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FORECASTING QUARTERLY RICE AND CORN PRODUCTION IN THE PHILIPPINES: A COMPARATIVE STUDY OF SEASONAL ARIMA AND HOLT-WINTERS MODELS

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Abstract

Rice and corn are essential crops for the Philippines, playing a critical role in the nation's economy and food security. However, the agricultural sector faces challenges, including climate variability, land constraints, and the need for imports to meet growing demand. Accurate forecasting of rice and corn production is crucial for informed decision-making and resource allocation. This research applied Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters exponential smoothing models to forecast rice and corn production. The study used quarterly production data from 1987 to 2023 obtained from the Philippine Statistics Authority. The Holt-Winters model with additive seasonality outperformed the SARIMA model for both rice and corn production, achieving lower Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) values. The findings have significant implications for policymakers, agricultural stakeholders, and commodity traders, guiding them in making informed decisions regarding import requirements. The volatility of global food prices and exchange rates can significantly impact the cost of imports, putting a strain on the country's financial resources. Accurate forecasting models are essential for ensuring food sufficiency and making informed decisions on the amount of imports required. By adopting the Holt-Winters model and continuously improving forecasting methodologies, the Philippines can enhance food sufficiency and promote rural economic growth. The study highlighted the importance of accurate forecasting models in ensuring stable and sufficient rice and corn supplies to meet the nation's growing demands, contributing to sustainable agricultural development and food security. Continuous research in agricultural forecasting methodologies is necessary to address the challenges posed by evolving agricultural dynamics and further enhance predictive accuracy.

Keywords:

SARIMA, Holt-Winters, Rice Production, Corn Production, Agricultural Forecasting

1. INTRODUCTION

Rice and corn are two staple crops that play a crucial role in the economy and food security of the Philippines. As essential components of the nation's agricultural sector, they are not only major sources of livelihood for farmers but also form the backbone of the country's domestic food supply [1]. According to recent data, the average annual rice consumption per capita in the country has reached approximately 103.25 kilograms, while corn consumption stands an average 9.14 kilograms per capita [2]. This surging demand for both grains is driven not only by population growth but also by evolving dietary preferences and the expansion of the food processing industry. In terms of production, the Philippines has been a substantial producer of rice and corn; however, the nation's agricultural sector faces multiple challenges. In 2022, rice production has reached 19.76 million metric tons, while corn production has been around 8.12 million metric tons in 2020 [3] [4]. Despite these considerable production figures, the country often grapples with fluctuations in output due to various factors, including climate change-induced weather variability, land constraints, and limited access to modern agricultural technologies. Moreover, despite the Philippines' efforts to enhance domestic production, there is still a need to import rice and corn to meet the growing demand. In certain years, rice imports have exceeded 2.97 million metric tons [5], and corn imports have surpassed 459,700 metric tons [6]. The volatility of global food prices and exchange rates can significantly impact the cost of imports, thereby straining the nation's financial resources.

The significance of studying and forecasting the production of rice and corn stems from the inherent need to ensure food sufficiency and make informed decisions regarding the importation of these commodities. Despite being major producers of rice and corn, the Philippines faces various challenges in maintaining a stable and sufficient supply of these grains. The agricultural sector is susceptible to the impact of climate change, unpredictable weather patterns, and extreme events such as typhoons, droughts, and floods. These factors can lead to fluctuating crop yields, affecting overall food availability and prices [7] [8]. Additionally, the ever-increasing population, coupled with changing dietary patterns, demands a steady growth in food production to meet the nutritional requirements of the nation. One of the critical concerns in recent years has been the shortfall in domestic production compared to the escalating demand for rice and corn. This has resulted in the necessity for importing these commodities to meet the nation's needs adequately [7] [9] [10]. Importing rice and corn can put a strain on the country's financial resources, given the fluctuating global market prices and exchange rates. Therefore, accurate and reliable forecasting models for rice and corn production are essential for policymakers, agricultural stakeholders, and commodity traders to make well-informed decisions on the amount of imports required.

In this context, the application of time series forecasting models, such as Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters, becomes invaluable. The ARIMA model is a widely used time series forecasting technique that combines autoregression, differencing, and moving average components to capture the underlying patterns and trends in a time series data. It is particularly effective for data exhibiting non-stationary behavior, where the mean and variance change over time. ARIMA is capable of handling seasonality and trends present in the data, making it suiTable.for quarterly rice and corn production forecasting, where seasonal patterns are often prevalent. However, the selection of appropriate orders (p, d, q) for the ARIMA model can be challenging and requires careful analysis of the data to ensure accurate predictions [11]. Meanwhile, the Holt-Winters exponential smoothing is a forecasting method specifically designed for time series data with seasonal patterns. This model captures the trend, seasonality, and level of the time series through three smoothing equations: one for the level, one for the trend, and one for the seasonal component. Holt-Winters is well-suited for quarterly rice and corn production forecasting, as it can handle data with seasonality, which is a common characteristic of agricultural production. The method adaptively updates the smoothing parameters and automatically adjusts to changes in the time series' patterns, making it particularly useful for datasets with evolving seasonality or trends. However, like ARIMA, determining the appropriate smoothing parameters is essential for accurate predictions, and the model's performance heavily relies on historical patterns in the data [12] [13].

