

Implementation of Moving Average and Weighted Moving Average for Forecasting Palm Oil Harvest and Income in a Web-Based GIS System

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Received : Mar 18, 2026; Revised : May 15, 2026; Accepted : May 15, 2026; Published : Jun 15, 2026

Abstract

Independent palm oil farmers face significant challenges in financial management due to inefficient manual recording, fluctuating harvest yields, and volatile Fresh Fruit Bunch (FFB) prices. This study aims to develop a web-based harvest and income recording system integrated with a Geographic Information System (GIS) and forecasting methods to support decision-making. The system is developed using a Research and Development (R&D) approach by comparing Moving Average and a dynamically weighted Moving Average that adapts to price fluctuations for predicting future net income. Model performance is evaluated using Mean Absolute Percentage Error (MAPE) and validated with the Diebold–Mariano test, while system usability is assessed through User Acceptance Testing (UAT). The results show that the dynamically weighted Moving Average achieves a prediction accuracy of 93.08% (MAPE 6.92%), slightly outperforming the standard Moving Average (93.03%), although no statistically significant difference is found based on the Diebold–Mariano test. The system also obtains a “Very Good” usability rating with a UAT score of 95.11%. These findings demonstrate that the proposed approach provides a practical and adaptive forecasting mechanism integrated within a spatial financial management system, contributing to improved decision support and offering methodological value in time-series forecasting for agricultural informatics.

Keywords : *Palm Oil, Forecasting, Weighted Moving Average, GIS, Web-based System.*

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1. INTRODUCTION

Palm oil is a leading and strategic commodity in Indonesia that contributes significantly to regional income and national foreign exchange [1]. The increasing global demand for palm oil requires improvements in the quality and quantity of its production [2]. However, palm oil production in the field is not always stable; fluctuations in harvest yields due to climate, maintenance, and plant age often pose challenges in production planning [3]. Several recent studies highlight that climate variability and external factors significantly influence agricultural forecasting accuracy, emphasizing the need for adaptive prediction models [4]. In addition, the price of fresh fruit bunches (FFB) of oil palm is dynamic, with daily price ranges varying between Rp2,000 and Rp3,000 per kg, making farmers' incomes less predictable [5]. To meet growing domestic and global demand, efforts to improve the quality and quantity of palm oil production are needed [6]. Therefore, studying historical monthly harvest data patterns is important for predicting future harvests so that anticipatory measures can be taken earlier. Based on interviews with independent palm oil farmers, they usually harvest their plantations every two weeks, with an average yield of around 1–2 tons per harvest (around 5 tons per month) and a selling price of around Rp2,000–3,000 per kg (average assumed value of Rp2,500/kg). This situation yields a gross income of around IDR 10–13 million per month. However, this income must be reduced by various significant operational costs, such as fertilizer costs, plantation maintenance costs, weed

spraying, pruning, labor, and harvesting operational costs. Fluctuations in selling prices and uncertain harvest yields make planning income and expenses increasingly complex. As a result, data recording of harvest yields and income is generally still done manually. This complex pattern of income and expenses requires accurate predictions of harvest yields and income so that operational cost planning can be carried out more effectively [7]. To overcome these problems, this study developed a web-based palm oil harvest and income recording system equipped with forecasting features using the Moving Average (MA) and Weighted Moving Average (WMA) algorithms. Previous studies have widely applied Moving Average methods for palm oil forecasting due to their simplicity and effectiveness in capturing trend patterns, with relatively low error values ($MAPE < 10\%$) [5]. However, more advanced approaches such as ARIMA and hybrid models (e.g., ARIMA–GRU) have demonstrated higher accuracy in handling complex and nonlinear data patterns, although they require higher computational complexity [8]. Comparative studies also show that ARIMA and neural network models can outperform traditional methods, but their implementation is often less practical for small-scale farmers [9]. Despite these developments, most existing studies focus only on prediction models without integrating them into user-friendly systems or combining them with spatial analysis tools such as GIS. Furthermore, conventional Weighted Moving Average methods generally use static weights, which do not adapt to dynamic price fluctuations. This indicates a research gap in developing an adaptive and integrated forecasting system that is both practical and accessible. The moving average algorithm is capable of analyzing historical data to identify trends and patterns of price fluctuations, thereby providing relevant estimates of future prices [5]. Meanwhile, the Weighted Moving Average method is a moving average method widely used to determine trends from a time series of the latest data [10]. The use of MA and WMA aims to predict the harvest and income for the next period based on historical patterns, so that farmers can anticipate production declines, estimate future income, and better plan operational costs. This forecasting approach is relevant to modern agricultural practices, such as land potential analysis, which can be used to monitor crop development and predict harvest yields, thereby supporting the provision of recommendations for appropriate land use and production inputs [11]. Simple prediction methods such as Moving Average have also been extensively tested in the context of oil palm agriculture. For example, Irawan et al. (2021) applied a 3-period Single Moving Average to forecast palm oil production and reported an error rate (MAPE) of around 10%, indicating relatively good accuracy [12]. Other studies emphasize that Moving Average is capable of capturing data trend patterns in a simple manner and is easy to implement by industry players [13]. Various previous studies have shown that the Moving Average algorithm is effective for agricultural forecasting. In a study by Agustian and Wibowo, several Moving Average methods were compared and it was found that weighted moving average produced harvest predictions with the smallest error [14].

