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Applied the Holt–Winter Forecasting Method for Rice Production: A Case Study of Cianjur and Indramayu Regencies, West Java, Indonesia

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ABSTRACT

The current food problem in Indonesia is uneven food availability. Differences in rice planting and harvesting areas due to land conversion from rice fields to residential areas and extreme climate change have caused instability in rice production. Cianjur and Indramayu, as rice production centers in West Java, have experienced rice production fluctuation from 2010 to 2023. The rice harvest area in both regions has even experienced a downward trend, which has had a direct impact on agricultural productivity. This study aims to predict rice production using the Holt-Winters multiplicative method for rice production from 2024 to 2030. By using yearly rice production data from 2010 to 2023 in Cianjur and Indramayu regencies, focusing on model evaluation by using Mean Absolute Percentage Error (MAPE). The analysis results show that by using multiplicative Holt Winters model, predicted rice production in Cianjur experienced downward then upward trend in 2030 with a MAPE value of 1.00% and for Indramayu Regency experienced upward trend in the following years with a MAPE value of 0.74%. Thus, these prediction results can be used as a basis in supporting policy formulation and strategic decision-making related to food security program planning.

1. INTRODUCTION

Food is the most important thing in human life for survival. Sufficient food production and availability that meets the food consumption needs of the community are important elements of food security (Schreer & Padmanabhan, 2020). The fulfillment of food at the household level, where all family members can access sufficient food to carry out daily activities, can be considered as household-level food security (Owasa & Fall, 2024). Recently, Indonesia's rice consumption stands at an average of 93.36 kg per capita annually (Sabarella *et al*., 2025). The challenges of food security itself have been a global problem for many years and have become a cross-cutting phenomenon, involving social, political, environmental, and economic issues (Amhamed *et al.,* 2023). In this case, the government maintains food security by increasing domestic rice production so that it is no longer dependent on imported products (Sulaiman *et al.,* 2017). Rice production can be used as one indicator of food security (Beltran-Peña *et al.,* 2020).

The Ministry of Agriculture has grouped 17 rice-producing provinces in Indonesia into four groups based on their production volume (PUSDATIN, 2024). Group 1 consists of provinces with the lowest rice production in 2023, ranging from 533 thousand tons (0.99%) to 844 thousand tons (1.49%), comprising five provinces. Group 2 consists of provinces with moderate rice production between 1.34 (2.62%) and 2.6 million tons (4.96%), comprising 8 provinces. Group 3 consists of provinces with high rice production of 5.05 million tons (9.21%), namely South Sulawesi Province. Group 4 consists of provinces with very high rice production ranging from 9.08 (16.81%) to 9.58 (17.83%) million tons, namely East Java, Central Java, and West Java provinces.

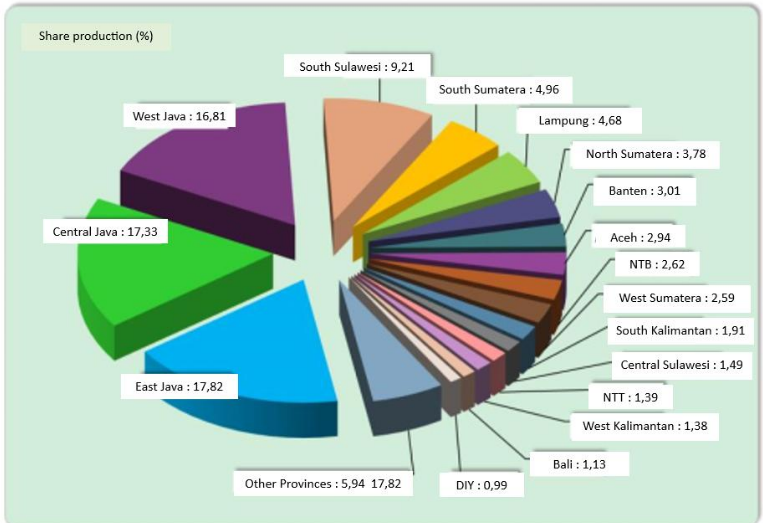

Figure 1. Rice production center provinces in Indonesia 2019-2023 (PUSDATIN, 2024)

