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RICE HARVEST AREA FORECASTING USING MOVING AVERAGE METHOD FOR FOOD SECURITY PLANNING

Andika Ellena Saufika Hakim Maharani
Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Mataram, Mataram City, Indonesia, a.ellena.saufika@staff.unram.ac.id

Helmina Andriani
Department of Statistics, Faculty of Mathematics and Natural Sciences, University of Mataram, Mataram City, Indonesia, helmina.andriani@staff.unram.ac.id*

Nuzla Af'idatur Robbaniyyah
Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Mataram, Mataram City, Indonesia, nuzla@unram.ac.id

Salwa
Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Mataram, Mataram City, Indonesia, salwa@unram.ac.id

Nafika Fatanaya
Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Mataram, Mataram City, Indonesia, naffatanaya@gmail.com

Abstract

Ensuring food security is a key part of sustainable development in Indonesia, especially since rice remains the country's staple crop. In regions like West Nusa Tenggara (NTB) Province, where rice harvest areas can vary significantly, having accurate forecasts is essential for effective planning. This study explores historical data on rice harvest areas in NTB to forecast future trends, uncover seasonal patterns, and assess long-term changes. To do this, we apply and compare three forecasting methods: Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA). Their performance is evaluated using accuracy measures such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), with results also presented visually to support data-driven decision-making. Among the methods tested, EMA with a 3-period window (EMA-3) produced the most accurate forecasts. This is reflected in its lower RMSE and MAPE values compared to the other methods. Based on the MAPE results, EMA-3 proves to be a reliable method for forecasting rice harvest areas in NTB.
Keywords: Food Security, Forecasting, Moving Average Method, Rice Harvest Area, West Nusa Tenggara Province.

INTRODUCTION

Food security is one of the important elements in national development, especially in an agricultural country like Indonesia (Haya & Sukandar, 2023). In this case, rice as the main staple food crop has a strategic role as a source of staple food for the majority of people (Putu et al., 2022; Rianti et al., 2023). The stability and availability of rice is highly dependent on the harvest area, which is an important indicator in measuring the productivity of the agricultural sector (Rachmawati, 2020). In NTB Province, rice is a leading commodity that has a significant contribution to regional food security (Iqbal, 2023). However, the rice harvest area in NTB often fluctuates due to various factors, such as seasonal changes, climatic conditions, government policies, and market influences. The fluctuation of harvest areas from year to year is certainly a challenge in food security planning. The uncertainty of accurate data on harvest areas makes it difficult for local governments to make strategic decisions, such as food reserve allocation, distribution planning and price control. Therefore, a forecasting method is needed that can provide a more accurate picture of future rice harvest areas to anticipate the risk of food shortages.

One of the main problems in food security management is the absence of an accurate forecasting system for estimating rice harvest areas. Inaccurate forecasting can lead to suboptimal decision-making (Salamah et al., 2025). With the availability of adequate historical data on harvest areas, it can serve as a foundation for accurate forecasting using appropriate methods to help local governments in planning data-based policies. One simple but effective method is the Moving Average method, which can provide an overview of harvest area trends based on past data patterns. With appropriate application, the forecast results from this method can be used as a reference in strategic decision-making, such as food reserve allocation, distribution management, and price stabilization so that they can be carried out more purposefully.

This research has high urgency because food security is a strategic issue that determines the sustainability of development and community welfare. In NTB, the agricultural sector, especially rice, is the backbone of the economy and food availability. Given the significant fluctuations in harvest areas from year to year, understanding the patterns and more accurate forecasting are key to reducing the risk of imbalance between food demand and availability. In addition, the moving average method applied in this study offers a simple yet effective approach to forecast future harvest areas based on historical data. By utilizing historical data and comparing several Moving Average methods, this research is expected to produce forecasting values that can be directly used by regional policy makers. The results of this research not only provide academic benefits in the form of contributions to the application of more optimal forecasting methods, but also have a real impact in supporting more adaptive and data-based food policy planning in NTB.