By comparing the performance of these two models, we can gain insights into their strengths, weaknesses, and overall predictive capabilities for rice and corn production. Such a comparative study is not only relevant but also beneficial for several reasons. Firstly, it allows us to identify the model that provides more accurate and reliable forecasts, thus guiding decision-makers in choosing the most appropriate model for practical applications. Secondly, it helps in understanding the distinct characteristics of rice and corn production data, enabling the refinement of forecasting techniques tailored to the specific needs of each crop. Additionally, considering the dynamic nature of agriculture, a comparative study can contribute to advancing forecasting methodologies, leading to improved prediction accuracy in the long run.

In light of the importance of rice and corn to the Philippines' economy and food security, and the challenges posed by climate variability and the need for imports, this research endeavors to bridge the gap in agricultural forecasting. By investigating the performance of Seasonal ARIMA and Holt-Winters models for predicting quarterly rice and corn production, this study aims to provide valuable insights that can aid in better planning, resource allocation, and policy formulation for sustainable agricultural development in the country.

2. RELATED WORKS

This section provides an in-depth examination of existing research related to the application of time series forecasting models, specifically focusing on Seasonal ARIMA, Holt-Winters exponential smoothing, and their comparative analysis.

In the study of Meher et al. [14], the application of ARIMA models for forecasting stock prices in financial markets was explored, demonstrating the effectiveness of ARIMA in capturing complex time series patterns. Meanwhile, in the research by Parreño [15], seasonal ARIMA and artificial neural networks were used for coincidental peak forecasting in the Philippines, highlighting the applicability of ARIMA in handling time series with seasonality. In another investigation by Parreño [16], ARIMA model was employed to forecast energy consumption, emphasizing the utility of ARIMA models in capturing annual patterns. Similarly, in the study conducted by Gourav et al. [17], ARIMA technique was used to analyze air quality data. In the study of Parreño [18], ARIMA was applied to forecast coal production and consumption data, showcasing the versatility of ARIMA in dealing with various types of time series data. Moreover, in the study of Zhang et al. [19], ARIMA was compared with Long Short-Term Memory (LSTM) neural networks for hand, foot and mouth disease incidence forecasting, providing insight into ARIMA's performance as a benchmark model in time series forecasting. Additionally, in the research by Kuizinienė et al. [20], ARIMA, Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Support Vector Regression (SVR) models were explored for analyzing the volatility of cryptocurrencies prices, highlighting ARIMA's versatility in analyzing financial time series data. Furthermore, in the study conducted by Parreño [21], ARIMA was for electricity demand forecasting, emphasizing ARIMA's potential in modeling time series data in local context.

On the other hand, in the research by Kozłowski et al. [22], Holt-Winters exponential smoothing was applied to forecast seasonal variations in water demand, demonstrating the effectiveness of the method in capturing seasonal patterns. In a separate investigation by Rossi and Brunelli [23], Holt-Winters exponential smoothing was used for data centers power consumption forecasting, showcasing its ability to handle time series data with seasonal components. Additionally, in the study conducted by Lima et al. [24], Holt-Winters exponential smoothing was explored for economic data, underlining its utility in managing time series with seasonality. Similarly, in the research by Heydari et al. [25], Holt-Winters exponential smoothing was applied for forecasting short-term environmental variables, providing insights into the method's effectiveness in handling time series data with seasonality. Additionally, in the study of Valakevicius and Brazenas [26], Holt-Winters exponential smoothing was applied to predict the volatility of the exchange rate of Euro against Dollar, demonstrating the model's capability in forecasting time series data with seasonal variations.

Regarding the comparison of ARIMA and Holt-Winters, the study by Da Veiga et al. [27] compared the performance of ARIMA and Holt-Winters models for sales forecasting in the retail industry, offering insights into the strengths and weaknesses of both models. The study found that HW performed better than ARIMA. Similarly, in the research conducted by Kurniasih et al. [28], ARIMA and Holt-Winters models were compared for forecasting the infant mortality rate in China, providing valuable insights into the two methods' predictive capabilities. Moreover, in the study by Ahmar et al. [29], a comparative analysis of ARIMA, NNAR, and Holt-Winters for food grains production forecasting was presented, highlighting the differences between the approaches. Additionally, the research by Rahman and Ahmar [30] compared ARIMA and Holt-Winters models for primary energy consumption prediction in the USA, offering valuable lessons on model comparison. Finally, in the investigation by Karadzic and Pejovic [31], ARIMA, NNAR, and Holt-Winters models were evaluated for inflation forecasting, providing insights into the models' applicability and performance in time series forecasting.

3. METHODOLOGY

In this section, we presented the dataset employed in this paper and the methods utilized for analyzing the rice and corn production in the Philippines. Fig.1 provides a comprehensive overview of the methodology employed in our research.

