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Research Article

Time Series Analysis of Commercial Yellowfin Tuna (*Thunnus albacares*) Production in South Cotabato, Philippines, Using the SARIMA Model

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ABSTRACT

A stochastic time series analysis was done through the SARIMA model to identify the characteristics of production in terms of trend and seasonality, develop the optimal SARIMA model based on certain information criteria and diagnostics, evaluate the accuracy of in-sample and out-of-sample forecast, and create a forecast for the production. Quarterly production data of commercial yellowfin tuna (*Thunnus albacares*) in South Cotabato during the years 2002 to 2021 were subjected to Box-Jenkins modeling procedure such as logarithmic transformation of data, differencing, checking for stationarity, identifying the optimal model through information criteria, estimating model parameters, and performing model diagnostics. It was found that the commercial yellowfin tuna production was fluctuating significantly but showed cyclical trend and seasonal pattern; the production is usually lower in Q3 but higher in Q2 and Q4. As for the results obtained from diagnostic checking, it could be deduced that SARIMA(1,1,1)(1,1,1)[4] model was deemed as the best-fitting model since it provided the minimum AIC and AICc values. Based on this model, it could be predicted in the next few years from 2026 to 2030 that there would be no remarkable growth or decline in production, and only slight fluctuation will be expected because of the season. It is essential to highlight, however, that there is a limit to the use of the univariate approach in time series forecasting, as even though the model will give accurate results when the environment remains constant, it does not account for sudden changes in ecological and economic environments.

Keywords*: ACF, Box-Jenkins approach, Commercial fisheries, PACF, SOCCSKSARGEN*

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Introduction

In today's global seafood market, yellowfin tuna (*Thunnus albacares*) is among the most economically important pelagic fishes, which serve both for the production of high-value sashimi and canned tuna products. Within the Philippines, SOCSKSARGEN province is famous as the "Tuna Capital," where South Cotabato together with its surrounding regions around the city of General Santos constitutes an important hub of the largest tuna landing centers in Southeast Asia. The General Santos Fish Port Complex has become one of the key nodes in domestic and international seafood chains, being the center for fishing, cold chain logistics, and export-oriented tuna processing that considerably boost national economic growth and bring foreign currency revenue (Hipolito & Vera, 2006; Pechon et al., 2022).

The economic importance of yellowfin tuna production in South Cotabato cannot be reduced solely to export activities. On the contrary, the fisheries industry sustains large volumes of labor-intensive occupations involving fishing, processing, transportation, and related services in the region. Nevertheless, economic dependency is also associated with serious sustainability challenges. Trends of the national fishing industry have revealed either stagnation or decline in the volume of catch since the 2000s amid the increase of market value and pressure on fish stocks, leading to their serial depletion (Anticamara & Go, 2016). The same tendencies may be noted in local fish landings in General Santos, where the shift in the composition of catches, gear use, and fishing effort has been registered.

Empirical studies conducted at the General Santos Fish Port Complex have shown that tuna makes up the bulk of catches, constituting nearly 89% of all fish landings during the period from 2008 to 2014, whereas yellowfin tuna accounts for about one-quarter of catches from the family Thunnus (Pechon et al., 2022). Catching dynamics demonstrate obvious seasonality when tuna catches take place year-round but have two peaks in May-June and October-December. Although in recent years the increase in catches has been observed, earlier studies have highlighted a considerable decrease in daily tuna catches by 26-34% between 2007 and 2008 (Yu, 2010). Considering statistics alone, structural disturbances of such nature become a serious hindrance to traditional modeling. These disturbances lead to instability and cause the non-stationarity of variance within the landing data, hence, making it mathematically necessary for one to transform the variance through logarithms and differentiation. At the same time, a gradual shift of fishing grounds occurred along with the expansion up to 70-1500 km offshore due to the declining catching success and changes in fish composition (Macusi et al., 2015; Macusi et al., 2017). The seasonal variations noted within the year call for going beyond descriptive static statistics and into dynamic modeling to effectively separate systematic quarterly shocks from secular long-run effects mathematically.

There has been a number of changes in fishing practices within the region. Purse seine, ring net, and handline constitute major gears that influence tuna catches differently. Namely, handline fisheries target primarily mature specimens of yellowfin tuna, while catches made using other gears comprise mostly juvenile or different species of tunas (Pechon et al., 2022). Also, the increasing use of Fish Aggregating Devices (FADs) is one of the adaptive methods utilized by fishermen in connection with the declining nearshore resources. In turn, the expansion of fishing grounds up to 1500 km is another adjustment method employed under current conditions (Macusi et al., 2015).

