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Performance of Time Series and Deep Learning Models for Predicting Severe Drought Areas in Lamongan Regency

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Abstract: Drought is one of the most significant natural disasters, greatly impacting the agricultural sector, water availability, and ecosystem balance. Therefore, predicting the extent of drought is crucial for effective mitigation and adaptation to climate change. This research aims to predict drought-affected areas using time-series data with the Weighted Moving Average (WMA) method and Landsat 8 imagery analyzed through deep learning. The data used in this research consist of satellite images, which are processed to assess drought extent using the Normalized Difference Drought Index (NDDI) within the Quantum Geographic Information System (QGIS) application. The satellite images were obtained from EarthExplorer. This research employs satellite image processing to extract NDDI values and spatial analysis to determine the distribution of drought in Lamongan District over a five-year period (2019-2023). The results indicate that the deep learning model, utilizing sub-district area images as input, provides the most accurate predictions of drought extent, achieving an average Mean Absolute Error (MAE) of 1,491,123. This research contributes to the development of spatial data-based techniques for mitigating the effects of drought more efficiently and sustainably.

Keywords: : *drought area, time series, deep learning, NDDI, severe drought.*

1. Introduction

Indonesia is a country with diverse and complex topography and a vast water area. This results in high climate variability across the region. Extreme climate conditions can lead to events such as extreme wet and extreme dry periods. One example of an extreme dry event is prolonged drought, which has a significant impact on human life. Due to its high climate variability, Indonesia is prone to natural disasters. One of the most impactful natural disasters affecting the environment, agricultural sector, water availability, and socio-economic conditions is drought. With ongoing climate change and increasing weather variability, drought occurrences are rising in various regions. Therefore, predicting the extent of drought is crucial to minimizing its impact and formulating better policies.

Drought is a natural disaster that develops gradually and can last for an extended period until the rainy season arrives. It has widespread impacts across various sectors, including the economy, society, health, education, and more. Water shortages, ecological degradation, reduced agricultural resources, and the risk of starvation or even loss of life are some of the significant consequences of drought on human life. However, with the advancement of Machine Learning, drought can be predicted. One of the algorithms commonly used for drought prediction is the Decision Tree (CART) (Han et al., 2021). This algorithm is well-suited for processing highly complex data. With increasing efficiency and affordability, machine learning has become the best solution for analyzing, exploring, and visualizing large datasets with high and complex observation frequencies, such as remote sensing imagery. Machine learning and deep learning (Mei et al., 2022) are used to overcome meteorological uncertainty and analyze remote sensing images. The vegetation index is derived from remote sensing image extraction and is used to predict drought disasters. The vegetation index includes VHI (Vegetation Health Index), VCI (Vegetation Condition Index), SAVI (Soil Adjusted Vegetation Index), and NDVI (Normalized Difference Vegetation Index) (Yang et al., 2024). Another drought index used to measure drought is NDDI (Normalized Difference Drought Index) (Artikanur et al., 2022); NDWI (Normalized Different Wetness Index) to measure the level of wetness (Rahmat et al., 2022); VITA (Variable Interval Time Averaging) modified used in conjunction with the drought index NEDI (Normalized Ecosystem Drought Index) to measure drought intensity based on ecosystem transition patterns with water availability (Chang et al., 2018). Measuring drought based on rainfall with the index SPI (Standardized Precipitation Index) (Dai et al., 2020), (Chanuwan Wijesinghe et al., 2024). Predicting the extent of drought is crucial as it helps governments, farmers, and communities mitigate its impacts. Drought indices, such as HDI (Hydrological Drought Index) (Nur Azizah Affandy et al., 2023), SMC (Soil Moisture Content) and TCI (Temperature Condition Index) (Kafy et al., 2023), (Ejaz et al., 2023), SPEI (Standardized Precipitation-Evapotranspiration Index) (Başakın et al., 2024), IDW (Inverse Distance Weighted) (Maipauw et al., 2020), climate data analysis using CI (meteorological drought index) (Shen et al., 2019), and AI (Artificial Intelligence) to predict drought damage to forests (Buthelezi et al., 2022). By generating the spatial distribution of SPEI, the BRF model provides detailed information about drought and can be applied to drought monitoring (Zhao et al., 2022), using the DroughtCast model to predict drought using machine learning (Brust et al., 2021), the Normalized Difference Drought Index (NDDI) to examine the drought-affected areas of agricultural land and analyze the connections between drought and related environmental factors (Dzakiyah et al., 2022).

In recent decades, various techniques have been developed to predict the extent of drought. These include hydrological modeling, climate data-based approaches, and the use of artificial intelligence and remote sensing. For example, drought prediction can be performed using satellite imagery data with the CWRPF (Chimp-based Wide ResNet Prediction Framework) method (D Jadhav et al., 2024), using the ConvLSTM (convolutional long short-term memory) method to monitor drought (Zhang et al., 2023). With these advancements, spatial data modeling and analysis-based methods (Gao et al., 2019) more reliable. Research (Chen & Zheng, 2025) propose a generative urban planning prediction model using adversarial networks integrated with index maps TVDI (Temperature Vegetation Dryness Index) to deal with drought problems. Research (Bojer et al., 2024) it emphasizes the importance of understanding the temporal and spatial aspects of drought for time-series-based drought prediction, providing valuable recommendations for decision-makers and planners to address and mitigate its impacts. Research (Nur A. Affandy et al., 2023) the results show that the SPEI-1 and NDVI causality models exhibit a strong relationship for managing drought in agricultural areas (irrigation zones) and serve as a reliable and effective tool for determining drought severity and duration in the research area. Research (Hashemi et al., 2024) found that the Salinity Index (SI) and Streamflow Drought Index (SDI) are effective indicators of the desertification process in the research area. They provide valuable information for monitoring and predicting desertification and aid in developing appropriate approaches for monitoring and controlling desertification using machine learning and remote sensing techniques. Research (Liu et al., 2020) showed that MCDI is suitable for observing meteorological drought, and multivariable linear regression MCDIs are suggested as effective methods and indices for monitoring drought in Shandong Province and similar areas. The research (Li et al., 2023) two machine learning (ML) methods, namely Random Forest and eXtreme Gradient Boosting, demonstrate high performance and accuracy in predicting dynamic drought in regions with complex terrain, diverse topographic and climatic factors, and scattered weather stations. The models developed can enhance drought monitoring efforts.