Research related to the forecasting of agricultural yields, especially in supporting food security, has been conducted with various approaches. Most studies use statistical methods such as Autoregressive Integrated Moving Average (ARIMA) (Amri et al., 2023; Paidipati & Banik, 2020; Viana et al., 2022) as well as artificial intelligence-based approaches such as Machine Learning (Satria et al., 2023) and Neural Network (NN) (Paidipati & Banik, 2020; Satria et al., 2023). These methods often show high forecast accuracy, but require complex computations, high-quality data, and technical resources that are not always available in their application to regional problems with local scope.

The problem-solving advantage offered in this research is to provide a simple yet effective approach through the Moving Average method that is able to forecast rice harvest areas based on historical data. Different from other studies that tend to focus on a single method or require high computation, this study is easy to implement using simple software such as Excel to facilitate implementation by regional policy makers; compares three types of Moving Average methods to provide a comprehensive understanding to determine the most optimal forecasting method; and focuses on data on rice harvest areas in NTB so that it is relevant to region-specific agricultural conditions and characteristics, such as the influence of weather and seasonal patterns.

Unlike more complex statistical or machine learning-based forecasting techniques such as ARIMA or neural networks, the Moving Average method offers a simple yet effective alternative that can be easily applied using accessible tools like Microsoft Excel. This makes it particularly suitable for regional governments with limited technical resources. The novelty of this research lies in the comparative application of three variants of the Moving Average method (SMA, WMA, EMA) within a unified analytical framework, which is rarely found in previous studies. The focus on monthly historical rice harvest area data from the past five years in NTB ensures that the forecasting results are highly relevant to the local agricultural context. This study contributes not only to methodological development in agricultural forecasting but also provides empirical evidence tailored to NTB’s seasonal and production characteristics. The findings are expected to directly support local policymakers in designing adaptive and data-driven food security strategies.

METHODS

The flowchart of the research method is shown in Figure 1 as follows:

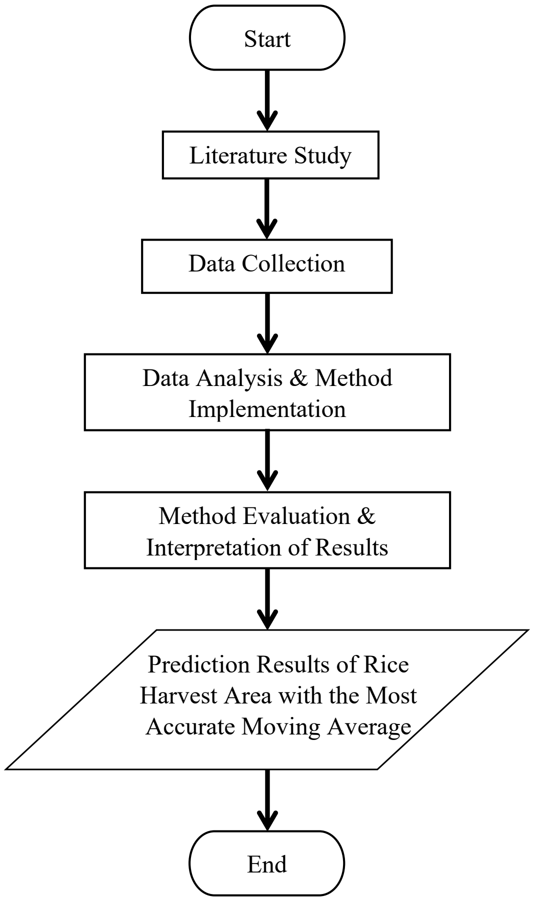

Figure 1. Flowchart of research methods

The following is an explanation of the research method process based on the research method flow chart:

1. Literature Study

The initial step in this research is a literature study, namely studying the theory of the Moving Average method and its application.

2. Data Collection

The data collected for this research includes monthly rice harvest area data in NTB Province for the last 5 years, since January 2020 until December 2024. The data obtained from the Central Bureau of Statistics/*Badan Pusat Statistik* (BPS) NTB Province. In the data collection process, it is necessary to ensure that the data used is complete, accurate, and consistent so that the results of the analysis and forecasting are reliable. In addition, the data also needs to be reviewed to identify possible missing values that could affect the forecasting results.

