

Forecasting Corn Production in Indonesia Using Holt–Winters Exponential Smoothing

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Abstract

Corn is a strategic agricultural commodity in Indonesia due to its important role in national food security and the livestock feed industry. However, national corn production exhibits strong seasonal fluctuations that pose challenges for production planning and policy formulation. This study aims to forecast national corn production in Indonesia using the Holt–Winters Triple Exponential Smoothing method. Monthly corn production data from January 2020 to October 2025 obtained from the Central Agency of Statistics (BPS) were analyzed. A multiplicative Holt–Winters model was applied to capture level, trend, and seasonal components in the data. Forecasting accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). The results show that the proposed model achieved a MAPE value of 18.64%, indicating reasonable forecasting accuracy. The forecasting results for the period November 2025 to December 2026 reveal a stable seasonal pattern in national corn production. These findings demonstrate that the Holt–Winters method is a practical and effective approach for short- to medium-term forecasting and can support agricultural planning and decision-making related to national food security.

Keywords

Corn Production; Forecasting; Holt–Winters; Triple Exponential Smoothing; Time Series.

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Introduction

Corn (*Zea mays*) is a strategic agricultural commodity in Indonesia due to its crucial role in national food security and the animal feed industry. As an agrarian country, Indonesia depends heavily on stable agricultural production to support economic growth and ensure food availability for its population. Fluctuations in corn production can directly affect supply stability, market prices, and government policy decisions related to stock management and imports (Hyndman & Athanasopoulos, 2021).

In practice, national corn production data exhibit substantial variability across months and years. These fluctuations are largely influenced by seasonal planting and harvesting cycles, climate variability,

changes in harvested land area, and agricultural input availability. Such characteristics are typical of agricultural time series data and present significant challenges for accurate forecasting. Inaccurate production forecasts may lead to supply shortages or excess inventory, both of which can negatively impact farmers' income and consumer prices (Rahman et al., 2018).

Forecasting techniques based on historical time series data are widely used to support decision-making in agriculture and economic planning. Among various approaches, exponential smoothing methods are widely applied due to their simplicity, adaptability, and interpretability. These methods place greater weight on recent observations while gradually reducing the influence of older data, making them suitable for dynamic production environments where conditions change over time (Hyndman et al., 2020).

However, simple exponential smoothing techniques, such as Single Exponential Smoothing, are only appropriate for time series data that do not exhibit trend or seasonal patterns. Empirical evidence shows that agricultural production data, particularly monthly crop production, generally contain both trend and seasonal components. Ignoring these components can reduce forecasting accuracy and limit the usefulness of predictions for policy formulation and strategic planning (Dewi, 2020; Rahman et al., 2018).

To address these limitations, Triple Exponential Smoothing—commonly known as the Holt-Winters method—was developed to incorporate level, trend, and seasonal components simultaneously. This method has been extensively used in forecasting seasonal time series across various domains, including agriculture, economics, and transportation. Previous studies have demonstrated that the Holt-Winters method provides superior performance compared to single and double smoothing approaches when applied to seasonal data (Pleños, 2022; Priyanka et al., 2022; Nurhamidah et al., 2020).

Recent empirical research further confirms the robustness and relevance of the Holt-Winters method. Amalia et al. (2024) showed its effectiveness in forecasting macroeconomic indicators in Indonesia, while Bustami and Thahira (2023) successfully applied triple exponential smoothing to predict export performance. Comparative studies also indicate that Holt-Winters remains competitive with more complex statistical and machine learning models, while maintaining transparency and interpretability—an important consideration for policy-oriented forecasting (Pratama et al., 2023; Togos & Rusgiyono, 2022; Wasono et al., 2024).

Moreover, contemporary studies emphasize that exponential smoothing methods continue to play a significant role in modern forecasting research. Sulistyono and Annabil (2025) demonstrated that Holt-Winters performs reliably when compared with seasonal ARIMA models in agricultural-related indicators. Similarly, Shakila and Wahid (2025) highlighted that Holt-Winters-based and hybrid models can enhance forecasting accuracy while preserving methodological simplicity.

Based on these considerations, this study aims to forecast national corn production in Indonesia using the Holt-Winters Triple Exponential Smoothing method. Monthly production data obtained from the Central Agency of Statistics (BPS) covering the period from January 2020 to October 2025 are utilized. Model performance is evaluated using the Mean Absolute Percentage Error (MAPE) to assess forecasting accuracy. The resulting forecasts for the period from November 2025 to December 2026 are expected to provide valuable insights for policymakers and stakeholders in planning corn supply, stabilizing prices, and strengthening national food security.

