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Research Article

Stochastic Time Series Analysis for Palay Production in South Cotabato, Philippines, Using the Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

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ABSTRACT

This study used SARIMA time series modeling to describe, model, and forecast quarterly palay production in South Cotabato, Philippines using data from 1987 to 2025 (i.e., 1987–2019 as training period and 2020–2025 as validation period), and then generate forecasts from 2026 to 2030. Specifically, it aimed to explore dynamics of palay production, determine the best SARIMA model specification, assess model forecasting ability, and create forecasts of future production. Results show that palay production shows a rising trend over the long term, together with a very significant seasonal variation with seasonality s = 4. Palay production peaks in Q3 and Q4 and bottoms out in Q2 every year. From among 29 potential model specifications, SARIMA(0,1,1)(1,1,1)[4] proved to be the optimal specification according to various criteria. The analysis of residuals shows that the model is good at capturing not only the seasonal component but also the non-seasonal one with residuals resembling white noise. Accuracy assessment of forecasts showed that the model has acceptable and stable accuracy both in-sample and out-of-sample. Even though the model underestimates production when validated, the errors made by the model in training data and validation data do not vary significantly, implying generalization without overfitting. The predicted level of palay production between 2026 to 2030 will be steady and feature recurring seasonal variations, with no increase or decrease in production over the five-year period considered. The prediction intervals widen as the length of prediction horizon increases, reflecting rising uncertainty about forecasts.

Keywords: *ACP Box-Jenkish Approach, PACF, Seasonality, Trend*

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Introduction

Palay is considered the primary staple crop in the Philippines, thus making its production vital in ensuring food security. Rice cultivation is one of the major sources of livelihood in South Cotabato since a large portion of the population relies on it as an income source and as food. Just like any other agricultural output, palay production has its dynamic characteristics, such as trends, seasonality, and cycles. Capturing this using time series methods such as ARIMA (Autoregressive Integrated Moving Average) and its seasonal equivalent SARIMA (Seasonal ARIMA) have been extensively done to analyze the historic data of crop production process. The characteristics of these time series methods make them suitable for investigating the dynamics of and making forecasts about palay production.

Several studies have been conducted on applying ARIMA/SARIMA models for forecasting agriculture production. For instance, Urrutia et al. (2017) developed SARIMA models to forecast production of rice and corn using data collected between 1987 and 2015 and forecasted the next five-year period (2016–2020). Moreover, Handa et al. (2023) conducted forecasting of palay production and prices by using ARIMA models and reported an overall increasing trend throughout the period studied. Another example can be found in the research of Pureza et al. (2019) whose objective was to examine rice stock in the Philippines with the help of SARIMA and develop recommendations for policymaking related to food supply.

Moreover, other methods can be used for the prediction of agricultural time series. As an example, Daproza et al. (2023) applied the Cobb-Douglas production function model to study factors influencing rice production, finding out that land, capital, and expenditures did not play a significant role in determining outputs. On the contrary, they found out that labor input, fertilizer utilization, irrigation, and agricultural loans affected agricultural output positively. Additionally, comparisons, such as those conducted by Picaza and Decano (2025) and Caquilala et al. (2025), indicate that although machine learning models can provide better prediction results, statistical models such as ARIMA are still valuable because of their ease of interpretation. As evidenced from recent comparisons, while machine learning methods may prove to be capable of delivering better predictive accuracy in some agricultural forecasting applications, their opaque nature poses difficulties for interpreting the underlying time-based mechanisms that are responsible for changes in production (Picaza & Decano, 2025; Caquilala et al., 2025). ARIMA models, in turn, are characterized by an explicit inclusion of a trend component, an autoregressive component, a moving average component, and a seasonal component into their structure.

Other models have also been used in different countries for the growth of rice. According to Mahajan et al. (2020), Noorunnahar et al. (2023), Nurviana et al. (2022), Zahid et al. (2024), Shafie et al. (2025), and Silfiani et al. (2024), there is a clear pattern of growth in the rice-growing countries using the ARIMA model. Nevertheless, it is necessary to note that the growth of rice is very sensitive to weather conditions. Such an approach is consistent with the recently conducted research which states that climate change, especially temperature and rainfall, is the major factor in global agricultural productivity (Joseph et al., 2023). As for South Cotabato, rice production was affected greatly by phenomena such as El Niño and La Niña (Stuecker et al., 2018). This climatic behavior provides a realistic context for the notable variation that exists in the historical production of palay, with a particular emphasis on the notable drops in 1991Q2 and 2016Q2. This variation suggests that there is no consistent upward trend in the production of palay in the province and that there is always a disruption due to seasonality and climatic issues. This necessitates the use of a time-series analysis method since it will help detect temporal and seasonal relationships in the data and predict future occurrences.

Although the general trend is positive, it can vary depending on environmental conditions (Aksenov et al., 2025).

While there is plenty of research dedicated to national-level analyses of rice or palay production or both, there are few studies that consider this topic from the provincial perspective, and even fewer studies focus on rice and palay production in South Cotabato. Despite being one of the most important palay producers, this province has been little studied. Palay production in South Cotabato has been increasing steadily by about 51.3%, with municipalities such as Norala, Banga, and Surallah making an essential contribution. However, this total increase can conceal important variations within provinces and across seasons, particularly where production is dependent on climatic conditions and changes in agricultural policy. Besides, South Cotabato is the pilot area of the Consolidated Rice Production and Mechanization Program (CRMP) promoting collective farming techniques (Teves & Ortuoste, 2025). It is especially important to mention the CRMP's implementation in terms of provincial level analysis because local agricultural programs may have an impact on production dynamics that cannot be seen on the national or aggregate levels. Innovative rice varieties such as MASIPAG have been cultivated in Tboli municipality (Francas, 2025). Overall, 85.2% of palay production in the region is made by irrigated rice cultivation systems, with upland farming making up the rest (Belo, 2025).

It can be seen from the above discussion that despite similarities between South Cotabato and other agricultural provinces in rice production, there is also uniqueness in its production patterns. These differences, together with the province's vulnerability to climate variability and the application of local agricultural programs, suggest that national-level production patterns may not fully reflect the dynamics of palay production in South Cotabato. Thus, local data on rice production can provide more accurate results that can help with local food production planning. Consequently, this study will focus on analyzing palay production in South Cotabato by applying the seasonal ARIMA model and forecasting it for the next five years with quarterly division. The use of quarterly provincial level data not only enables the forecasting of future production but also ensures the presence of seasonality and local-level interpretability for food security planning and agricultural decisions in South Cotabato.

Research Questions

Self This study conducted a stochastic time series analysis using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to describe, model, and forecast quarterly palay production in South Cotabato, Philippines. It answered the following questions:

1. What are the temporal characteristics of quarterly palay production in South Cotabato from 1987 to 2019 in terms of trend and seasonality?
2. What is the most appropriate SARIMA model that best fits the quarterly palay production series based on statistical adequacy, information criteria, and diagnostic checking?
3. How accurate is the selected SARIMA model in forecasting palay production based on in-sample fitted values (1987–2019 training period)?
4. How accurate is the selected SARIMA model in forecasting palay production based on out-of-sample forecasts compared with actual observations (2020–2025 validation period)?
5. What are the projected quarterly palay production levels in South Cotabato for the forecast horizon 2026 to 2030 based on the final validated SARIMA model?.