This study focused on rice production data in West Java Province from 2010 to 2023. West Java Province does not only provide food on a provincial scale but also contributes to national rice production. According to data from the BPS (2024), Indramayu and Cianjur Regencies are among the rice granaries in West Java Province, which experienced fluctuations in rice production from 2010 to 2023. Rice harvest area in Indramayu regency ranged from 201,361 ha to 255,983 ha with the lowest at 201,361 in 2015, peaked at 255,983 ha in 2016 then in the following years experienced fluctuations from 215,731 ha to 245,329 ha. Indramayu Regency ranked first as the largest rice granaries in West Java, with rice production peaking 1.23 million tons of unhulled rice in 2021 then experienced a downward trend in the following years at 1.22 million tons of unhulled rice in 2022 and 1.31 million tons of unhulled rice in 2023. Meanwhile, Cianjur Regency experienced fluctuations in rice harvest area ranged 139,932 ha to 165,451 ha from 2010-2016 and significantly decline during 2017 to 2023 and hit the lowest rice harvest area at 113,538 ha in 2021. The highest rice production in Cianjur occurred in 2016 at 939.73 thousand tons of unhulled rice then experienced a downward trend in 2017 at 859.87 thousands tons of unhulled rice and the lowest in 2021 at 611 thousands tons of unhulled rice. This significant decline in rice production in Cianjur regency in 2016 to 2021 is a concern because it can disrupt food security not only at the regency level but also at the provincial level. To anticipate a decline in rice production that could cause a drop in rice prices in the community, rice production forecast is important. For example, rice production forecasting is vital to maintain food security in Indonesia.

The Holt–Winters Exponential Smoothing (HWES) model is one of the most widely adopted time series forecasting methods in agricultural research due to its ability to simultaneously capture the three fundamental components of a time series: level, trend, and seasonality. Unlike the ARIMA model, which generally requires data transformation and differencing to achieve stationarity as well as careful identification of model orders, the Holt–Winters approach directly models these components through three smoothing parameters corresponding to level (α), trend (β), and seasonal effects (γ). This makes the method computationally efficient, straightforward to implement, and particularly suitable for agricultural production data, which commonly exhibit strong seasonal patterns associated with planting and harvesting cycles. Consequently, Holt–Winters has been widely recognized as a robust forecasting technique for short- to medium-term prediction in agricultural and food production systems.

Numerous empirical studies have demonstrated the effectiveness of the Holt–Winters model in forecasting agricultural production and commodity markets. Parreño *et al*. (2023) reported that the Holt–Winters model outperformed the Seasonal ARIMA (SARIMA) model in forecasting rice and corn production in the Philippines, achieving lower RMSE and MAPE values while providing reliable information for food security planning and import policy decisions. Similarly, Mgale *et al*. (2021) found that the additive Holt–Winters model produced slightly better forecasting accuracy than ARIMA for wholesale rice prices in Tanzania, whereas Ahmar *et al*. (2023) identified Holt–

Winters as one of the best-performing models for forecasting food grain production in India. Furthermore, Holt–Winters has been successfully applied to a wide range of agricultural forecasting problems, including rice production (Abotaleb *et al*., 2021; Smitha, 2025), rice stocks (Chatterjee *et al*., 2021), rice supply (Sugiarto *et al*., 2021), rice prices (Sijabat & Suharjito, 2025), and potato prices (Bulut, 2025). This highlighting broad applicability and reliability of HWES for forecasting agricultural time series characterized by recurring seasonal behavior.

This current study aims to forecast rice production and rice harvested area from 2024 to 2030 based on historical data from 2010 to 2023 by using the Holt-Winters method. This research is the implementation and evaluation of the Holt-Winters method as support strategic agricultural planning, including food security management and agricultural machinery distribution management. The benefits of this research are expected to be used as a basis for decision-making and anticipating a decline in rice production to maintain food security by the government and policy makers.

