationship between IOD and rainfall in general or still on a spatial scale [6], [7]; this study offers a machine learning-based approach that utilizes local extreme statistical features as input to predict IOD conditions. This approach not only provides robust

* Corresponding author: mellyariska@fkip.unsri.ac.id

classification results with an accuracy of more than 80% but also highlights the most important features that are the main determinants in IOD identification, such as prcptot, CDD, and r95p [8], [9], [10]. Thus, it contributes to the development of more precise predictive models in order to support climate early warning systems in drought-prone areas such as NTT. With the development of analytical technology and the availability of historical weather data, the application of machine learning algorithms in climate analysis has become an increasingly widespread trend [11], [12], [13].

Several recent studies have demonstrated the potential of machine learning in the classification and prediction of global climate phenomena. For example, research by Zheng [14] utilized a support vector machine to detect El Niño Southern Oscillation (ENSO) patterns, while Schneider [15] integrated Random Forest and XGBoost to classify seasonal rainfall patterns in the South Asian region. However, there are still very few studies that explicitly link extreme seasonal rainfall parameters with the classification of IOD events using a supervised learning approach, especially in areas prone to drought and rainfall variability such as NTT.

This study builds an IOD event classification model based on a Random Forest Classifier using nine extreme rainfall parameters as input features. The labeling process of IOD events is distinguished based on the DJFM rainy season (December–March) and the JJAS dry season (June–September), which are then linked to rainfall observation data from three meteorological stations in NTT. The main contribution of this study is the development of a local data-based IOD classification system that is able to quantitatively identify extreme rainfall patterns and provide new understanding of the spatio-temporal influence of IOD on extreme weather variability. In addition, by displaying the feature importance of the model, this study provides insight into which parameters are most crucial in predicting IOD conditions, so that they can be utilized in early warning systems and data-based climate change mitigation strategies in the future.

Experimental part

Location

NTT is an archipelago province in the southeastern part of Indonesia consisting of the main islands of Flores, Sumba, and West Timor (Fig. 1). Geographically, this region is located in the transition zone between the wet tropics and dry areas, with varying topography ranging from lowlands to mountains.

Fig. 1. Map of Indonesia and Nusa Tenggara Timur (NTT)

This condition causes NTT to have distinctive climate characteristics, namely a semi-arid (dry) tropical type, different from most parts of Indonesia, which tend to be wet throughout the year. According to the Saji and Yamagata climate classification, most of the NTT region is included in climate zones D and E, which are characterized by a long dry season (6–9 months) and a relatively short and uneven rainy season [16], [17], [18]. Annual rainfall in NTT ranges between 800–1500 mm per year, with rainfall distribution strongly influenced by global conditions such as ENSO and IOD, which often cause climate anomalies in the form of extreme droughts or heavy rain in a short period of time [19], [20], [21]. Figure 1 shows the location of the NTT region in the Indonesian Archipelago in detail.

Materials

The data used consists of daily rainfall from three meteorological stations in NTT, namely Salahuddin Station, Umbu Mehang Kunda, and El Tari (Table 1). Each station has its own dataset that records the date and value of rainfall. This data is recorded daily and converted for monthly and annual temporal analysis to see the distribution and trends of rainfall over time. The observation years range from 1983 to 2019.

Table 1. Three Meteorological Stations in NTT

Stasions	Latitude	Longitude	Climate Parameters
Umbu Mehang Kunda	-9.667°	120.333°	CDD, CWD, prcptot, RX1day, RX5day, R10 and R20, R95p and R99p
El Tari	-10.171°	123.671°	
Salahuddin	-8.489°	118.769°	

The dataset is able to identify extreme weather patterns, model the relationship between rainfall and IOD categories (negative, neutral, and positive), and make predictions using machine learning approaches such as Random Forest. Through the process of combining data from the three stations and coding IOD labels based on season (DJFM and JJAS), this data allows for spatial and temporal analysis of IOD events and their impacts on rainfall in eastern Indonesia. Figure 2 presents the positions of 3 meteorological stations in the NTT Region.