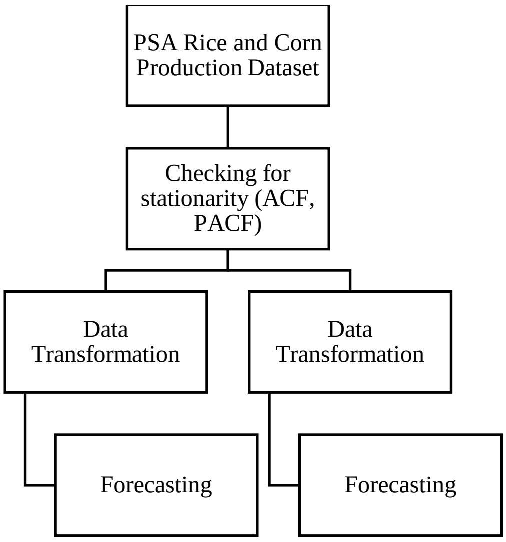

Fig.1. Methodology flowchart

3.1 DATASET

The data used in this study are the quarterly rice and corn production (in metric tons) in the Philippines from 1987 to the first quarter of 2023, a total of 145 observations. The dataset was retrieved from the Philippine Statistics Authority (PSA). The first 116 observations, or 80% of the data, have been used to train the model. The remaining 29 observations, or 20% of the data, have been used for evaluating the seasonal ARIMA model forecasts. Also, the last 29 observations have been used to compare the forecasted values and select the best model between seasonal ARIMA and Holt-Winters exponential smoothing. The descriptive results for quarterly rice and corn production are presented in Table.1 and Table.2, respectively. The volume of production of rice and corn in the Philippines are visualized in Fig.2.

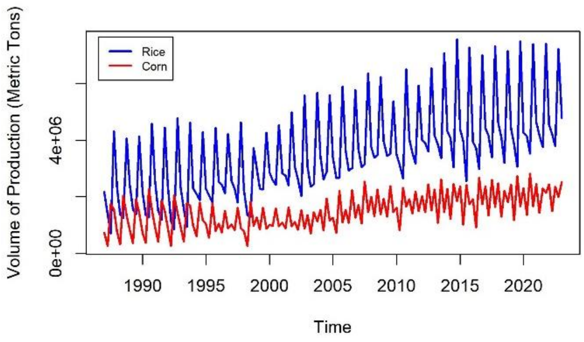

Fig.2. Rice and corn production in the Philippines

Table.1. Descriptive results of the quarterly rice production

Measure	Values
Mean	3579188
Median	3435019
Standard Deviation	1610582
Minimum	690926
Maximum	7560865

Table.2. Descriptive results of the quarterly corn production

Measure	Values
Mean	1479993
Median	1451348
Standard Deviation	625718.4
Minimum	248244
Maximum	2817375

3.2 SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE

Seasonal Autoregressive Integrated Moving Average (Seasonal ARIMA) is an extension of the traditional ARIMA model designed to handle time series data with seasonality. Seasonality refers to patterns that repeat at regular intervals, such as quarterly or monthly cycles, which are often observed in agricultural production, including rice and corn. The seasonal ARIMA model is denoted as ARIMA$(p, d, q)(P, D, Q)s$, where p represents the order of the autoregressive (AR) component, indicating the number of lagged values of the time series included in the model, d denotes the degree of differencing required to make the time series stationary, q stands for the order of the moving average (MA) component, which indicates the number of lagged forecast errors used in the model, P represents the seasonal order of the autoregressive (SAR) component, which captures the seasonal patterns in the data, D denotes the seasonal order of differencing required to make the seasonal component of the time series stationary, Q stands for the seasonal order of the moving average (SMA) component, which captures the seasonal variations in forecast errors, and s indicates the seasonality period, representing the number of time steps in each seasonal cycle. The formula for the seasonal ARIMA model can be expressed as follows:

$$(1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p)\times(1-B^s)^D\times(1-\Theta_1 B-\Theta_2 B^2-\ldots-\Theta_q B^q)\times(1-\Phi_1 B^s-\Phi_2 B^{2s}-\ldots-\Phi_P B^{Ps})\times X_t = Z_t \quad (1)$$

where X_t is the observed time series data at time point t, B is the backward shift operator, where $BX_t = X_{t-1}$, $\phi_1, \phi_2, \ldots, \phi_p$ and $\Theta_1, \Theta_2, \ldots, \Theta_q$ are the autoregressive and moving average coefficients, respectively, $\Phi_1, \Phi_2, \ldots, \Phi_P$ are the seasonal autoregressive coefficients, D and d are the seasonal and non-seasonal orders of differencing, respectively, and X_t is the error term [11]. The procedure for finding the appropriate ARIMA model involves a systematic and iterative approach. It begins with an inspection of the time series data, looking for underlying patterns, trends, and seasonality. If the data is non-stationary, stationarity tests are conducted, and differencing is applied to stabilize the series. Next, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are analyzed to identify potential autoregressive (p) and moving average (q) orders. A grid search is then performed to explore various combinations of seasonal autoregressive (P) and seasonal moving average (Q) orders. Based on AIC, the best-fitting model parameters are selected. The identified values of p, d, q, P, D, and Q are used to fit the seasonal ARIMA model to the data using maximum likelihood estimation. Model evaluation is carried out by examining the residuals for white noise patterns. Diagnostic plots are used to ensure that the model captures the data's patterns effectively. Once the ARIMA model is deemed satisfactory, it is utilized to generate forecasts for future time periods, and prediction intervals may be calculated to assess forecast uncertainty [18].

