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AI-Deep Learning Based Agroclimatic Mapping for Ideal Planting Zone Classification in East Nusa Tenggara

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A B S T R A C T

East Nusa Tenggara (NTT) Province has varied climate characteristics, so agroclimatic mapping is important in adaptive agricultural planning. This study aims to map agroclimatic zones in NTT based on rainfall and air temperature using remote sensing techniques and the Convolutional Neural Network (CNN) model. The mapping results show that NTT consists of several agroclimatic zones with different levels of rainfall and temperature, which significantly affect cropping patterns and agricultural productivity. This mapping produces recommendations for farmers in determining the types of crops appropriate to each region's agroclimatic conditions. In areas with low rainfall, drought-resistant plant varieties and efficient irrigation systems are recommended. In addition, local governments can consider building reservoirs and ponds to increase resilience to the dry season. In terms of technology, the CNN model developed in this study has the potential to be further refined by adding more historical data and other environmental variables, such as vegetation indices from satellite imagery, to improve prediction accuracy. The implementation of artificial intelligence technology in agricultural planning in NTT can be a strategic step in increasing food security and supporting the sustainability of the agricultural sector in this region.

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1. INTRODUCTION

The agricultural topography potential of East Nusa Tenggara (NTT) Province is substantial. This region has made substantial contributions to a variety of agricultural sectors, such as food crops, horticultural crops, plantation crops, livestock, agricultural services, and hunting, forestry, and fisheries, despite its parched, arid environment and topography (Badan Pusat Statistik, 2024). The agricultural sector significantly influences the regional economy's structure. In 2023, the agricultural sector made the highest contribution to the Gross Regional Domestic Product (GRDP) at 29.31%, compared to other sectors. Non-rice agricultural land accounted for 74.04% of the GRDP, while rice field land accounted for 3.98% (Badan Pusat Statistik, 2024).

A decrease in agricultural yields is a consequence of unpredictable climate change. This is a result of modifications to cultivation schedules and patterns. Consequently, it is crucial to identify and classify agroclimatic conditions to identify plant species appropriate for specific climates (Faraslis et al., 2023). Tropical climate analysis has been conducted in Indonesia using agroclimatic categorization systems, including Schmidt-Ferguson and Oldeman. The objective of Oldeman's Agroclimatic Zone is to guarantee cultivation patterns based on monthly rainfall data accumulated for a minimum of 30 years. This zone emphasizes the Wet Month (BB) and Dry Month (BK) indicators (Fathurrahman et al., 2023). The primary variable in this method is rainfall data, which describes the agroclimatic conditions of a given region.

Nevertheless, the methodology must be updated to account for the more dynamic climate conditions arising from global climate change. Oldeman's agroclimatic zone map is antiquated, as it is predicated on historical rainfall data and neglects to consider contemporary climate variability. It disregards critical variables, including extreme weather, temperature, and humidity. This methodology must be revised to incorporate real-time data, advanced modeling, and multiple climate variables to guarantee accurate agricultural planning in climate change.

In terms of location and temporal distribution, rainfall is the most variable climate element (Alemu & Bawoke, 2020). The primary criterion for climate classification in Indonesia is rainfall (Putra et al., 2024). Even though meteorological stations are the primary criterion for observing rainfall data, the imbalance between the number of available observation stations and the observation area has not yet resulted in a high level of spatial representation. Climate analysis and agricultural planning are significantly influenced by remote sensing, which is exemplified by the utilization of Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) data (Auliyani & Wahyuningrum, 2021). Furthermore, CHIRPS data can produce data with a high correlation, covering a wider area and estimating rainfall with high accuracy (Aksu & Akgül, 2020; Cavalcante et al., 2020). Remote sensing rainfall data encompasses TRMM, GPM, and PERSIANN, in addition to CHIRPS. In contrast to other data that may have limited regional coverage or accuracy, CHIRPS was selected due to its high accuracy, global coverage, and excellent spatial-temporal resolution, which render it effective for climate analysis and agricultural planning.

Consequently, it may serve as an alternative to address issues with rainfall data. Agroclimatic is a scientific discipline investigating the correlation between climate conditions and agriculture (Maximova et al., 2019). This field encompasses variables such as temperature, rainfall, and humidity influencing crop productivity. Zone mapping is a critical component of agroclimatic analysis, as it aids in comprehending a region's climate characteristics and identifying the most appropriate agricultural strategy. Agroclimatic zone mapping is essential to facilitate adaptive agricultural planning in the NTT region, which is characterized by fluctuating rainfall patterns and a tendency to be arid. The Oldeman climate

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classification is one approach that can be implemented, categorizing regions according to the number of rainy and dry months in a year (Sumartono et al., 2021). Agroclimatic zone mapping is facilitated by CHIRPS data, which is particularly effective in identifying optimal planting season patterns (Aisyah et al., 2023). In addition, CHIRPS data can also be integrated with other remote sensing data to enhance the spatial resolution of agricultural climate mapping (Sandeep et al., 2021).

Agricultural analysis and agroclimatic mapping are among the numerous disciplines in which artificial intelligence and deep learning technology have developed rapidly. The classification of optimal planting zones with greater precision than traditional methods is made possible by integrating AI and deep learning, particularly in intricate climate variability. Deep learning has been demonstrated to enhance the accuracy of predictions in analyzing climate and rainfall patterns compared to conventional statistical methods (Endalie et al., 2022). Furthermore, utilizing remote sensing data and climate parameters by Convolutional Neural Network (CNN)-based AI models can further enhance the accuracy of agricultural area classification (Kattenborn et al., 2021; Ridwana et al., 2024). AI's capacity to analyze intricate spatial and temporal data facilitates enhanced efficiency and accuracy in sustainable agricultural planning.