Although extensive research on drought has been conducted, the main challenges in predicting its extent remain the uncertainty of climate patterns, the lack of accurate historical data, and the need for models that can provide highly precise predictions. Therefore, advancements in more efficient methods, such as spatial data-based modeling and machine learning, are crucial for enhancing drought prediction capabilities. More accurate prediction systems can help governments formulate better water resource management policies, enable farmers to adopt more adaptive planting strategies, and allow communities to better prepare for the impacts of drought. To support socio-economic and environmental resilience in the face of increasingly dynamic climate change, research and development in drought prediction are essential. This research proposes two scenarios: (1) predicting drought-affected areas using time-series data as in research (Maipauw et al., 2020), (Bojer et al., 2024) and the Weighted Moving Average (WMA) method (Nafi'iyah et al., 2022); and (2) predicting drought-affected areas using Landsat 8 imagery and deep learning techniques.

2. Dataset

This research uses Landsat 8 Collection 2 Level 1 data from January to December 2019–2023, with Lamongan Regency as the research location and the Administrative Boundary Map of Lamongan Regency. Landsat 8 image processing was conducted using the Quantum Geographic Information System (QGIS), with data obtained from EarthExplorer. The research began with a preparation phase, which involved collecting literature on agricultural land drought models and processing data. Landsat 8 image data was used for the NDDI method, as shown in Equation (1); NDVI, as shown in Equation (2); and NDWI, as shown in Equation (3).

The NDVI value determines the greenness of a plant, while the NDWI value indicates its wetness, ranging from -1 to 1. An NDVI value between 0.35 and 1 falls into the high greenness category, whereas an NDWI value between -1 and 1 is classified as high wetness, with an index range of 0.33 to 1. NDDI is used to extract the drought index by combining NDVI and NDWI. A high NDDI value, within the interval of -1 to 1, indicates that an area is experiencing drought. Low NDVI and NDWI values also suggest drought conditions. However, NDDI values vary across countries due to differences in drought thresholds.

Since geometric correction has already been applied to Landsat 8 data, radiometric correction is performed to obtain the actual image values, and atmospheric correction is applied to eliminate atmospheric effects. Without atmospheric correction, the obtained values still contain atmospheric interference, making the results invalid. Before proceeding with the NDVI and NDDI correction and processing, the images must be merged and cropped according to the research location, Lamongan Regency. This step is necessary because Lamongan Regency in Landsat 8 is divided into two scenes. Image cropping ensures that the processing focuses on the research location while also reducing the file size for more efficient analysis. In Landsat 8 imagery, the red band (Band 4) and the Near Infrared (NIR) band (Band 5) are used to process NDVI. Meanwhile, NDWI is extracted using the NIR band (Band 5) and the Shortwave Infrared 2 (SWIR2) band (Band 7).

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \quad (1)$$

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} \quad (2)$$

$$NDWI = \frac{\rho NIR - \rho SWIR_2}{\rho NIR + \rho SWIR_2} \quad (3)$$

Explanation: ρNIR is Band 5 (*Near Infrared/*NIR) which has been corrected for the atmosphere with a wavelength of 0.851-0.879 µm. ρRED is Band 4 (*Red*) which has been corrected for the atmosphere with a wavelength of 0.636-0.673 µm. $\rho SWIR_2$ is Band 7 ($SWIR_2$) which has been corrected for the atmosphere with a wavelength of 2.107-2.294 µm.

3. Method

This research predicts land drought in sub-districts across Lamongan District using Deep Learning and Time Series analysis. Two models are developed in this research: one utilizing image data with the Deep Learning method and the other using drought land data with the Weighted Moving Average (WMA) time series method (Nafi'iyah et al., 2022). Figure 3.1 illustrates the stages of this research, which aims to evaluate the best prediction model. The research explores prediction models using image data (as shown in Figure 3.2) with Deep Learning and time series data (as presented in Table 3.1) using the Weighted Moving Average (WMA) method. Grayscale images of each sub-district in Lamongan are used to develop the Deep Learning model, with 1,034 images for training and 524 images for testing. The drought land data table, as shown in Table 3.1, represents the dataset used for time series analysis (m^2) Landsat 8 image processing was conducted using QGIS. The Landsat 8 data, obtained from EarthExplorer for the period 2019–2023, was processed to determine the extent of drought-affected land each month across all sub-districts in Lamongan District. For time series prediction using the Weighted Moving Average (WMA) method, a total of 60 rows of dry land area data from 2019 to 2023 were used. This research focuses on developing a severe drought prediction model through two scenarios: (1) using image input data, as shown in Figure 3.2, and (2) using time series table data, as presented in Table 3.1. Table 3.1 is specifically used to predict the extent of severe drought using the WMA time series method, as described in Equation 1 (Nafi'iyah et al., 2022). F_t is the predicted result in month (t), Y is the actual data of the extent of drought in month (t), w is the weight. The overall severe drought data for sub-districts in Lamongan is presented in Figure 3.3. This figure illustrates that the extent of drought varies depending on the month.

$$F_t = \frac{w_1 Y_t + w_2 Y_{t-1}}{\sum w} \quad (1)$$

Input images, as shown in Figure 3.2, are used to develop a deep learning model for predicting severe drought, (Shen et al., 2019), (Maipauw et al., 2020), (Brust et al., 2021), (Mei et al., 2022), (Bojer et al., 2024), (D Jadhav et al., 2024). The proposed deep learning model for predicting severe drought is presented in Table 3.2 and Figure 3.4. Figure 3.4 illustrates the detailed architecture of the deep learning model. The model is evaluated using the Average Absolute Error (Mei et al., 2022) as shown in Equation 2. Equation 2 is calculate the absolute difference value of actual drought area (Y), and drought area prediction (F).