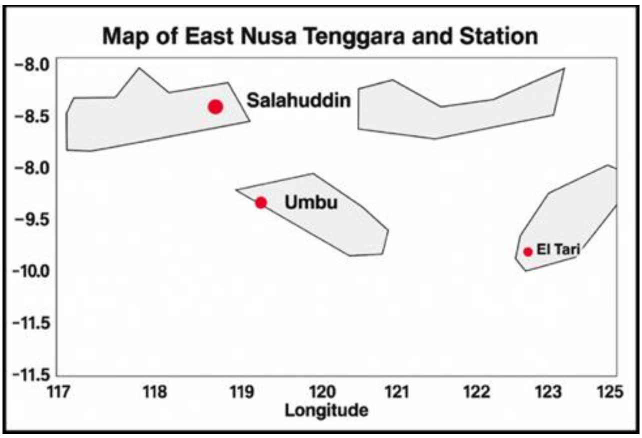

Fig. 2. Map of NTT and 3 stations

The use of data from several stations also enriches the accuracy of the analysis because it includes differences in topography and microclimate conditions between regions in NTT, which are important for understanding the risk of drought or flooding locally.

Methods

Each season is analyzed separately because the influence of IOD on rainfall can be very different depending on the time of year. Seasonal IOD index values are categorized into three classes, positive, neutral, and negative, based on thresholds of +0.4 and –0.4 [22]-[24]. These labels are then used as classification targets in machine learning models, specifically to evaluate how extreme rainfall characteristics such as prcptot, CDD, and r95p correlate with specific IOD categories. With this approach, the study can capture the relationship patterns between seasonal IOD dynamics and local climate anomalies more precisely. In preparing this manuscript, generative artificial intelligence (ChatGPT, Quillbot, and Grammarly) was employed to assist in language refinement and improvement of the abstract's readability. The use of AI was limited to linguistic editing only and did not affect data analysis, methodological procedures, or the interpretation of results.

Next, all the calculated rainfall and climate parameter data are combined into one main data frame, but it is still equipped with information about the observation station of origin. The separation of data by station allows spatial analysis so that it can be compared how rainfall patterns and IOD impacts vary across regions. In this way, the study not only identifies general trends but also highlights local differences in climate response to IOD events, which is very important for adaptation planning and water resource management policies at the regional level. The Random Forest Classifier algorithm is used as a machine learning method to build a classification model that is able to predict the category of IOD events based on extreme rainfall characteristics. This algorithm was chosen because of its superior ability to handle non-linear data, reduce the risk of overfitting, and produce good interpretations through feature importance analysis.

The model is trained using nine extreme rainfall index parameters as input features, namely prcptot, CDD, CWD, Rx1day, Rx5day, R10, R20, R95p, and R99p. Meanwhile, the IOD labels, divided into three classes (Positive, Neutral, and Negative), are used as output targets. Through this training process, the model is expected to be able to recognize patterns of relationships between extreme rainfall dynamics and IOD categories and provide accurate predictions to support regional climate analysis. Model performance evaluation is carried out using a classification report and feature importance analysis to understand the model's ability to classify IOD events [25]. The classification report provides quantitative information on key evaluation metrics such as precision, recall, and f1-score for each IOD class. Through these metrics, it can be seen to what extent the model is able to recognize patterns from each category accurately. The results show that features such as prcptot, CDD, and r95p have a significant contribution in determining the IOD classification, which provides important insights in understanding the relationship between extreme rainfall patterns and IOD phenomena in the study area.

Results and discussion

Distribution of IOD Events

NTT is a region that is included in the monsoon climate type, namely, an annual climate pattern influenced by the Asian Monsoon and the Australian Monsoon [26], [27].

Figure 3 displays two Fast Fourier Transform (FFT) periodogram graphs that illustrate the frequency components and dominant periods of rainfall in the NTT region based on monthly time series data.

The first graph (top) shows a frequency spectrogram, where the horizontal axis represents the frequency (1/month) and the vertical axis represents the magnitude of each frequency component. Two dominant peaks are visible at frequencies around 0.083 and 0.14, indicating a consistent seasonal pattern in the rainfall data. The inset in the upper right corner enlarges the frequency range of 0.05–0.20 to clarify the dominant peaks.