The efficacy of AI and deep learning in agroclimatic mapping has been demonstrated in numerous studies, with deep learning models based on Recurrent Neural Networks (RNN) proving capable of more accurately identifying temperature and rainfall patterns, thus enabling more precise classification of planting zones (Ouma et al., 2022; Choudhary & Ghosh, 2023). Integrating AI with satellite data has also been shown to enhance the ability to identify land use changes (Janga et al., 2023). In addition, crop yield predictions can be optimized by employing deep learning techniques in conjunction with environmental and meteorological variables (Jabed & Murad, 2024; Khaki & Wang, 2019). Unlike previous research, this study concentrates on an agroclimatic mapping system based on AI deep learning. It can deliver a more accurate classification of planting zones in East Nusa Tenggara Province.

2. METHODS

2.1 Study Area

The agricultural sector encompasses over 50% of NTT's land, which indicates that agricultural production is the primary source of income for the community and the region. This investigation concentrates on the region of NTT, Indonesia (**Figure 1**), which boasts a geographical location of 118° —125° East Longitude and 8° —12° South Latitude.

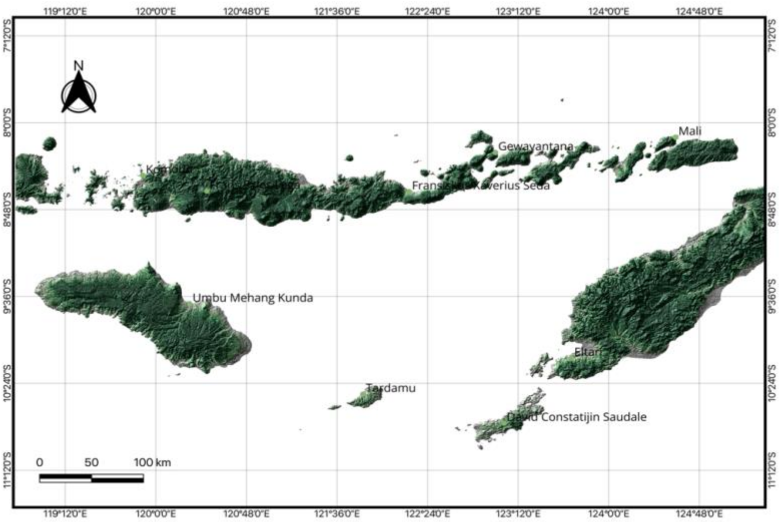

Figure 1. Study Area

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2.2 Tools and Research Data

This study utilizes BMKG climatology data and CHIRPS to make precise rainfall estimates. Data processing employs Python, TensorFlow, and Keras, with Google Earth Engine (GEE) enhancing large-scale analysis. QGIS is used for agroclimatic mapping visualization. Key climate attributes include temperature (Tn, Tx, Tavg), humidity (RH_avg), rainfall (RR), sunlight duration (SS), and wind parameters (ff_x, ddd_x, ff_avg, ddd_car). These factors influence hydrology, plant physiology, and weather patterns. **Table 1** displays the rainfall ranges based on four criteria.

Table 1. Rainfall Range

Rainfall	Information
0-20	Low (1)
21-50	
51-100	
101-150	Intermediate (2)
150-200	
201-300	
301-400	Height (3)
401-500	
>500	Very High (4)

The Oldeman climate classification method was employed to analyze the average monthly rainfall data to identify the agroclimatic zones. The Oldeman climate classification is determined by the consecutive occurrence of arid and rainy months. **Table 2** and **Table 3** illustrate the Oldeman climate classification.

Table 2. Oldeman climate classification provisions

Zone	Length of Wet Month (Rainfall >200)	Sub-Zone	Length of Dry Month (Rainfall <100)
A	>9 Months	1	<2 Months
B	7-9 Months	2	2-3 Months
C	5-6 Months	3	4-6 Months
D	3-4 Months	4	7-9 Months

Table 3. Agroclimatic zones and their relationship to cropping patterns

Climate Type	Agricultural System/Crop Pattern	Information
A	Suitable for continuous rice cultivation; however, production results may be diminished because of low solar radiation flux.	3 Short-duration Lowland Rice or 2 Lowland Rice + 1 Palawija
B1	Suitable for continuous rice planting, provided that meticulous planning is implemented. With high production, if harvested during the arid season, one secondary crop should be planted.	3 Short-duration Lowland Rice or 2 Lowland Rice + 1 Palawija

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B2	In the brief dry season, it is possible to plant one secondary crop and then plant two times as much rice with short-term varieties.	2 Lowland Rice + 1 Palawija
C1	It is possible to plant secondary crops twice and rice once.	1 Lowland Rice + 2 Palawija
C2, C3, C4	It is permissible to plant rice once, provided that secondary commodities are not cultivated during the arid season.	1 Lowland Rice + 1 Palawija
D1	Short-term rice, maximum production, in one-time, secondary crops	1 Lowland Rice + 1 Palawija
D2, D3, D4	It is possible that only one secondary crop or one rice planting will be feasible.	1 Lowland Rice or 1 Palawija
E	It is possible that only one secondary crop can be planted due to the excessive dryness.	1 Palawija

2.3 Data Analysis Techniques

The data undergoes preprocessing, including interpolation and normalization, before training deep learning models for agroclimatic classification. The dataset is split into training and testing subsets to learn climate variable correlations and evaluate model performance. Classification results are validated against historical data and agroclimatic maps using accuracy metrics. The final agroclimatic zoning map highlights agricultural potentials and recommends optimal sowing strategies for each zone, supporting climate-adaptive farming in East Nusa Tenggara. **Figure 2** illustrates the transfer learning process in Convolutional Neural Networks (CNN).