This system is also equipped with Geographic Information System (GIS) integration to display the distribution of harvest locations and farmer income. GIS-based systems have been widely adopted in agriculture for spatial analysis, production monitoring, and decision support, particularly in large-scale plantation management [15]. Therefore, this study proposes a dynamically weighted Moving Average approach that adapts to commodity price changes and integrates it into a web-based GIS system. The main contribution lies in combining adaptive forecasting with spatial financial management to support decision-making for independent farmers. With GIS, farmers can see variations in income based on specific plantation locations, thereby supporting analysis of which areas have higher or lower productivity. GIS technology has been widely used in agricultural information systems for land mapping, production monitoring, and harvest distribution analysis [16]. With the national oil palm plantation area now reaching more than 17 million hectares, the application of technology in its management is an important step to improve efficiency while ensuring transparency in every process [17]. Therefore, the implementation of MA and WMA in a web-based harvest and income recording

system equipped with GIS integration is expected to help farmers anticipate possible production declines, estimate income, and plan operational costs more accurately. With data-driven management and accurate predictions, the sustainability of independent oil palm farming businesses can be maintained and further improved.

2. METHOD

This study applies a Research and Development (R&D) approach by adopting the Waterfall system development model. This approach was chosen because of its systematic and sequential characteristics, starting from needs analysis to testing and maintenance [18]. The main objective of this research is to produce an integrated information system for recording palm oil farmers' harvests and income with intelligent forecasting and geographic mapping (Geographic Information System) modules. The dataset used in this study consists of time-series data of harvest yields, selling prices, and operational costs collected from independent palm oil farmers. The data were recorded on a monthly basis over a period of approximately 12–24 months, resulting in N observations used for forecasting experiments. The data include variables such as harvest quantity (kg), Fresh Fruit Bunch (FFB) price (IDR/kg), and total operational costs. The stages of this research can be seen in the research flowchart in Figure 1. Each stage in the flowchart represents a sequential process starting from problem identification to system evaluation, ensuring that both system development and forecasting model validation are conducted systematically.



Figure 1. Research Flowchart

The research procedure was carried out through six main stages as illustrated in Figure 1. The first stage is Problem Identification, which involves mapping the main constraints faced by independent oil palm farmers, including the inefficiency of manual harvest recording, the instability of Fresh Fruit Bunch (FFB) prices, and the absence of spatial and predictive decision support tools. The results of this identification form the basis for the Needs Analysis stage, which involves collecting functional and nonfunctional system data through in-depth interviews and literature studies that produce detailed system specifications, recording, forecasting, and GIS). The data used in this study is time-series data sourced from Independent Oil Palm Farmers. Secondary data was obtained from weighing notes and manual cash books belonging to farmers during a certain period as input to the web system. Based on these specifications, the System Design phase was carried out, which included architectural design using Unified Modeling Language (UML), relational database design (ERD), and ergonomic User Interface (UI) design, ensuring that the system had a robust and user-friendly structure before the code development process began. The functional design of the system is illustrated through a Use Case Diagram that defines the interaction between Palm Oil Farmers as the main actors and the functionality of the system within a single process boundary (system boundary).

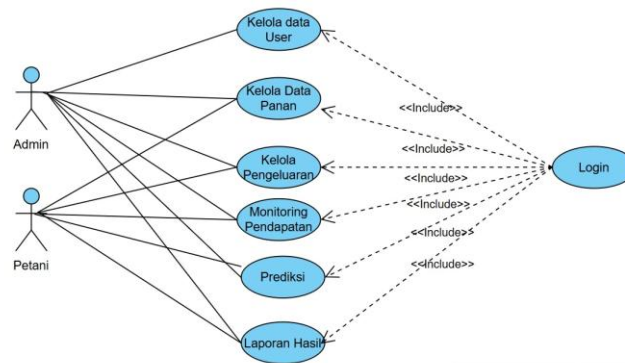


Figure 2. Sisawit System Use Case

The Sisawit information system design maps the functional interactions between two main actors, namely the Admin and Farmers, which are regulated through role-based access control to maintain data integrity. The system flow begins with the authentication process at the Login unit, which determines access limitations, where the Admin holds managerial authority through the Manage Account feature and monitors the distribution of plantation locations using the GIS Visualization feature. On the other hand, Farmers have exclusive access to operate the Manage Harvest Data and Manage Expenditures features, which are automatically integrated into the Income Monitoring function to present a private profit and loss recap. The core of this system lies in the Predictive Analysis feature, where cumulative historical data is processed using a comparison of the Moving Average (MA) and Weighted Moving Average (WMA) algorithms to generate estimates of future net income for each individual farmer. After the design was completed, the research entered the execution and validation phase, which began with Algorithm Implementation. In this phase, the Moving Average (MA) and Weighted Moving Average (WMA) forecasting models were modified for application on the backend, where WMA was given dynamic weighting that was sensitive to fluctuations in the price of TBS commodities, so that predictions were more responsive to market changes. Then, Model Evaluation is carried out to measure the reliability level of both algorithms, namely using the Mean Absolute Percentage Error (MAPE) metric to determine the percentage error accuracy, followed by the Diebold-Mariano Test (DM Test) to verify whether the difference in accuracy performance between MA and WMA is statistically significant. To ensure the validity and reproducibility of the forecasting results, an experimental scenario was designed. The dataset was divided into training data (80%) and testing data (20%) to evaluate model performance. The Moving Average (MA) model was tested using several window sizes ($n = 3, 5, \text{ and } 7$) to identify the optimal smoothing parameter. Meanwhile, the Weighted Moving Average (WMA) model applied a dynamic weighting scheme with a sensitivity parameter (α) to adjust weights based on price fluctuations. Model performance was evaluated using Mean Absolute Percentage Error (MAPE), and statistical significance between models was validated using the Diebold–Mariano (DM) test. The final stage was comprehensive System Testing: Black Box Testing was conducted to verify that all system functions (recording, calculation, graphics, and GIS visualization) ran according to specifications, while a User Acceptance Test (UAT) was conducted with farmer respondents to measure the level of acceptance, usability, and feasibility of the system in a real operational context.

This study compares two time series analysis methods for predicting farmers' net income, namely Moving Average (MA) and Weighted Moving Average (WMA).