2. MATERIALS AND METHODS

2.1. Materials

This study used a quantitative approach by creating models and analyzing data and descriptive explanations. The data used was secondary data in the form of rice production data for Cianjur and Indramayu Regencies from 2010 to 2023, obtained through official BPS publications. Data analysis used the Holt-Winters multiplicative method because rice production data fluctuates unpredictably each year and shows trend and seasonal patterns, making it easier to predict rice production for the coming years.

2.2. Methods

This study applied the Holt-Winters method and the following research procedures were carried out:

1. Collected rice production data for Cianjur and Indramayu Regency from 2010 to 2023 through official publications from the West Java BPS.
2. Identified the data obtained to determine whether there are trend and seasonal patterns, then determining the appropriate additive or multiplicative approach.
3. Determined the initial values of the smoothing parameters α (alpha) for level, β (beta) for trend, and γ (gamma) for seasonality.
4. Calculated the initial values for level (L_0), trend (T_0) and seasonal (S_0).
5. Calculated the smoothing of the level (L_t), trend (T_t), and seasonal component (S_t) in year t using the Holt-Winters multiplicative equation.
6. Calculated the predicted value for the upcoming period (F_{t+m}) using the results of the smoothing of L_t, T_t, and S_t.
7. Evaluated the prediction results using Mean Absolute Percentage Error (MAPE) for modeling accuracy.
8. Optimized the parameter values α (alpha), β (beta), and γ (gamma) and compared with the initial condition parameters to find the optimum values for α, β, γ and MAPE by using Microsoft Excel.

2.3. Holt-Winters Method Data Analysis

The Holt-Winters method is a time series prediction method that can read trend and seasonal patterns. This method is used when the data obtained shows irregular patterns, then calculates seasonal factors for the first year and the initial level and trend after the first year. The data commonly used in the Holt-Winters method is monthly and quarterly data per 4 months. Compared to simple models such as moving averages, Holt-Winters provides a more complete model because it separates three parameters: level, trend, and seasonality (Tirkeş *et al.,* 2017).

The Holt-Winters exponential smoothing method uses three parameters, namely alpha (α) for the original data/level smoothing constant, beta (β) for the trend pattern smoothing constant, and gamma (γ) for the seasonal pattern smoothing constant. The parameters α, β, and γ indicate how responsive the level, trend, and seasonal models are to data changes. Their values range from 0 to 1. The level smoothing value is represented by α (alpha), which serves to adjust the base level over time. The greater the value of α (α = 1), the more responsive the level is to the latest data. However, if the value of α = 0 or is small, the level does not change. The trend smoothing value is represented by β (beta), which presents the rate of change in the trend. If the β value is large (β=1), the trend adjusts quickly to the acceleration/deceleration of the level, but if the β value is small (β=0), the trend experiences a slowdown/decline, which is useful if the trend is stable and avoids fluctuations. The seasonal smoothing value is represented by γ (gamma), which provides information about seasonal indices/recurring patterns in the data. If the γ value is large (γ=1), the seasonal index changes quickly following the latest data, while if the γ value is small (γ =0), the seasonal index is stable (Hyndman & Athanasopoulos, 2018).

The equation forms for data analysis using the Holt-Winters method is as follows (Montgomery *et al.,* 2016):

(a) Level smoothing
$$L_t = \alpha\frac{X_t}{S_{t-m}} + (1-\alpha) \times (L_{t-1} + T_{t-1}) \quad (1)$$

(b) Trend smoothing
$$T_t = \beta \times (L_t - L_{t-1}) + (1-\beta) \times T_{t-1} \quad (2)$$

(c) Seasonal smoothing
$$S_t = \gamma\frac{X_t}{L_t} - (1-\gamma) \times S_{t-m} \quad (3)$$