Materials and Methods

Research Design

For this research, a quantitative research design involving stochastic time series analysis was used to analyze and forecast palay production in South Cotabato, Philippines. The research employed the SARIMA model to investigate the nature of palay production, develop a suitable forecasting model, test its forecast accuracy, and produce forecasts. The Box-Jenkins approach was used, involving exploratory data analysis, testing for stationarity, model identification, estimation of parameters, diagnostic checks, model verification, and forecasting. The choice of the SARIMA model was based on the consideration of the presence of time-dependent, trend, and seasonal components in the agricultural data.

Data Source and Data Description

Information concerning the quarterly output of palay in South Cotabato was collected from the PSA. The quantity of palay output was measured in metric tons from the first quarter of 1987 to the fourth quarter of 2025, resulting in 156 data points. The quarterly frequency enabled exploration of seasonality in production related to agricultural cycles. Prior to analysis, data were screened for any missingness, inconsistency, and errors. The data were used for the purpose of model identification, validation, and forecasting.

Data Analysis

Analysis of the data was guided by the Box-Jenkins modeling approach in pursuit of the research objectives. The Box-Jenkins modeling framework is a step-by-step, four-phase procedure that includes: Model Identification; Model Estimation; Diagnostic Check or Validation; and Forecasting.

Prior to model identification, data were split into training and validation datasets. All exploratory analysis, stationarity test, ACF and PACF plot, model estimation, and diagnostics were based on the training data (1987-2019). On the other hand, forecast accuracy was only tested using validation data (2020-2025). About 15% of observations, the last six years, were devoted to validation of the forecast accuracy.

Exploratory Time Series Analysis

Exploratory analyses were performed initially. Plots for time series were created to visualize trends, seasonality, cyclicity, and outlier detection. Descriptive statistics (mean, median, standard deviation, minimum, maximum) were also obtained. Finally, seasonal decomposition was used to decompose the series into trend, seasonality, and irregular component.

Variance Stabilization and Stationarity Testing

Since stationarity is key to SARIMA, testing was done on the palay production series to determine whether it was stable with constant variance (homogeneity). Variance stabilization was considered first, before differencing. When necessary, the original palay production series Y_t was transformed using the natural logarithm, $Z_t = ln\ ln\ (Y_t)$, to reduce heteroscedasticity and stabilize its variance. After the variance-stabilizing transformation, stationarity of the series was assessed using visual analysis of time series, ACF, and PACF plots. Statistical stationarity testing was carried out using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The ADF tests the null hypothesis of unit root (non-stationarity), whereas the KPSS test assumes stationarity under the null. However, if the log-transformed series Z_t was not found stationary and non-seasonal, then non-seasonal and seasonal differences were performed on it if needed. Non-seasonal differencing is expressed by $\nabla^d Z_t = (1 - B)^d Z_t$, whereas seasonal differencing is expressed by $\nabla_4^D Z_t = (1 - B^4)^D Z_t$, where B is the backshift operator and s = 4 indicates the frequency is quarterly. Therefore, the final series used for SARIMA model estimation is:

$$W_t = (1 - B)^d (1 - B^4)^D\ ln\ ln\ (Y_t)$$

where d and D indicate non-seasonal and seasonal differencing, respectively. The process of differencing was stopped at the point when all stationarity criteria were satisfied with the help of the ADF and KPSS tests and corresponding ACF and PACF. Thus, variance stabilization with the use of logarithms was conducted before differencing.

Here, seasonal difference had $s = 4$ since the series was quarterly. The resulting orders d and D were then incorporated into the SARIMA specification, $SARIMA\ (p, d, q)(P, D, Q)_4$.

Identification and Estimation of SARIMA Model

The identification and estimation of the most suitable SARIMA model were addressed by developing several SARIMA models from the stationary series. Model identification involved analyzing the patterns found in the ACF and PACF plots. SARIMA models were defined as $SARIMA(p,d,q)(P,D,Q)_4$ where p, d, and q represent the autoregressive, differencing, and moving-average orders respectively, and P, D, and Q denote seasonal autoregressive, differencing, and moving-average orders with a seasonal period of four quarters. Parameters in the model were estimated by maximum likelihood estimation. Only those models with statistically significant parameter estimates and appropriate diagnostics were selected.

SARIMA Model Selection

The identified SARIMA models were compared based on their goodness of fit to choose the best model. Comparison was based on Akaike Information Criterion (AIC), Corrected AIC (AICc), and Bayesian Information Criterion (BIC). The lower the value, the better the fit of the model. Additionally, the principle of parsimony was utilized whereby models with similar fit were preferentially simplified by choosing those with fewer parameters.

Model Diagnostics

Once the SARIMA model was selected based on information criteria (AIC and BIC values), its appropriateness was evaluated via model diagnostics. Residual diagnostics included inspecting the time series of residuals to detect white noise behavior about zero and constant variance. Also, residual autocorrelation was assessed using the residual ACF plot and Ljung-Box test. Significance of the latter test means that there is still some autocorrelation left in the residuals implying that some aspect of the series has been overlooked by the model. Other residual diagnostics included histogram and normal Q-Q plot to confirm normality of residuals.

Forecast Accuracy Evaluation

The forecast accuracy was evaluated using in-sample data (1987-2019) and out-of-sample data (2020-2025). In-sample forecast accuracy was evaluated using fitted values obtained from model estimation. On the other hand, out-of-sample forecast accuracy was tested against the observed data.

Several measures were calculated, namely: Mean Error (ME); Mean Squared Error (MSE); Root Mean Squared Error (RMSE); Mean Absolute Error (MAE); Mean Percentage Error (MPE); Mean Absolute Percentage Error (MAPE); and Symmetric Mean Absolute Percentage Error (SMAPE). A low value for all measures except ME and MPE implies good forecasting accuracy.

Forecast Generation

To accomplish the forecast of the palay production in the next five years, the final SARIMA model was estimated again using all the available data (1987-2025). Following that, the selected model was used to forecast the quarterly palay production from 2026 to 2030 (20 quarters). Forecasts, together with point forecasts and prediction intervals, were presented in tabular and graphical formats.

Result and Discussion

Temporal Characteristics of Quarterly Palay Production (1987–2019)

Descriptive Statistics of Palay Production

Quarterly palay production in South Cotabato, Philippines during the 1987-2019 periods demonstrates significant variation across time. As indicated in Table 1 below, the sample includes 132 valid observations (training set) of palay production in South Cotabato, Philippines, characterized by a mean of 64,102.48 metric tons and a standard deviation of 28,271.01 metric tons.

Table 1. Descriptive Statistics

Valid	Mean	Std. Dev.	Variance	Min	Max
132	64102.48	28271.01	7.99E+08	5556.00	131284.00

As one can see in Table 1 above, the minimum palay production in South Cotabato, Philippines is equal to 5,556 metric tons, while the maximum is equal to 131,284 metric tons. Hence, the production range exceeds 125,000 metric tons. This, in turn, along with a variance equal to 7.99 x 10^8, indicates the volatility of production in the area under review and the existence of several reasons influencing palay production. For instance, there have been times when palay production has dropped dramatically (e.g., 5,556 metric tons in 2016Q2 and 6,512 metric tons in 1991Q2). The observed declines may reflect the influence of external factors not examined in the present study (which may be thermal conditions, amount of precipitation, or pest invasion). It follows from this comparison that there have been years when the production of palay was extremely low, whereas the opposite is true in other years. Consequently, the differences between minimum and maximum values of quarterly palay production are quite pronounced.