3. Data Analysis and Application of Methods

Once the data has been collected, the next step is visualizing the data in the form of time series graphs and describe the data to identify important patterns such as months with consistently high or low yields each year. In addition, the analysis also includes identifying long-term trends, such as whether the harvested area tends to increase, decrease or stabilize over the study period.

Once the data has been analyzed, the next step is to apply three variants of the Moving Average method, namely Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA).

- SMA calculates a simple average of the same month's data over the previous few years, giving equal weight to each data point in the time period (Widiarto & Kurniawan, 2024). The formula for SMA method is:

$$\hat{x}_{t+1} = \frac{\sum_{i=t-n}^{t-1} x_i}{n} \quad (1)$$

Description:
$\hat{x}_{t+1}$: the forecasting value of the $t+1$ period,
x_i : the actual value of the i period,
n : the number of periods.

- WMA gives greater weight to the most recent data, making it more responsive to recent changes in data patterns (Amali et al., 2022; Haryati & Israwan, 2020; Puspitasari et al., 2023; Rizqi et al., 2021; Welda et al., 2024). The formula for WMA method is:

$$\hat{x}_{t+1} = \frac{\sum_{i=t-n}^{t-1} (w_i . x_i)}{\sum_{i=t-n}^{t-1} w_i} \quad (2)$$

Description:
$\hat{x}_{t+1}$: the forecasting value of the $t+1$ period,
x_i : the actual value of the i period,
c_i : the weight assigned to the i^{th} actual value,
n : the number of periods.

- EMA uses a decreasing exponential weighting of the previous data, giving greater focus to the most recent data than WMA (Anggraeni & Sutrasni, 2023; Fauziah & Fauziah, 2022). The formula for EMA method is:

$$\hat{x}_{t+1} = \alpha(x_t - \hat{x}_t) + \hat{x}_t \quad (3)$$

Description:
$\hat{x}_{t+1}$: the forecasting value of the $t+1$ period,
x_t : the actual value of the t period,
α : the exponential parameter ($\alpha = \frac{2}{t+1}$).

Each method is applied to monthly harvested area data for the last 5 years to generate monthly harvested area forecasting for the next period.

In this study, two period lengths (2 and 3) were selected for all three Moving Average methods (SMA, WMA, EMA) to evaluate the effect of shorter versus moderately longer smoothing windows. The 2-period captures very recent data changes, making the model more responsive, while the 3-period balances responsiveness with the ability to smooth out irregularities, especially during high variability in harvest seasons. All calculations, visualizations, and evaluations in this study were performed using Microsoft Excel. This tool was chosen for its accessibility and ease of use, enabling regional planners and policymakers to replicate the forecasting process without requiring complex statistical software.

4. Evaluation of Methods and Interpretation of Results

To determine the most optimal method, the forecasting results of each Moving Average variant need to be validated and evaluated using accuracy indicators, which is RMSE and MAPE. The following is the formula given for RMSE and MAPE (Mangiwa et al., 2025):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \tag{5}$$

Description:
$\hat{x}_i$: the forecasting value of the i^{th} observation,
x_i : the actual value of the i^{th} observation,
n : the total number of the observation.

The method with the lowest RMSE and MAPE value is considered the most optimal method for the data pattern of harvest areas in NTB. This evaluation is done by comparing the forecasting results to the actual data. Furthermore, given in Table 1 accuracy measurement scale of MAPE percentage.

Table 1. Accuracy measurement scale of MAPE

MAPE value	Valuation of Measurement Scale
< 10%	Highly Accurate Forecasting
10% - 20%	Good Forecasting
20% - 50%	Reasonable Forecasting
> 50%	Inaccurate Forecasting

In addition, a comparison graph between the forecasting results and historical data is also provided to visualize the actual data and the forecasting results of the harvest area. The comparison graph is depicted in the form of a curve with the x-axis being the time period and the y-axis being the rice harvest area. Furthermore, the results of the method evaluation and the forecasting of the harvest area obtained are interpreted to draw conclusions.