3.3 HOLT-WINTERS EXPONENTIAL SMOOTHING

Holt-Winters exponential smoothing is a widely used forecasting method designed to capture and forecast time series data with seasonality and trends. The model involves three components: the level (also known as the base or intercept), the trend, and the seasonal component. These components are updated iteratively to generate forecasts for future time periods. The Holt-Winters model is particularly effective for data with recurring seasonal patterns, making it suitable for quarterly rice and corn production forecasting in the Philippines. The general formula for the Holt-Winters Exponential Smoothing model is given as follows:

Initialization:

L_0 = initial level

T_0 = initial trend

S_t = initial seasonal component at time t

Forecasting:

$$\text{Level: } L_t=\alpha(X_t-S_{t-m})+(1-\alpha)(L_{t-1})+T_{t-1} \tag{2}$$

$$\text{Trend: } T_t=\beta(L_t-L_{t-1})+(1-\beta)T_{t-1} \tag{3}$$

$$\text{Seasonal Component: } S_t=\gamma(X_t-L_t)+(1-\gamma)S_{t-m} \tag{4}$$

Forecast: Forecast at time $t+h$:

$$F_{t+h} = L_t+h\cdot T_t+S_{t+h-m} \tag{5}$$

where L_t is the level component at time t, T_t is the trend component at time t, S_t is the seasonal component at time t, X_t is the observed value of the time series at time t, α, β, γ are the smoothing parameters, and F_{t+h} is the forecast value at time $t+h$. The Holt-Winters Exponential Smoothing model can be adapted to handle both additive and multiplicative seasonality, depending on the nature of the time series being forecasted [12] [13].

3.4 ERROR METRICS

To compare the performance of the ARIMA and Holt-Winters models for forecasting the quarterly rice and corn production in the Philippines, error metrics were used to evaluate their predictive accuracy. These metrics quantify the differences between the actual observations and the model's forecasts. The lower the values of these metrics, the better the model's predictive performance.

Root Mean Squared Error:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2} \tag{6}$$

Mean Absolute Percentage Error:

$$MAPE=\frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \tag{7}$$

4. RESULTS AND DISCUSSIONS

In this section, the application of the two forecasting models are presented. To evaluate the forecasting methods, we calculated their RMSE and MAPE.

4.1 SARIMA MODEL

The steps presented in Fig.1 were followed in implementing the seasonal ARIMA model.

4.1.1 Rice Production:

We applied the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to the rice production data to generate accurate forecasts. The first step was to check the stationarity of the training set using the Augmented Dickey-Fuller (ADF) test. The ADF test revealed that the training set was nonstationary, prompting the need for transformation to achieve stationarity. To make the training set stationary, we applied the Box-Cox transformation, and the optimal lambda value was determined to be 0.808480. Additionally, a first-order seasonal differencing was applied, which successfully rendered the training set stationary, with a p-value of the ADF test less than 0.05. Next, we proceeded to visualize the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the appropriate values of the parameters (p, q, P, and Q) for the SARIMA model (Fig.3). The ACF plot exhibited a spike at lag 1, indicating a value of q = 1, and a spike at lag 4, indicating a value of Q = 1. Conversely, the PACF plot displayed a spike at lag 1, indicating a value of p = 1, and spikes at lags 4 and 8, indicating values of P = 2. After analyzing the ACF and PACF plots, a grid search was performed to explore alternative combinations of p, d, P, and Q orders based on the Akaike Information Criterion (AIC). Ultimately, the SARIMA model with orders $(1,0,0)(0,1,1)_4$ was found to have the smallest AIC with significant parameters, making it the best model for the rice production data.

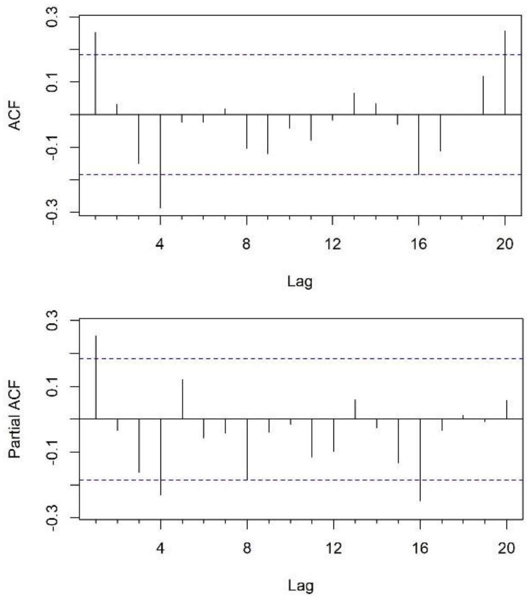

Fig.3. ACF and PACF plots of log-transformed and seasonally differenced rice production data.

Further assessment was conducted using the Ljung-Box test, which yielded a *p*-value of 0.4026, indicating that the residuals followed a Gaussian white noise process, validating the model's goodness-of-fit. Additionally, the Shapiro-Wilk normality test yielded a *p*-value of 0.1896, further confirming that the residuals adhered to a Gaussian distribution. The Fig.4 shows the residuals plot.

To validate the SARIMA model's performance, 29 forecasts were generated and compared with the testing set. Forecast errors were computed to assess the model's accuracy. Based on the ACF plot and the Shapiro-Wilk test (p = 0.07063) performed on the forecast errors, it was determined that the forecast errors also followed a Gaussian white noise process. This observation reinforced the robustness of the SARIMA model in producing reliable forecasts for rice production, essential for informed agricultural planning and decision-making.