Time Series Visualization

The plot of quarterly palay production in South Cotabato over the period of 1987–2019 shows an upward pattern but considerable short-run variability over time. During the initial period of the series (late 1980s – early 1990s), the palay production levels were rather low and showed high short-run variability, signaling a period of significant instability in output.

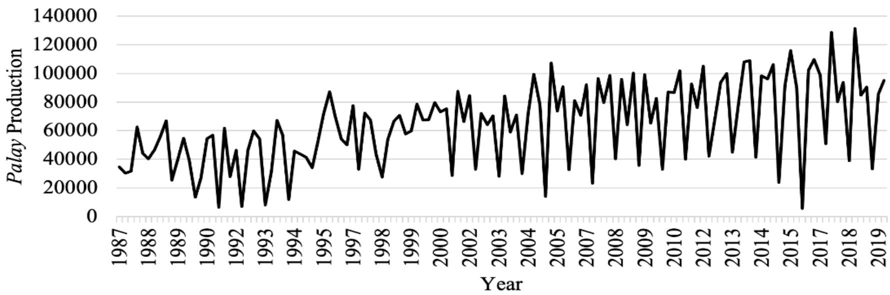

Figure 1. Volume of Palay Production in South Cotabato, Philippines

Thereafter, beginning from the mid-1990s, there is a visible increasing trend in the volume of production, with most observations surpassing 90,000 metric tons per year and reaching 100,000 metric tons per year towards the end of the period under analysis. The highest observation is registered in 2018Q3, where production was estimated at 131,284 metric tons. Nonetheless, the series is not without a number of spikes in palay production. These are related to short-term variability inherent in time-series models of agricultural output, rather than deterministic trends in the variable. Some unusual observations include 1991Q2 and 2016Q2, where production reached only 6,512 metric tons and 5,556 metric tons, respectively. Again, no explanations are being provided at this point, as the task is descriptive in nature.

Trend Component Analysis and Seasonal Pattern Analysis

According to the plot of the trend component, there is a gradual increase in palay production in the selected period.

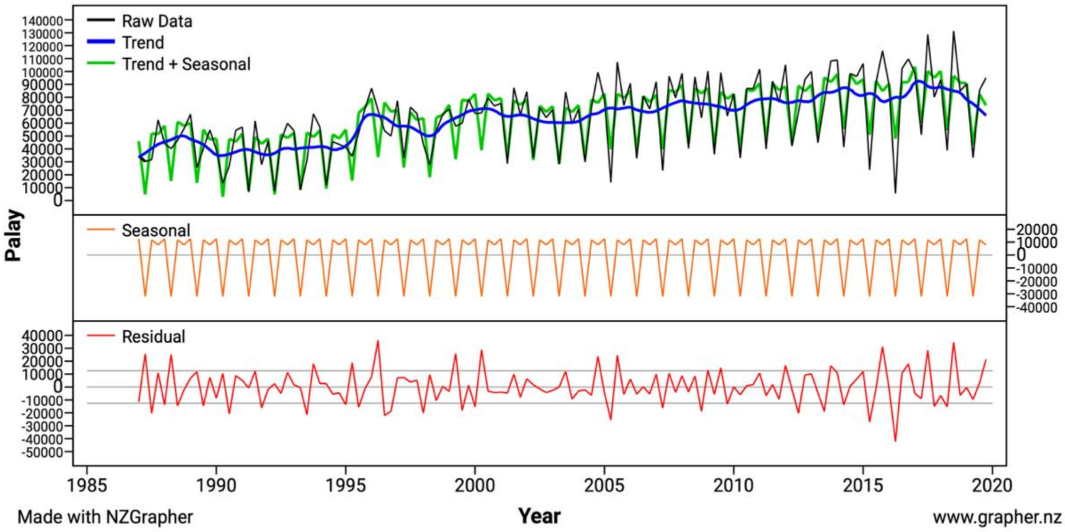

Figure 2. Trend, Seasonality, and Residual of the Palay Volume of Production

Specifically, palay production levels were relatively low with considerable variability until 1995. Thereafter, a steady upward movement started, implying structural improvements over time. However, it should be noted that the increasing trend was interrupted by some decreasing periods throughout the series. As mentioned above, these deviations are related to the combination of deterministic movements and short-term variability observed in the time series model of the selected variable.

Furthermore, the seasonal plot revealed a stable quarterly pattern of palay production in South Cotabato, Philippines.

The analysis of seasonality results in the statement that quarterly patterns of palay production are persistent throughout the observation period. Production volumes are high in the third and fourth quarters and low in the second quarter. Such patterns are characteristic of the whole analyzed period, including years with low-production periods (such as 1991Q2, 1993Q2, 2005Q2, 2016Q2, etc.). The identified quarterly pattern of palay production levels persists throughout time, demonstrating relative stability of seasonal behavior of the selected variable. The seasonal structure estimation (s = 4) corroborates the results of the analysis, showing that there is quarterly seasonality in the time series model of the selected output, implying SARIMA model application for further analysis.

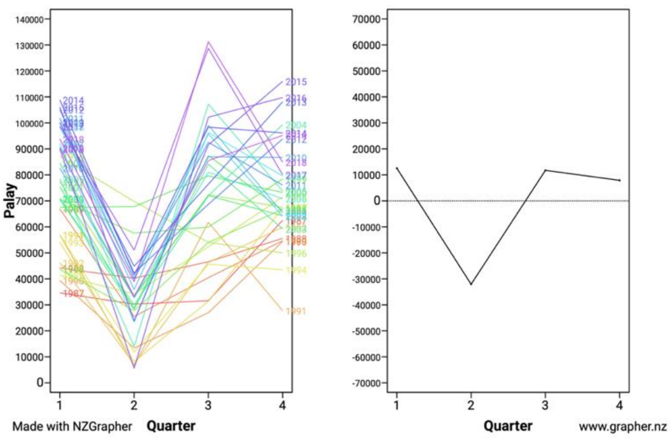

Figure 3. Seasonality Effects

SARIMA Model Identification, Estimation, and Selection

Variance Stabilization and Transformation and Stationarity Assessment Results

Prior to SARIMA modeling, the quarterly *palay* production series was subjected to a logarithmic transformation followed by first-order differencing to address potential non-stationarity in variance and mean. The resulting transformed series, as shown in Figure 4, exhibits fluctuations around a constant mean of approximately zero, suggesting that long-term trend components have been effectively removed.

The series displays relatively constant variance throughout the whole period. The majority of values are confined within a certain range from -0.5 to 0.5, whereas a number of observations are far outside this range. The presence of sporadic extreme values in the series is indicative of the fact that the time series shows some episodes of increased variance rather than a change in the variance level. As was stated before, this can be explained by the nature of agricultural production, which may be influenced by external factors, including climatic factors and agricultural disturbances. Episodes of increased volatility can be noted in the early 1990s and around 2016-2017, when there were sharp drops and jumps in the series. This implies that there were some temporary structural breaks in the time series, which could not be fully adjusted using transformation and differencing techniques. In addition, the absence of any upward or downward trends indicates that the series is stationary in mean. Another important feature of the series is regular fluctuations, which are characterized by the appearance of a "sawtooth" structure throughout the entire observation period. Such a repetitive oscillatory pattern clearly indicates the presence of a strong seasonal component in quarterly agricultural production. Thus, a seasonal time series analysis is quite reasonable here since quarterly periodicity can be assumed ($s = 4$).