$$MAE = \frac{\sum_{i=1} |Y - F|}{n} \quad (2)$$

Table 3.1. *Severe Drought*

Years	Month	Drought
2019	1	34420000
2019	2	4174200
2019	3	465300
2019	4	3810600
2019	5	3368700
2019	6	2671200
2019	7	865800
2019	8	25100100
2019	9	25153200
2019	10	24548400
2019	11	17307900
2019	12	18126000
2020	1	3832200
2020	2	3591000
2020	3	5810400
2020	4	3819600
2020	5	2948400
2020	6	4295700
2020	7	5896800
2020	8	17461800
2020	9	27778500
2020	10	2502000
2020	11	7418700
2020	12	1736100

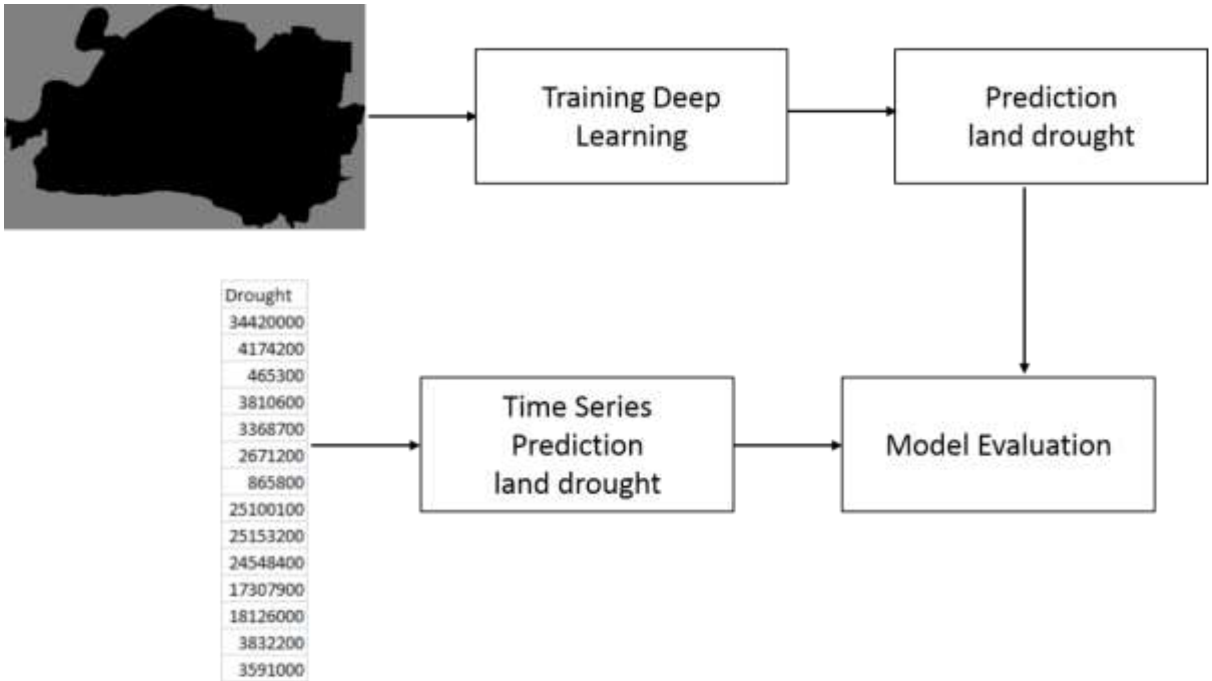


Figure 3.1. *Research Stages*

Table 3.2. *Deep Learning Architecture*

Layer	Shape	Neuron
Input	128x128	
Conv2D	126x126	32
Conv2D	124x124	64
MaxPooling	62x62	
Conv2D	60x60	64
MaxPooling	30x30	
Flatten		
Dense		128
Dense output		1