Yellowfin tuna production also reflects the socio-cultural context of fisheries. Specifically, the sector includes both large-scale commercial operations that provide huge export incomes and municipal fishing businesses exposed to income instability and competitive pressure (Pechon et al., 2022). Such an inconsistency highlights the so-called labor-livelihood paradox within the fisheries sector. Moreover, the tuna industry has influenced the socio-cultural environment in the region through migration processes, community growth, and transformation of artisanal fishing into industrial production (Pechon et al., 2022). The prediction of these production variations can provide a tool by which to predict significant economic declines that will be needed as a scientific basis for securing the vulnerable municipal economies from any decline during lean quarters.

Studies on the time-series analysis of yellowfin tuna productivity in global seas are common, especially in the Pacific Ocean, Indian Ocean, and others. Time-series modeling allows estimating the impacts of climatic factors and fishing effort on yellowfin tuna dynamics and production. Numerous researchers have studied the relationship of CPUE (catch-per-unit-effort) with climatic parameters and assessed multidecadal changes in tuna productivity driven by climate factors and ocean-atmospheric phenomena, such as El Niño Southern Oscillation (Wu et al., 2020; Singh et al., 2015). Besides, surplus production and state-space models are used to estimate the MSY (maximum sustainable yield) in different oceans (Li et al., 2026; Kalhoro et al., 2024). On the other hand, however, both mechanistic models that require numerous parameters and climate-linked models need huge amounts of data, which are normally not only scarce but also limited to some degree by location. Thus, this shortage of information leads to the development of completely data-oriented univariate stochastic models that do not take into consideration any biological variables that could otherwise significantly complicate the model.

Despite numerous time-series studies concerning yellowfin tuna productivity worldwide, only a limited amount of them focuses on the Philippines and even less of them examines this topic in General Santos specifically. Available empirical studies are descriptive and concentrate primarily on catch composition and fishery behavior rather than on systematic time-series analysis. Thus, there is a great research gap associated with applying the latest time-series approaches, such as SARIMA, to analyze and forecast tuna production. While modern machine learning techniques are available, there is no shortage of effectiveness found in a classical statistical approach, namely, SARIMA. This model is specifically designed to handle time-series data with regular predictable seasonal patterns. And so, it can help analyze the historical data on yellowfin tuna catches in South Cotabato for further forecasts and sustainable fishery management purposes.

With this in mind, the current study provides a univariate SARIMA model based on quarterly yellowfin tuna catch data from 2002 to 2021 (training period) at commercial fisheries. In doing so, the study provides characterization of the trend and seasonality contained within historical catches, determination of the optimum SARIMA parameters for the transformed log series, and short-term forecast of future catches based on the above.

Research Questions

This study used stochastic time series analysis employing the Seasonal Autoregressive Integrated Moving Average (SARIMA) approach to describe, model, and forecast quarterly commercial yellowfin tuna (*Thunnus albacares*) production in South Cotabato, Philippines. This study particularly answered the following research questions:

1. What are the features of the quarterly commercial yellowfin tuna production in South Cotabato in terms of trend and seasonality from 2002 to 2021?
2. Which is the best-fitting SARIMA model that will adequately describe the quarterly commercial yellowfin tuna production series through information criteria and diagnostic checks?
3. How well does the chosen SARIMA model fit the commercial yellowfin tuna production through its fitted values from 2002 to 2021?
4. How well does the chosen SARIMA model forecast commercial yellowfin tuna production when compared to the actual values from 2022 to 2025?
5. What will be the future forecasts of quarterly commercial yellowfin tuna production levels in South Cotabato from 2026 to 2030?

Materials and Methods

Research Design

This research paper employed a quantitative research design using stochastic time series analysis to examine and forecast commercial yellowfin tuna (Thunnus albacares) production in South Cotabato, Philippines. Specifically, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was employed to investigate the temporal behavior of commercial yellowfin tuna production, develop an appropriate forecasting model, evaluate its predictive performance, and generate future production forecasts. The Box-Jenkins methodology was adopted, which consists of exploratory data analysis, stationarity testing, identification of the optimal model, estimation of parameter or coefficients, diagnostic evaluation, validation of the chosen model, and forecasting/predicting. The SARIMA model was selected because fisheries production data may exhibit trend, cyclical fluctuations, and seasonal variations over time.

Data Source and Data Description

Data on commercial yellowfin tuna (Thunnus albacares) production in South Cotabato were obtained from the Philippine Statistics Authority (PSA). Production volume was measured in metric tons and covered the period from the Q1 of 2002 to the Q4 of 2025, yielding a total of 96 observations. The quarterly frequency allowed the investigation of possible seasonal patterns associated with fishing activities, environmental conditions, and market dynamics. Prior to analysis, the time series data were examined for completeness, consistency, and potential errors. The data served as the foundation for model development, validation, as well as forecasting.