2.1. Moving Average (MA)

The Simple Moving Average (SMA) method is used to smooth out short-term data fluctuations by calculating the average of the most recent historical data. This method is effective for stationary data but has weaknesses in responding to rapid trend changes [19].

$$MA_t = \frac{1}{n} \sum_{i=1}^n A_{t-i} \tag{1}$$

Where MA_t = Moving Average at time t , A_{t-i} = actual value at previous period, n = number of periods. This method smooths short-term fluctuations and is suitable for relatively stable data [5].

2.2. Weighted Moving Average (WMA)

Unlike MA, which gives equal weight to each data point, Weighted Moving Average (WMA) gives different weights to each period of historical data. Theoretically, the most recent data is assumed to be more relevant to the future, so it is given a greater weight [20]. However, in this study, developed a hybrid approach in which the determination of the weight is dynamic depending on the deviation of commodity prices from the global average, in order to capture the volatility of palm oil prices. The general formulation of WMA is:

$$WMA_t = \frac{\sum_{i=1}^n w_i A_{t-i}}{\sum_{i=1}^n w_i} \tag{2}$$

Where w_i is the weight given to period i . The use of this weighting aims to minimize prediction lag, which often occurs in conventional moving average methods [21]. The weights are dynamically adjusted based on price fluctuations using:

$$w_i = 1 + \alpha \cdot \left| \frac{P_i - \bar{P}}{\bar{P}} \right| \tag{3}$$

Where P_i = price at time i , \bar{P} = average price and α = sensitivity parameter. To measure the reliability of the developed prediction model, this study uses two evaluation parameters, namely error rate measurement and model difference significance test. Mean Absolute Percentage Error (MAPE) MAPE is used to measure the average absolute percentage error between the actual value and the predicted value. The advantage of MAPE is that it is scale-independent, making it easy to interpret in percentages [22].

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \tag{4}$$

The second test of the two models uses the Diebold-Mariano (DM) Test. To validate whether the difference in performance between the MA and WMA algorithms is statistically significant or merely coincidental, the Diebold-Mariano (DM) Test is used. This test is used to determine whether the differences in predictive accuracy produced by the two models are statistically significant or merely the result of data fluctuations [23]. Statistic The DM Test is formulated as:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi f_d(0)}{T}}} \tag{5}$$

Where $d_t = e_{1,t} - e_{2,t}$ to compares forecasting errors. This test compares the forecasting accuracy of the two models based on the differential loss function [24]. The final stage of the method involves Black Box Testing to validate the functional suitability of the system against the requirements specifications without examining the internal code structure [25]. In addition, a User Acceptance Test (UAT) was conducted with farmer respondents to measure the level of acceptance and usefulness of the system in real operations. User Acceptance Testing (UAT) is one of the alpha testing methods conducted by end-users specifically, company staff or employees who directly interact with the system to verify whether the system's functions are operating in accordance with their intended purposes [26].

3. RESULTS

This chapter presents the results of the research focusing on the presentation of data, system implementation, and model evaluation outcomes without in-depth interpretation. The results of the study include a comparative evaluation of the performance of the Moving Average (MA) and Weighted Moving Average (WMA) algorithms, which were validated using the Diebold-Mariano Test (DM Test). Furthermore, this chapter presents an in-depth analysis of the influence of price variables in determining the dynamic weight of the WMA model, followed by a description of the implementation of the system interface and GIS features, system testing, interpretation of the results obtained, algorithm limitations, and potential for future system development.

3.1. Model Comparison

In this study, a performance comparison was conducted between the Moving Average and Weighted Moving Average (WMA) algorithms for predicting crop yields for the next 3 months. This study manages time-series data on harvest yields and the income of independent oil palm farmers from January 2024 to October 2025, which includes production data in the form of Fresh Fruit Bunch (FFB) volume in kilograms and financial data such as selling price fluctuations (Rp2,000–Rp3,000/kg) and details of operational costs. The system integrates data management features (CRUD) for the digitization of physical notes, GIS visualization features that present land productivity distribution through interactive maps with color indicators (red, yellow, blue), and line and bar graph dashboards to monitor cash flow trends in real-time. All of this data is processed automatically to provide a transparent overview of plantation management, which was previously done manually.

The revenue estimation process is carried out through a forecasting module using the Moving Average (MA) and Weighted Moving Average (WMA) algorithms with a three-month time window period (n=3). The MA method calculates the arithmetic mean evenly, while WMA applies greater dynamic weighting to the latest data and periods with high price volatility to minimize prediction lag against TBS market fluctuations.

Detail Hasil Per Bulan Export CSV

Bulan	Aktual (Rp)	Prediksi MA (Rp)	Prediksi WHMA (Rp)	Error (MA)	Error (WHMA)	MAPE (MA)	MAPE (WHMA)
Apr-2025	6.437.350,00	–	–	6.437.350,00	6.437.350,00	100,00%	100,00%
Mei-2025	6.728.933,33	–	–	6.728.933,33	6.728.933,33	100,00%	100,00%
Jun-2025	6.914.741,11	–	–	6.914.741,11	6.914.741,11	100,00%	100,00%
Jul-2025	7.332.158,15	6.693.674,81	6.657.213,54	638.483,33	674.944,60	8,71%	9,21%
Agu-2025	7.508.966,42	6.991.944,20	7.030.648,24	517.022,22	478.318,18	6,89%	6,37%
Sep-2025	7.795.374,86	7.251.955,23	7.272.144,50	543.419,63	523.230,35	6,97%	6,71%
Okt-2025	7.968.113,76	7.545.499,81	7.537.789,92	422.613,95	430.323,84	5,30%	5,40%

Figure 3. Comparison of MA and WMA Performance

As shown in Figure 3, the forecasting performance of both models is evaluated using the MAPE metric across the testing period. The results of the revenue forecasting system implementation present a performance comparison between the Moving Average (MA) and Weighted Hybrid Moving Average (WMA) methods during the period from April to October 2025 with a three-month rolling window scheme. Based on the data in the figure, the forecasting process began in July 2025 after meeting the minimum historical data requirements, where the MAPE (Mean Absolute Percentage Error) value

continued to show a significant downward trend as actual data increased, reaching its highest accuracy point in October 2025 with a MAPE value of 5.30% for MA and 5.40% for WMA. The detailed visualization of the monthly shows the trend of prediction error reduction as the amount of actual data increases, resulting in precise estimates with low error rates to support financial decision-making for independent palm oil farmers.