The second graph (bottom) presents data in the period domain, where the frequency is converted to periods (months) with a 1/f transformation. This graph shows that the dominant period of rainfall occurs around 12 months (1 year), as well as secondary peaks at around 6-7 months, which strengthens the indication of annual and sub-annual cycles in the rainfall pattern. The inset on the top right provides a zoom view of the period between 3 and 15 months. Overall, Figure 2 indicates that the rainfall pattern in NTT has a strong seasonal component with an annual period of a monsoon climate type, as well as sub-annual variations that also affect its distribution throughout the year. This analysis is very useful to support climate modeling, agricultural planning, and hydrometeorological disaster risk mitigation.

Figure 4 shows the monthly rainfall trends of three climatology stations; the horizontal axis shows time in years, while the vertical axis shows rainfall in millimeters (mm). Visually, it is apparent that El Tari station (green) has the largest rainfall fluctuations compared to the other two stations, with peak monthly rainfall that can exceed 800 mm in some years. In contrast, Umbu and Salahuddin stations show relatively lower and more consistent rainfall patterns, with monthly rainfall generally below 400 mm. All three stations show a clear seasonal pattern with an annual cycle, characterized by repeated peak rainfall every year. This indicates a strong influence of seasonal climate patterns in the region. Furthermore, despite the annual variation, there is no visually significant long-term trend of increasing or decreasing rainfall.

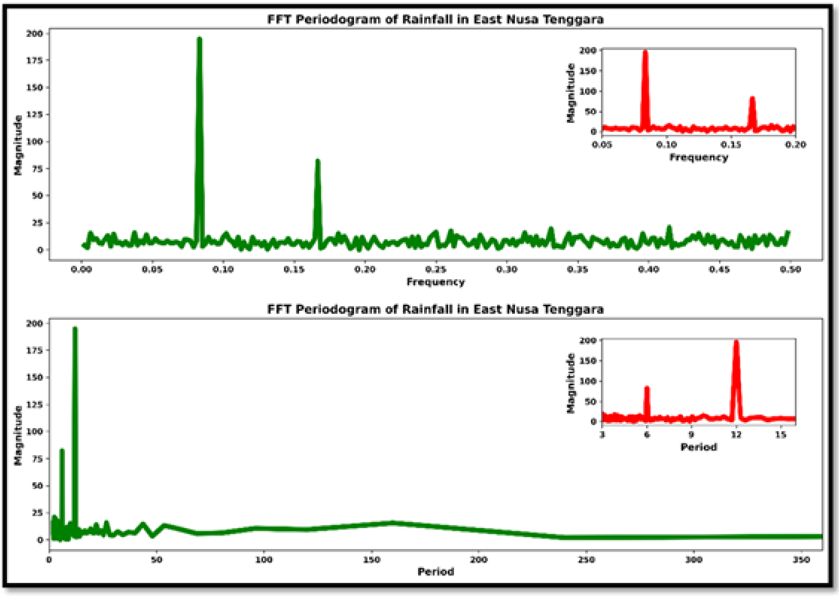

Fig. 3. FFT Spectrum of Rainfall in NTT

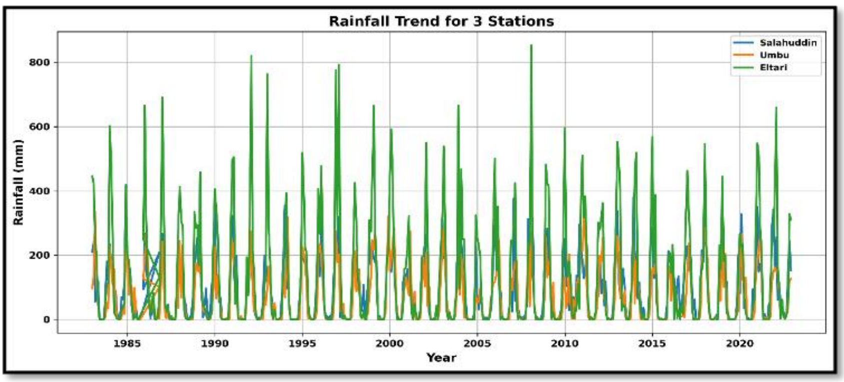

Fig. 4. Rainfall Trend for 3 Stations

Figure 5a shows the distribution of IOD labels during the JJAS season (June, July, August, September). Each station records the number of IOD events classified into three categories: neutral, negative, and positive. The visualization results show that Neutral IOD conditions dominate significantly at all three stations, with each recording as many as 30 events. Meanwhile, Negative and Positive IOD labels are recorded much less, with each around 5–6 events per station. This uniform distribution pattern indicates that during the observation period, neutral conditions occur more often than extreme conditions (negative or positive) across all locations. This finding is important in the context of the study because it shows the limited variation of IOD data that may affect the predictive power of the model in linking the IOD index to local climate variables, especially precipitation. With the dominance of neutral data, special attention is needed in the design of the spatio-temporal analysis model to ensure that the influence of extreme IOD conditions can still be detected representatively.