Method

Data Source and Type

The data utilized in this study is secondary data comprising the time series of national corn production. The data was obtained from official publications by the Central Agency of Statistics (BPS) of Indonesia. The dataset consists of monthly production volumes (in Tons) spanning from January 2020 to October 2025, resulting in a total of 70 observation points. A sample of the data used is presented in Table 1.

Table 1. National Food Crop Production (Tons)

Month	2020	2021	2022	2023	2024	2025
January	508,421.86	1,030,207.63	1,244,613.98	1,393,695.93	512,956.73	1,245,211
February	528,630.19	1,270,303.72	1,731,349.56	1,425,593.88	838,313.85	1,861,567
March	1,548,819.97	1,283,394.40	1,503,239.09	1,198,467.48	2,051,817.40	1,635,993
April	1,838,764.16	863,275.60	890,849.42	820,298.64	1,619,123.87	1,272,189
May	575,911.65	877,744.34	1,182,737.11	1,270,587.13	1,077,228.41	989,19
June	830,756.51	1,040,559.30	1,477,545.89	1,223,915.86	1,048,234.08	1,553,659
July	1,343,943.12	1,186,252.02	1,480,627.76	1,363,394.14	1,357,547.42	1,475,558
August	1,405,358.87	1,336,641.57	1,593,490.43	1,219,499.30	1,519,989.33	1,390,151
September	1,403,539.57	1,177,988.22	1,493,694.59	1,508,030.47	1,718,240.47	1,341,172
October	1,240,377.70	1,290,214.10	1,665,570.36	1,315,572.56	1,337,793.93	1,237,870
November	998,982.49	1,125,220.49	1,413,351.14	1,198,194.50	978,083.10	–
December	705,434.71	933,120.35	850,203.29	837,182.64	1,079,583.39	–
TOTAL	12,928,940.81	13,414,921.72	16,527,272.62	14,774,432.52	15,138,911.98	–

Research Stages

The research procedure is conducted through a series of systematic stages to ensure the validity and accuracy of the forecasting results. The overall research workflow, ranging from data acquisition to the final projection, is visualized in Figure 1.

Figure 1 illustrates the research workflow employed in this study. The process begins with data collection from the Central Agency of Statistics (BPS), followed by data preprocessing to ensure completeness and consistency. The prepared data are then modeled using the Holt–Winters Triple Exponential Smoothing method. Model parameters are optimized to minimize forecasting error, which is evaluated using the Mean Absolute Percentage Error (MAPE). Finally, the optimal model is used to generate forecasts for the period November 2025 to December 2026.

Holt–Winters Triple Exponential Smoothing Method

The forecasting method applied in this study is Holt–Winters Triple Exponential Smoothing. This method extends exponential smoothing by incorporating three components: level, trend, and seasonality. The inclusion of these components allows the model to effectively capture recurring seasonal patterns and long-term movements in agricultural production data.

Considering that seasonal fluctuations in corn production tend to increase proportionally with the overall production level, this study adopts the multiplicative Holt–Winters model. The seasonal length is defined as 12, representing monthly seasonality within one year. The mathematical formulation of the Holt–Winters multiplicative model is expressed as follows:

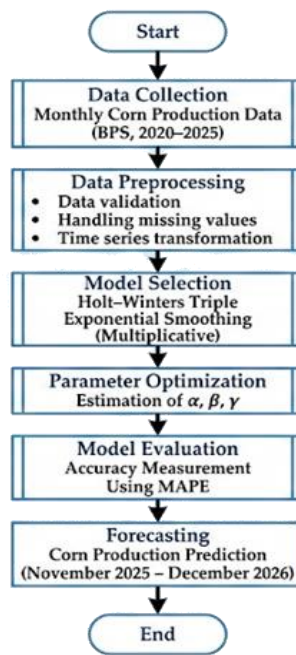


Figure 1. Research Flowchart

$$L_t = \alpha \left(\frac{Y_t}{S_{t-m}} \right) + (1 - \alpha)(L_t - 1 + T_t - 1) \quad (1)$$

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

$$S_t = \gamma \left(\frac{Y_t}{L_t} \right) + (1 - \gamma)S_{t-1} \quad (3)$$

$$\hat{Y}_{t+h} = (L_t + hT_t) \times S_{t-m+h} \quad (4)$$

where:

L_t : Level at time t

T_t : Trend at time t

S_t : Seasonal component

Y_t : Actual value at time t

$\hat{Y}_{t+h}$: Forecast for h periods ahead

α, β, γ : Smoothing parameters ($0 < \alpha, \beta, \gamma < 1$)

m : Seasonal length ($m = 12$ for monthly data)

h : Forecast horizon

Parameter Estimation

The smoothing parameters α , β , and γ are estimated through an optimization process aimed at minimizing the forecasting error. A grid search approach is employed to evaluate combinations of parameter values within the interval (0, 1). The optimal parameter set is selected based on the lowest forecasting error obtained during the training period.