The system automatically accumulates historical data from the last three months to project net income for the next three months, providing a basis for farmers to plan maintenance and operational costs more precisely based on prediction accuracy results that reach 93.08%.

 **Prediksi 3 Bulan Ke Depan**

Bulan	Pendapatan Prediksi (Rp)
Nov-2025	Rp 7.774.953
Des-2025	Rp 7.857.553
Jan-2026	Rp 7.881.269

Figure 4. 3-Month Income Forecast

Figure 4 presents the predicted income values for the next three months generated using the forecasting model. In the image above, the 3-Month Forecast shows the system applying the best model to project revenue for the upcoming period. The estimation results show a stable income trend with a slight upward trend, namely IDR 7,774,953 in November 2025, IDR 7,857,553 in December 2025, and reaching IDR 7,881,269 in January 2026. This predictive data provides strategic value for independent palm oil farmers in planning cash flow management and allocating plantation operating costs in a more measurable and accurate manner for the short term. The evaluation was conducted using the DieboldMariano statistical test (DM Test) to statistically test the two algorithms. The comparison results of MA and WMA methods are shown in Table 1. The quantitative evaluation results of both models are summarized in Table 1.

Table 1. Comparison of Evaluation Metrics for MA and WMA

Metrik Evaluasi	Moving Average (MA)	Weighted Hybrid MA (WMA)
MAE	530.384,78	526.704,24
MSE	287.220.097.584,80	285.821.776.449,24
MAPE	6,97%	6,92%
Akurasi	93,03%	93,08%

The statistical significance of the model comparison is evaluated using the Diebold-Mariano test as presented in Table 2.

Table 2. Diebold-Mariano Statistical Test (DM Test)

Hasil Uji Statistik Diebold-Mariano (DM Test)	
Parameter	Nilai
DM Statistic	0.224
P-Value	0.8228
Keterangan	Tidak signifikan

Based on the table above, it can be seen that Weighted Hybrid MA (WMA) has a slightly better performance than Moving Average (MA), as indicated by lower error values (MAE, MSE, MAPE) and higher accuracy (93.08%).

However, based on the Diebold-Mariano Test, a P-Value of 0.8228 (greater than the significance standard of 0.05) was obtained. This indicates that although WMA is superior in terms of numbers, the difference in accuracy between the two models is not statistically significant.

3.2. The Influence of Price Variables in Determining Dynamic Weights

Unlike the standard Moving Average, which gives equal weight to each data point, the WMA model developed in this study applies a dynamic weighting mechanism. Weighting is determined by considering an external variable, namely the average monthly commodity price. Based on the implemented algorithm, the price variable plays a crucial role in correcting the prediction results. This influence is calculated through the value of the monthly price deviation from the global average price. The algorithm gives greater weight to months with high price fluctuations (large deviations). This approach is based on the characteristics of palm oil commodities, where net income is highly sensitive to market price changes. Therefore, extreme price spikes or declines are considered to contain more significant information than when prices are stable, and are thus given greater weight in the forecasting process.

3.3. System Interface Implementation

This system is implemented in a web-based platform that integrates recording, geographic mapping, and prediction menu features.

3.3.1. GIS-Based Harvest Location Distribution Visualization

The system integrates a Geographic Information System (GIS) to spatially map the location of oil palm plantations. As shown in Figure 5, the digital map displays harvest location points with color indicators. These indicators divide the area based on income categories: Low (Red), Medium (Yellow), and High (Blue). This feature makes it easier for farmers to identify the most productive areas of land, as seen in the location points in the Muara Tebo region.

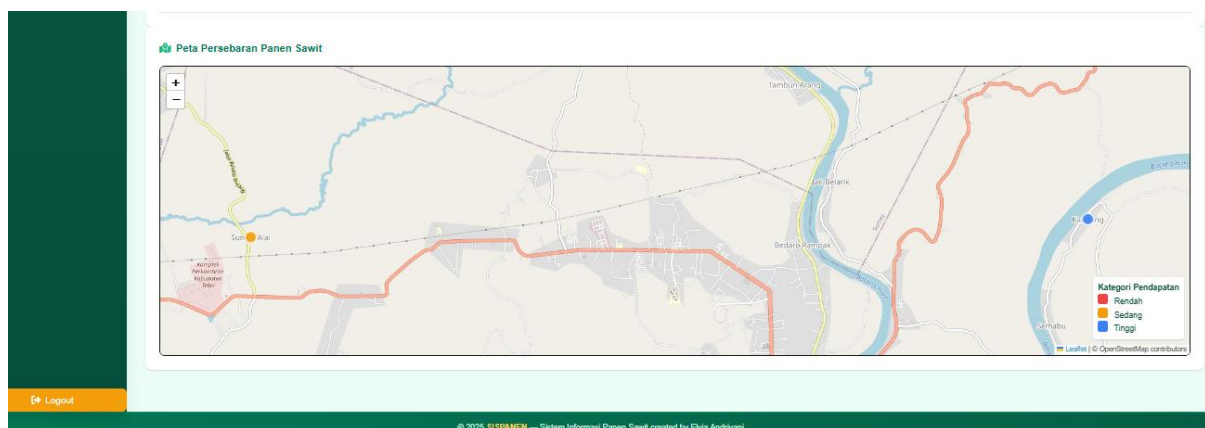


Figure 5. Map of Palm Oil Harvest Distribution with Category Indicators

3.3.2. Prediction and Income Estimation Menu

On the Prediction page, users can monitor the performance of the forecasting model, which works with a 3-month rolling window scheme. The system automatically takes the last three actual income data points to project future income. For example, to generate an income estimate for November 2025, the algorithm accumulates and weights the data for August, September, and October 2025. The results of processing this quarterly data are then presented in the form of interactive line graphs and detailed error tables to facilitate evaluation of the model's accuracy.