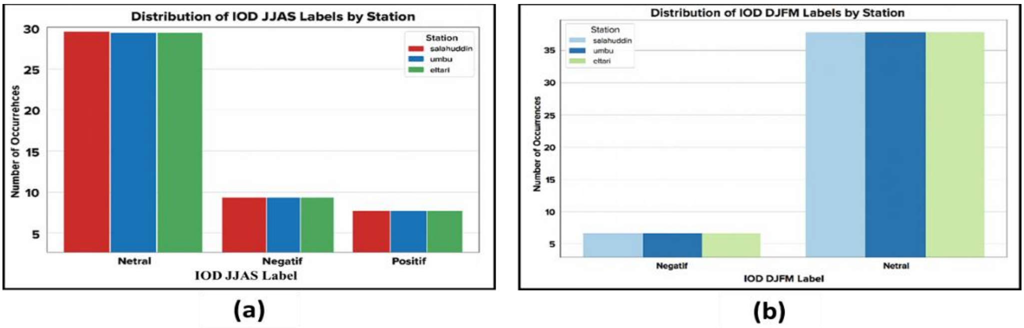

Fig. 5. Distribution of IOD Labels by Station **(a)** JJAS **(b)** DJFM

These results are in line with a study by Simanjuntak et al. [28], which showed that over the past two decades, the frequency of extreme IOD events tends to be less frequent than neutral conditions, but their impact on rainfall anomalies in the Indonesian maritime region is very significant when they occur. Likewise, research by Iskandar et al. [29] emphasized that the imbalance in the IOD distribution can cause bias in the prediction model if no data balancing or special modeling approaches are carried out, such as augmentation based on extreme data synthesis. Therefore, in this context, a machine learning approach that considers class imbalance is important to ensure model generalization to extreme IOD events, even though their frequency is low in historical data.

Figure 5b presents the distribution of IOD labels in the DJFM season. It can be seen that all stations show absolute dominance of Neutral IOD conditions, with the number of occurrences reaching around 37 cases for each station. In contrast, Negative IOD conditions only occur around 6 times at each station, and there is not a single Positive IOD occurrence in the DJFM season. This distribution confirms that during the rainy season in eastern Indonesia, the influence of extreme IOD is very rare, and neutral conditions dominate. This finding is very relevant in the context of the study because it provides an illustration that the analysis of the relationship between IOD and rainfall patterns in the DJFM season must consider the limitations of IOD condition variability. Therefore, the spatio-temporal model developed needs to strengthen its sensitivity to extreme conditions that rarely occur but can have a significant impact on weather anomalies in the study area.

This finding is in line with research by Lyon et al. [30], which showed that negative IOD is consistently associated with decreased rainfall in southern and eastern Indonesia, including East Nusa Tenggara, due to shifts in tropical convection patterns and decreased moisture supply from the Indian Ocean. In addition, research by Iskandar et al. [31] confirmed that both positive and negative IOD have an asymmetric impact on seasonal rainfall in Indonesia, where the negative phase is more often correlated with drought in the eastern region, while the positive phase is more inconsistent but still affects precipitation patterns. Therefore, information on rainfall distribution based on IOD labels is important to support the development of early warning systems and prediction models based on spatial-temporal data that are responsive to global climate fluctuations [32], [33], [34].

Figure 6a shows the distribution of the number of CDD during the DJFM season (December–March) based on the IOD labels, consisting of two categories: Negative and Neutral. From this visualization, it can be seen that the median CDD value for Neutral conditions is slightly lower than that for Negative IOD conditions. However, the range of CDD values in Neutral conditions is much wider, showing greater variation, including outliers in both categories. CDD in the Neutral label ranges from around 30 to more than 200 days, while in the Negative label it ranges from around 50 to 150 days. This indicates that in the DJFM season, Neutral IOD conditions allow for extreme fluctuations in the number of days without rain, while in Negative IOD conditions, the distribution of dry days tends to be more stable and centralized. These findings indicate the influence of IOD variability on drought patterns in the study area, which is important to consider in water resource management planning and drought risk mitigation.