(d) Forecasting
$$F_{t+m} = (L_t + T_t\ k) \times S_{t-k+m} \quad (4)$$

where L_t is the level smoothing value in year t, T_t is the trend smoothing value in year t, S_t is the seasonal smoothing value in year t, k is the number of periods to be forecasted, m is the length of the season, X_t is the data t, α is the original level data smoothing parameter ($0 < \alpha < 1$), β is the parameter value for the trend smoothing ($0 < \beta < 1$), L_{t-1} is the level smoothing value in year $t-1$, T_{t-1} is the trend smoothing value in year $t-1$, γ is the parameter value for the seasonal smoothing ($0 < \gamma < 1$), and $F_{(t+m)}$ is the forecasted value for m.

2.4. Data Validation

The validation of the forecasted model data can be measured by the mean absolute percent error (MAPE). To calculate MAPE, the difference between the predicted data and the actual data is needed, which is done by looking at the average prediction results that have an average percentage error or during a certain period multiplied by 100% to obtain a percentage result (Baykal *et al.,* 2022). The equation used to calculate MAPE is as follows:

$$MAPE = \sum_{t=1}^{N}\frac{\left|\left(\frac{X_t - Y_t}{X_t}\right) x\ 100\right|}{N} \quad (5)$$

where X_t is the actual data in year t, Y_t is the current prediction data, and N is the number of periods. The smaller MAPE value in the estimated results, the better the forecasting model used. The interpretation of the obtained MAPE value can be explained through Table 1 (Baykal *et al.*, 2022).

Table 1. MAPE value interpretation

MAPE (%)	Interpretation
MAPE < 10	Highly accurate
10 < MAPE ≤ 20	Good
20 < MAPE ≤ 50	Fair
MAPE ≥ 50	Weak and innacurate

3. RESULTS AND DISCUSSION

3.1. Rice Production in Cianjur and Indramayu Regencies

Rice production data in Cianjur and Indramayu Regencies for the period 2010 to 2023 shows a fluctuating pattern with a downward trend in the long term. The data shows a rapidly changing level and trend component, as well as a seasonal pattern. Rice production in Cianjur Regency in Table 2 shows that the increase in production that occurred in the early period was mainly influenced by relatively large availability of rice fields, there was no massive conversion of agricultural land to residential areas and favorable climate conditions in Cianjur Regency. During this period, there was an increase in the number of agricultural machinery and agricultural intensification programs that supported increased agricultural productivity. Agricultural machinery acts as a key material foundation for transitioning from traditional to modern agriculture. Mechanical inputs primarily drive labor productivity, reduce timeline bottlenecks, and minimize post-harvest losses. For example two wheels tractor, significantly improves farm productivity and farmers' income (Elisabeth, 2022). This condition indicated improvements in agricultural infrastructure and facilities for example improvements in irrigation networks, the use of superior rice varieties and increased use of agricultural machineries in Indramayu regency. Meanwhile, the significant decline in rice production after 2017 is likely related to land use changes and climate change that reduced the harvest area. The decline in production indicates the influence of climate factors, shifts in the planting calendar, and changes in harvest area.

Based on Table 2, which shows rice production in Indramayu Regency from 2010 to 2023, it can be seen that rice production shows annual fluctuations with an increasing trend. From 2010 to 2016, rice production fluctuated fairly steadily, with the highest production of 1.19 million tons in 2015 (Figure 2). This condition indicates improvements in agricultural infrastructure and facilities, such as improvements in irrigation networks, the use of superior rice varieties such as INPARI 32 due to its good adaptability and an improvement of Ciherang for its resistance to bacterial disease. Inpari 32 also have a higher productivity than Ciherang and Inpari 30 Agustian *et al.* (2022) and increased use of agricultural machinery in Indramayu Regency. Rice production in Indramayu Regency subsequently experienced fairly stable fluctuations, due to the role of irrigation networks, an increase in the planting index, and the optimization of agricultural machinery use, reaching the highest rice production in 2021 at 1.23 million tons.