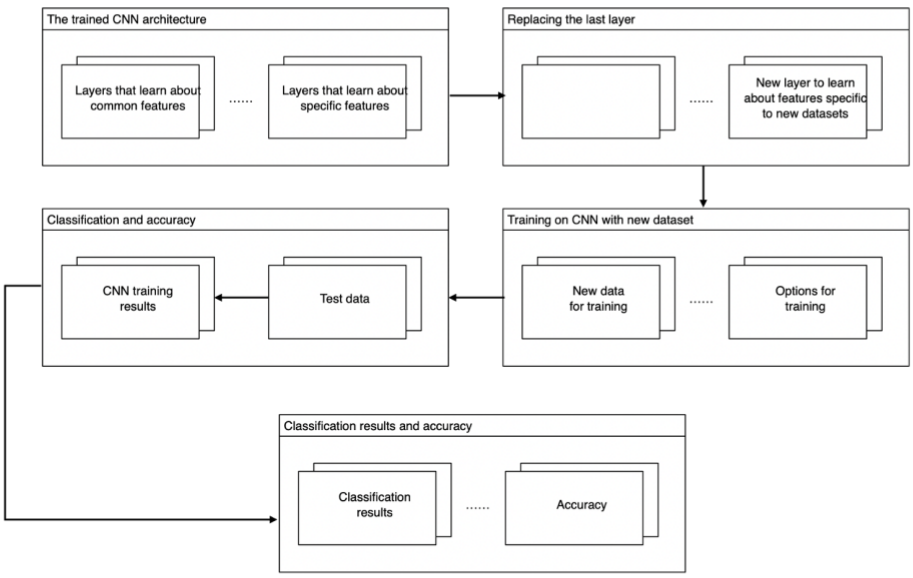

Figure 2. Flow of Transferred Learning Method Utilization with float64 and int64 data types

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Figure 3 illustrates the architecture and workflow of CNN for optimum cropping zone classification. The procedure begins with input climate data, which is then transmitted through a series of convolution and pooling layers for feature extraction. Each convolution layer is succeeded by a ReLU (Rectified Linear Unit) activation function. After feature extraction, the data is homogenized and transmitted to a fully connected layer for classification. Finally, a SoftMax activation function generates a probabilistic distribution of output classes. This diagram clearly visualizes the transition from the feature extraction stage to the classification stage in the CNN architecture, demonstrating how visual information is transformed into classifiable representations.

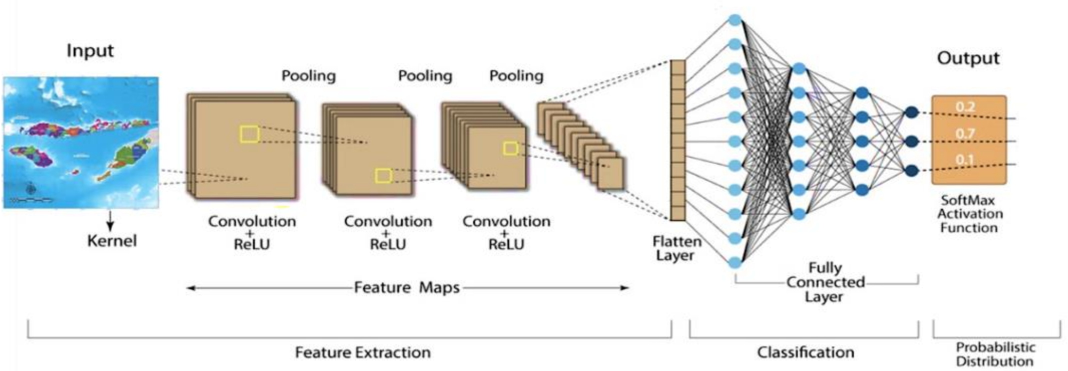
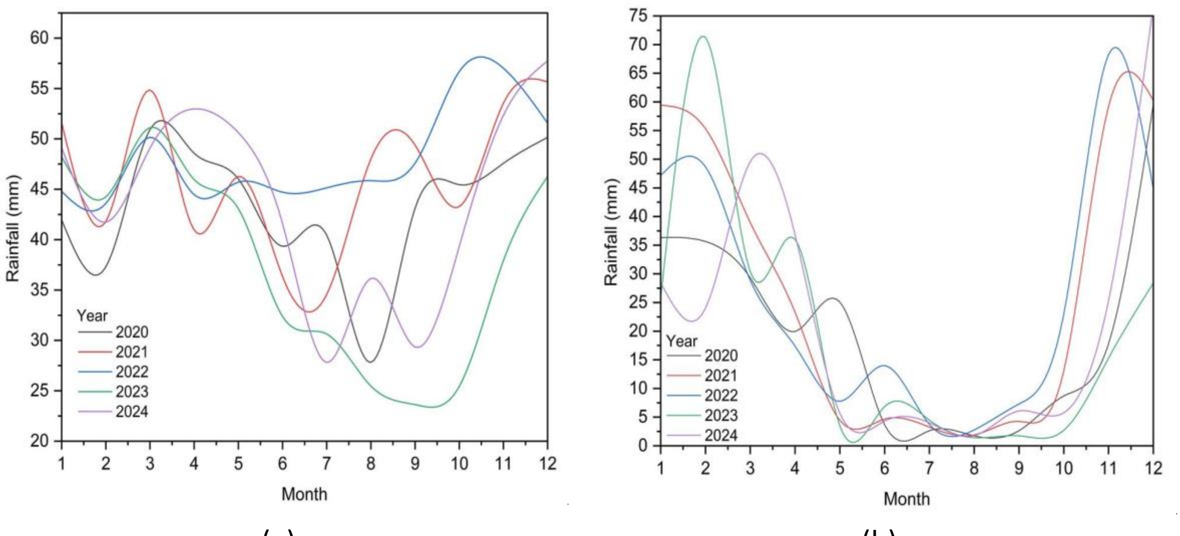


Figure 3. AI Deep Learning models

3. RESULTS AND DISCUSSION

3.1 Analysis of Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) Data



(a) (b)

Figure 4. Climate Hazards Group Infrared Precipitation with Stations (CHIRPS); (a) Indonesia, (b) Nusa Tenggara Timur

Figure 4 depicts Indonesia's monthly rainfall pattern (2020–2024) based on CHIRPS data. The fluctuation reflects Indonesia's tropical climate, with distinct rainy and drier seasons. At the national level (Panel a), rainfall remains relatively stable with seasonal maxima. In contrast, East Nusa Tenggara (NTT) (Panel b) experiences protracted dry periods (May–October) and heavy rainfall at year-end, verifying its drier monsoon climate. Climate variability, influenced by El Niño and La Niña, affects NTT's agriculture, particularly sowing schedules. Early or late rainy seasons disrupt sowing cycles, highlighting the need for accurate weather predictions and adaptive agricultural strategies in agroclimatic-challenging areas.