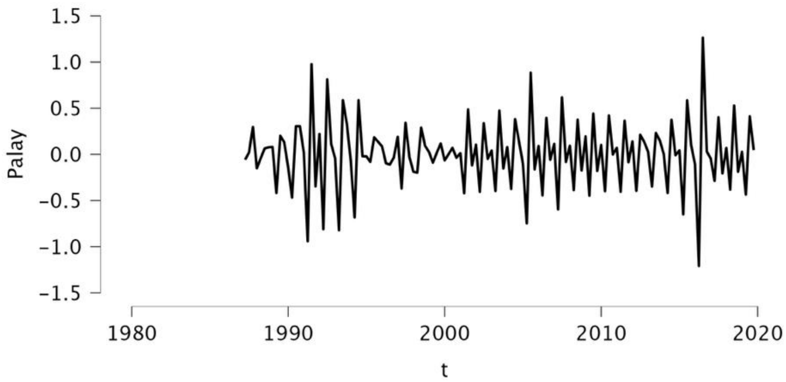

Figure 4. Logarithmic Transformation and Differencing

Additionally, stationary tests were performed using the Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

Table 2. Stationarity Test of the Log-Transformed and Differenced Series

Test	Statistic	Truncation lag parameter	p	H_0
ADF t	-6.321	5	< 0.01	Non-stationary
KPSS Level η	0.016	4	0.100	Level stationary
KPSS Trend η	0.016	4	0.100	Trend stationary

The Augmented Dickey-Fuller test resulted in the following outcomes: the test statistic equals to -6.321, and the p-value < 0.01. This means that the null hypothesis of the unit root in the series is rejected at the 5% significance level, which implies stationarity of the transformed and differenced time series in mean. When applying the KPSS test, extremely low test statistics were obtained for the level and trend specifications; the p-values were found to exceed 0.1. Thus, the null hypothesis of stationarity in level and trend specifications cannot be rejected. The results of both the ADF and KPSS tests thus indicate the stationarity of the log-transferred and differenced series.

ACF and PACF Analysis

The autocorrelation function and partial autocorrelation function were analyzed for determination of autoregressive and seasonal structures in the time series.

The results of analysis of the autocorrelation function demonstrate strong and significant positive correlations at the following lags: 4, 8, 12, 16, and 20. It is obvious that the repetition of spikes at every fourth lag is indicative of the presence of quarterly seasonality in the time series (s = 4), since the production in the particular quarter is positively correlated with the production in the same quarter in previous years. At the same time, the significant autocorrelations occurring at the lags that are multiples of 4 confirm that there is persistent seasonality at quarterly lags. These findings along with the outcomes from stationarity test justify the application of seasonal differencing (D = 1). An additional important point is that there is a negative spike at lag 1 indicating that there is a reversal tendency in quarterly palay production in South Cotabato. Thus, increases in production in one quarter are followed by decreases in the next quarter.

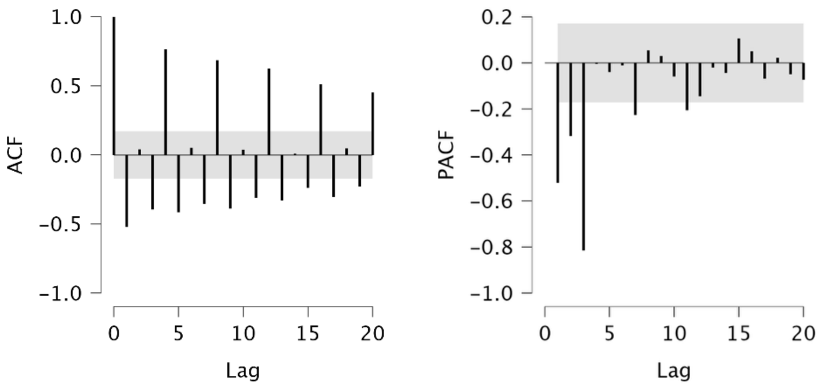

Figure 5. ACF and PACF Plots

When analyzing the partial autocorrelation function, it should be pointed out that significant negative spikes at the following lags can be observed: 1, 2, and 3. The largest spike occurs at lag 3. In the case when most of the values lie within the confidence bounds after lag 3, it implies that the order of non-seasonal autoregression is likely 3 (p ≤ 3). Additionally, the remaining spikes at higher lags are rather small and insignificant.

Summing up the findings, quarterly seasonality can be observed in the series (s = 4), seasonal differencing is needed (D = 1), and the order of non-seasonal autoregression is likely 3 (p ≤ 3).

Candidate SARIMA Models

Candidates for the final SARIMA model were generated based on the obtained results of correlation analysis and then compared by AIC, AICc, and BIC. A total of 29 candidate models were generated, see the table in the appendix.

Table 3. Comparison of Candidate SARIMA Models

Candidate Models	AIC	AICc	BIC
SARIMA(3,1,0)(0,1,1)[4]	-91.706	-91.210	-77.485
SARIMA(3,1,1)(0,1,1)[4]	-90.577	-89.877	-73.512
SARIMA(3,1,0)(1,1,1)[4]	-91.205	-90.505	-74.140

Candidate Models	AIC	AICc	BIC
SARIMA(0,1,1)(1,1,1)[4]	**-97.995**	**-97.667**	**-86.618**
SARIMA(1,1,1)(1,1,1)[4]	-96.001	-95.505	-81.780
SARIMA(2,1,1)(1,1,1)[4]	-94.093	-93.393	-77.028
SARIMA(3,1,1)(1,1,1)[4]	-92.219	-91.278	-72.310

Note. Complete results are presented in the Appendix. For SARIMA(0,1,1)(1,1,1)[4], the sigma squared is 0.023 and the log-likelihood is 52.997.

To compare candidate SARIMA models, information criteria (AIC, AICc, and BIC) were calculated. It was revealed that the performance of the model tends to improve significantly as the model becomes more complicated. At the same time, more complicated models are characterized by high values of the specified criteria. Based on the comparison of candidate models according to their information criteria, it was found that the model SARIMA(0,1,1)(1,1,1)[4] shows the lowest values of the criteria, and thus this model can be considered the best performing among the others.

Final Model Selection

When choosing the final model, information criteria (AIC, AICc, and BIC), statistical significance of parameters, and model complexity were taken into consideration. Consequently, SARIMA(0,1,1)(1,1,1)[4] model was selected as the final one since it showed the best results according to the criteria and included only significant parameters. This model includes non-seasonal and seasonal moving averages (q = 1 and Q = 1) as well as seasonal autoregression (P = 1). Also, this model accounts for quarterly seasonality and seasonal differencing.

The estimated parameters of the selected SARIMA(0,1,1)(1,1,1)[4] are given in the table below:

Table 4. Coefficients

	Estimate	Std. Error	t	p	95% CI	
					Lower	Upper
MA(1)	-0.931	0.043	-21.509	< 0.001	-1.016	-0.845
seasonal AR(1)	0.361	0.092	3.930	< 0.001	0.180	0.543
seasonal MA(1)	-0.947	0.054	-17.433	< 0.001	-1.054	-0.840

Note. An ARIMA(0, 1, 1)(1, 1, 1)[4] model was fitted.

All estimated coefficients are statistically significant at the 0.001 level, and therefore, it can be concluded that both non-seasonal and seasonal components of the model make a substantial contribution to the explanation of the behavior of quarterly palay production in South Cotabato.