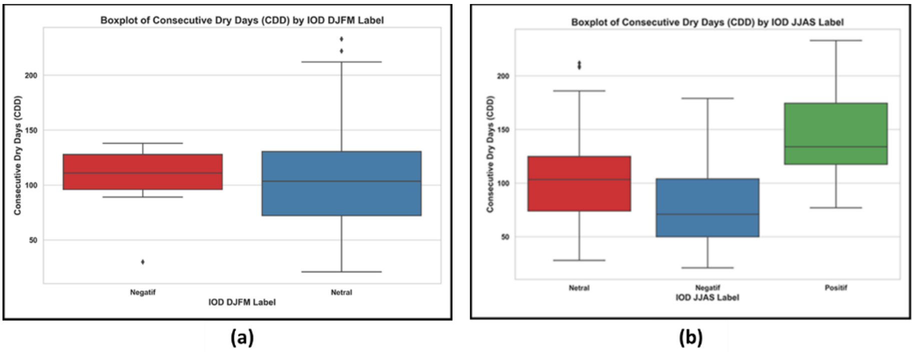

Fig. 6. Boxplot of CDD by IOD JJAS Label **(a)** DJFM **(b)** JJAS

Figure 6b explains the distribution of CDD or consecutive dry days based on the IOD category in the JJAS season. There are three categories of IOD labels: Neutral, Negative, and Positive. In the Neutral IOD condition, the median CDD value is around 100 days, with a fairly wide data distribution from around 30 to almost 190 days, and there are outliers reaching more than 200 days. Meanwhile, in the Negative IOD condition, the median CDD is lower, around 70 days, indicating that this condition tends to produce fewer consecutive dry days. The interquartile range also looks narrower than the other categories, with a minimum value of around 20 days. Conversely, the Positive IOD condition shows the highest median CDD, which is around 130 days, with the data distribution indicating a significant increase in dry days, even up to a maximum of around 230 days. In general, this visualization shows that Positive IOD events are associated with longer dry periods, while Negative IOD events tend to cause fewer consecutive dry days. This indicates a significant influence of the IOD phenomenon on the drought pattern in the Lombok region during the JJAS season.

This finding is in line with the research results of Lyon [30], which stated that the extreme Positive IOD contributed to decreased humidity and reduced rainfall in the southern region of Indonesia due to shifts in atmospheric circulation patterns and strengthening of easterly winds, which extended the dry season. In addition, a study by Annamalai et al. [35] showed that the frequency and intensity of extreme dry days in Indonesia increased significantly during the Positive IOD phase, especially in the eastern and southeastern regions, including Nusa Tenggara. Local research by Iskandar [36] also confirmed that the high CDD value in the Lombok region during the Positive IOD had a direct impact on increasing the risk of meteorological drought, especially in relation to the planting season and water availability. Therefore, the distribution of CDD based on the IOD phase provides a strong scientific basis for integrating global climate indicators into local drought monitoring and mitigation systems more adaptively [37], [38].

Figure 7 shows the Pearson correlation coefficient, where values approaching 1 indicate a strong positive correlation, while values approaching -1 indicate a strong negative correlation. From the visualization, it can be seen that rainfall features such as prcptot, r10, and r20 have a very high correlation with each other (above 0.90), indicating that they are closely related to each other in representing rainfall intensity and frequency. However, when associated with the IOD index in the JJAS season, only the CDD shows a moderately positive correlation to the JJAS IOD ($r = 0.38$), while other features such as prcptot, rx1day, and r99p show a very weak or even negative correlation to the JJAS IOD index. This indicates that the influence of IOD on rainfall parameters in the study area is not uniform and is more prominent on the drought indicator than the extreme rainfall indicator. This finding is important in designing spatio-temporal machine learning model features and shows the great potential of utilizing CDD as a key indicator to detect the impact of IOD in the central part of Indonesia in the context of climate data-based learning.