Data Analysis

The analysis followed the Box-Jenkins time series modeling framework in order to deal with the objectives of this time series analysis. The framework consists of four major stages: Identification of the Model, Estimation of the Model, Diagnostic Checking, and Forecasting.

Prior to model development, the data were partitioned into training and validation datasets. Exploratory analysis, stationarity assessment, model identification, parameter estimation, and diagnostic procedures were conducted using the training dataset (2002–2021). The validation dataset (2022–2025) was reserved exclusively for evaluating forecasting performance. Approximately 17% of the observations, corresponding to the last four years of data, were allocated for validation purposes. In the time series analysis standard methodology, it is usual to reserve 15% to 20% of out-of-sample sequence data points for testing, ensuring the maintenance of chronological order while better simulating actual forecast scenarios (Hyndman & Athanasopoulos, 2021; Tashman, 2000).

Exploratory Time Series Analysis

Preliminary exploratory analyses were conducted to examine the characteristics of the commercial yellowfin tuna production series. Time series plots were generated to identify trends, seasonal patterns, cyclical movements, and potential outliers. Descriptive statistics, which include the mean, median, standard deviation, minimum, and maximum values, were determined to get an overview of the distribution of production volumes. Furthermore, seasonal decomposition analysis was performed to separate the series into trend, seasonal, and irregular components.

Variance Stabilization and Stationarity Testing

Since stationarity is a fundamental assumption in SARIMA modeling, the commercial yellowfin tuna production series was assessed for constant variance and stable mean behavior over time. When necessary, logarithmic transformation was employed to stabilize the variance and reduce heteroscedasticity.

Stationarity was initially evaluated through visual inspection of the time series graph, autocorrelation function (ACF), and partial autocorrelation function (PACF) plots. Formal statistical tests were subsequently performed using the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF test determined stationarity by evaluating the null hypothesis of a unit root (indicating non-stationarity), whereas the KPSS test assumes stationarity under the null hypothesis. If non-stationarity would be detected, non-seasonal and seasonal differencing procedures would be applied. For quarterly data, the seasonal differencing period was set at $s = 4$. Differencing continued until a stationary series suitable for SARIMA modeling was obtained.

Identification and Estimation of the SARIMA Model

The identification and estimation of suitable SARIMA models were performed using the stationary production series. Model identification involved examining the patterns exhibited by the ACF and PACF plots to determine plausible autoregressive and moving average orders.

Candidate models were specified in the form SARIMA(p,d,q)(P,D,Q)$_4$, where p is the non-seasonal autoregressive component, d represents the non-seasonal differencing order, and q equals the non-seasonal moving average component, while P is the seasonal autoregressive component, D represents the seasonal differencing order, and Q equals the seasonal moving average component with seasonal period of four quarters. Model parameters were computed with the use of the maximum likelihood estimation method. Only models with statistically significant parameter estimates and acceptable diagnostic properties were considered for further evaluation.

SARIMA Model Selection

Competing SARIMA models were compared to determine the most appropriate forecasting model. Model selection was premised on the Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC). Values of these criteria that are relatively lower indicate better model fit. In addition, the principle of parsimony was considered, whereby simpler models with fewer parameters were preferred when competing models exhibited comparable performance.

Model Diagnostics

The adequacy of the selected SARIMA model was assessed through residual diagnostic procedures. Residual time series plots were examined to verify that the residuals behaved as white noise with constant variance and zero mean. Residual autocorrelation was further evaluated using residual ACF plots and the Ljung-Box test.

A non-significant Ljung-Box test result indicates that the residuals are independently distributed and that the model has adequately captured the temporal framework of the series. Additional diagnostic assessments included residual histograms and normal Q-Q plots to evaluate the normality assumption of the residuals.

Forecast Accuracy Evaluation

Forecast accuracy was assessed using both in-sample and out-of-sample data. In-sample accuracy was evaluated using fitted values generated during model estimation, whereas out-of-sample accuracy was assessed by comparing forecasts with actual production values from the validation dataset (2022–2025).

The following accuracy measures were computed: 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). Lower values of these statistics generally indicate superior forecasting performance, except for ME and MPE, which primarily assess forecast bias.

Forecast Generation

Following model validation, the final SARIMA model was re-estimated using the complete dataset covering the period 2002–2025. The selected model was then employed to forecast commercial yellowfin tuna (Thunnus albacares) production in South Cotabato for the succeeding five years, from 2026 to 2030, corresponding to 20 quarterly forecast periods.