Figure 3.2. *Image of the District Area*

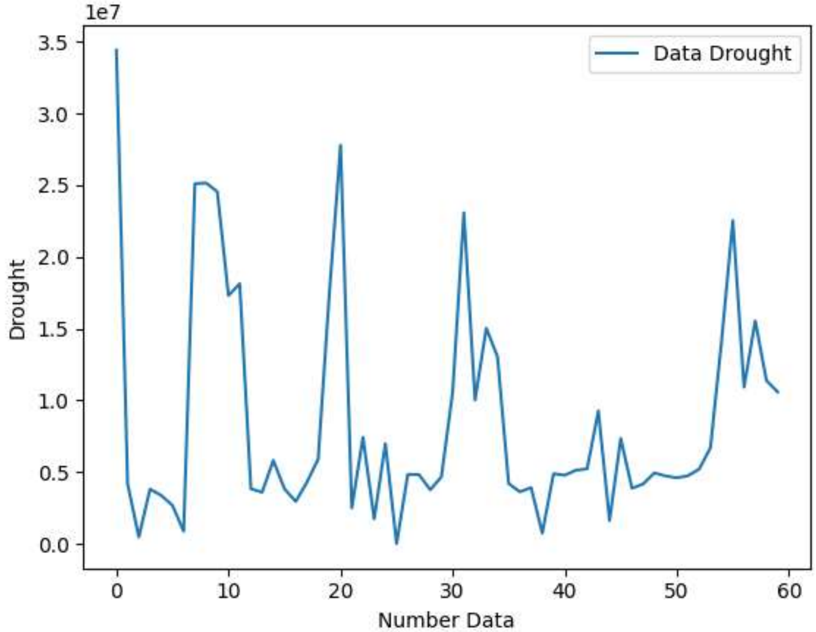


Figure 3.3. *Severe Drought Data*

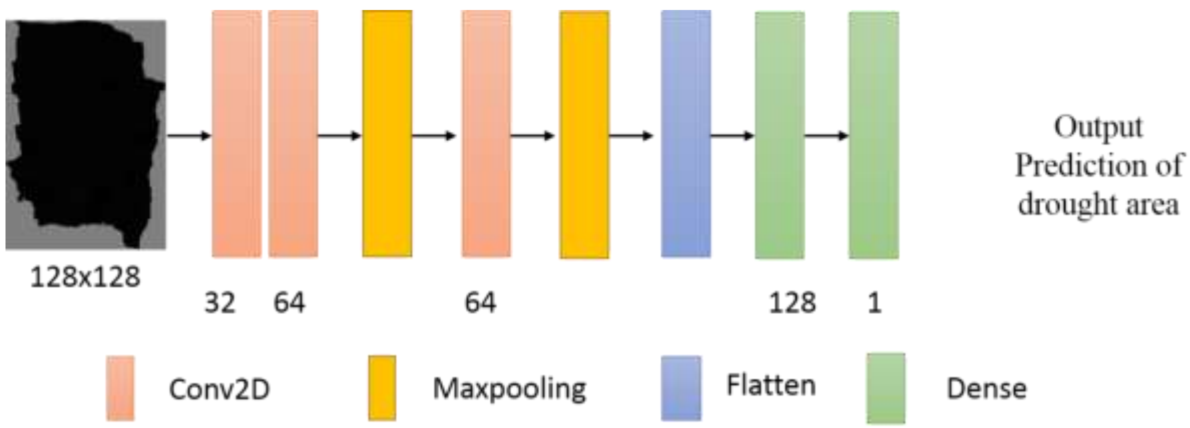


Figure 3.4. *Deep Learning Architecture*

4. Results and Discussion

This research conducted training and evaluation three times using the settings outlined in Table 4.1. The evaluation results of the deep learning model are presented in Table 4.2. Figure 4.1 illustrates the WMA prediction results time $t = 2$, with MAE value=2,184,679 based on two months of drought area data. Table 4.3 WMA prediction process, with weight $(w = 2,1)$. In Figure 4.1, the blue graph represents the actual data, while the yellow graph shows the prediction results. Based on the evaluation results, the deep learning model has the lowest MAE value of 1,491,123, whereas the WMA method has an MAE of 2,184,679. This indicates that deep learning is the best model for predicting drought areas. The deep learning model uses image data of each sub-district in Lamongan Regency, as shown in Figure 3.2, while the WMA method predicts drought areas using time series data, as presented in Table 3.1. The prediction results are evaluated using MAE, with the deep learning model's MAE values detailed in Table 4.4.

Deep learning was trained and tested three times, and the smallest average MAE value was achieved using the RMSprop optimizer with a learning rate of 0.01. Based on the MAE value, deep learning is the best prediction model, providing results that closely match the actual data, as seen in Figure 4.5 (Optimizer='RMSprop', Learning Rate = 0.01). The variation in the MAE value across different optimizers and learning rates is influenced by the fact that input images from multiple sub-districts share similar visual representations, even though the extent of drought varies each month.

Table 4.1. *Experiment Settings*

Parameters	Value
Optimizer	‘Adam’, ‘RMSprop’
Epoch	30
Batch Size	2
Loss function	Mean absolute error
Learning Rate	0.1, 0.01, 0.2, 0.02

Table 4.2. *MAE Evaluation*

Optimizer	RMSprop				Adam			
Experiment	0.1	0.01	0.2	0.02	0.1	0.01	0.2	0.02
1	8101302	1493408	9863959	1703225	8096363	1563273	8124792	1550024
2	8260297	1359172	8150728	1649794	4598893	3220346	8113657	7984872
3	8118539	1620788	5271855	1431218	8094030	7692993	7397660	1356949
Mean	8160046	1491123	7762181	1594746	6929762	4158871	7878703	3630615

Table 4.3. *WMA Prediction Process*

Drought	Prediction	Process
34420000	0	0
4174200	14256133	=((4174200*2)+(34420000*1))/3
465300	1701600	=((465300*2)+(4174200*1))/3
3810600	2695500	=((3810600*2)+(465300*1))/3
3368700	3516000	=((3368700*2)+(3810600*1))/3
2671200	2903700	=((2671200*2)+(3368700*1))/3
865800	1467600	=((865800*2)+(2671200*1))/3
25100100	17022000	=((25100100*2)+(865800*1))/3
25153200	25135500	=((25153200*2)+(25100100*1))/3
24548400	24750000	=((24548400*2)+(25153200*1))/3
17307900	19721400	=((17307900*2)+(24548400*1))/3
18126000	17853300	=((18126000*2)+(17307900*1))/3
3832200	8596800	=((3832200*2)+(18126000*1))/3
3591000	3671400	=((3591000*2)+(3832200*1))/3