These results are consistent with a study by Nur'utami et al. [39], which showed that changes in climate patterns due to the IOD are more evident in drought indicators than extreme rainfall, especially in tropical regions that have high sensitivity to tropical ocean anomalies. This study also confirms that the IOD signal has a non-linear relationship with precipitation extremes, which makes some rainfall parameters difficult to capture statistically without a dynamic feature-based approach. In addition, research by Robial et al. [40] in eastern Indonesia showed that CDD has the highest sensitivity to IOD index variations compared to other extreme parameters, making it a prime candidate for developing a machine learning-based drought prediction model. Therefore, the correlation results shown in Figure 11 provide strong support for using CDD as a priority feature in developing a climate data-based early warning system for the Nusa Tenggara region and its surroundings.

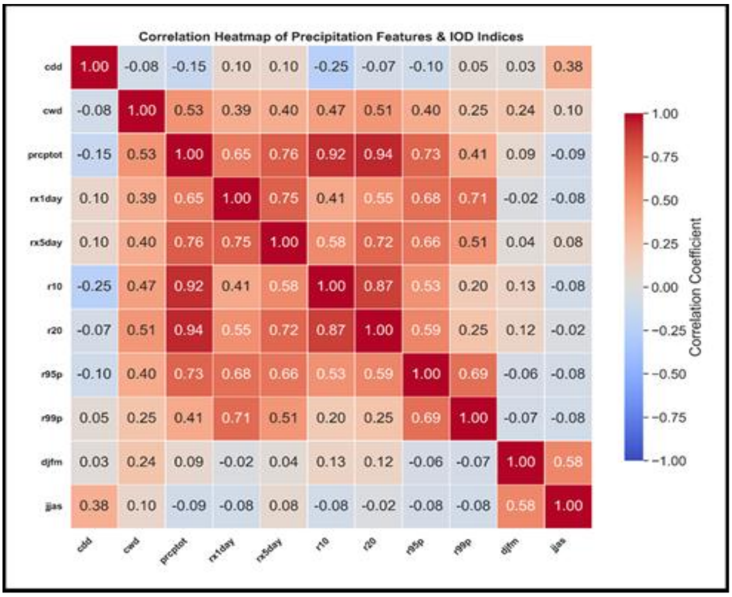

Fig. 7. Correlation Heatmap of Precipitation Features & IOD Indices

Furthermore, the correlation between IOD indices in DJFM (December–March) and JJAS (June–September) seasons shows moderate values to each other (r = 0.58), indicating the interseasonal linkages in regional climate patterns. However, most of the rainfall features have low correlations to both seasonal indices, indicating that although IOD plays a role as a global climate factor, its contribution to daily rainfall variability at local scales requires more complex and contextual modeling, such as machine learning-based spatio-temporal approaches. Therefore, this analysis provides a solid foundation for filtering the most relevant and sensitive features to IOD changes to improve prediction accuracy in adaptive learning-based environmental systems.

The Random Forest Classifier model is used to identify the most influential features in determining the classification of IOD events. The results of the feature importance analysis show that prcptot ranks first as the most contributing variable. This reflects that the accumulation of rainfall during the season is closely related to IOD conditions, where ocean and atmospheric anomalies can trigger a significant increase or decrease in rainfall in affected areas such as NTT. High or low prcptot data can be an early indicator of a particular IOD phase, especially when associated with the phenomenon of strengthening or weakening convection in the Indian Ocean. In addition, the CDD and r95p features also contribute significantly to the classification process. CDD represents a prolonged dry period, which usually occurs during a positive IOD phase when rainfall decreases drastically in parts of Indonesia. Conversely, r95p measures the number of days with very heavy rainfall exceeding the 95th percentile, generally increasing during a negative IOD phase. These two features reflect the extreme nature of the rainfall pattern that occurs due to IOD fluctuations and help the model in recognizing the different characteristics of each IOD phase. Thus, the existence of these parameters is very important in predicting and understanding the hydrometeorological impacts of IOD dynamics. These important features are classified in Figure 8.