Figure 6. Prediction Menu

The prediction analysis page displays a line graph comparing actual data (green line) with WMA prediction results (yellow line). The system automatically calculates revenue estimates for the next 3 months. Based on the test results, the system projects revenue for November 2025, December 2025, and January 2026 to be stable in the range of IDR 7.7 million to IDR 7.8 million.

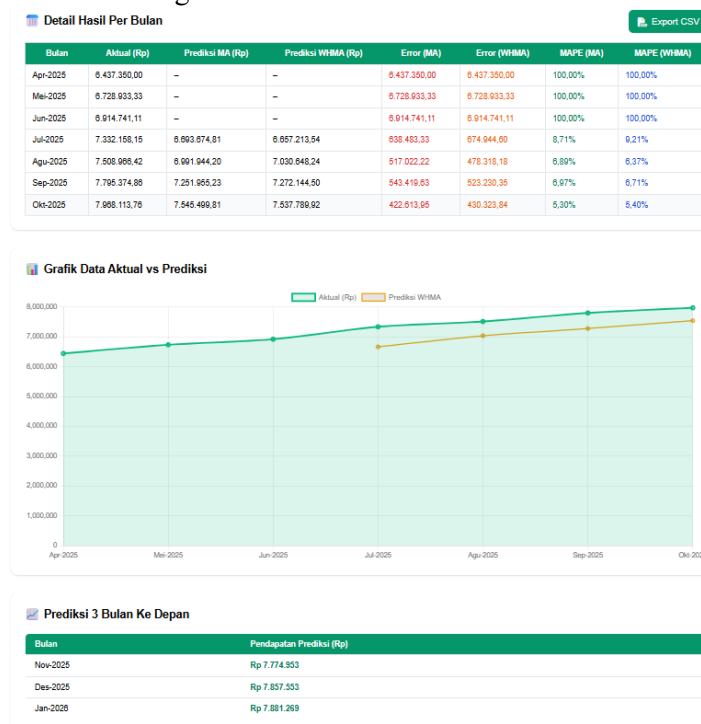


Figure 7. Comparison Chart of Actual Data vs. WMA Predictions and Estimates for the Next 3 Months

3.3.3. Harvest Data Management

The Harvest Data menu serves as the main database that records all palm oil production activities in detail. As shown on the interface, users can input harvest information, including the harvest date, production volume (kg), selling price per kilogram, and specific plantation location (such as "Kandang" or "Sungai Alai"). The system automatically calculates the total gross income from for each harvest transaction and displays it in a chronological table. In addition to the recording function (Create), this module is equipped with data management features (Edit/Delete) and data export capabilities (Export CSV) for archiving and external reporting purposes, thus ensuring the accuracy of historical data, which is the main basis for the income forecasting algorithm.

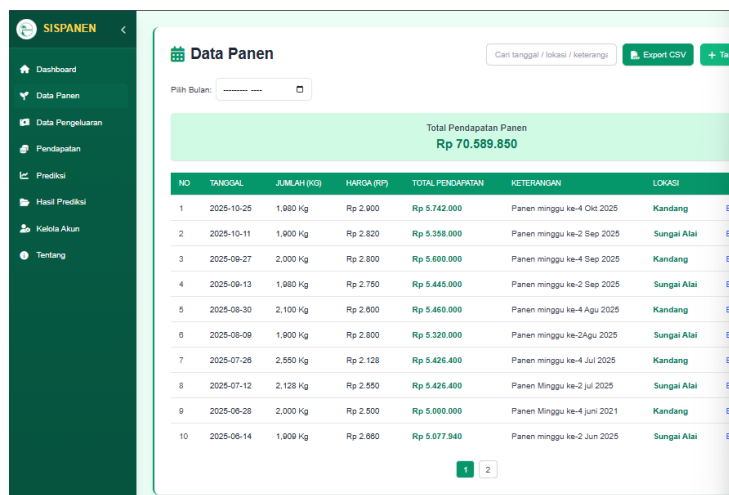


Figure 8. Harvest Data Management

3.3.4. Expense Data Management

The Expenditure Data menu is designed to facilitate the structured recording of all operational costs of the plantation. On this interface, users can input various types of expenditures that are categorized specifically, such as Salaries, Maintenance (fertilization/spraying), Operational (transportation), and Cleaning costs. The system automatically aggregates this data and displays a summary of total costs at the top of the dashboard to provide a quick overview of cash outflows. In addition, this feature is equipped with an option to export financial reports in Excel or PDF format, which is useful for documentation and evaluation of farming cost efficiency.