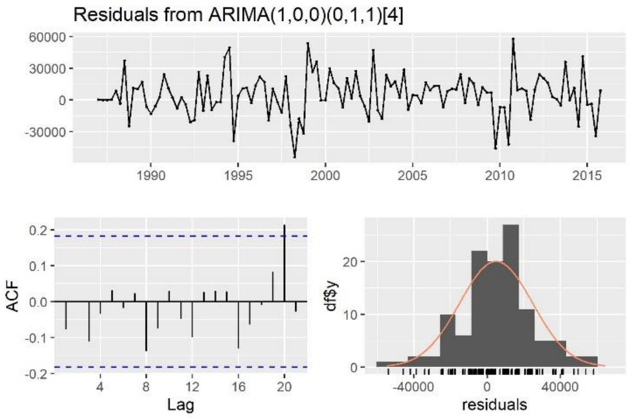

Fig.4. Residuals plot from ARIMA(1,0,0)(0,1,1)$_4$

4.1.2 Corn Production:

The SARIMA model was applied to the corn production data to generate accurate forecasts. The initial step involved assessing the stationarity of the training set using the ADF test, revealing that the data was nonstationary. To achieve stationarity, we implemented the Box-Cox transformation with an optimal lambda value of 1.045027 and applied first-order seasonal differencing. Following the transformation, we conducted the ADF test again, and the results indicated that the data had been made stationary, as the *p*-value was less than the significance level of 0.05. This essential preprocessing step ensured that the time series data met the stationarity assumption required for reliable forecasting. Subsequently, we visualized the ACF and PACF plots to determine suitable values for the parameters (p, d, P, and Q) for the SARIMA model (Fig.5). The ACF plot displayed a prominent spike at lag 4, suggesting a value of Q = 1. Simultaneously, the PACF plot exhibited a significant spike at lag 4, indicating a value of P = 1. With insights from the ACF and PACF plots, we performed a grid search to explore alternative combinations of p, d, P, and Q orders based on the AIC. Ultimately, the ARIMA (0,0,0)(0,1,1)$_4$ model emerged with the lowest AIC and significant parameters, establishing it as the most suiTable.model for the corn production data. To further verify the model's suitability, we conducted the Ljung-Box test and obtained a *p*-value of 0.3439, affirming that the residuals adhered to a Gaussian white noise process. Moreover, the Shapiro-Wilk test yielded a *p*-value of 0.04732, indicating that the residuals were closely consistent with a Gaussian distribution (Fig.6).

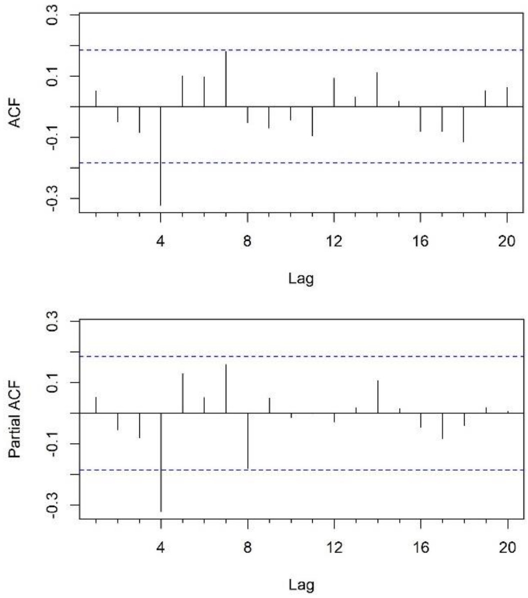

Fig.5. ACF and PACF plots of log-transformed and seasonally differenced corn production data

For model validation, we generated 29 forecasts and compared them with the testing set, calculating forecast errors for assessment. The ACF plot and the Shapiro-Wilk test (p = 0.6151) applied to the forecast errors collectively demonstrated that they followed a Gaussian white noise process (Fig.6). This robustness of the SARIMA model in generating reliable forecasts for corn production is of utmost significance for informed agricultural planning and decision-making.

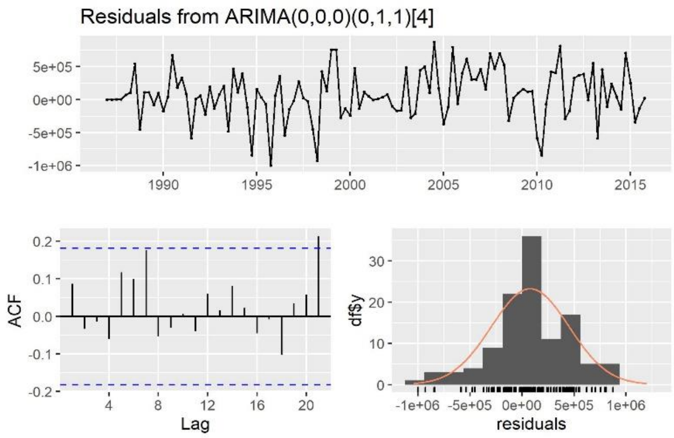

Fig.6. Residuals plot from ARIMA(0,0,0)(0,1,1)$_4$

4.2 HOLT-WINTERS EXPONENTIAL SMOOTHING MODEL

The procedure presented in Fig.1 were followed in implementing the Holt-Winters exponential smoothing model.