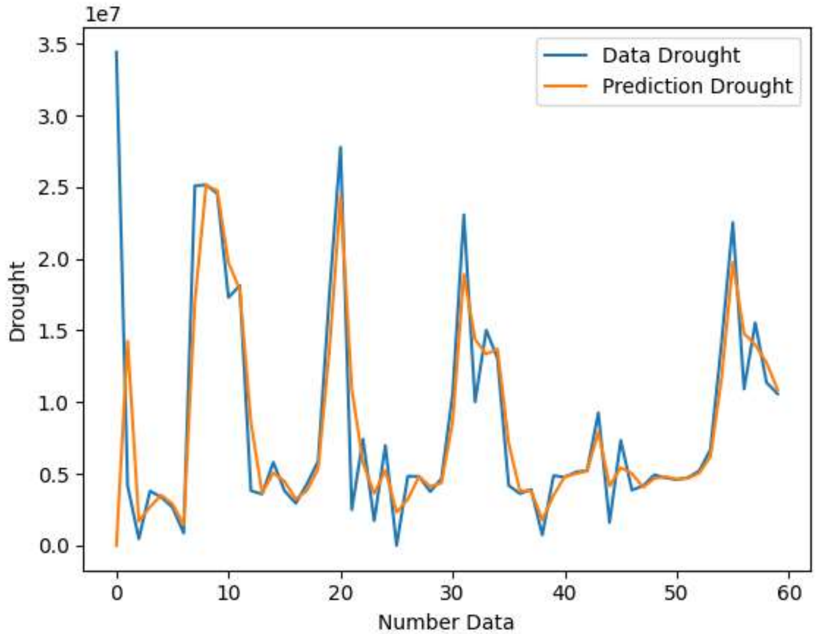


Figure 4.1. *WMA Result Prediction*

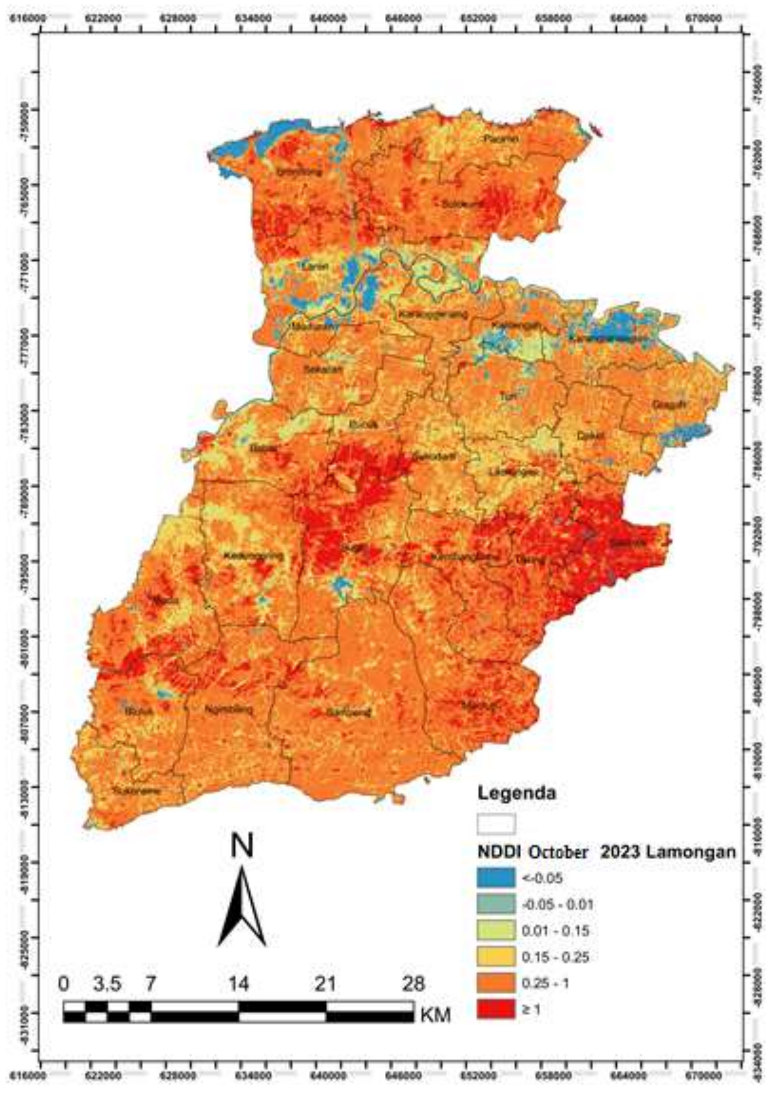


Figure 4.2. *Drought Map of Lamongan Regency in October 2023*

Figure 4.2 presents six classifications, each represented by a different color (determined by the researcher). The classifications are as follows: blue represents water or clouds, green indicates normal conditions, light green signifies mild drought, yellow denotes moderate drought, orange represents severe drought, and red indicates very severe drought. Landsat 8 satellite imagery was processed using the NDDI method to analyze the drought index in Lamongan Regency. The results show that 2023 was the hottest and driest year, with October 2023 experiencing the most extensive severe drought. The drought map of Lamongan Regency for October 2023 is shown in Figure 4.2, while Figure 4.3 illustrates the largest areas of severe drought in each sub-district from 2019 to 2023.

Based on Figure 4.2, it is evident that the orange and red classifications dominate Lamongan Regency. Among all sub-districts, Sambeng District has the highest concentration of the orange classification, indicating severe drought, covering approximately 83% of its total area. Over the five-year research period (2019-2023), severe drought in Sambeng District was most significant in October 2023. The extent of severe drought in each year for the most affected districts is as follows (as shown in Figure 4.3): October 2019: Sambeng District 115,563,600 m^2; September 2020: Solokuro District 64,273,500 m^2; October 2021: Solokuro District 67,139,100 m^2; October 2022: Solokuro District 44,795,700 m^2; October 2023: Sambeng District 120,381,300 m^2. These findings highlight the increasing severity of drought in specific regions over the years, with Sambeng District experiencing the most extensive drought conditions in 2023.