The use of 5-year data in this study is based on technological advancements, particularly AI modeling, which can provide a fairly accurate understanding of agro-climate patterns, even though the period used may be considered less representative for long-term climate conditions. Many references recommend using data for at least 30 years. However, prior research has shown that short-term data, when combined with advanced modeling techniques, can generate reasonably accurate projections for characterizing rainfall trends and their impacts on agriculture, especially in regions with significant climate fluctuations like NTT (Fung et al., 2020; Hachimi et al., 2023).

Figure 5 is a rainfall map from CHIRPS data for 2020–2024, depicting rainfall distribution in the NTT region with color variations reflecting rainfall intensity. Red dominates most of the land area, indicating high rainfall, possibly exceeding the annual average. This can be attributed to seasonal rainfall patterns influenced by monsoons and climate phenomena such as La Niña, which often increase rainfall in this region. In some areas, especially in the northern and eastern parts of the NTT region, zones are seen with yellow to green colors. Yellow indicates moderate rainfall, while green indicates lower rainfall. This could reflect areas with higher topography or those in the rain shadow due to mountains, thus receiving less rainfall than other areas.

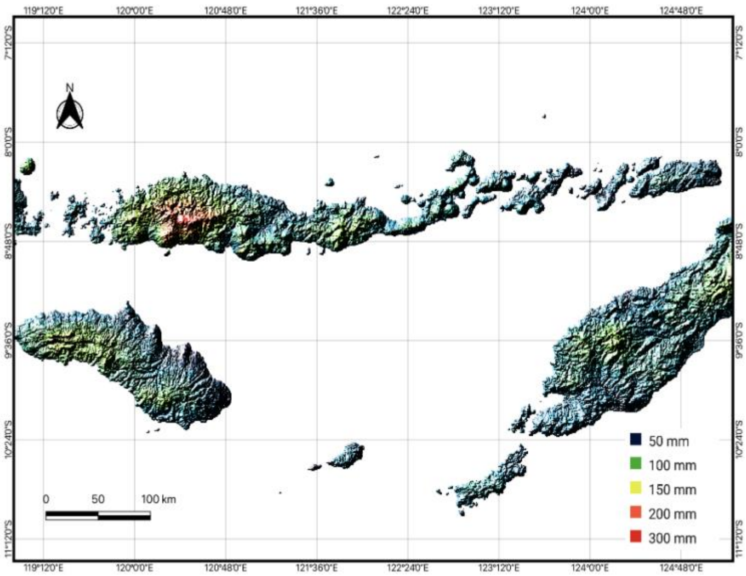


Figure 5. Rainfall map from 2020-2024 in NTT based on CHIRPS data

The results of the CHIRPS data analysis for the period 2020 to 2024 reveal variations in rainfall that reflect the dynamics of Indonesia's tropical climate and agroclimatic challenges in NTT. These findings are in accordance with previous studies that emphasize the impact of rainfall variability on the agricultural sector and water resources in areas with limited rainfall. The El Niño phenomenon, for example, tends to decrease rainfall in southern Indonesia, including NTT, leading to delayed monsoon seasons and an increased risk of drought (Karuniasa & Pambudi, 2022). This is in accordance with the rainfall pattern observed in CHIRPS data, where the dry season in NTT lasts longer with very limited rainfall from May to October. Furthermore, areas with an arid monsoon climate, such as NTT, experience rainfall patterns influenced not only by the annual cycle but also by interactions with global atmospheric systems like the Madden-Julian Oscillation (MJO) (Sudirman et al., 2023). CHIRPS data

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corroborate that despite the typical seasonal pattern, interannual variability remains significant, indicating that short-term atmospheric factors also play a role in rainfall dynamics.

3.2 Analysis of BMKG Meteorological Station Data

Figure 6 depicts the average monthly rainfall in BMKG stations, exhibiting seasonal fluctuations. Rainfall varies by location due to topography, proximity to the sea, and microclimate factors. Highlands like Manggarai receive more rain, while coastal areas like Rote Ndao remain arid.

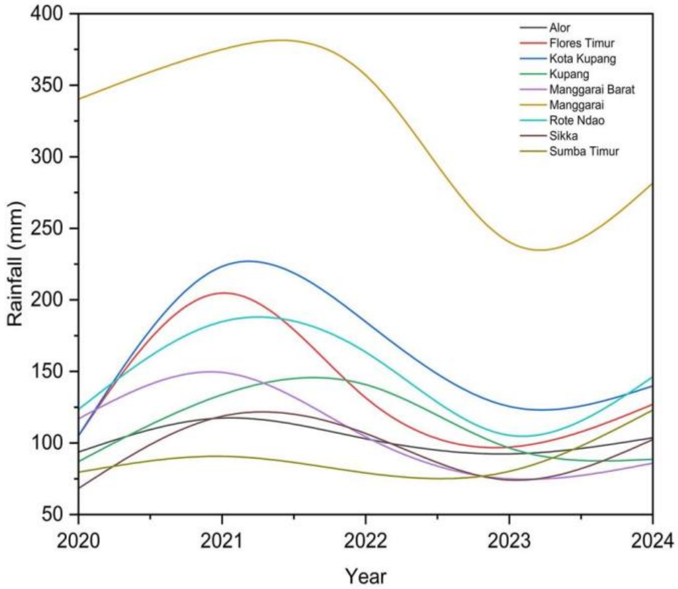
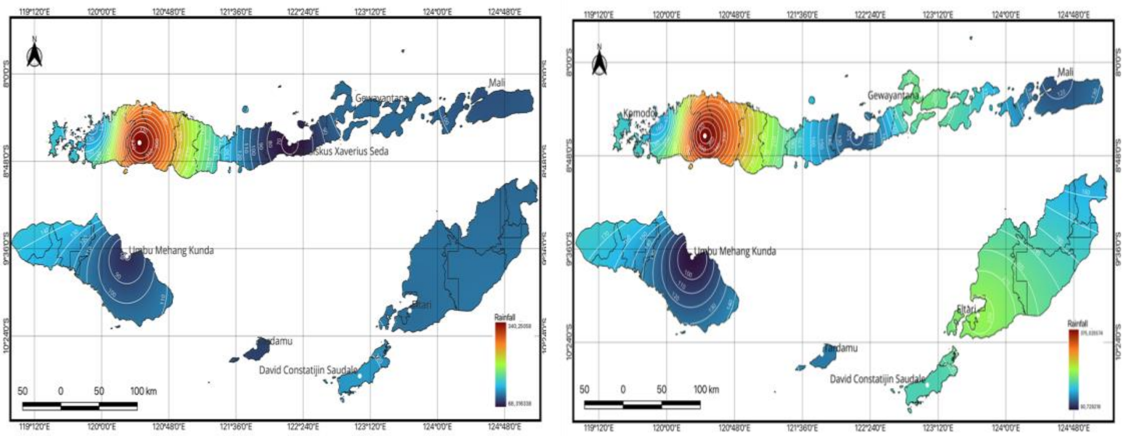