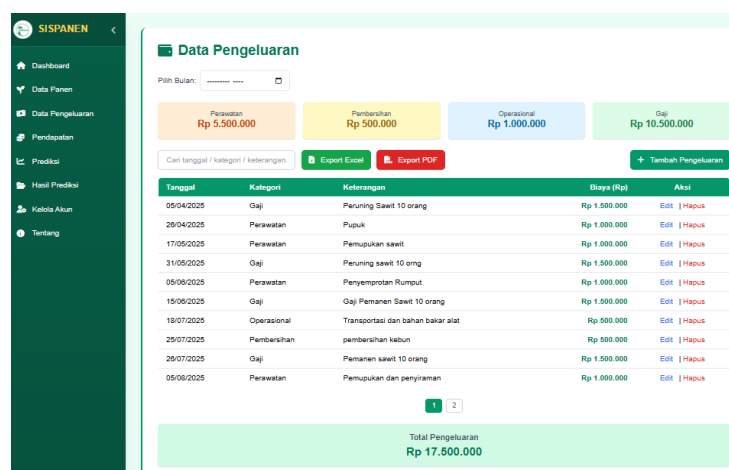


Figure 9. Expenditure Recording Management

3.3.5. Financial Recapitulation

To support prediction accuracy, the system provides an operational data recording module. The Harvest Data page records production volume (kg) and selling price, while the Expense Data page records maintenance costs and wages. This data is summarized in a bar chart (Figure 3) that visualizes the comparison of Gross Income, Total Expenses, and Net Income on a monthly basis, ensuring that predictions are based on real net income.

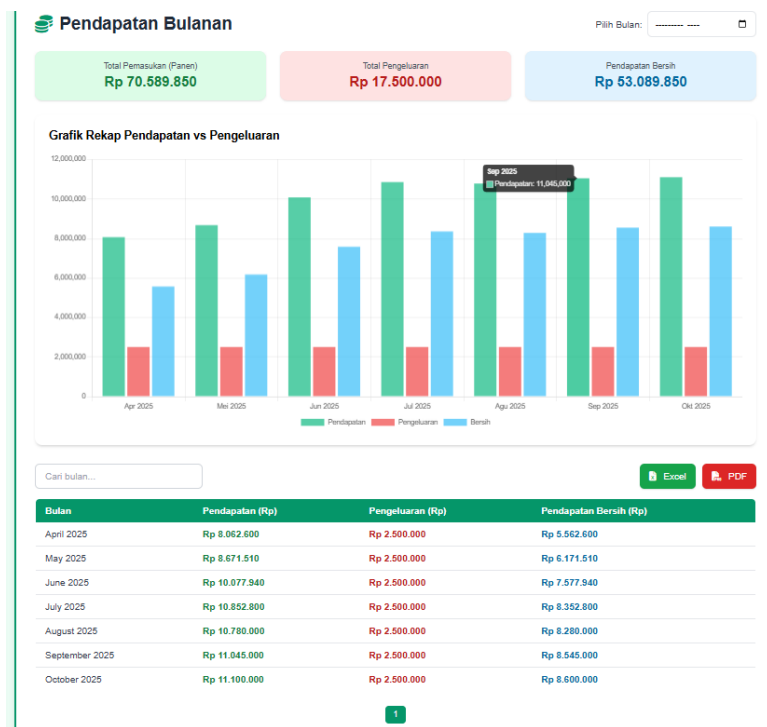


Figure 10. Harvest Data Recording Interface and Financial Recapitulation Chart

3.4. System Testing

System testing is a crucial stage to ensure that the application built meets functional requirements and is acceptable to end users. In this study, testing was conducted through two approaches, namely Black Box Testing to validate system functions and User Acceptance Testing (UAT) to measure respondent satisfaction levels.

3.4.1. Black Box Testing

System functionality testing was carried out using the Black Box Testing method, which involved three expert testers to validate the conformity between software input and output. The testing focused on crucial aspects such as login authentication, harvest and expenditure data management (CRUD), the accuracy of automatic income calculations, the functionality of map visualization in the GIS feature, and the accuracy of the MA and WMA forecasting algorithms in presenting predictive data. Based on the test results for all defined scenarios, the three testers stated that the system functioned validly, indicating that the application had met the functional requirements specification () without any logical errors found in the user interface.

3.4.2. User Acceptance Testing

After functional validation, user acceptance testing was conducted involving palm oil farmers and system users as respondents. The User Acceptance Test was conducted on 9 respondents consisting of

system administrators and users. The questionnaire covered 10 indicator questions grouped into three main aspects: The User Acceptance Test (UAT) involved 9 respondents, including system administrators and users. The questionnaire consisted of 10 indicators grouped into three aspects: usefulness, ease of use, and interface. The summary of the evaluation results is presented in Table 3.

Table 3. Summary of User Acceptance Testing Results

No	Assessment	Average Score (%)	Category
1	Utility Aspect	97.78	Very Good
2	Usability Aspect	89.63	Very Good
3	User Interface Aspect	97.22	Very Good
4	Overall Average	95.11	Very Good

Based on the recapitulation results in Table 2, the SISSPANEN system obtained an overall average score of 95.11% with a rating of "Very Good/Excellent". The Usefulness aspect obtained the highest score (97.78%), indicating that the income prediction and harvest recording features are considered very helpful in improving user work efficiency.

4. DISCUSSIONS

4.1. Interpretation of Analysis Results

Based on the results of the experiments conducted, the interpretation of the prediction model's performance can be described as follows:

4.1.1. Responsiveness of the Weighted Moving Average (WMA) Model

Advantages of WMA Responsiveness Although the difference in Mean Absolute Percentage Error (MAPE) values between Weighted Moving Average (WMA) (6.92%) and Moving Average (MA) (6.97%) is relatively small, the WMA algorithm shows conceptual advantages in capturing market dynamics. In this system, WMA is designed to give greater weight to periods where there are extreme price fluctuations. This reflects the reality in the field that palm oil farmers' income is very sensitive to changes in the price of Fresh Fruit Bunches (FFB). Therefore, WMA is considered more representative for use as a reference for decision making than MA, which averages all historical data.

4.1.2. Statistical Significance of Model Performance

Statistical Significance The Diebold-Mariano test results show a P-Value of 0.8228, which is well above the significance level ($\alpha = 0.05$). Statistically, this indicates that in the dataset used at this time, the two models do not have a significant difference in accuracy. This phenomenon may be caused by the income data pattern in the test period, which tends to be stable or has not shown a drastic enough price shock to make the WMA weighting mechanism work optimally. However, the absence of statistical significance does not necessarily negate the practical usefulness of the WMA model in anticipating future volatility.