Table 2. Rice production in Cianjur and Indramayu Regencies from 2010 to 2023

Year	Rice Production in Cianjur (ton)	Rice Production in Indramayu (ton)
2010	862,228	1,113,978
2011	790,824	1,135,863
2012	868,538	1,076,066
2013	882,662	1,147,212
2014	830,545	1,122,582
2015	851,649	1,188,633
2016	939,731	1,149,484
2017	859,877	1,112,697
2018	696,726	1,133,671
2019	641,804	1,117,814
2020	622,992	1,087,874
2021	611,773	1,234,134
2022	618,950	1,227,509
2023	650,123	1,131,977

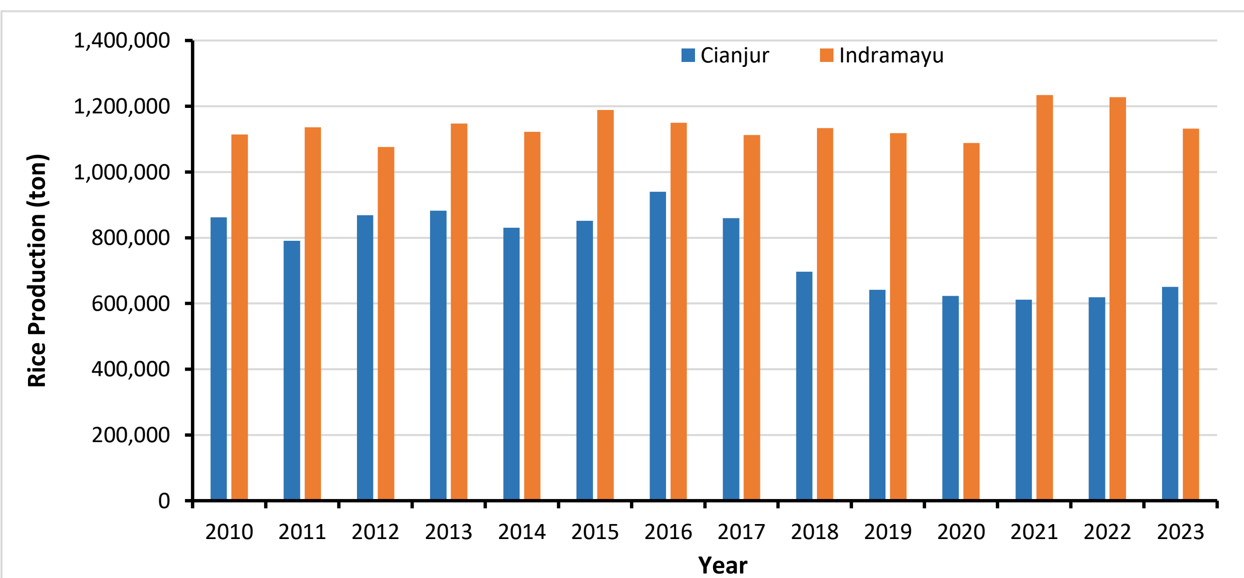

Figure 2. Rice production in Cianjur and Indramayu Regencies from 2010 to 2023

During COVID-19 pandemic in 2020, both regencies experienced significant decreasing in the number of rice production. The occurence of this phenomena affected the forecast because it changed in data structure and lead to disrupt with the Holt-Winters parameters such as trend or level of variables. These changes of data structure affected in long term forecast (Drop & Bohdan, 2025).

Based on the results of identifying the rice production data graph from Cianjur and Indramayu Regencies in Figure 3, it shows that rice production in Cianjur and Indramayu Regencies is not static but is influenced by seasonal patterns and trends. Therefore, the Holt-Winters forecasting method was chosen to be applied because it is able to adapt to trend changes based on past data. The Holt-Winters method approach has proven effective for agricultural data that shows fluctuations and unstable trends (Hyndman & Athanasopoulos, 2018).