Forecast results were presented as point forecasts together with 80% and 95% prediction intervals. The forecasts were summarized in both tabular and graphical forms to facilitate interpretation and provide useful insights into the future trajectory of commercial yellowfin tuna production in the province.

Result and Discussion

Temporal Characteristics of Commercial Yellowfin Tuna Production in South Cotabato (2002–2021)

Table 1 summarizes the summary statistics of quarterly commercial yellowfin tuna production with 80 observations.

Table 1. Descriptive Statistics

Valid	Mean	Std. Dev.	Variance	Min	Max
80	11,311.96	4,557.43	2.08E+07	4,764.13	25,948.90

Over the study period, the average value of quarterly production is estimated to be 11,311.96 metric tons with a standard deviation of 4,557.43 metric tons, implying the presence of variability. The minimum level of production is 4,764.13 metric tons while the maximum level is 25,948.90 metric tons. The wide range and large variance of commercial yellowfin tuna production (2.08×10^7) signify notable variation.

Figure 1 shows notable variation in quarterly production over the study period.

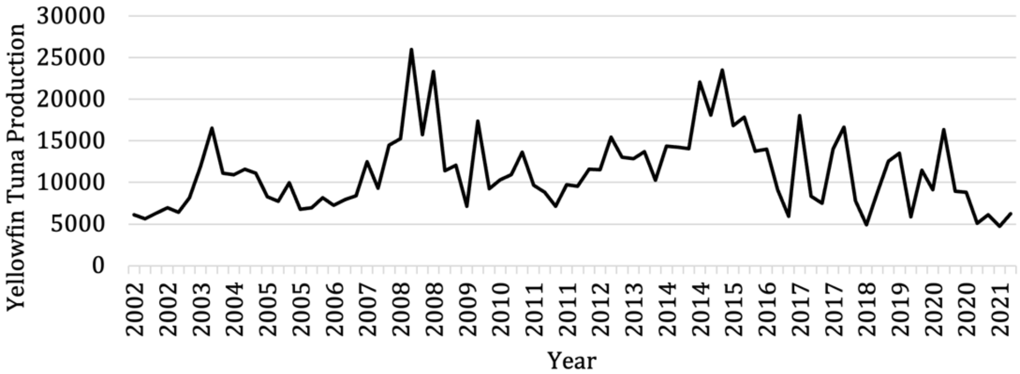

Figure 1. Volume of Commercial Yellowfin Tuna Production in South Cotabato, Philippines

Quarterly production shows a gradual rise in its value until 2008 when it achieves exceptionally high production. After reaching its peak level in 2008, quarterly production drops significantly until it starts to vary widely, eventually growing again during 2014-2015. Second period with relatively higher production levels appears to be during 2014-2015 where quarterly production surpasses 20,000 metric tons. From 2015 onwards, there emerges another period characterized by a persistent decline coupled with increased volatility in production. Towards 2021, quarterly production reaches its low values, estimated roughly to be 4,764 to 6,211 metric tons.

Decomposition was performed in order to grasp the temporal properties of commercial yellowfin tuna production. Figure 2 presents the decomposition of the data.

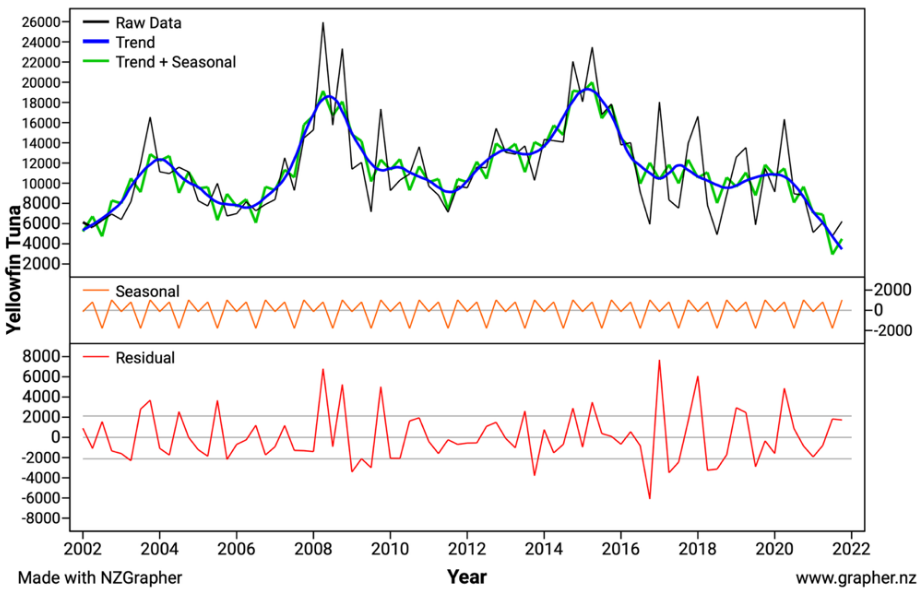

Figure 2. Trend, Seasonality, and Residuals of the Commercial Yellowfin Tuna Production