Model Accuracy Measurement

Model Evaluation

To assess the accuracy of the forecasting model, this study employs the Mean Absolute Percentage Error (MAPE). MAPE is widely used in forecasting studies because it expresses prediction error in percentage terms, allowing for intuitive interpretation across different scales of data. The MAPE formula is defined as:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\% \quad (5)$$

where n is the number of observations, Y_t is the actual value, and $\hat{Y}_t$ is the forecasted value.

Forecasting Procedure

Once the optimal Holt–Winters model is established, forecasting is conducted for the future period from November 2025 to December 2026. The resulting forecasts represent expected monthly corn production levels and are used to analyze future production trends. These projections are intended to provide actionable insights for policymakers and stakeholders involved in agricultural planning and national food security management.

Result and Discussion

Result

The monthly national corn production data from January 2020 to October 2025 exhibit considerable variability over time. Recurrent peaks and troughs are observed in similar months across different years, indicating a strong seasonal pattern. In addition, variations in overall production levels suggest the presence of a trend component. These characteristics confirm that the data are appropriate for modeling using the Holt–Winters Triple Exponential Smoothing method, which explicitly accounts for level, trend, and seasonality.

Based on these data characteristics, the Holt–Winters multiplicative model was applied with a seasonal period of 12 months. The fitted values generated by the model closely follow the actual production data during the historical period, indicating that the model is able to capture the underlying production dynamics and seasonal fluctuations.

Forecast Accuracy Evaluation

The forecasting performance of the Holt–Winters model was evaluated using the Mean Absolute Percentage Error (MAPE). Table 2 presents a sample of absolute percentage error values obtained during the training period. The overall MAPE value of 18.64% was calculated as the average of absolute percentage errors across all observations from January 2020 to October 2025. Considering the high

Volatility and strong seasonal nature of agricultural production data, this level of accuracy is acceptable and indicates that the model provides a reliable representation of historical corn production patterns.

Forecasting Results

After validating the model performance, monthly forecasts were generated for the period from November 2025 to December 2026. The numerical forecast results are presented in Table 3, while a visual comparison between the actual data, fitted values, and forecasted values is shown in Figure 2.

Table 2. Test Results of MAPE

Month	Actual (Y_t)	Fitted ($\hat{Y}_t$)	Absolute Percentage Error (%)
Jan 2020	508,422	566,910	11.50
Feb 2020	528,630	601,482	13.79
Mar 2020	1,548,820	1,438,920	7.10
Apr 2020	1,838,764	1,712,035	6.89
...	...	...	...

Month	Actual (Y_t)	Fitted ($\hat{Y}_t$)	Absolute Percentage Error (%)
Oct 2025	1,237,870	1,305,422	5.45

Table 3. Forecasted Monthly National Corn Production Using Holt-Winters Method

Month	Forecast Production (Tons)
November 2025	1,272,484
December 2025	891,943
January 2026	1,115,343
February 2026	1,408,653
March 2026	1,615,439
April 2026	1,120,444
May 2026	1,173,383
June 2026	1,270,757
July 2026	1,486,248
August 2026	1,528,695
September 2026	1,532,043
October 2026	1,501,364
November 2026	1,287,360
December 2026	902,360

Table 3 summarizes the forecasted monthly national corn production values for the forecast horizon. The results exhibit a recurring seasonal pattern consistent with historical production cycles, with higher production levels projected during typical harvest months and lower values during off-season periods.

Figure 2 illustrates the comparison between actual production data and the fitted and forecasted values generated by the Holt-Winters model. The close alignment between the actual and fitted values during the training period indicates that the model effectively captures seasonal fluctuations and trend components. The forecasted values extend this seasonal pattern into the future period, suggesting that future production dynamics are primarily driven by recurring seasonal effects rather than abrupt structural changes.