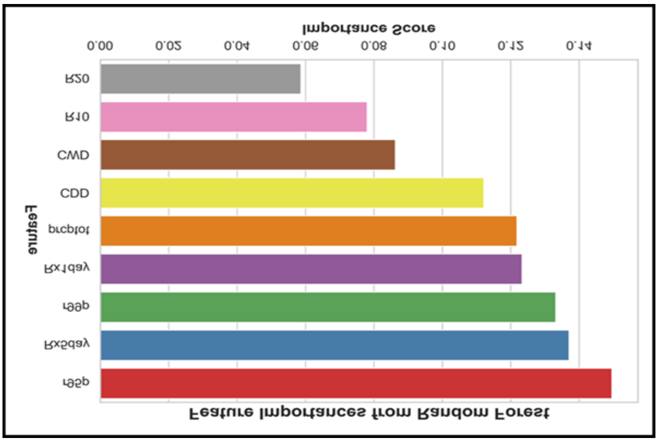

Fig. 8. Feature Importances from Random Forest

The Y-axis shows the feature names, while the X-axis displays the normalized importance scores. r95p is at the top with a score of around 0.15, indicating that the frequency of extreme rainfall is the most informative predictor. Close behind, Rx5day and r99p score around 0.14, confirming the importance of multi-day rainfall and extreme rainfall events in detecting the Dipole phase. Intermediate features such as Rx1day (~0.12) and prcptot (~0.12) show the importance of daily maximum values and seasonal total rainfall. CDD also has a significant role (~0.11), while other variables, CWD, R10, and R20, have lower importance (0.08-0.06), indicating that the number of wet days or days exceeding a certain threshold is less crucial in the model decision. Overall, the top three features, r95p, Rx5day, and r99p, indicate that the intensity and frequency of extreme rainfall are the main determinants of the IOD classification. That is, changes in total rainfall and wet-dry day duration have a strong relationship with the IOD dynamics in this region.

This finding is consistent with a study by As-syakur [41], which stated that the positive phase of the IOD is often associated with an increase in extreme rainfall events in parts of western Indonesia and conversely contributes to drought in the eastern region, so that extreme features such as r95p and Rx5day play an important role in identifying this pattern. Furthermore, a study by Aldrian and Susanto [7] emphasized that the use of percentile-based precipitation features (such as r95p and r99p) is more effective in detecting the impact of climate teleconnections due to their sensitivity to shifts in rainfall distribution due to sea surface temperature anomalies in the Indian Ocean. In addition, a study by Ariska et al. [42] proved that in the development of an ensemble learning-based prediction model, the extreme rainfall intensity feature contributed more to the accuracy of the IOD index classification than the total rainfall parameter or light rain frequency. Therefore, these results strengthen the understanding that spatio-temporal modeling based on machine learning needs to give higher weight to extreme precipitation features in detecting and projecting the influence of the IOD on regional climate variability.

Conclusions

This study shows that machine learning, especially Random Forest, is effective in classifying IOD events based on extreme rainfall parameter data. Most IOD events occur in the neutral category, with a tendency for negative IOD to increase in the JJAS season. Salahuddin Station shows the highest sensitivity to negative IOD. This study opens up opportunities for integrating machine learning models into regional climate monitoring systems. This study successfully identified patterns of IOD events in the DJFM and JJAS seasons at three meteorological stations (Salahuddin, Umbu, and El Tari) by utilizing extreme rainfall parameter data and the Random Forest algorithm. The exploration results show that IOD conditions are predominantly in the neutral category in both seasons, while negative events occur more frequently in JJAS, especially at Salahuddin Station. The Random Forest model trained using nine rainfall features, including total rainfall (prcptot), number of consecutive dry days (CDD), and extreme indices (r95p, r99p, Rx1day, Rx5day, R10, and R20), achieved an overall accuracy above 80%, with the best detection ability in the neutral class (100% recall).

These findings suggest that the intensity and frequency of extreme rainfall, together with the total rainfall volume and dry day duration, are key indicators in predicting the IOD phase; thus, this methodology can be used as a basis for early warning and mitigation systems for hydrometeorological disasters. The use of an ensemble approach that combines Random Forest with deep learning models or boosting methods (e.g., XGBoost) is worth considering to explore improvements in classification performance. In terms of application, the results of this model can be integrated into a web-based early warning system or mobile application that provides real-time information, so that local governments and policymakers can respond to potential hydrometeorological impacts more quickly and accurately

Acknowledgments

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