Trend of the series can be identified as a non-monotonic function with a cycle pattern rather than any steady growth or decline in production. Trend shows increasing values from 2002 to 2008, declines up to 2011-2012, increases again and reaches a secondary peak close to 2015. Afterwards, there is a continuous decline until the end of the studied period. This pattern suggests alternating phases of increasing and declining production values.

Quarterly variations in production are indicated by the seasonal component of the series. Regularity of the series is shown with consistent peaks and troughs that appear every year. This means that the variations in production might be associated with yearly events, such as changes in fishing conditions, oceanography, migration pattern of yellowfin tuna, climate, etc.

Figure 3 demonstrates the seasonal pattern in production using the seasonal effects.

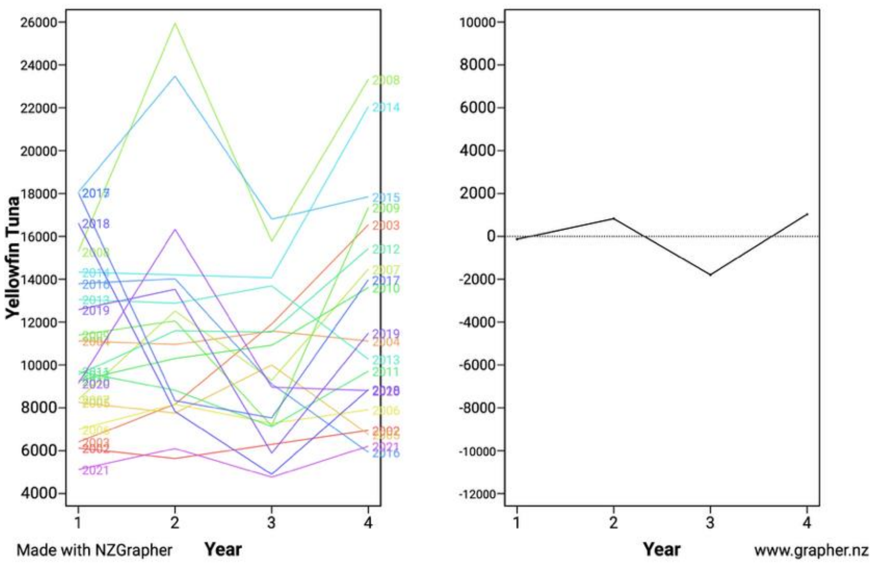

Figure 3. Seasonality Effects

According to the results, mean seasonal effect reveals slightly below average production in Q1, growth in Q2, drop in Q3, and recovery in Q4. In terms of magnitude, third quarter is characterized by the largest negative seasonal effect, while second and fourth quarters exhibit the positive one. Supporting the above results, seasonal sub-series plot demonstrates similar trends – many yearly patterns have a significant dip from Q2 to Q3 and rise from Q3 to Q4.

Residuals in Figure 2 demonstrate random variations that are not accounted for trend and seasonal components. Majority of the residuals lie very close to zero, but there are periods when outliers are present. Significant outliers emerge at 2008-2009 and 2016-2018 suggesting production shocks or external forces that influence production.

It can then be said that there is noticeable variation in quarterly production of commercial yellowfin tuna in South Cotabato, a shifting trend and strong seasonality. Presence of trend and seasonality makes the series suitable for Seasonal Autoregressive Integrated Moving Average (SARIMA).

Best-Fitting SARIMA Model for Commercial Yellowfin Tuna Production

Due to the non-stationarity of the series at the beginning, logarithm transformation and first differencing were performed. It can be seen from Figure 4 that the transformed and differenced series oscillates about the mean, which is relatively constant and close to zero; however, the presence of volatile periods can still be detected.