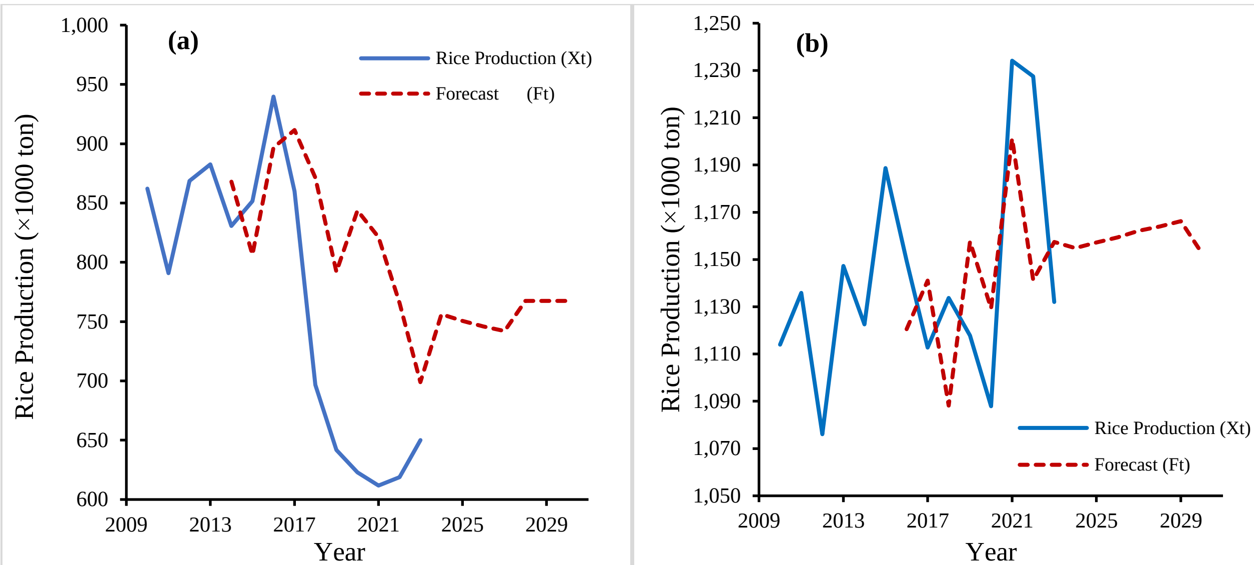

Figure 3. Rice Production Prediction for Cianjur Regency: (a) Initial conditions α = 0.1, β = 0.1, and γ = 0.1; (b) Parameters changed to α = 0.9, β = 0.05 and γ = 0.5