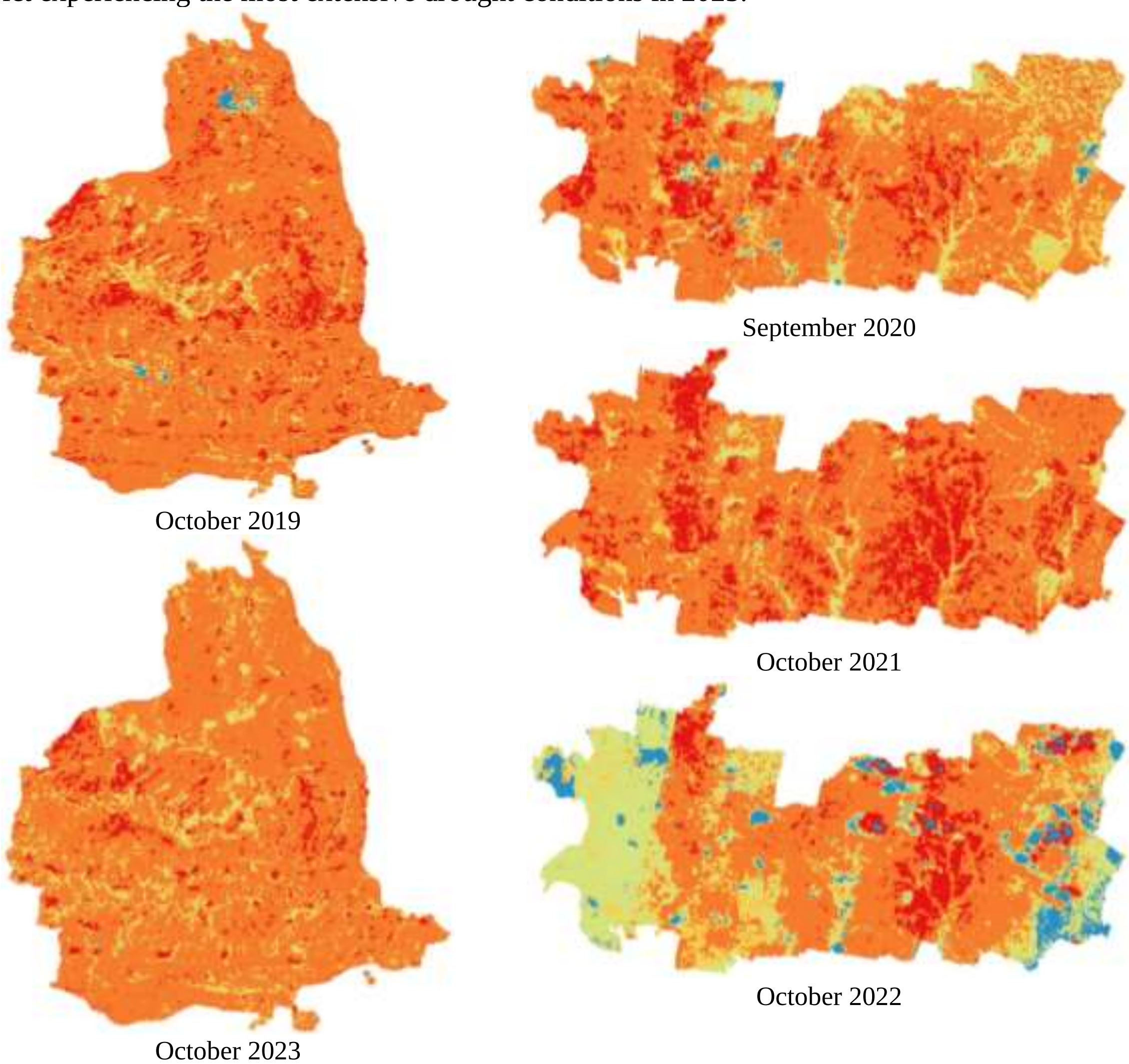
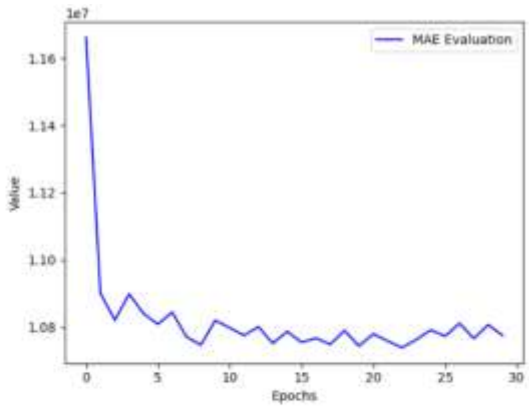
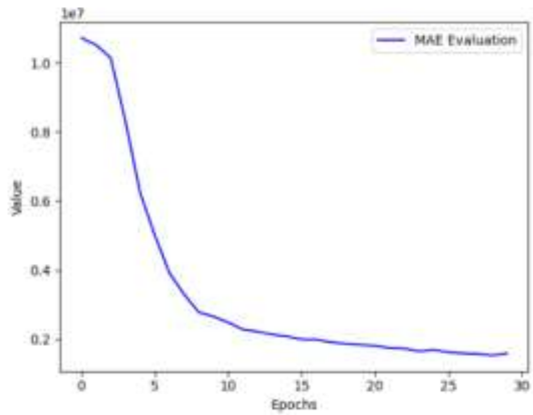


Figure 4.3. *Areas with the Largest Severe Drought*

Figure 4.4 presents the MAE values during deep learning training, while Figure 4.5 displays the prediction results for test data using the deep learning model. These figures highlight only the lowest MAE values for each optimizer and learning rate. During deep learning training (Figure 4.4), the MAE values for the Adam and RMSprop optimizers fluctuate across epochs. However, in the final epoch, all deep learning models using Adam and RMSprop optimizers achieved lower MAE values. When predicting the drought area in the test dataset using the deep learning model (Figure 4.5), the blue graph represents the actual drought area, while the yellow graph represents the model's predicted results. The prediction results using the Adam and RMSprop optimizers with a learning rate of 0.1 significantly deviate from the actual data, although the predicted values tend to be stable. The deep learning model that produced predictions closest to the actual data used the RMSprop optimizer with a learning rate of 0.01, achieving an MAE of 1,359,172. The MAE values from Figure 4.5 for different optimizers and learning rates are as follows: RMSprop (learning rate 0.1): 8,101,302; RMSprop (learning rate 0.01): 1,359,172; RMSprop (learning rate 0.2): 5,271,855; RMSprop (learning rate 0.02): 1,431,218; Adam (learning rate 0.1): 4,598,893; Adam (learning rate 0.01): 1,563,273; Adam (learning rate 0.2): 7,397,660; Adam (learning rate 0.02): 1,356,949. These results suggest that the RMSprop optimizer with a learning rate of 0.01 is the most effective in predicting drought areas, yielding the lowest MAE and predictions closest to the actual data.