RESULT AND DISCUSSION

DESCRIPTIVE STATISTICS

The following graph and table in Figure 2 and 3 shows the trend of monthly rice harvest area in NTB Province for the last 5 years (January 2020 – December 2024) which is used as the basis for analysis in this study:

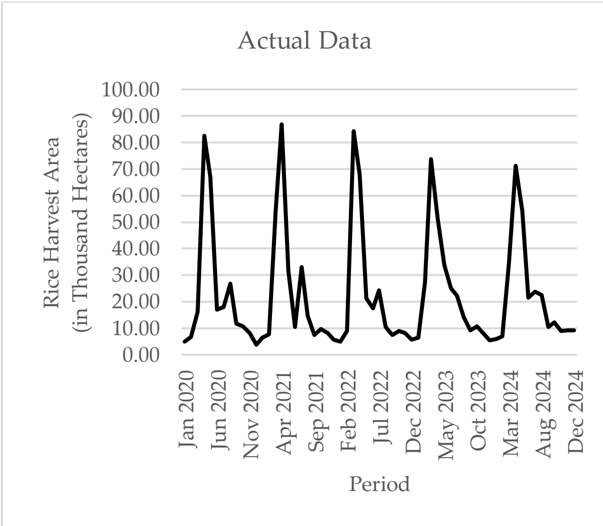

Figure 2. Actual data monthly rice harvest area in NTB province

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Rice_Harvest_Area (in thousands of hectares)	60	3.77	86.86	23.1497	22.84829
Valid N (listwise)	60				

Figure 3. Table of descriptive statistics of actual data

As illustrated in Figure 2, the monthly rice harvest area in NTB Province from January 2020 to December 2024 demonstrates a consistent seasonal pattern, with significant peaks typically occurring between January and April each year. This recurring trend reflects the region's cyclical agricultural calendar, likely influenced by climate and planting schedules. According to the Figure 3, the rice harvest area varies substantially across the observed period, ranging from a minimum of 3.77 thousand hectares to a maximum of 86.86 thousand hectares. The mean harvest area is 23.15 thousand hectares, with a relatively high standard deviation of 22.85, indicating considerable monthly fluctuations. These characteristics (seasonality and high variability) support the use of time series forecasting methods such as the Moving Average technique to enhance the accuracy of harvest forecasting, which are vital for effective food security planning in the region.

APPLICATION OF MOVING AVERAGE METHODS

The performance of various Moving Average techniques (SMA, WMA, EMA) was evaluated to forecast the rice harvest area in NTB Province from January 2020 to December 2025. The comparison graphs in Figures 4, 5, and 6 visually demonstrate the ability of each model to follow the seasonal trend and fluctuations present in the actual historical data.

As shown in Figure 4, the SMA method with 2-period (SMA-2) and 3-period (SMA-3) was able to capture the general seasonal pattern of the actual data. However, the period in response caused by averaging results in a smoother curve that tends to underrepresent sharp increases and decreases, especially during peak harvest periods.

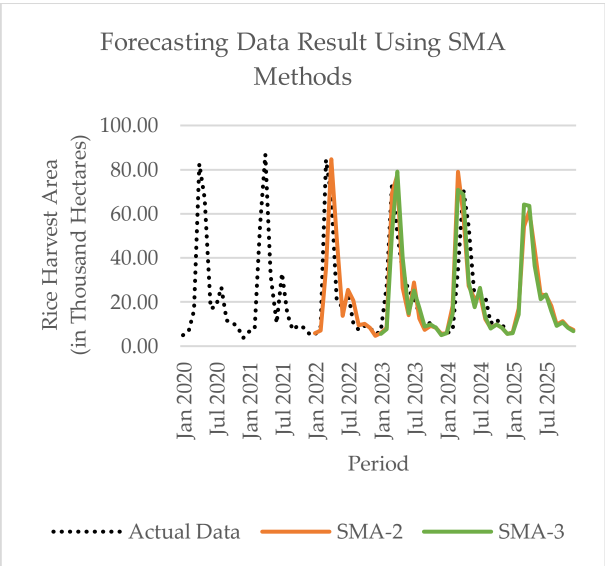

Figure 4. Comparison graph of forecasting data result using SMA methods

In contrast, Figure 5 illustrates the results of the WMA method, where the WMA-2 and WMA-3 models show a more responsive trend compared to SMA, especially in capturing the rising and falling patterns of the rice harvest data. This is due to the application of weights that prioritize more recent observations, making WMA more adaptive to recent changes.