4.2.1 Rice Production:

The Holt-Winters exponential smoothing method to the rice production data using the R programming language, utilizing the *stats* and *forecast* libraries. After implementing the Holt-Winters model, we examined the results to assess the presence of seasonality. Upon analyzing the model output, we found that the beta value was close to 0, indicating an additive seasonality in the rice production data. The additive seasonality suggests that the seasonal fluctuations in rice production are relatively constant over time, independent of the overall level of production. The smoothing parameters obtained from the Holt-Winters model were as follows: α (level smoothing parameter): 0.10298, β (trend smoothing parameter): 0.03586228, and γ (seasonal smoothing parameter): 0.4945273. To validate the model's performance, we checked the residuals to ensure that they satisfied the assumptions of a well-fitted model. We examined the ACF plot of the residuals and found that the spikes were within an acceptable region, indicating that the residuals did not exhibit significant autocorrelation. Additionally, we conducted the Ljung-Box test on the residuals, obtaining a *p*-value of 0.2138. The non-significant *p*-value suggests that the residuals did not show significant autocorrelation at different lags, further supporting the adequacy of the model. Furthermore, we performed the Shapiro-Wilk test on the residuals and obtained a *p*-value of 0.1324. The non-significant *p*-value implies that the residuals approximately followed a normal distribution, indicating that the assumption of Gaussian white noise was satisfied (Fig.7).

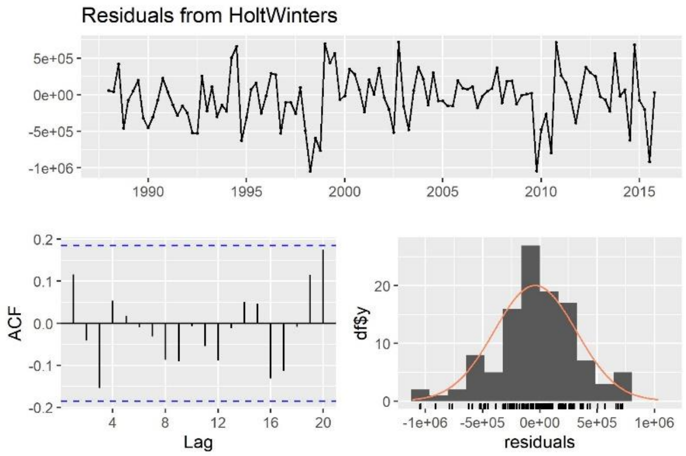

Fig.7. Residual plot of the Holt-Winters model for rice production

Overall, the Holt-Winters exponential smoothing model with additive seasonality demonstrated satisfactory performance in capturing the patterns and fluctuations in rice production. These findings provide valuable insights for agricultural planning and decision-making, facilitating informed resource allocation and forecasting in the rice production sector.

4.2.2 Corn Production:

Similarly, we utilized the *stats* and *forecast* libraries in R to apply the model to corn production data. Upon implementing the Holt-Winters model, we determined that the corn production data also exhibited additive seasonality. This finding suggests that the seasonal fluctuations in corn production remained relatively constant over time, independent of the overall production level. The resulting smoothing parameters from the Holt-Winters model for corn production were as follows: α: 0.06220898, β: 0.2615605, and γ: 0.5243619. These smoothing parameters play a critical role in determining the weights assigned to different components of the model - the level, the trend, and the seasonal component. The values obtained allow for a better understanding of how each component contributes to the overall forecast.

To validate the model's performance, we thoroughly analyzed the residuals to ensure they met the assumptions of a well-fitted model. We investigated the ACF plot of the residuals and observed that the spikes were within acceptable regions, indicating the absence of significant autocorrelation. Furthermore, we conducted the Ljung-Box test on the residuals, which yielded a *p*-value of 0.4988. This result suggests that the residuals did not exhibit significant autocorrelation at various lags, reinforcing the adequacy of the model. Additionally, we performed the Shapiro-Wilk test on the residuals, obtaining a *p*-value of 0.261 indicating that the residuals closely adhered to a normal distribution, further supporting the assumption of Gaussian white noise in the model (Fig.8).

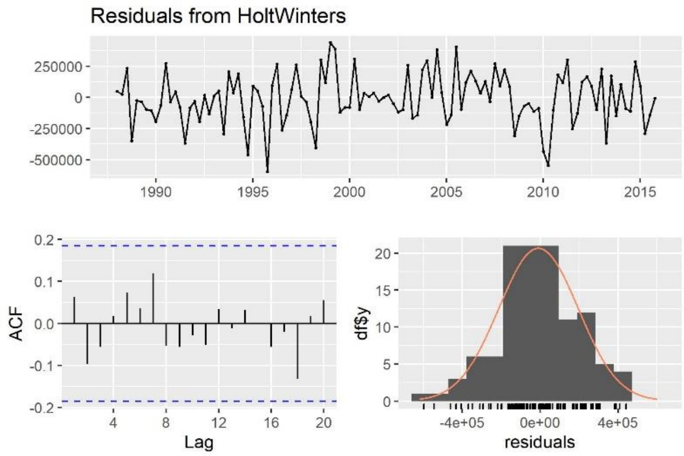

Fig.8. Residual plot of the Holt-Winters model for corn production

The successful application of the Holt-Winters exponential smoothing model to corn production data provides valuable insights for forecasting and decision-making in the agriculture sector. The model's ability to capture additive seasonality patterns aids in generating accurate forecasts, enabling informed planning and resource allocation for optimizing corn production efforts.