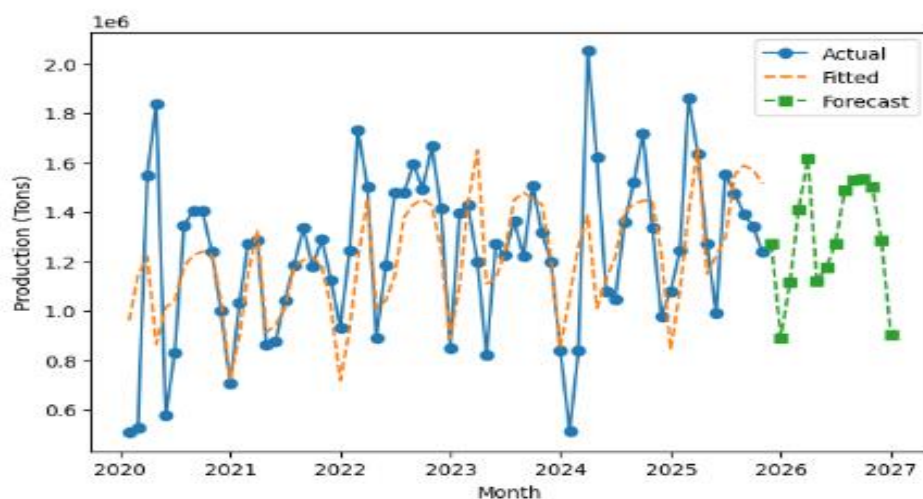


Figure 2. Actual vs Forecast of National Corn Production

Discussion

The forecasting results demonstrate that the Holt–Winters Triple Exponential Smoothing method is capable of modeling the seasonal and trend components of national corn production in Indonesia. The strong seasonal patterns observed in the historical data are effectively captured by the multiplicative Holt–Winters model, as reflected by the close alignment between actual and fitted values shown in Figure 2. This confirms that incorporating a seasonal component is essential for accurately modeling monthly agricultural production data.

The obtained MAPE value of **18.64%** indicates that the forecasting performance of the model falls within the *reasonable accuracy* category. Given the high volatility of corn production, which is influenced by climatic conditions, harvesting cycles, and agricultural practices, this level of accuracy is considered acceptable. Similar levels of forecasting accuracy have been reported in previous studies that applied Holt–Winters models to agricultural and economic time series data, supporting the robustness of the method in seasonal forecasting contexts.

The forecasted values presented in Table 3 show a recurring seasonal pattern consistent with historical production cycles. Higher production levels are projected during typical harvest months, while lower values occur during off-season periods. This pattern suggests that future corn production dynamics are likely to remain stable and primarily driven by seasonal factors, assuming no major structural changes in agricultural policy or production conditions.

From a practical perspective, the forecasting results provide valuable insights for policymakers and stakeholders involved in agricultural planning. The ability to anticipate periods of high and low production can support better supply chain management, inventory planning, and policy formulation related to national food security. Although the Holt–Winters method does not explicitly incorporate external explanatory variables, its simplicity and interpretability make it well suited for policy-oriented forecasting where transparency is an important consideration.

Despite its strengths, this study has several limitations. The forecasting model relies solely on historical production data and does not account for external factors such as climate anomalies, input price changes, or policy interventions, which may affect future production levels. Consequently, unexpected shocks may lead to deviations between forecasted and actual values. Future research could address these limitations by incorporating exogenous variables or by comparing the Holt–Winters approach with more advanced forecasting models to improve prediction accuracy.

Overall, the discussion confirms that the Holt–Winters Triple Exponential Smoothing method is an appropriate and practical approach for forecasting national corn production in Indonesia. The consistency between numerical forecasts, visual analysis, and accuracy evaluation supports the reliability of the results and highlights the method's potential as a decision-support tool in agricultural planning and national food security management.

Conclusion

This study concludes that the Holt–Winters Triple Exponential Smoothing method is an effective and appropriate approach for forecasting national corn production in Indonesia. By incorporating level, trend, and seasonal components, the model is able to capture the key characteristics of monthly corn production data, which exhibit strong seasonal fluctuations and temporal variation.

The forecasting results demonstrate reasonable accuracy, as indicated by a Mean Absolute Percentage Error (MAPE) value of **18.64%**. The numerical forecasts presented in Table 3 and the visual comparison shown in Figure 2 consistently indicate that the model provides a reliable representation of historical production patterns and future production dynamics. The forecasts for the period from

November 2025 to December 2026 suggest that national corn production is expected to follow a stable seasonal pattern, with variations primarily driven by recurring seasonal effects.

From a practical perspective, the findings of this study provide useful quantitative insights to support agricultural planning, supply management, and policy formulation related to national food security. Although the Holt–Winters method relies solely on historical data and does not account for external factors, its simplicity and interpretability make it a valuable decision-support tool. Future research may enhance forecasting performance by incorporating exogenous variables or by comparing the Holt–Winters approach with more advanced forecasting models.

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