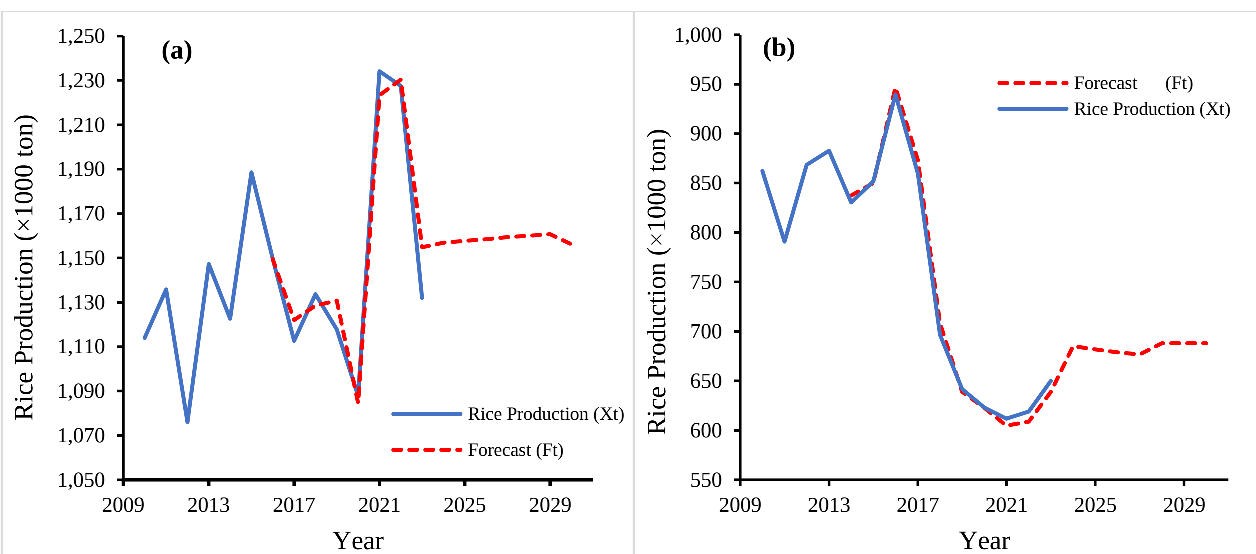

Figure 4. Rice Production Prediction for Indramayu Regency: (a) Initial conditions α = 0.1, β = 0.1 and γ = 0.1; (b) Parameters changed to α = 0.8, β = 0.2 and γ = 0.6

The difference in rice production data between Cianjur and Indramayu Regencies lies in the seasonal patterns that occur. Based on the assumptions made during the training data process, Cianjur Regency has a seasonal pattern of 4, while Indramayu Regency has a seasonal pattern of 6. This occurs due to the influence of climate change in both regencies. Cianjur Regency is influenced by El Nino, while Indramayu Regency is influenced by La Nina. Indonesia experienced normal climate conditions after experiencing weak to very strong El Niño events in 2015, and another weak El Niño event occurred again in 2019. El Niño reduced harvested area and productivity, whereas La Niña generally increased planting area and improved productivity per hectare (Khairullah *et al*., 2021). One of the advantages of the Holt-Winters method is its ability to reduce fluctuations and downward trends by optimizing smoothing parameters, thereby revealing the non-linear rice production patterns in Cianjur and Indramayu which were well suited to adapting trend and seasonal changes in time series data (Drop & Bohdan, 2025). Previous studies, including rice price and rice production predictions, indicate that the Holt-Winters approach is effective for agricultural data that shows fluctuations and unstable trends (Hyndman & Athanasopoulos, 2018).

Overall, the application of the Holt-Winters method with the combination of these parameters proved to be effective in capturing the patterns of levels, trends, and seasonality of rice production in Cianjur and Indramayu Regencies. The MAPE values obtained from smoothing parameter optimization were 1.00% and 0.74%. These values were obtained through tuning the parameters α, β, and γ. With such a low error rate, the Holt-Winters model is considered capable of representing the dynamics of rice production well. The high accuracy of the model makes these prediction results worthy of consideration as a basis for production planning, determining the need for production facilities and agricultural machinery, and formulating more adaptive and data-based regional agricultural policies. From the results of this study, it is known that the Holt-Winters method performs very well in predicting agricultural data that fluctuates and is influenced by seasonal factors.

The evaluation of the Holt-Winters parameters shows that increasing the values of α and γ significantly improves the model's ability to follow the actual dynamics of rice production. A comparison of the performance of the Holt-Winters model can be seen in Tables 3. Before and after parameter optimization, there was a very significant increase in forecasting accuracy. Before optimization, the MAPE value for Cianjur Regency was 16.97% and for Indramayu Regency was 3.5%, indicating that the model was not yet able to capture the dynamics of rice production optimally. After parameter adjustment, the MAPE value for Cianjur Regency decreased dramatically to 1.00% and Indramayu Regency to 0.74%, indicating a very high level of prediction accuracy. These results confirm that parameter optimization is an important stage in applying the Holt-Winters method to rice production data, which is volatile and influenced by seasonal factors.