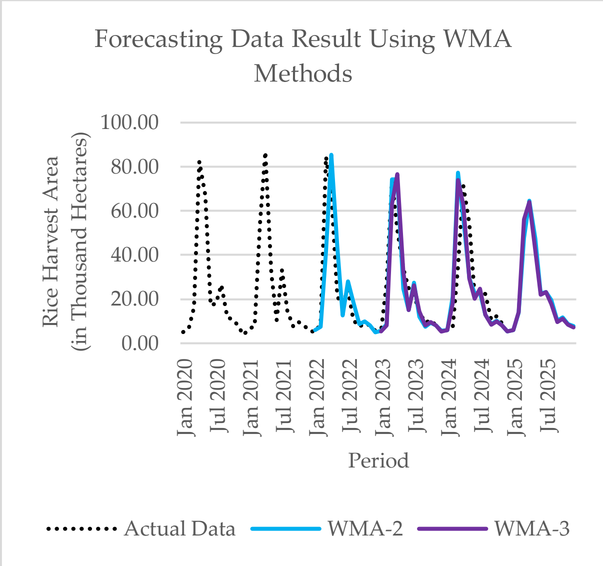

Figure 5. Comparison graph of forecasting data result using WMA methods

Figure 1. Further improvement in responsiveness is demonstrated in Figure 6, where the EMA method is applied. Both EMA-2 and EMA-3 tracks the actual data more closely, particularly during the transition between high and low harvest seasons. The exponential smoothing approach in EMA allows the model to react faster to fluctuations in recent months, making it potentially more suitable for short-term forecasting of rice harvest areas.

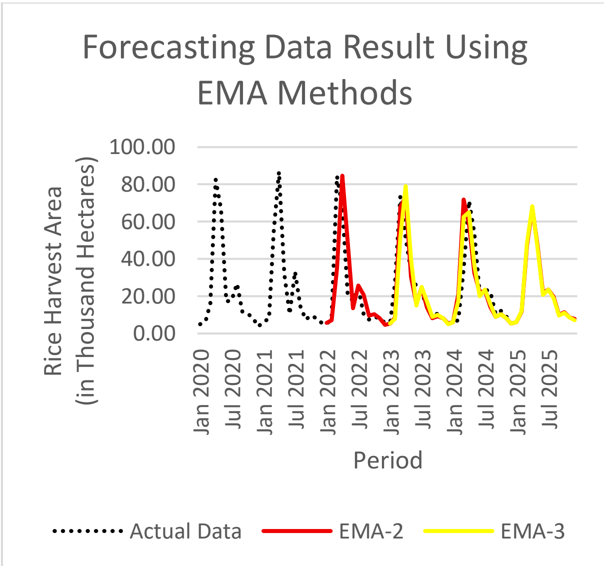

Figure 6. Comparison graph of forecasting data result using EMA methods

Overall, the comparison across Figures 4, 5, and 6 indicates that while SMA provides a foundational trend approximation, WMA and especially EMA offer improved tracking accuracy by incorporating weighting schemes, which are crucial for capturing dynamic changes in agricultural time series data.

The numerical performance of each forecasting method is summarized in Table 2, which presents a comparison of RMSE and MAPE values for SMA, WMA, and EMA models with two different period settings.

Table 2. Comparison table RMSE and MAPE of the forecasting methods

	RMSE	MAPE (%)
SMA-2	13.47	32.21
SMA-3	12.82	29.63
WMA-2	12.97	33.21
WMA-3	12.45	29.4
EMA-2	11.67	29.7
EMA-3	**11.37**	**28.1**

These metrics provide a quantitative basis for evaluating the accuracy and reliability of the forecasts generated by each method.