4.2. Limitations of the Algorithm and System

This study has limitations in that the prediction model is still univariate because it only relies on historical income data and price fluctuations without taking into account agroclimatic variables such as rainfall. In addition, the accuracy of the system is highly dependent on the discipline of manual input by farmers, which is prone to human error, as well as the limited range of historical data (time series) available to optimally capture long-term seasonal patterns. Potential for Future Development.

4.3. Future Development Potential

For further development, it is recommended to apply a multivariate approach by integrating real-time weather data and Internet of Things (IoT) sensors to improve the accuracy of predictions of natural conditions. In addition, developing the system into a mobile application is highly recommended to make it easier for farmers to record operational data directly (onsite) in the plantation.

5. CONCLUSION

web-based information system for recording palm oil harvests and farm income that is integrated with a Geographic Information System (GIS) and intelligent forecasting features. Based on the comparative evaluation results, the Weighted Moving Average (WMA) algorithm with a dynamic weighting mechanism proved to have reliable performance with an accuracy rate of 93.08% (MAPE 6.92%), slightly superior numerically to the Moving Average (MA) which had an accuracy of 93.03%. Although the Diebold-Mariano statistical test showed that the difference in performance between the two models was not significant in the tested dataset, WMA was considered more relevant for implementation due to its sensitivity in responding to fluctuations in the price of Fresh Fruit Bunches (FFB), which is a major factor of uncertainty for farmers. This indicates that both models perform similarly under relatively stable data conditions.

Functionally, the system has been verified to run well through Black Box testing, which shows a valid status for all key features. The user acceptance rate is also very high, as evidenced by a User Acceptance Test (UAT) score of 95.11% with a rating of "Very Good." The presence of GIS spatial visualization and automatic financial management features in this system provides strategic contributions to independent farmers, enabling more transparent monitoring of land productivity and more precise operational budget planning for the future. The main contribution of this study lies in the development of a dynamically weighted forecasting approach that incorporates price fluctuations into the weighting mechanism, as well as its integration into a web-based decision support system with GIS visualization.

From an informatics perspective, this research contributes to the field of decision support systems and agricultural informatics by demonstrating how time-series forecasting methods can be integrated with spatial information systems to support real-world decision-making. For future research, it is recommended to apply multivariate forecasting models by incorporating additional variables such as weather conditions and production factors. Furthermore, integrating real-time data and implementing more advanced methods such as ARIMA, LSTM, or hybrid models can improve prediction accuracy. The development of mobile-based applications is also suggested to enhance usability in field conditions.

REFERENCES

- [1] A. Nurjanah, Aries Sukariawan, and Dina Arfianti Saragih, "PERBANDINGAN KERAGAAN TANAMAN KELAPA SAWIT (*Elaeis guineensis* Jacq.) PADA SISTEM PEREMAJAAN KONVENSIONAL DAN UNDERPLANTING," *J. Agro Estate*, vol. 5, no. 2, pp. 82–88, 2021, doi: 10.47199/jae.v5i2.87.
- [2] A. Anto, D. Prameswari, A. Febriansyah, and Z. Saputra, "SISTEM MONITORING DAN PENGUKURAN KADAR pH, JARAK DAN SUHU PADA LIMBAH CAIR KELAPA SAWIT (POME) BERBASIS DISPLAY DIGITAL IoT," *Pros. Semin. Nas. Kefarmasian Ke-3*, vol. 3, pp. 24–31, 2023.
- [3] A. Asnawi and R. Kurniawan, "SISTEM INFORMASI PREDIKSI HASIL PANEN KELAPA SAWIT BERDASARKAN DATA PRODUKSI TBS DENGAN MENGGUNAKAN METODE DOUBLE EKSPONENTIAL SMOOTHING," *J. Inform. Teknol. dan Sains*, vol. 7, pp. 282–288, Mar. 2025, doi: 10.51401/jinteks.v7i1.5549.
- [4] Z. Mahbub, A. N. Hadi, R. Afandi, and M. A. Azzam, "Memprediksi Dampak Anomali Cuaca