As was mentioned above, q = 1. Thus, the non-seasonal MA parameter includes MA(1). Its estimated coefficient is -0.931 (p < 0.001), which indicates the presence of the short-term adjustment process in the time series. Any unexpected growth or fall in the production volume in one quarter is expected to be compensated for by a decrease or increase in the next quarter, respectively. Furthermore, the estimated confidence interval for the parameter (-1.016 to -0.845) is very narrow, which means that the coefficient of the MA(1) term is accurate and consistently differs from zero.

The seasonal AR parameter involves the seasonal AR(1) component with the estimated coefficient equal to 0.361 (p < 0.001). A positive value of the coefficient indicates that there is a positive relationship between palay production volumes in the current quarter and in the previous year at the corresponding quarter.

The last component of the SARIMA(0,1,1)(1,1,1)[4] is the seasonal MA(1) parameter, whose coefficient is -0.947 ($p < 0.001$). Like the coefficient of the MA(1) component, it indicates the presence of the seasonal adjustment process in the series, i.e. an unexpected deviation in palay production in one quarter will be partially compensated for in the next year at the corresponding quarter.

Residual Diagnostics

After determining the final SARIMA(0,1,1)(1,1,1)[4], residual diagnostics were performed.

When observing the plot of standardized residuals, one can conclude that the series does not show any systematic deviations because of the fact that the residuals are randomly dispersed around zero. The residual variance fluctuates randomly between approximately -0.2 and +0.2, excluding certain time points from 2000 to 2015. There are also several periods with increased variances, e.g. in the early 1990s and around 2005, when there were spikes in residual variance. However, the maximum value occurs in 2016, when a large negative residual is followed by a jump in the opposite direction.

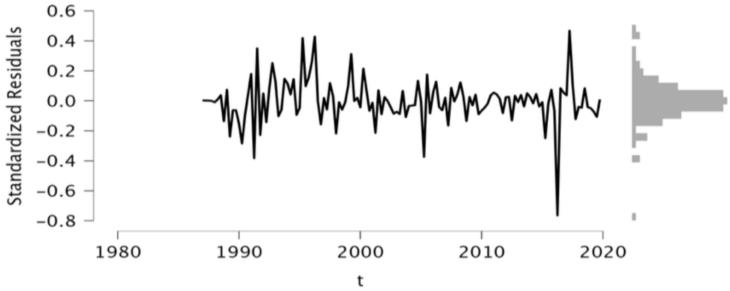

Figure 6. Time Series Plot (Standardized Residuals)

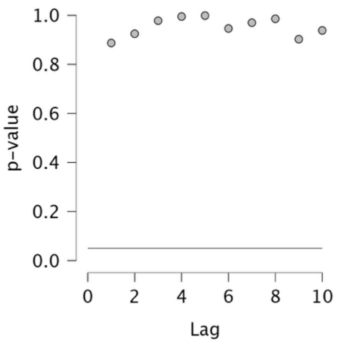

Figure 7. Ljung-Box Plot

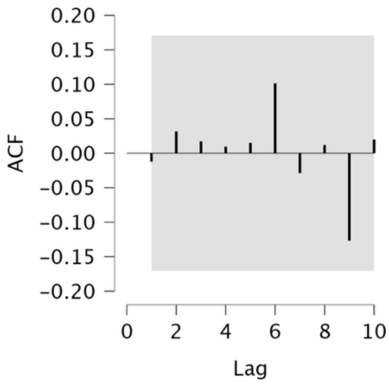

Figure 8. ACF (Standardized Residuals)

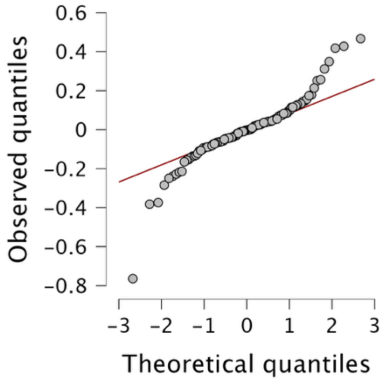

Figure 9. Q-Q Plot

When analyzing the shape of the histogram, one should pay attention to the approximately bell-like form of the residuals. They are concentrated around zero, while at the same time, there is a slight heaviness at the tails of the histogram, which reflects the presence of several extreme observations in the data set.

The Ljung-Box test results reveal that the values of p vary from 0.90 to 1.00, and therefore the hypothesis of lack of autocorrelation in residuals cannot be rejected.

When analyzing the ACF plot of the residuals, it should be pointed out that all autocorrelation values are less than the 95% confidence bound up to lag 10. Consequently, there is no autocorrelation in the residuals.

The QQ-plot shows that the residuals approximately coincide with the normal line in the center, although there are some deviations at both tails. It means that the residuals of the fitted SARIMA model are normally distributed for the most part.

In-Sample Forecast Accuracy (Training Period: 1987–2019)

Fitted vs Actual Values

To assess the in-sample forecasting accuracy of the selected SARIMA model, fitted values were compared with observed values of quarterly palay production from 1987 to 2019. The fitted vs. actual plot is shown in Figure 10 below:

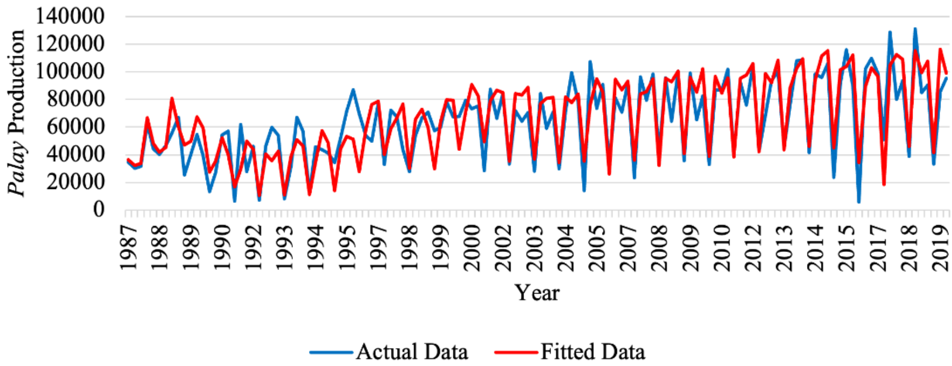

Figure 10. Forecast (Back-Transformed) versus Actual Values

Visually inspecting the above graph, it appears that the fitted series generally follows the trend and seasonality of the observed series. The fitted series has captured both the upward trend and the recurrent quarterly fluctuations in palay production, thus reflecting that the selected SARIMA model has accounted for both trend and seasonality of the series.

Despite such successful replication, major deviations occur during periods where there is extremely low or high production. In these instances, the selected model is observed to smooth out any sudden declines and rises in the series, which is expected of SARIMA models as they try to model the general structure rather than specific outliers. However, despite these major deviations, the fitted series shows good conformity to the observed series at almost all periods.

In-Sample Error Measures

Measures of in-sample forecasting accuracy are presented in Table 5 below:

Table 5. Error Statistics

ME	MSE	RMSE	MAE	MPE	MAPE	SMAPE
-2981.34	2.31E+08	15194.50	11875.84	-0.1414	0.2725	0.2236

From the table above, it can be seen that the ME value of -2,981.34 means that the model slightly underpredicts palay production, thus resulting in a slightly negative bias in the fitted series. The bias in question is rather small compared to the series' scale. On the other hand, the MAE and RMSE values of 11,875.84 and 15,194.50 metric tons respectively reflect that common deviations are in the 12,000 to 15,000 metric ton range, which is considered moderate when looking at the level of production in the series. Similarly, the MSE value of 2.31 x 10^8 indicates that the large deviations in the series, specifically those caused by exogenous shocks, have influenced the measure of error. Finally, percentage-based measures support the above analysis. For example, the MAPE and SMAPE values of 27.25% and 22.36% represent the typical moderate prediction error that characterizes agricultural time series, while the MPE of -0.1414 reiterates the fact that the model slightly underpredicted palay production.