Figure 6. Average Rainfall from 2020 to 2024 Based on BMKG Meteorological Station data

This finding aligns with previous research indicating that rainfall variability in Indonesia, including NTT, is significantly influenced by the El Niño and La Niña phenomena (An et al., 2023). The comparison is that several meteorological stations reveal significant differences between years, most likely related to the influence of the global climate cycle. Additionally, differences in rainfall patterns across NTT are influenced by topography and distance from the sea, with higher rainfall observed in areas like Manggarai due to orographic effects, while coastal regions such as Rote Ndao tend to receive lower rainfall (Sekaranom et al., 2021).

(a) (b)



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(c) (d)

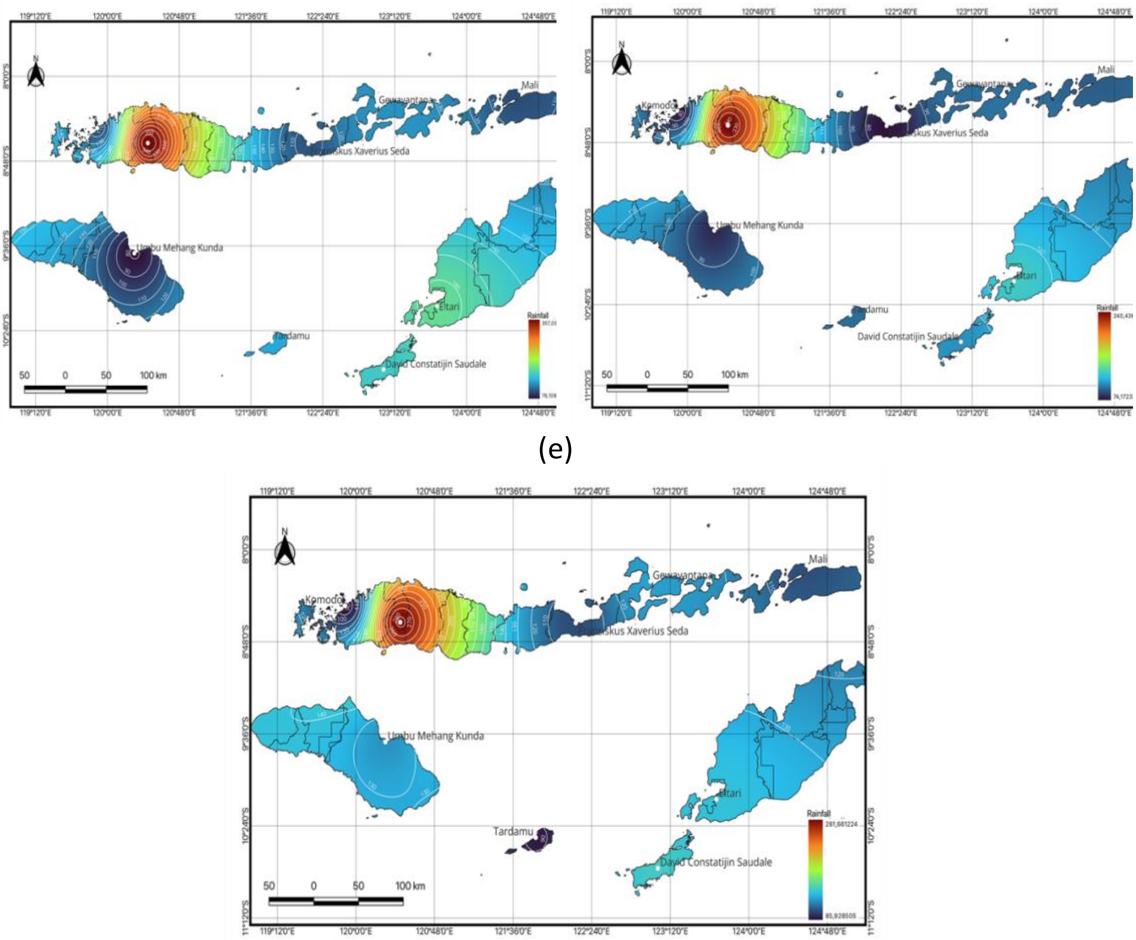

Figure 7. Classification of rainfall in each district and city in NTT; (a) 2020, (b) 2021, (c) 2022, (d) 2023, and (e) 2024.

A map of average rainfall and stormy days spanning the 30-year period 1991-2020 (**Figure 8**) is depicted as a comparison of BMKG data.