Optimizer='RMSprop' Learning Rate=0.1



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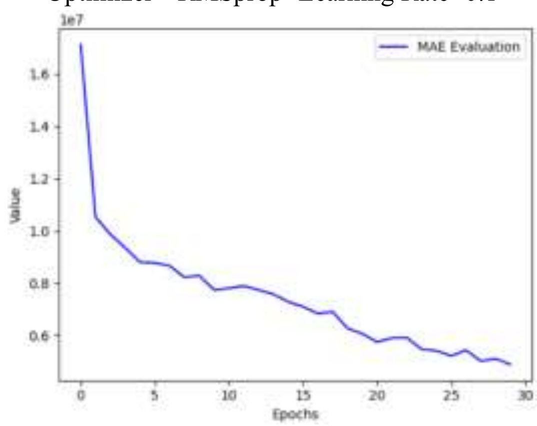

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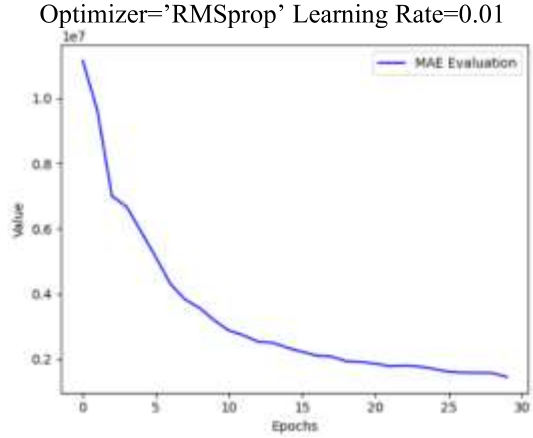

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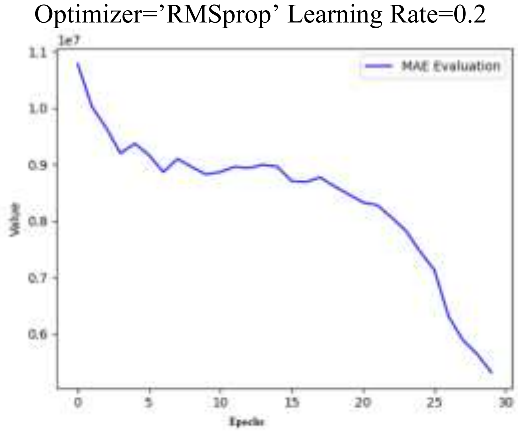
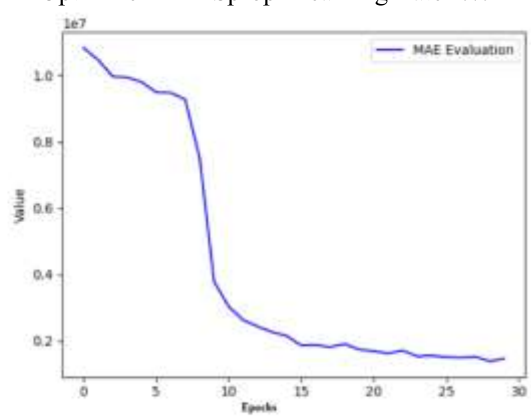


Optimizer='Adam' Learning Rate=0.1



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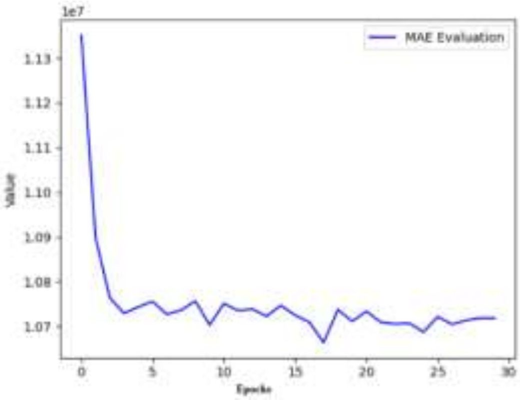

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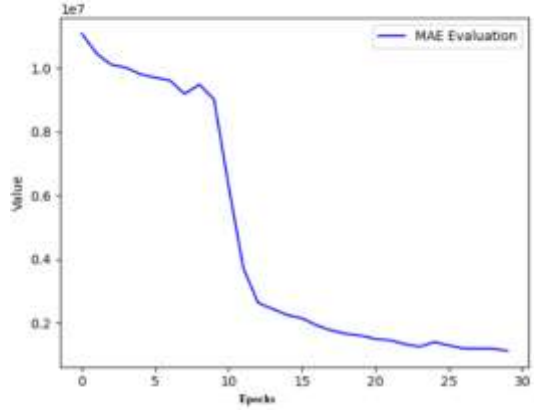

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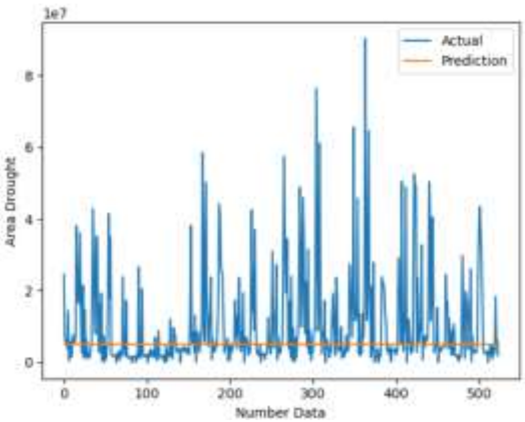
Figure 4.4. *Deep Learning Training*