It can be concluded that the in-sample performance of the SARIMA model is satisfactory since it manages to reproduce the structure of quarterly palay production data, namely the trend and seasonality. Nonetheless, the inability of the model to predict extreme production fluctuations is notable, which is not surprising since SARIMA models are unable to capture sudden exogenous shocks to the series. Still, the small error measures imply that the selected model has satisfactory in-sample predictive accuracy and may be used to forecast palay production, provided that it proves itself in out-of-sample testing.

Out-of-Sample Forecast Accuracy (Validation Period: 2020–2025)

Forecast (Back-transformed) vs Actual Comparison

The out-of-sample forecasting accuracy of the selected SARIMA model was analyzed using the validation data set consisting of quarterly palay production data from 2020 to 2025. The results are presented in the graph below (Figure 11):

As evident from the graph above, the model replicates the seasonal structure of palay production as reflected by the quarterly pattern, which features lower values in the second quarter and higher values in the third and fourth quarters. Therefore, the selected SARIMA model has managed to preserve the seasonal structure of the data. Nevertheless, the deviation between the model-generated forecasts and the observed values occurred when sudden declines in actual production occurred. Specifically, the fitted series tended to overestimate production during such times, which led to the appearance of smooth forecasts rather than forecasts that would follow sharp declines. Again, this result is explained by the inability of SARIMA models to capture such exogenous variables as a cause of sharp production decline.

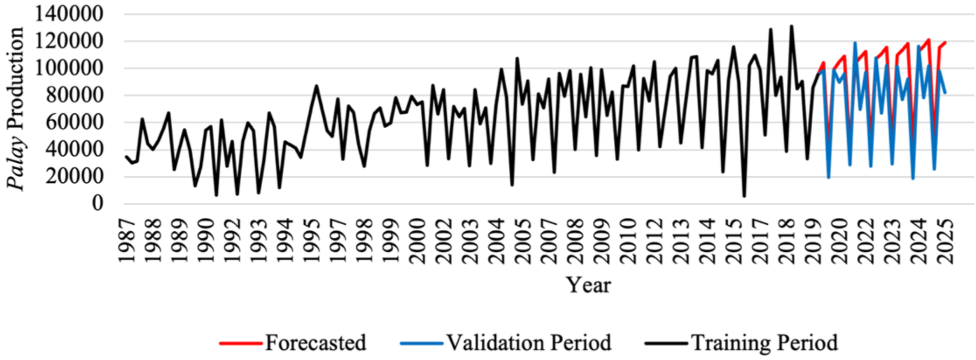

Figure 11. Forecast vs Actual Palay Production Volume

Table 6. Error Statistics

ME	MSE	RMSE	MAE	MPE	MAPE	SMAPE
-17171.40	4.98E+08	22327.07	18817.33	-0.3479	0.3619	0.2781

Out-of-Sample Error Measures

The quantitative results of the out-of-sample validation are shown in Table 6.

Firstly, the table shows that there is an ME of -17,171.40, which implies a significant underprediction of palay production due to the nature of the SARIMA model during the validation period. Thus, since the selected model forecasts using mostly the past temporal dependencies, it is going to systematically underpredict palay production because the relationships in the training period are assumed to be valid in the validation period. However, the 2020-2025 period involves a set of production conditions that may differ significantly from the conditions covered by the historical data used for modeling. Disturbances such as global supply chain issues, sharp increases/ decreases in the price of fertilizer and other agricultural inputs, and local weather disturbances may have changed the production conditions beyond the reach of inference from the past palay production values only. Thus, since external factors may have shifted the levels of actual palay production both up and down from those predicted based on the historical patterns, an autoregressive approach may not be able to predict these shifts. Secondly, the MAE and RMSE are 18,817.33 and 22,327.07 metric tons, which demonstrates that there is an out-of-sample error that is somewhat higher but still is acceptable given the volatility of the variable. In particular, the increase in the RMSE value means that there is a somewhat smaller accuracy in predicting the new observations compared to the in-sample forecasting. Thirdly, the MSE of 4.98×10^{8} suggests that there are significant forecasting errors during the times when significant changes in palay production occur. Thus, there are errors due to atypical shocks to production rather than just seasonal variations. Fourthly, the percentage-based measures are higher than the in-sample ones, which means that the proportion of out-of-sample forecasting errors is higher. In particular, the MAPE and SMAPE values of 36.19% and 27.81%, respectively, show that out-of-sample accuracy is somewhat lower compared to the in-sample one. Finally, the MPE of -0.3479 confirms the underprediction issue with the SARIMA model. Therefore, the negative ME and MPE values imply the presence of directional bias, which might be caused by the influence of external factors not covered by the SARIMA specification. This is the reason why there is a motivation to consider the expansion of the model to the SARIMAX model or another exogenous variable approach where such factors as rainfall, temperature, fertilizer prices, input availability, irrigation conditions, or agricultural interventions can be used.

Comparative Accuracy Analysis

Based on the comparison of in-sample and out-of-sample errors presented above, it is possible to conclude that the SARIMA model manages to retain the seasonal structure of palay production while exhibiting lower accuracy in predicting unseen data. As seen from Table 5 above, in-sample error measures are consistently smaller than out-of-sample measures, which means that the model performs better when it comes to in-sample predictions compared with new data forecasting. At the same time, the consistent ME and MPE measures indicate that the model continues to underforecast production, yet with a somewhat increased intensity.

Model Predictive Validity

It could be said that the SARIMA(0,1,1)(1,1,1)[4] model demonstrates reasonable yet somewhat low performance when forecasting new data. On one hand, the model manages to maintain the seasonal and general trend patterns in quarterly palay production. On the other hand, out-of-sample accuracy of forecasting is somewhat decreased, which makes the model unreliable when predicting extreme palay production. Such decrease in predictive accuracy might be explained by the failure of the model to replicate recently emerging production trends or some exogenous influences impacting the series.

Still, since the model demonstrates structurally coherent error distribution, it can be concluded that the model has demonstrated moderate predictive performance. Although the model captures well the seasonal pattern of the time series, its predictive power deteriorates significantly for out-of-sample predictions, especially during times of high variability in production output.

Forecasted Quarterly Palay Production (2026–2030)

Point Forecast Results

The final SARIMA(0,1,1)(1,1,1)[4] model was used to generate quarterly forecasts of palay production in South Cotabato for the period 2026 to 2030. The results, including point forecasts and their corresponding 80% and 95% prediction intervals, are presented in Table 6.