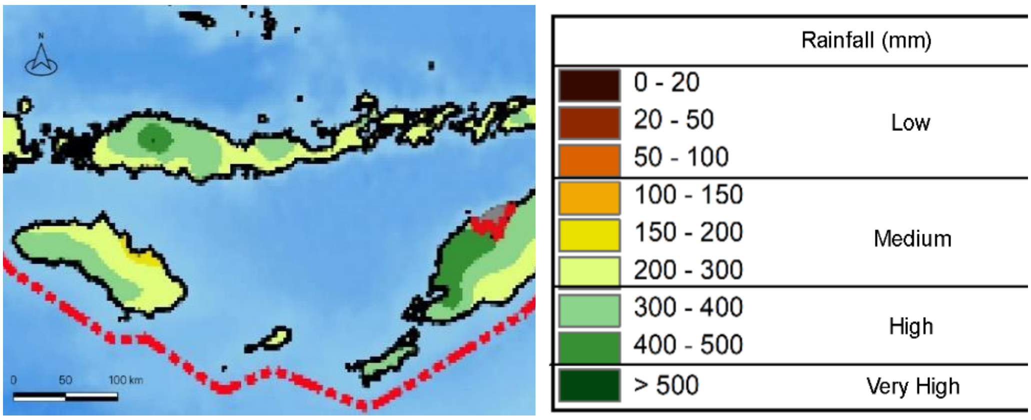

Figure 8. Map of average rainfall and rainy days for the period 1991-2020 (BMKG, 2021)

The mapping results show that East Nusa Tenggara Province has six agroclimatic zones, namely B2, C3, D3, D4, E3, and E4 (**Figure 7**). Zone B2 is located around the peak of Mount Ranakah, while zone C3 is distributed across the districts of Central Sumba, East Manggarai, West Sumba, and Manggarai Regency. Zone D3 covers Sumba Island, Malaka, East Manggarai, Belu, West Manggarai, North Central Timor, Nagekeo, Ngada, South Central Timor, and

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Manggarai. Zone D4 is in the southern portion of the province, encompassing Kupang and Rote Ndao Regencies. Zone E3 was identified in the Ende Regency, while zone E4 dominates the northeastern region, including the Alor and Lembata Regencies.

The change in the Oldeman climate type in East Nusa Tenggara Province towards arid conditions in several locations has impacted the cropping pattern system. Land suitability for rice cultivation has decreased, while land has become more suitable for secondary commodities (Rejekiningrum et al., 2022). Several areas, such as Alor, Ende, Lembata, Sikka, Sabu Raijua, Nagekeo, East Flores, West Manggarai, and East Sumba, have changed from zones E4 to C3, D3, and D4. These areas that previously only allowed one planting of secondary crops based on rain can now sustain a planting pattern with one rice and one secondary crop (C3) or only one rice or secondary crop (D3 and D4). The regencies of Rote Ndao, Kupang, Belu, North Central Timor, West Sumba, East Sumba, West Manggarai, Manggarai, South Central Timor, East Manggarai, Central Sumba, and Kupang City have shifted from zone D4 to C3 and D3. This transition indicates that areas previously appropriate for two rice plantings and one rice crop are now more suitable for a planting pattern of one rice and one other crop. In addition, the Gunung Ranakah area has changed from climate type B2 to C2, meaning that land that was previously good for two plantings and one crop is now more suitable for one rice planting and one other crop. Likewise, zones D3 and D4 distributed across Manggarai, East Manggarai, and West Manggarai Regencies have shifted to C3, which permits a change in cropping patterns from one crop or rice to one rice and one other crop.

Changes in climate types in this region are caused by alterations in rainfall patterns that impact the duration of dry and wet months (Firmansyah et al., 2022). Changes in climate zones can also impact cropping pattern systems by influencing the timing of seasonal transitions, which may be delayed or accelerated (Indrajaya et al., 2022). Therefore, farmers must modify planting periods to varying conditions so that the cropping pattern system also adapts.

3.3 Model Training

Figure 9 shows the data attributes used in model training. The selected data include TN, TX, TAVG, RH_AVG, RR, SS, FF_X, DDD_X, FF_AVG'.

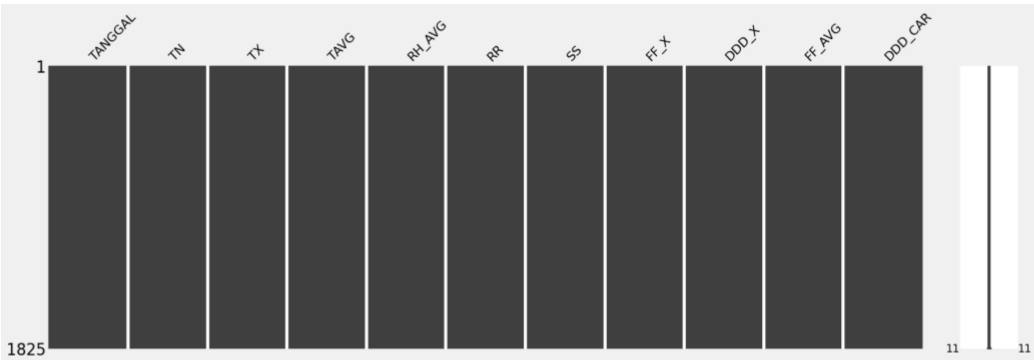

Figure 9. Data Attributes

Correlation analysis of meteorological data in NTT reveals significant relationships between climatic variables (**Figure 10**). A strong positive correlation exists between minimum (TN) and maximum temperatures (TX), signifying stable weather. Rainfall (RR) and relative humidity (RH_AVG) also demonstrate a strong positive correlation, confirming that rain increases humidity. Conversely, sunshine (SS) and rainfall (RR) have a significant negative correlation, aligning with climatology theory. Wind speed demonstrates weaker correlations with other variables.