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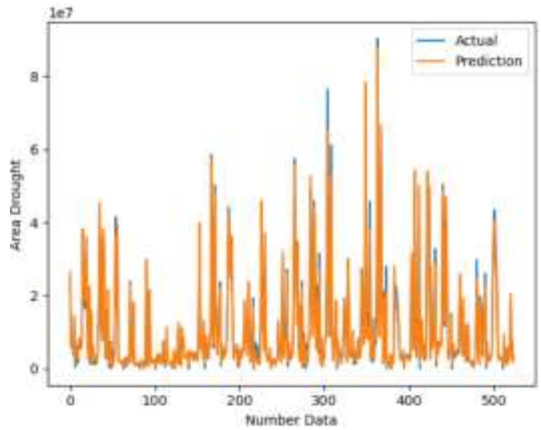

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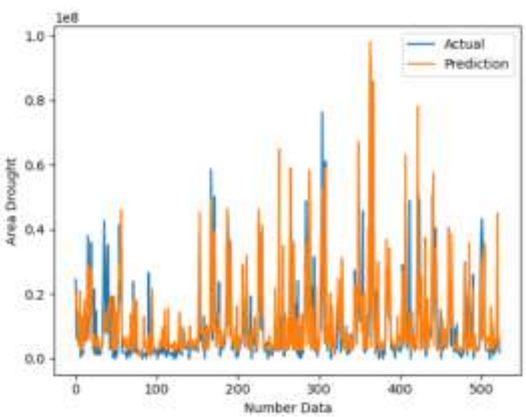

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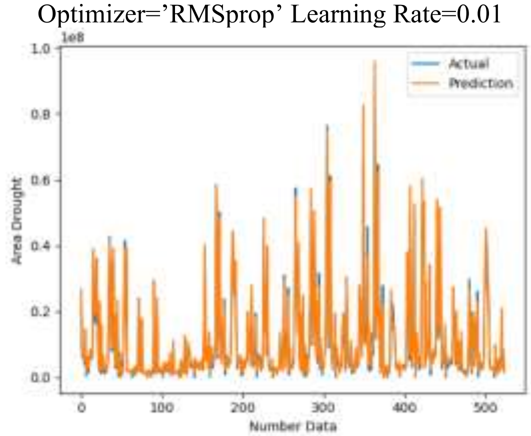

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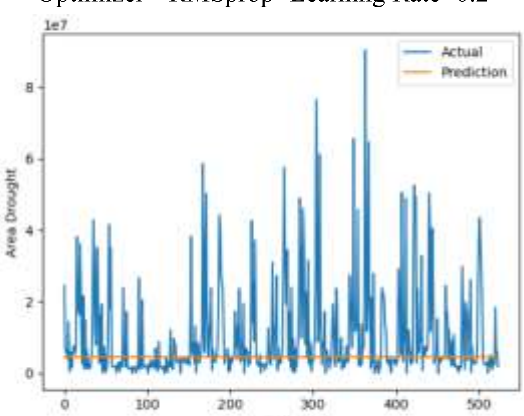
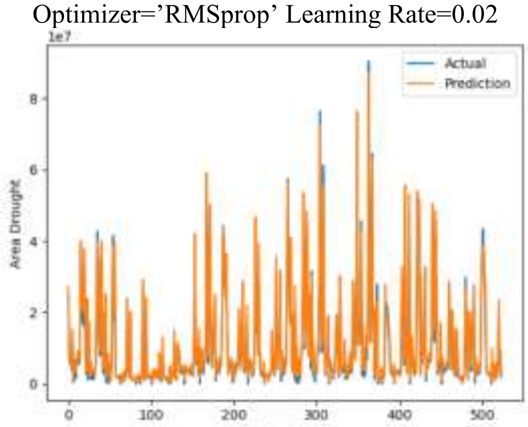
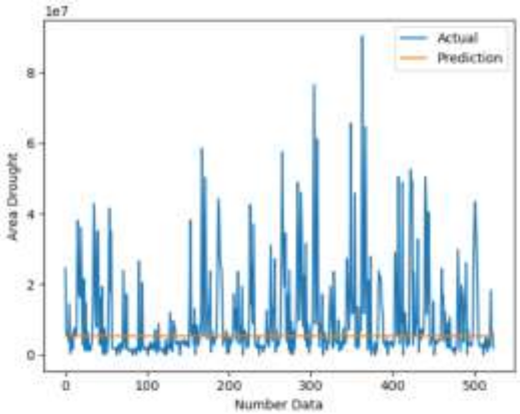
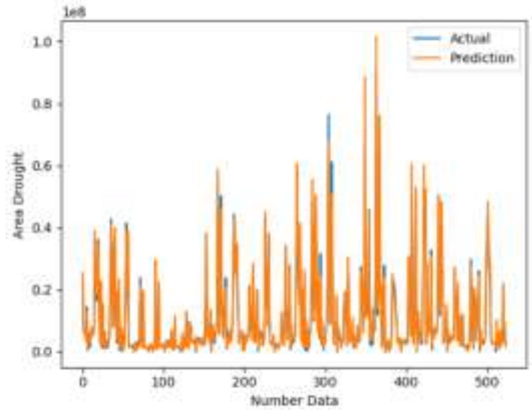


Optimizer='Adam' Learning Rate=0.1



Optimizer='Adam' Learning Rate=0.01





Optimizer='Adam' Learning Rate=0.2 Optimizer='Adam' Learning Rate=0.02

Figure 4.5. *Deep Learning Prediction Results*

5. Conclusion

This research predicts drought areas using image data with deep learning and time series drought area data with the WMA method. The prediction results were evaluated using MAE, where the deep learning model achieved an MAE of 1,491,123, while the WMA model had an MAE of 2,184,679. Based on these results, the deep learning model outperformed the WMA model, making it the best approach for predicting drought areas. The deep learning model, which utilizes image data from each sub-district in Lamongan Regency, provides more accurate and reliable predictions for assessing drought conditions. Further research suggestions include collecting 10 years of satellite imagery data to produce a better drought prediction model.

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