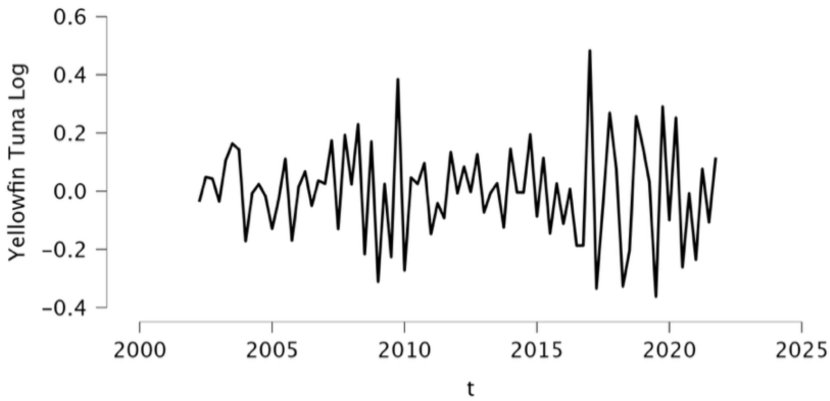

Figure 4. Logarithmic Transformation and Differencing

The first part of the series (roughly speaking, it covers the period between 2002 and 2008) experiences rather moderate volatility; moderate volatility is observed from 2008 till 2011. From 2016 to 2020, there are several significant up and down moves, and the values of this series reach both very high and very low values, i.e., this part displays higher volatility than other parts. However, despite the presence of some volatility, the transformations help increase the stability of the mean and make the series stationary enough for analysis.

The results of formal testing for stationarity confirm the adequacy of transformations.

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

Test	**Statistic**	**Truncation lag parameter**	**p**	**H_0**
ADF t	-4.270	4	< 0.01	Non-stationary
KPSS Level η	0.120	3	0.100	Level stationary
KPSS Trend η	0.033	3	0.100	Trend stationary

Table 2 contains the Augmented Dickey-Fuller statistics value equal to -4.270, which allows rejecting the hypothesis of the presence of non-stationarity since $p < 0.01$. At the same time, the KPSS statistics are equal to 0.100 in both cases of testing the null hypotheses of stationarity at the level and trend, meaning that we cannot reject the hypotheses. As a result, it could be concluded that the transformed and differenced series demonstrates sufficient stationarity to analyze them through a time-series approach.

The choice of the SARIMA models was based on patterns found in the ACF and PACF plots.

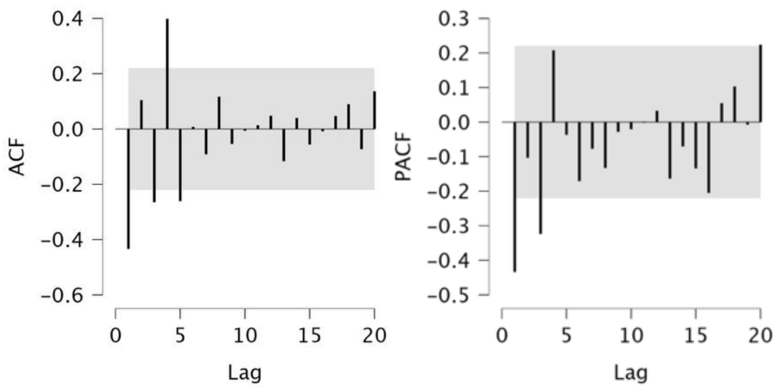

Figure 5. ACF and PACF Plots

According to the plot in Figure 5, there is a significant negative spike on lag 1 for the ACF plot. After that, there were two other significant negative spikes on lag 3 and 5 and one significant positive spike on lag 4. The PACF plot displays a significant negative spike on lag 1 and lag 3. There is also a borderline spike on lag 4. These findings indicate the presence of short-term dependence with AR and MA processes and also seasonal dependence with lag equal to 4. Thus, it is necessary to include both AR and MA parts in SARIMA models, as well as the seasonal part.

Several models have been estimated on the basis of these properties, and their performance in terms of the AIC, AICc, and BIC criteria was compared.

Table 3. Comparison of Candidate SARIMA Models

Candidate Models	AIC	AICc	BIC
SARIMA(1,1,0)(0,1,1)[4]	-63.075	-62.737	-56.123
SARIMA(0,1,1)(0,1,1)[4]	-64.988	-64.650	-58.035
SARIMA(1,1,1)(0,1,1)[4]	-63.066	-62.494	-53.796
SARIMA(3,1,0)(0,1,1)[4]	-63.637	-62.767	-52.049
SARIMA(3,1,1)(0,1,1)[4]	-63.126	-61.890	-49.221
SARIMA(1,1,1)(1,1,1)[4]	**-66.349**	**-65.480**	**-54.762**
SARIMA(2,1,1)(0,1,1)[4]	-63.730	-62.861	-52.143

Note. Complete results are presented in the Appendix. For SARIMA(1,1,1)(1,1,1)[4], the sigma squared is 0.020 and the log-likelihood is 38.175.