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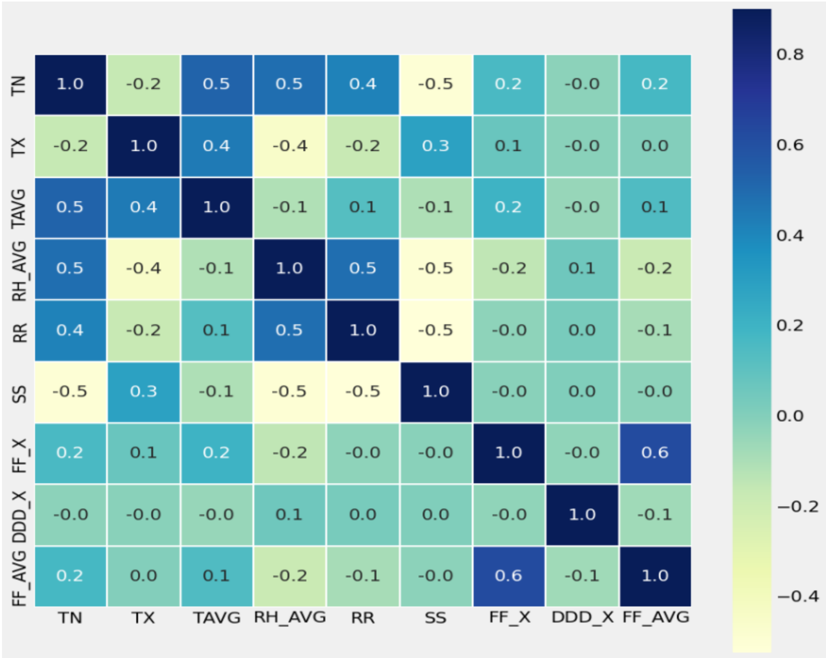

Figure 10. Correlation between Features

Figure 11 is a visualization of the elbow method used in cluster analysis (clustering). This method is used to determine the optimal number of clusters in a dataset.

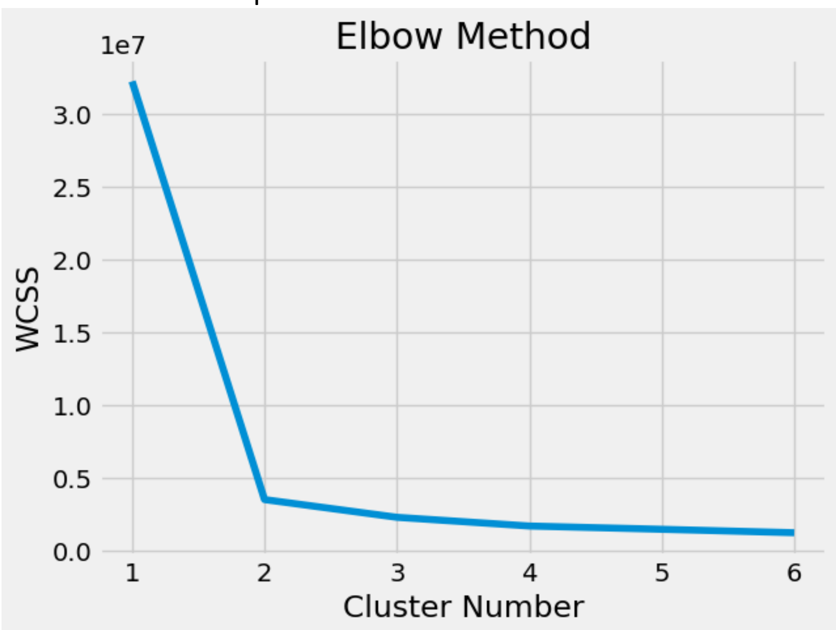

Figure 11. Elbow Method

The CNN model classifies optimal cultivation zones in NTT using agroclimatic data, analyzing rainfall, temperature, humidity, and wind speed. Its architecture comprises six layers: Conv1D (64 filters) extracts features, followed by MaxPooling1D to reduce dimensions. A second Conv1D layer (128 filters) refines time-pattern relationships. The Flatten layer converts data into a 1D vector, supplying two Dense layers (128 and 64 neurons) for feature learning and dimensionality reduction. The final Dense layer (4 neurons) predicts planting zones. With 49,988 trainable parameters, this model effectively processes agroclimatic data, optimizing classification accuracy for climate-adaptive cultivation in East Nusa Tenggara.

Several studies on AI-based prediction models for agroclimatology have shown the effectiveness of artificial intelligence models in weather prediction and agroclimatic zone

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classification. For instance, the use of a Convolutional Neural Network (CNN) model to analyze climate patterns has shown high accuracy in agroclimatic classification (Zahir et al., 2024). The results of this research support this approach, with the CNN model used in this study attaining 100% accuracy in classifying ideal planting zones in NTT. The implications of developing this model for agriculture and water resource management are significant, particularly in organizing planting times, selecting crop varieties, and water management strategies. The changes in rainfall patterns in tropical regions require greater adaptation from producers to reduce the risk of crop failure (Anderson et al., 2020). The findings in this study indicate that rainfall data and agroclimatic variables can be utilized to enhance the accuracy of agricultural management in NTT, enabling farmers to make data-based decisions to determine more efficient sowing schedules and irrigation strategies.

3.4 Model Evaluation

The evaluation results of the model applied to the test data showed very satisfactory performance, with an accuracy level reaching 100%. This model effectively classified the test data with a perfect accuracy of 1.0, indicating that the predictions generated were very precise and in accordance with the actual data. In addition, the recorded loss value of 6.4993e-08 indicates that this model can minimize prediction errors very well, reflecting a high level of precision in the learning process. This shows that the developed model has extraordinary generalization capabilities, making accurate predictions on training data and accommodating data that has never been seen before, making it very effective for use in applications that require high accuracy and stability in prediction. With these results, the model can be relied on for further implementation in the context of prediction or classification that requires optimal accuracy and performance. The training process is presented in **Figure 12**.