Table 7. Forecasts (Back-Transformed)

Year	Quarter	Volume of *Palay* Production	80% CI		95% CI	
			Lower	Upper	Lower	Upper
2026	Q1	104034.44	67480.32157	160021.0602	53725.08898	201454.5791
	Q2	30632.13	19869.05187	47225.56294	15782.5489	59453.46127
	Q3	102607.04	66554.45684	158553.9783	52866.08422	199607.6324
	Q4	90193.90	58368.3133	139372.5171	46363.59927	175459.6034
2027	Q1	103318.27	63705.53151	167562.6204	49337.50046	216360.085
	Q2	32149.716	19823.35432	52260.93116	15317.12101	67480.32157
	Q3	103080.65	63266.98572	167562.6204	48885.17154	216858.8466
	Q4	92082.51	56516.74528	150029.6664	43568.955	194167.7703
2028	Q1	103795.17	62686.9505	172257.1048	47882.53596	224997.2155
	Q2	32974.42	19823.35432	54850.06461	15141.78738	71808.71306
	Q3	103795.17	62398.93013	173052.2074	47552.9149	227079.0891
	Q4	93363.50	55869.80345	156018.8755	42675.35509	204727.9527
2029	Q1	104755.57	62112.23309	177083.1112	47116.94715	233441.0046
	Q2	33510.210	19823.35432	56647.02983	15002.96664	74847.47321
	Q3	104997.06	61826.8533	177900.4897	46792.59637	235601.0076
	Q4	94662.320	55613.10502	160759.6839	41993.02335	212900.7265
2030	Q1	105968.59	61684.65548	181625.6341	46363.59927	241644.6273
	Q2	33976.38	19732.27428	58368.3133	14797.11822	77835.39675
	Q3	106212.87	61542.78471	182884.6028	46044.4345	244442.7402
	Q4	95758.46	55230.26709	165644.547	41321.60134	221399.7588

According to the forecasted data, the production is expected to demonstrate stable seasonal tendencies in the analyzed horizon. Each year shows a clear tendency to exhibit a recurrent quarterly pattern, in which palay production tends to be lower in the second quarter but higher in the rest three months. That means that historical data showed seasonal structure and the model was able to reproduce such patterns in the form of forecasted values. In this respect, the magnitudes of the predicted values can differ within the range of approximately 30 thousand to more than 106 thousand metric tons of production per quarter depending on the year. Although some quarters show slight growth trends in their production, no apparent linear pattern of growing or decreasing production is observed.

Forecast Visualization

Figure 12 shows the forecast trajectory that combines both historical data and future forecasts.

As can be seen from the chart above, forecasted palay production is mainly based on seasonal fluctuation rather than any structural breaks in its dynamics. Indeed, the chart shows how palay production continues its previous pattern, implying the same conditions and circumstances in the future. Although slight increases in quarterly production can be observed in some periods, they are too insignificant as compared to the level of seasonality. Thus, in case there are no significant structural changes, production should continue to grow similarly to the past dynamics.

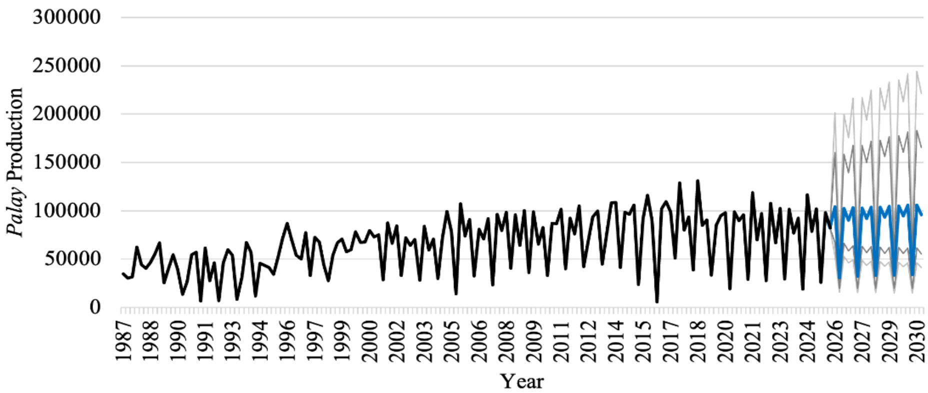

Figure 12. Forecast Time Series Plot

Prediction Intervals

In addition to point predictions of palay production, prediction intervals were calculated for 80% and 95% levels of confidence. These intervals tend to become wider in proportion to the increasing length of forecast period due to the fact that uncertainty grows significantly over the long-term periods. Specifically, 80% confidence level provides relatively narrow intervals of palay production that can be considered as moderately reliable. In turn, 95% prediction intervals become wider at the last years of the forecast horizon, meaning increased uncertainty over the long-term horizon. For instance, in 2030Q3, point estimate of palay production amounts to approximately 106,213 metric tons while its 95% prediction interval ranges from almost 46,000 to 244,000 metric tons. This result reveals significant uncertainty over long-term forecasts made using only historical data on palay production.

Long-Term Forecast Interpretation

From the long-term forecast one can conclude that palay production will likely continue having stable seasonal tendencies with only weak changes in trends. First of all, no dramatic increase of production is expected, and gradual increases observed in the forecast are very minor. The most significant factor affecting palay production would still remain to be its quarterly seasons with s = 4. Namely, every year palay production will remain to be lower in the second quarter, whereas in other quarters the harvest rate will be higher with special emphasis on the first and third quarters. It should be noted that all these tendencies are merely forecasted and reflect structural characteristics of historical patterns of palay production observed in the analyzed region.

Policy Implications

Overall, the analysis reveals several important implications that can be used by policymakers. Firstly, it is clear from the analysis that interventions are required at specific seasonal periods as the productivity in the second quarter of the year is the lowest among the four quarters. Secondly, there are no significant long-term increases in palay production that could help increase the amount of harvest over the years. Thus, new agricultural technologies need to be developed and implemented to increase palay production. Finally, uncertainty increases with longer horizons which requires taking it into account in policy-making activities.

Conclusion

The present study has shown that the use of SARIMA stochastic time series modeling is a valid way of description, modeling, and forecasting quarterly production of palay in South Cotabato, Philippines. It is evident that the palay production in the period of 1987 to 2025 features a stable long-term trend along with the strong quarterly seasonality (s = 4). Specifically, the second quarter demonstrates the lowest level of production, while the third and fourth quarters feature higher output values. Among all tested models, it was established that SARIMA(0,1,1)(1,1,1)[4] is the best fitting one due to information criteria, model diagnostics, and properties of residuals. According to the findings, the model is quite suitable for capturing the dynamics of both seasonality and non-seasonality. In particular, it produces white-noise residuals and is free of any autocorrelation. Model evaluation revealed that, although SARIMA demonstrates reasonable fit within the sample, it shows increased forecasting error and higher probability of producing underforecasts, especially for periods of high production volume. However, the magnitude of errors in each case remains relatively stable indicating that the model demonstrates deterioration of forecasting quality while forecasting out-of-sample data. Nonetheless, the model still demonstrates sufficient forecasting quality without signs of severe overfitting. Based on the forecast produced using the model, it can be argued that the palay production will remain in the range of the stable seasonal cycle with only a small amount of expected growth until 2030. However, wider prediction intervals observed across the whole forecasting period highlight increased uncertainty associated with long-term forecasts. Thus, the SARIMA model seems statistically adequate in capturing seasonality and making predictions for medium-term baseline forecasts; however, forecast accuracy decreases when it is used on out-of-sample data. Its inability to properly account for unexpected shocks highlights the need for considering additional explanatory variables.