It can be noted that according to Table 3, the values of information criteria for all alternative models are relatively close to each other; nevertheless, there is a difference between the values of AIC, AICc, and BIC. While SARIMA(1,1,1)(1,1,1)[4] had the lowest AIC and AICc values, a much simpler model which is SARIMA(0,1,1)(0,1,1)[4] produced a lower BIC. Nevertheless, SARIMA(1,1,1)(1,1,1)[4] was still selected because of its superior overall information criteria performance, significant coefficients, and satisfactory diagnostics.

In addition to the evaluation based on information criteria, one should look at significance of coefficients and diagnostics of residuals. First, it should be checked that all of the parameters are significant.

Table 4. Coefficients

	Estimate	Std. Error	t	p	95% CI	
					Lower	Upper
AR(1)	0.528	0.135	3.920	< 0.001	0.260	0.797
MA(1)	-0.904	0.088	-10.295	< 0.001	-1.080	-0.729
seasonal AR(1)	0.337	0.155	2.180	0.033	0.029	0.646
seasonal MA(1)	-0.944	0.195	-4.830	< 0.001	-1.334	-0.554

Note. A SARIMA(1, 1, 1)(1, 1, 1)[4] model was fitted.

As presented in Table 4, in the SARIMA(1,1,1)(1,1,1)[4] model all of the coefficients turned out to be significant at the 5% significance level. Thus, the estimated model included the following parameters. Non-seasonal AR(1) equal to 0.528 indicated positive short-term persistence. Also, MA(1) = -0.904 meant that the model included a strong correction of short-run errors. Seasonal part included both significant coefficients: AR(1) = 0.337 and MA(1) = -0.944, indicating the presence of seasonal dependence in the quarterly series.

Residuals diagnostics also confirm the validity of choosing the current model. The graph depicting standardized residuals shows that they do not demonstrate any particular structure, except that a few extremely deviant observations occur during periods of highest volatility (2016-2018).

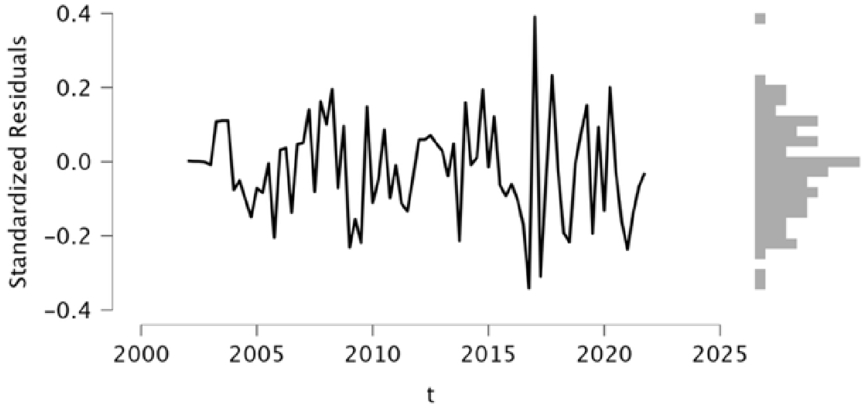

Figure 6. Time Series Plot (Standardized Residuals)

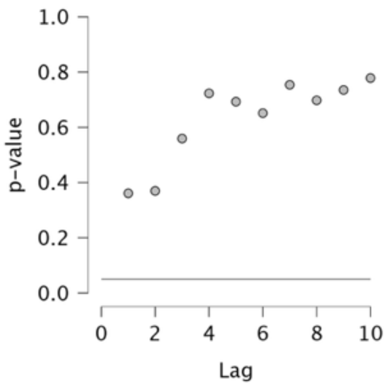

Figure 7. Ljung-Box Plot

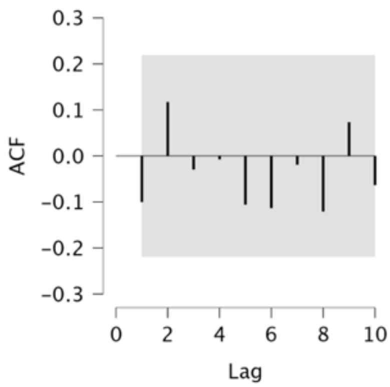

Figure 8. ACF (Standardized Residuals)