Referring to Figure 4, both SMA-2 and SMA-3 models capture the general seasonal behavior of rice harvesting but tend to smooth out peak values due to equal weighting across periods. SMA-3 offers a slightly improved accuracy over SMA-2, as reflected in its lower RMSE (12.82 vs 13.47) and MAPE (29.63% vs 32.21%). In Figure 5, the Weighted Moving Average approach shows enhanced responsiveness to trend changes due to the use of weights favoring more recent data. Among them, WMA-3 provides the best performance, with an RMSE of 12.45 and a MAPE of 29.40%, outperforming WMA-2 (RMSE = 12.97, MAPE = 33.21%). The most accurate forecasting results were achieved by the Exponential Moving Average model, as illustrated in Figure 6. EMA-2 and EMA-3 responds more dynamically to recent data variations, making them especially effective in capturing sharp increases and decreases in harvest area. EMA-3 yields the lowest error values across all models tested, with RMSE = 11.37 and MAPE = 28.10%, followed closely by EMA-2 (RMSE = 11.67, MAPE = 29.70%). Based on these results, EMA-3 consistently outperforms the other models with the lowest RMSE and MAPE values, as shown in Table 2. Its responsiveness to recent data makes it the most suitable model for short-term rice harvest area forecasting to support regional food security strategies.

The findings of this study are in line with previous research that highlights the effectiveness of exponential smoothing methods in agricultural forecasting. Similar with this research, among all the moving average method used for the Haasan and Sarker (Hasan & Sarker, 2023) and Hanggara (Hanggara, 2021) study, SMA has the highest forecasting error value. For instance, they demonstrated that the EMA outperformed SMA and WMA methods, when the forecasting error lower the the two others. These result similar with Jaya and Desyani (Jaya & Teti Desyani, 2020) research that EMA method consistently outperformed other moving average methods. In addition, Huriati et al. (Huriati et al., 2022) and Vaidya (Vaidya, 2020) compared the moving average models with two and more periods respectively. The result is the greater period moving average is better than another less period based on the forecasting error value comparison. These previous study results are consistent with the outcomes of the present study, in which EMA-3 achieved the best forecasting accuracy for rice harvest area in West Nusa Tenggara, with the lowest RMSE and MAPE values (11.37 and 28.10%, respectively).

To conclude, this study finds that the Exponential Moving Average (EMA) method (specially using a 3-period) offers a strong and reliable approach for forecasting agricultural time series data. The findings support previous research while also providing context-specific insights for West Nusa Tenggara, a region known for its seasonal patterns and policy-related shifts in rice harvests.

However, there are some limitations to note. First, the analysis relies solely on five years of historical data (2020–2024), which may not fully capture longer-term patterns or unusual external events. Second, the models used in this study focus only on past harvest area figures and do not take into account other important factors like climate anomalies, government policy changes, shifts in input costs, or pest infestations that all of which can significantly influence harvest results. To enhance accuracy and reliability, future research should consider integrating these external variables into more advanced or hybrid forecasting models.

CONCLUSIONS

This study highlights the crucial role of accurate rice harvest forecasting in supporting food security planning in NTB Province, Indonesia. By examining monthly harvest data from January 2020 to December 2024, the research revealed clear seasonal patterns and notable fluctuations in rice production. To address these variations, three types of Moving Average methods (SMA, WMA, EMA) were applied and compared using standard accuracy measures: RMSE and MAPE. Among the methods tested, EMA with a 3-period (EMA-3) delivered the best performance, showing the lowest RMSE (11.37) and MAPE (28.10%). This indicates that EMA-3 is well-suited for forecasting rice harvest areas in NTB, as it effectively responds to recent trends and adapts to changes in the agricultural cycle.

The findings serve as a useful reference for policymakers and stakeholders aiming to develop more data-driven and adaptive food security strategies. For future studies, incorporating external factors, such as rainfall patterns, climate variability, or shifts in agricultural policy could enhance model accuracy. Moreover, exploring machine learning-based forecasting approaches may offer new perspectives for optimizing regional food planning.

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