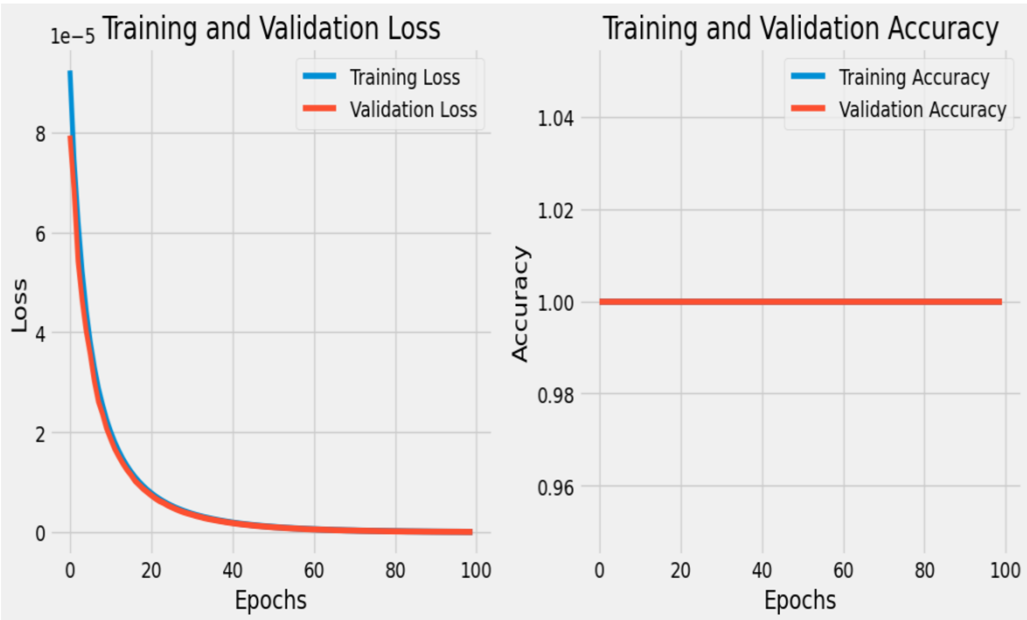

Figure 12. Model Evaluation

3.5 Deploy Model

Figure 13 displays the interface of the deployed application for agroclimatic mapping. This application is designed to analyze meteorological data and provide predictions related to climate conditions that affect agriculture. It seeks to help farmers identify agroclimatic zones suitable for certain planting patterns to increase efficiency in selecting crop varieties and planting periods.

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After the data is inputted, the user can select the "Predict" button to execute the model, which will then process the data and generate output in the form of a predicted category of agroclimatic suitability. The output generated by this application is divided into four categories: Low (1), Medium (2), High (3), and Very High (4) (Table 1). These categories define the level of suitability between climate conditions and plant requirements in an area. For example, if the prediction results show the category "Very High," the area is suitable for producing rice. At the same time, if the category that appears is "Low," it will be more suitable for varieties of plants that are more resistant to drought or require less water.

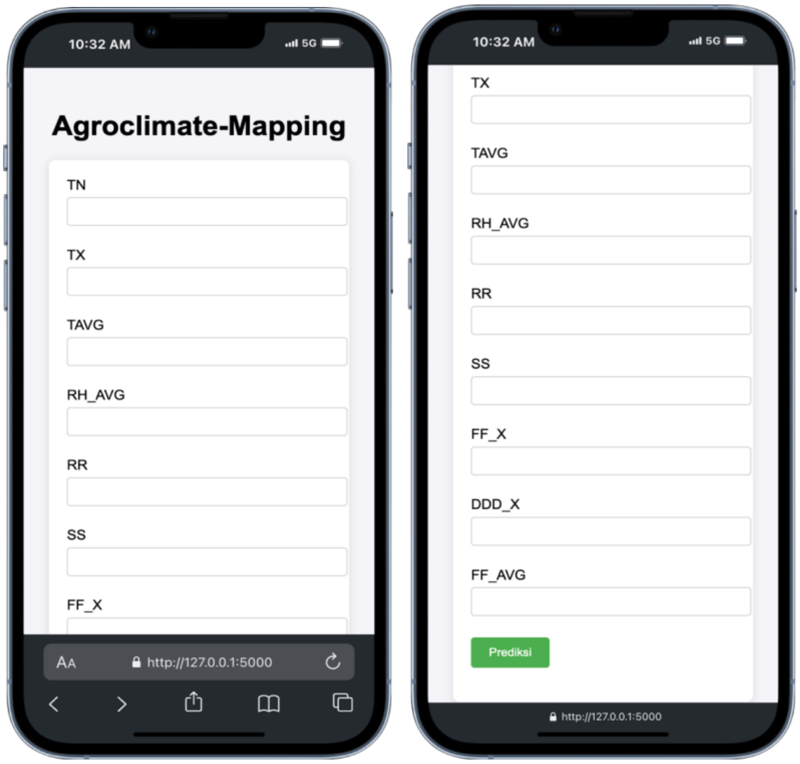

Figure 13. Deploy Model

The use of artificial intelligence-based models, such as CNN, in agroclimatic mapping has been supported by previous research, demonstrating an increase in the accuracy of predicting optimal planting zones (Espinel et al., 2020). Although wind speed contributes less to agroclimatic suitability, it should still be considered, particularly in areas with high drought risk (Rejekiningrum et al., 2022).

4. CONCLUSIONS

Climate-type variations in East Nusa Tenggara Province indicate a transition in agroclimatic zones that significantly impact the cropping pattern system in the region. This shift is caused by changes in rainfall patterns that affect the duration of dry and rainy months, prompting farmers to modify planting times and the types of crops cultivated. Several areas that previously had limitations in cultivation patterns are now experiencing increased land suitability for rice and secondary crops, while other areas are becoming arid and less suitable for rice farming. The role of BMKG and the Agricultural Extension Center (BPP) is essential in providing climate information and extension to farmers so that they can adapt to changing conditions. In addition, deep learning-based artificial intelligence technology in agroclimatic mapping can help predict weather patterns more accurately, allowing for more adaptive and sustainable agricultural planning. With this strategy, food security in East Nusa Tenggara can

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continue to be enhanced despite the challenges of climate change. This investigation is subject to numerous constraints, including the use of historical climate data that may be incomplete, technological constraints in AI modeling, and the difficulty of predicting local climate variations. The success of adaptation is also influenced by the ongoing institutional support and farmer readiness to address climate change.

5. RECOMMENDATIONS

AI-based agroclimatic mapping enhances climate adaptation by enabling predictive modeling beyond historical data. In low-rainfall areas, drought-resistant crops, efficient irrigation, and reservoirs are recommended. Refining the CNN model with more data improves accuracy. AI implementation in NTT supports food security and agricultural sustainability amid climate change.

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