4.3 MODEL COMPARISON

We compared the performances of the ARIMA and Holt-Winters models for forecasting rice and corn production in the Philippines. The evaluation is based on the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. From Table.3, it is evident that the Holt-Winters model outperformed the SARIMA model in forecasting rice production. The Holt-Winters model achieved a lower RMSE of 349999.4 and a lower MAPE of 5.90% compared to the SARIMA model with an RMSE of 394037.7 and a MAPE of 8.70%.

Table.3. RMSE and MAPE values of forecasting models for rice production.

Forecasting Model	RMSE	MAPE
SARIMA	394037.7	8.70%
Holt-Winters	349999.4	5.90%

Similarly, Table.4 illustrates that the Holt-Winters model performed better than the SARIMA model in forecasting corn production. The Holt-Winters model achieved a lower RMSE of 182415.9 and a lower MAPE of 7.31% compared to the SARIMA model with an RMSE of 221975.4 and a MAPE of 11.53%.

Overall, the comparison of the ARIMA and Holt-Winters models for both rice and corn production indicates that the Holt-Winters method demonstrated superior forecasting accuracy. It achieved lower RMSE and MAPE values for both commodities, indicating its ability to capture the underlying patterns and seasonality in the agricultural data more effectively.

Table.4. RMSE and MAPE values of forecasting models for corn production.

Forecasting Model	RMSE	MAPE
SARIMA	221975.4	11.53%
Holt-Winters	182415.9	7.31%

As a result, the Holt-Winters model is recommended as the preferred forecasting approach for rice and corn production in the Philippines, as it provides more accurate and reliable predictions to support agricultural planning and decision-making processes.

5. CONCLUSIONS AND RECOMMENDATIONS

Rice and corn production are vital pillars of the Philippine economy, serving as major sources of livelihood and key components of the country’s food security. However, the agricultural sector faces various challenges, including climate variability and the need for imports to meet growing demand. Accurate forecasting of rice and corn production is essential to ensure food sufficiency and make informed decisions regarding imports. In this research, we applied the Seasonal ARIMA and Holt-Winters models to forecast rice and corn production in the Philippines. For rice production, the Holt-Winters model with additive seasonality outperformed the SARIMA model, achieving a lower RMSE of 349,999.4 and MAPE of 5.90% compared to the SARIMA model’s RMSE of 394,037.7 and MAPE of 8.70%. Similarly, for corn production, the Holt-Winters model displayed better forecasting accuracy, with an RMSE of 182,415.9 and MAPE of 7.31% compared to the SARIMA model’s RMSE of 221,975.4 and MAPE of 11.53%. Based on these results, we recommend the adoption of the Holt-Winters model as the preferred forecasting approach for rice and corn production in the Philippines. The Holt-Winters method has demonstrated superior predictive capabilities, effectively capturing the underlying patterns and seasonality present in the agricultural data. Its ability to adapt to changes in patterns and trends makes it well-suited for quarterly forecasting in a dynamic agricultural environment. Furthermore, accurate forecasting of rice and corn production can significantly aid policymakers, agricultural stakeholders, and commodity traders in making informed decisions on import requirements. By having more reliable forecasts, the country can better manage imports, reducing the strain on financial resources caused by fluctuating global market prices and exchange rates. While the Holt-Winters model showcased its forecasting prowess in this study, ongoing research in agricultural forecasting methodologies is vital. As agriculture is a dynamic sector susceptible to various influences, continuous refinement and improvement of forecasting techniques are necessary. Future research should explore the application of more advanced forecasting models, such as neural networks and machine learning algorithms, to further enhance predictive accuracy and address the challenges posed by evolving agricultural dynamics.

REFERENCES

[1] J.D. Urrutia, J.L.B. Diaz and F.L.T. Mingo, “Forecasting the Quarterly Production of Rice and Corn in the Philippines: A Time Series Analysis”, *Journal of Physics: Conference Series*, Vol. 820, No. 1, pp. 12007-12013, 2017.

[2] Philippine Statistics Authority, “2018 Family Income and Expenditure Survey”, Available at: https://psa.gov.ph/sites/default/files/FIES%202018%20Final%20Report.pdf, Accessed on 2023.

[3] Philippine Rice Research Institute, “State of the Rice Sector in the Philippines”, Available at: https://www.philrice.gov.ph/ricelytics/, Accessed on 2023.

[4] Philippine Statistics Authority, “Corn Production in the Philippines”, Available at: https://psa.gov.ph/sites/default/files/Corn%20Production%20in%20the%20Philippines%2C%202018%20-%202020%20%20%281%29.pdf, Accessed on 2023.

[5] Philippine Rice Research Institute, “Imports and Exports”, Available at: https://www.philrice.gov.ph/ricelytics/impexports, Accessed on 2023.

[6] Statista, “Total Volume of Corn Imported from the Philippines from 2016 to 2021”, Available at: https://www.statista.com/statistics/1268973/philippines-corn-import-volume/, Accessed on 2023.

[7] R.M. Briones, “Philippine Agriculture: Current State, Challenges, and Ways Forward”, *Policy Notes*, Vol. 14, No. 2, pp. 1-8, 2021.

[8] G.J. Perez, O. Enricuso, K. Manauis and M.A. Valete, “Characterizing the Drought Development in the Philippines using Multiple Drought Indices during the 2019 EL NINO”, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 3, pp. 463-470, 2022.