- Ekstrem terhadap Hasil Panen Padi Menggunakan Model Deret Waktu SARIMA Seasonal Autoregressive Integrated Moving Average (SARIMA) dikenal luas karena kemampuannya menangkap tren jangka panjang sekaligus pola musiman yang berulang , peramalan berbasis SARIMA yang mengintegrasikan data produksi dan variabel anomali beberapa tahun terakhir , terutama di wilayah yang kinerja tanamannya sangat dipengaruhi oleh,” no. November, 2025.
- [5] F. Fruit and B. Ffb, “Algoritma Moving Average untuk Peramalan Harga TBS Kelapa Sawit The Moving Average Algorithm for Forecasting Palm Oil,” *Sist. J. Sist. Inf.*, vol. 14, no. 1, pp. 455–469, 2025.
- [6] F. Irawan, S. Sumijan, and Y. Yuhandri, “Prediksi Tingkat Produksi Buah Kelapa Sawit dengan Metode Single Moving Average,” *J. Inf. dan Teknol.*, pp. 251–256, Sep. 2021, doi: 10.37034/jidt.v3i4.162.
- [7] M. Fikran Pontoh, Lahinta Agus, and Rohandi Manda, “Sistem Informasi Perkembangan Komoditi Tanaman Pangan Berbasis Web pada Dinas Pertanian Kabupaten Bolaang Mongondow Utara,” vol. 2, no. 1, pp. 62–76, 2022, [Online]. Available: <https://ejurnal.ung.ac.id/index.php/diffusion/article/view/12843/3944>
- [8] S. Sarana, D. Kurniasari, T. P. Shella, and M. Usman, “Integra: Journal of Integrated Mathematics and Computer Science A Hybrid ARIMA – GRU Model for Forecasting Palm Oil Prices at PT Sawit,” vol. 2, no. 1, pp. 7–14.
- [9] H. Mardesci and D. Fitriani, “Performance Evaluation of ARIMA and ANN Models for Forecasting Oil Palm Production Trends,” pp. 75–83, 2025.
- [10] F. Ustadatin, A. Muqtadir, and A. Arifia, “Fahreza, A. (2022). Penerapan Data Mining dengan Metode Single Moving Average dalam Pengolahan Data Penerimaan Siswa Baru. Proceeding Seminar Nasional Ilmu Komputer, 2(1), 25–34.,” *Komputika J. Sist. Komput.*, vol. 12, no. 2, pp. 83–90, 2023.
- [11] F. Akmal, F. Ramdani, and A. Pinandito, “Sistem Informasi Pengelolaan Perkebunan Kelapa Sawit Berbasis Web GIS,” *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 5, pp. 1894–1901, 2018.
- [12] B. Irawan, D. Nining, and I. Soesilo, “DAMPAK KEBIJAKAN HILIRISASI INDUSTRI KELAPA SAWIT TERHADAP PERMINTAAN CPO PADA INDUSTRI HILIR (The Impact of Palm Oil Industry’s Downstream Policy on Downstream Industry CPO Demand),” *J. Ekon. Kebijak. Publik*, vol. 12, no. 1, pp. 29–43, 2021, [Online]. Available: <https://dx.doi.org/10.22212/jekp.v11i1.2023>
- [13] R. T. Subagio, D. V. Kartika, and F. Sururiyah, “Penerapan Metode Moving Average untuk Memprediksi Penjualan Tiket Wisata Guna Meningkatkan Kualitas Layanan,” *Remik Ris. dan E-Jurnal Manaj. Inform. Komput.*, vol. 8, no. 3, pp. 924–937, 2024, [Online]. Available: <http://doi.org/10.33395/remik.v8i3.14010>
- [14] S. A. and H. Wibowo, “Perbandingan Metode Moving Average untuk Prediksi Hasil Produksi Kelapa Sawit,” *Perbandingan Metod. Mov. Aver. untuk Prediksi Has. Produksi Kelapa Sawit* No Title,” no. 1, vol. no. 1, pp. 156–162, 2019.
- [15] D. Brilian and Y. Safitri, “Palm Oil Production Forecasting in 2025 Using the Single Exponential Method to Support Operational Planning at PT Perkebunan Nusantara IV Region IV,” vol. 6, 2025.
- [16] Chintya Giba Alvia Burhanuddin, Yustina Rada, and Erwianta Gustial Radjah, “Agricultural Land Use Mapping Analysis Using the Geographic Information System in Temu Village,” *J. Artif. Intell. Eng. Appl.*, vol. 4, no. 1, pp. 117–123, 2024, doi: 10.59934/jaiea.v4i1.568.
- [17] E. S. Lubis, “Vol . 13 No . 1 , Bulan Maret Tahun 2025 Review : Program Sawit Rakyat (PSR) sebagai Akselerasi Swasembada Pangan dan Energi,” vol. 13, no. 1, pp. 210–226, 2025.
- [18] E. D. Wahyuni, S. Kom, M. Kom, F. N. Ramadha, D. Deo, and V. Septa, “SDLC Big Bang dan Waterfall : Perbandingan Pendekatan dalam Pengembangan Perangkat Lunak,” vol. 18, pp. 41–45, 2024.
- [19] W. Nurlela, A. I. Pratiwi, and H. T. Yulianti, “Analisis Metode Moving Average , Exponential Smoothing , dan Arima dalam Peramalan Permintaan untuk Pengendalian Stok Floor Rear,” vol. 4, no. 3, pp. 1066–1075, 2025.
- [20] F. Amir, “KOMPUTA : Jurnal Ilmiah Komputer dan Informatika ANALISIS

-
- PERBANDINGAN AKURASI METODE MOVING AVERAGE DAN METODE EXPONENSIAL SMOOTHING DALAM KOMPUTA: Jurnal Ilmiah Komputer dan Informatika,” vol. 12, no. 2, pp. 30–38, 2023.
- [21] B. A. Celik and S. Celik, “Hybrid forecasting of agricultural commodity prices: Integrating machine learning, time series, and stochastic simulation models,” *Borsa Istanbul Rev.*, vol. 25, no. 6, pp. 1440–1462, 2025, doi: <https://doi.org/10.1016/j.bir.2025.10.004>.
- [22] L. S. Ihzaniah *et al.*, “JAMBURA JOURNAL OF PROBABILITY AND STATISTICS Volume 4 Nomor 1, Mei 2023,” vol. 4, pp. 17–29, 2023.
- [23] F. I. Komputer and U. A. Purwokerto, “Comparative Study of LSTM and GRU Accuracy in Predicting BBRI Stock Closing Price,” vol. 10, no. 1, pp. 837–846, 2026.
- [24] L. Junaedi, N. Damastuti, and A. Widodo, “Penerapan Metode Seasonal ARIMA (SARIMA) untuk Peramalan Penjualan Barang dengan Pola Musiman Tahunan,” vol. 01, pp. 38–48, 2025.
- [25] S. Nidhra and J. Dondeti, “BLACK BOX AND WHITE BOX TESTING TECHNIQUES – A LITERATURE REVIEW,” vol. 2, no. 2, pp. 29–50, 2012.
- [26] N. Hartono, A. A. Muin, U. Islam, and N. Alauddin, “Penggunaan User Acceptance Testing (UAT) Pada Pengujian Sistem Informasi Pengelolaan Keuangan Dan Inventaris Barang,” 2025.