Tabel 3. Comparison of MAPE for Rice Production in Cianjur Regency and Indramayu Regency before and after smoothing

Cianjur Regency			**Indramayu Regency**		
Parameter	**Before**	**After**	**Parameter**	**Before**	**After**
α	0.1	0.9	α	0.1	0.8
β	0.1	0.05	β	0.1	0.2
γ	0.1	0.5	γ	0.1	0.6
MAPE (%)	16.97	1.00	MAPE (%)	3.5	0.74

The improvement in modeling was influenced by changes in the level smoothing parameter (α) from 0.1 to 0.8-0.9. A higher α parameter value is considered more appropriate as it reflects the presence of relatively rapid level changes in rice production over time. Consequently, the Holt–Winters model assigns greater weight to recent observations, enabling the forecasting process to adapt more effectively to production dynamics influenced by climatic conditions, planting seasons, and environmental variability. The trend parameter (β) value of 0.05-0.2 indicates that the production trend is more stable and less sensitive, which is sufficient to avoid short-term fluctuations. Meanwhile, the seasonal parameter (γ) value of 0.1 to 0.5-0.6 indicates that the Holt-Winters model can accurately and stably capture the latest seasonal dynamics.

The similarity between the historical rice production pattern and the Holt-Winters forecast results shows that this method can be used as a supporting method for regional agricultural planning. To predict for rice production in 2030 should be interpreted as projections derived from historical patterns under the assumption that such patterns will persist in the future. It may still be affected by external factors not fully represented in historical data, including climate change, El Niño and La Niña events, land-use conversion, agricultural policy shifts, technological developments, and rainfall variability.

The novelty of this study lies in developing an optimized Holt–Winters forecasting framework for rice production in two key Indonesian rice-producing regions characterized by different production dynamics and environmental conditions. Unlike previous studies that primarily focused on model comparison or commodity forecasting, this research systematically optimizes the Holt–Winters smoothing parameters to achieve highly accurate long-term predictions (MAPE < 1%) and demonstrates their practical relevance for regional food security planning, agricultural machinery allocation, and strategic agricultural policy. The findings provide a simple yet robust forecasting framework that can support evidence-based decision-making in regions facing production variability due to climate change and land-use conversion. For farmers, this forecasting can be used as information to anticipate climate change, to make a plan for planting and harvest schedules. Furthermore, the projected increase in production by the Holt-Winters model also indicates the need for sustainability policies, particularly in maintaining the availability of production facilities. Without appropriate policy measures, the positive trends generated by the model may not be optimally realized.

4. CONCLUSIONS

The Holt-Winters method shows that this method is effective and accurate in predicting rice production because it can capture seasonal patterns and trends based on historical rice production data in Cianjur and Indramayu Regencies from 2010 to 2023. The predicted rice production in Cianjur Regency fluctuates from 2024 to 2030, ranged from 678 to 688 thousands tons of unhulled rice with the optimal parameters for Cianjur Regency being $\alpha = 0.9$, $\beta = 0.05$, $\gamma = 0.5$, with a MAPE of 1.00%, and for Indramayu Regency fluctuated from 2024 to 2030, ranged from 1.15 to 1.16 million tons of unhulled rice being $\alpha = 0.8$, $\beta = 0.2$, $\gamma = 0.6$, with a MAPE of 0.74%. The MAPE value indicates that the prediction results are very good and accurate because the MAPE value produced is <10%. This research highlights the importance of adaptive forecasting approaches in agricultural systems affected by environmental uncertainty, such as climate fluctuations, El Niño–La Niña, and changing seasonal patterns and to support strategic agricultural planning, including food security management and agricultural machinery distribution management.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE MANUSCRIPT PREPARATION

Not applicable. The authors did not use any generative AI tools or services in the preparation of this manuscript. All content is entirely the intellectual work of the authors.

AUTHOR CONTRIBUTION

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ima	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓
SH		✓				✓		✓	✓	✓	✓	✓		
MS	✓		✓	✓			✓	✓	✓	✓	✓	✓		

C: Conceptualization	Fo: Formal Analysis	O: Writing - Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing - Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

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