[9] J.S. Davidson, “Why the Philippines Chooses to Import Rice”, *Critical Asian Studies*, Vol. 48, No. 1, pp. 100-122, 2016.

[10] Global Rice Science Partnership, “Rice Almanac”, 4th Edition, Available at http://books.irri.org/9789712203008_content.pdf, Accessed on 2013.

[11] D. Montgomery, C. Jennings and M. Kulachi, “*Introduction to Time Series and Forecasting*”, John Wiley and Sons, 2015.

[12] M. Panda, “Application of ARIMA and Holt Winters Forecasting Model to Predict the Spreading of COVID-19 for India and its States”, *Proceedings of International Conference on Recent Trends in Artificial Intelligence*, pp. 1-8, 2020.

[13] P.S. Kalekar, “Time Series Forecasting using Holt-Winters Exponential Smoothing”, Available at https://caohock24.files.wordpress.com/2012/11/04329008_exponentialsmoothing.pdf, Accessed on 2004.

[14] S. Khanderwal and D. Mohanty, “Stock Price Prediction using ARIMA Model”, *International Journal of Marketing and Human Resource Research*, Vol. 2, No. 2, pp. 98-107, 2021.

[15] S. Parreno, “Forecasting the Total Non-Coincidental Monthly System Peak Demand in the Philippines: A Comparison of Seasonal Autoregressive Integrated Moving Average Models and Artificial Neural Networks”, *International Journal of Energy Economics and Policy*, Vol. 13, No. 5, pp. 1-13, 2023.

[16] S.J. Parreno, “Forecasting Electricity Consumption in the Philippines using ARIMA Models”, *International Journal of Machine Learning and Computing*, Vol. 13, pp. 1-14, 2022.

[17] G. Gourav, J.K. Rekhi, P. Nagrath and R. Jain, “Forecasting Air Quality of Delhi using ARIMA Model”, *International Journal of Environmental Research and Public Health*, Vol. 18, No. 11, pp. 6174-6179, 2021.

[18] S.J.E. Parreno, “Application of Time Series Analysis in Forecasting Coal Production and Consumption in the Philippines”, *ICTACT Journal on Soft Computing*, Vol. 13, No. 1, pp. 2798-284, 2022.

[19] R. Zhang, “Comparison of ARIMA and LSTM in Forecasting the Incidence of HFMD Combined and Uncombined with Exogenous Meteorological Variables in Ningbo, China”, *International Journal of Environmental Research and Public Health*, Vol. 18, No. 11, pp. 6174-6183, 2021.

[20] D. Kuiziniene, A. Varoneckiene and T. Krilavicius, “Cryptocurrencies Short-Term Forecast: Application of ARIMA, GARCH and SVR Models”, *Proceedings of International Conference on Information Technologies*, pp. 1-8, 2019.

[21] S. Parreno, “Analysis and Forecasting of Electricity Demand in Davao Del Sur, Philippines”, *International Journal on Soft Computing, Artificial Intelligence and Applications*, Vol. 11, pp. 25-33, 2022.

[22] E. Kozłowski, “Application of Holt-Winters Method in Water Consumption Prediction”, Ople Publishing House, 2018.

[23] M. Rossi and D. Brunelli, “Forecasting Data Centers Power Consumption with the Holt-Winters Method”, *Proceedings of International IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems*, pp. 210-214, 2015.

[24] S. Lima, A.M. Goncalves and M. Costa, “Time Series Forecasting using Holt-Winters Exponential Smoothing: An Application to Economic Data”, *AIP Conference Proceedings*, Vol. 2186, pp. 1-6, 2019.

[25] M. Heydari, “Application of Holt-Winters Time Series Models for Predicting Climatic Parameters (Case Study: Robat Garah-Bil Station, Iran)”, *Polish Journal of Environmental Studies*, Vol. 29, No. 1, pp. 617-627, 2020.

[26] E. Valakevicius and M. Brazenas, “Application of the Seasonal Holt-Winters Model to Study Exchange Rate Volatility”, *Inzinerine Ekonomika*, Vol. 26, No. 4, pp. 384-390, 2015.

[27] C. P. Da Veiga, “Demand Forecasting in Food Retail: A Comparison Between the Holt-Winters and ARIMA Models”, *WSEAS Transactions on Business and Economics*, Vol. 11, No. 1, pp. 608-614, 2014.

[28] N. Kurniasih, “Forecasting Infant Mortality Rate for China: A Comparison between α-Sutte Indicator, ARIMA, and Holt-Winters”, *Journal of Physics: Conference Series*, Vol. 1028, No. 1, pp. 12195-12198, 2018.

[29] A.S. Ahmar, “Comparison of ARIMA, Sutte ARIMA, and Holt-Winters, and NNAR Models to Predict Food Grain in India”, *Forecasting*, Vol. 5, No. 1, pp. 138-152, 2023.

[30] A. Rahman and A.S. Ahmar, “Forecasting of Primary Energy Consumption Data in the United States: A Comparison between ARIMA and Holter-Winters Models”, *AIP Conference Proceedings*, Vol. 1885, pp. 1-9, 2017.

[31] V. Karadzic and B. Pejovic, “Inflation Forecasting in the Western Balkans and EU: A Comparison of Holt-Winters, ARIMA and NNAR Models”, *Amfiteatru Economic Journal*, Vol. 23, pp. 517-532, 2021.