Recommendations

Based on the results obtained, it can be recommended that agricultural planners and policymakers in South Cotabato make use of the SARIMA(0,1,1)(1,1,1)[4] model for medium-term forecasting. In light of strong and reliable quarterly seasonality, it can be suggested that intervention measures be season specific, especially with regard to the second quarter characterized by lower production volumes. In order to mitigate this effect, irrigation, input allocation, and climate resilient approaches might be considered. In this respect, the schedule for irrigation can also be revised in preparation for the low-producing second quarter to ensure that there is adequate availability of water at crucial growth periods of the crops, particularly in places where irrigation is essential for the success of the crop cultivation process. The inputs for agriculture such as fertilizers and seeds could also be made available before the period of low agricultural output begins. Early-maturing and climatically resilient varieties of rice could be introduced for growing periods that coincide with the trough period of the second quarter. Finally, due to observed bias towards underforecasting and inability to capture sudden changes in production volume, forecasts should be utilized along with the agricultural monitoring system and climate indices.

As for future research, it might be helpful to build forecasts with consideration of rainfall, temperature, ENSO index, fertilizers' application rate, and policies using SARIMAX or similar models. Additionally, the use of different types of forecasting models, including machine learning-based approaches to time series analysis, might improve predictive accuracy of forecasts.

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APPENDIX

Table 8. Candidate Models

No.	Candidate Models	Rationale based on the plots
1	SARIMA(1,1,0)(0,1,0)[4]	PACF shows a significant spike at lag 1, suggesting a simple AR(1) structure after differencing.
2	SARIMA(2,1,0)(0,1,0)[4]	PACF remains significant through lag 2, indicating a possible AR(2) process.
3	SARIMA(3,1,0)(0,1,0)[4]	PACF cuts off after lag 3, providing strong evidence for AR(3).
4	SARIMA(0,1,1)(0,1,0)[4]	Included as a competing MA model since the negative lag-1 ACF spike may indicate an MA(1) effect.
5	SARIMA(0,1,2)(0,1,0)[4]	Tests whether the short-term dependence is better explained by MA rather than AR terms.
6	SARIMA(1,1,1)(0,1,0)[4]	Mixed ARMA model to accommodate both significant PACF and ACF behavior.
7	SARIMA(2,1,1)(0,1,0)[4]	Combines AR(2) behavior with possible residual MA structure.
8	SARIMA(3,1,1)(0,1,0)[4]	Extends the preferred AR(3) model by allowing an additional MA component.
9	SARIMA(1,1,0)(1,1,0)[4]	Seasonal ACF decay at multiples of 4 suggests a seasonal AR(1) term.
10	SARIMA(2,1,0)(1,1,0)[4]	AR(2) plus seasonal AR(1), consistent with PACF and seasonal ACF patterns.
11	SARIMA(3,1,0)(1,1,0)[4]	Strongest candidate; PACF cutoff at lag 3 and seasonal ACF decay indicate AR(3) with SAR(1).
12	SARIMA(0,1,1)(1,1,0)[4]	Seasonal AR(1) with non-seasonal MA(1), accounting for the negative lag-1 ACF spike.
13	SARIMA(1,1,1)(1,1,0)[4]	Mixed non-seasonal ARMA and seasonal AR structure.
14	SARIMA(2,1,1)(1,1,0)[4]	AR(2) with MA(1) and SAR(1) effects.
15	SARIMA(3,1,1)(1,1,0)[4]	Extends the strongest AR(3) model by adding MA(1).
16	SARIMA(1,1,0)(0,1,1)[4]	Seasonal MA(1) tested because seasonal spikes remain strong after differencing.
17	SARIMA(2,1,0)(0,1,1)[4]	AR(2) with seasonal MA(1).
18	SARIMA(3,1,0)(0,1,1)[4]	AR(3) with seasonal MA(1).
19	SARIMA(0,1,1)(0,1,1)[4]	Pure MA representation with seasonal MA effects.
20	SARIMA(1,1,1)(0,1,1)[4]	Mixed ARMA model with seasonal MA.
21	SARIMA(2,1,1)(0,1,1)[4]	AR(2), MA(1), and SMA(1) combination.
22	SARIMA(3,1,1)(0,1,1)[4]	AR(3), MA(1), and SMA(1), useful when residual autocorrelation remains.
23	SARIMA(1,1,0)(1,1,1)[4]	Seasonal AR and MA effects combined.
24	SARIMA(2,1,0)(1,1,1)[4]	AR(2) with both seasonal AR and MA components.
25	SARIMA(3,1,0)(1,1,1)[4]	AR(3) with seasonal AR(1) and MA(1).
26	SARIMA(0,1,1)(1,1,1)[4]	MA(1) with seasonal ARMA effects.
27	SARIMA(1,1,1)(1,1,1)[4]	Fully mixed seasonal and non-seasonal model.
28	SARIMA(2,1,1)(1,1,1)[4]	AR(2) with non-seasonal and seasonal MA corrections.
29	SARIMA(3,1,1)(1,1,1)[4]	Most comprehensive model consistent with observed patterns.

Table 9. Comparison of Candidate SARIMA Models

Candidate Models	AIC	AICc	BIC
SARIMA(1,1,0)(0,1,0)[4]	-22.469	-22.372	-16.780
SARIMA(2,1,0)(0,1,0)[4]	-38.209	-38.014	-29.676
SARIMA(3,1,0)(0,1,0)[4]	-36.210	-35.882	-24.833
SARIMA(0,1,1)(0,1,0)[4]	-69.129	-69.032	-63.440
SARIMA(0,1,2)(0,1,0)[4]	-67.176	-66.980	-58.643
SARIMA(1,1,1)(0,1,0)[4]	-67.175	-66.980	-58.643
SARIMA(2,1,1)(0,1,0)[4]	-65.175	-64.848	-53.799
SARIMA(3,1,1)(0,1,0)[4]	-63.461	-62.965	-49.240
SARIMA(1,1,0)(1,1,0)[4]	-35.219	-35.024	-26.687
SARIMA(2,1,0)(1,1,0)[4]	-49.196	-48.868	-37.819
SARIMA(3,1,0)(1,1,0)[4]	-52.451	-51.955	-38.230
SARIMA(0,1,1)(1,1,0)[4]	-78.455	-78.260	-69.922
SARIMA(1,1,1)(1,1,0)[4]	-76.738	-76.410	-65.361
SARIMA(2,1,1)(1,1,0)[4]	-74.768	-74.272	-60.547
SARIMA(3,1,1)(1,1,0)[4]	-73.024	-72.324	-55.959
SARIMA(1,1,0)(0,1,1)[4]	-46.996	-46.801	-38.464
SARIMA(2,1,0)(0,1,1)[4]	-58.238	-57.910	-46.861
SARIMA(3,1,0)(0,1,1)[4]	-91.706	-91.210	-77.485
SARIMA(0,1,1)(0,1,1)[4]	-85.631	-85.436	-77.098
SARIMA(1,1,1)(0,1,1)[4]	-83.799	-83.471	-72.422
SARIMA(2,1,1)(0,1,1)[4]	-83.085	-82.589	-68.864
SARIMA(3,1,1)(0,1,1)[4]	-90.577	-89.877	-73.512
SARIMA(1,1,0)(1,1,1)[4]	-59.536	-59.209	-49.160
SARIMA(2,1,0)(1,1,1)[4]	-72.449	-71.954	-58.228
SARIMA(3,1,0)(1,1,1)[4]	-91.205	-90.505	-74.140
SARIMA(0,1,1)(1,1,1)[4]	-97.995	-97.667	-86.618
SARIMA(1,1,1)(1,1,1)[4]	-96.001	-95.505	-81.780
SARIMA(2,1,1)(1,1,1)[4]	-94.093	-93.393	-77.028
SARIMA(3,1,1)(1,1,1)[4]	-92.219	-91.278	-72.310