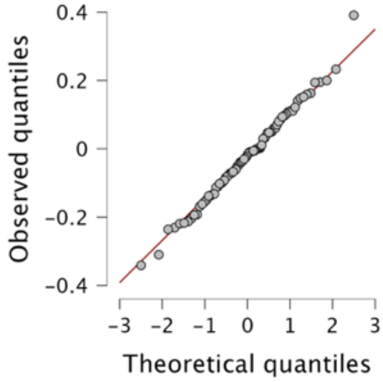

Figure 9. Q-Q Plot

The histogram of standardized residuals is roughly normal (centrally located at zero) and so does the Q-Q plot. Indeed, it can be seen that almost all residuals fall along the normality line with only some deviation in tails (right-tailed in this case). All the lags in the Ljung-Box test have $p > 0.05$, and the residual ACF plot contains all spikes within the 95% confidence interval. Thus, taking into account the coincidence in the values of information criteria, parameter significances, and residual diagnostics, we may conclude that the best-fitting SARIMA model for quarterly yellowfin tuna production in South Cotabato is SARIMA(1,1,1)(1,1,1)[4].

In-Sample Fit of the SARIMA Model for Commercial Yellowfin Tuna Production

Figure 10 presents the visual comparison between observed and fitted values of the variable under analysis.

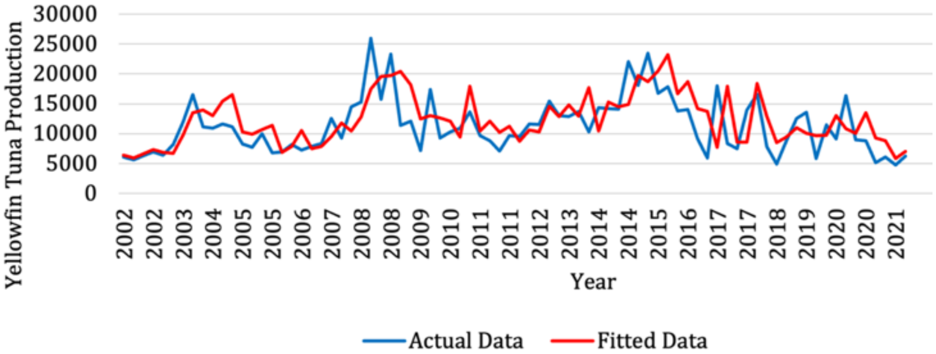

Figure 10. Forecast (Back-Transformed) versus Actual Values

Generally, the trend in fitted values matches the trend in the observed values of the series, which means that the fitted values demonstrate the cyclical growth and decline in commercial yellowfin tuna production. However, certain periods with an increase in production (e.g., in 2008, from 2014 till 2015, and in 2017-2018), are adequately captured by the model, yet the model fails to catch extreme values as it smoothes them out. Such behavior of SARIMA is normal and can be explained by the fact that the model focuses on explaining the stochastic structure of the analyzed process.

However, at the same time, differences between observed and fitted values exist. The biggest differences between actual and fitted values occur when actual data experiences sharp fluctuations. Years like 2008, 2010, 2013, and 2017 have shown significant deviations when it comes to the level of production. Fitted values tend to underestimate or overestimate actual extreme observations, which means that although the SARIMA model explains trends in the series, it is not efficient in dealing with abrupt changes.

Table 5 provides the error statistics used for assessing the quality of forecasting performed by the SARIMA(1,1,1)(1,1,1)[4] model.

Table 5. Error Statistics

ME	MSE	RMSE	MAE	MPE	MAPE	SMAPE
-944.35	14,873,377	3,856.60	3,042.85	-0.16	0.2898	0.2526

The mean error of -944.35 metric tons shows that on average; the model tends to underestimate commercial yellowfin tuna production. When it comes to the accuracy of predictions, the value of MAE is 3,042.85 metric tons, which means that the difference between actual and fitted values tends to be quite high. At the same time, the value of root mean squared error of 3,856.60 metric tons is even higher as it is sensitive to larger forecasting mistakes.

Moreover, MAPE equals 0.2898 (28.98%), which means that, on average, the deviation between actual and fitted values accounts for 29% of the actual values. In the same vein, SMAPE equals 0.2526 (25.26%), which is another indication of relatively high error rates when it comes to the accuracy of predictions.

Finally, MPE equal to -0.16 also implies that the fitted values experience slight negative bias, just as it can be concluded after observing ME value.

To sum up, according to the results obtained, one may say that the SARIMA model gives a reasonably good fit to the historical commercial yellowfin tuna production series.

Out-of-Sample Forecast Accuracy of the SARIMA Model for Commercial Yellowfin Tuna Production

Figure 11 presents the comparison between forecast and actual values throughout the out-of-sample period.

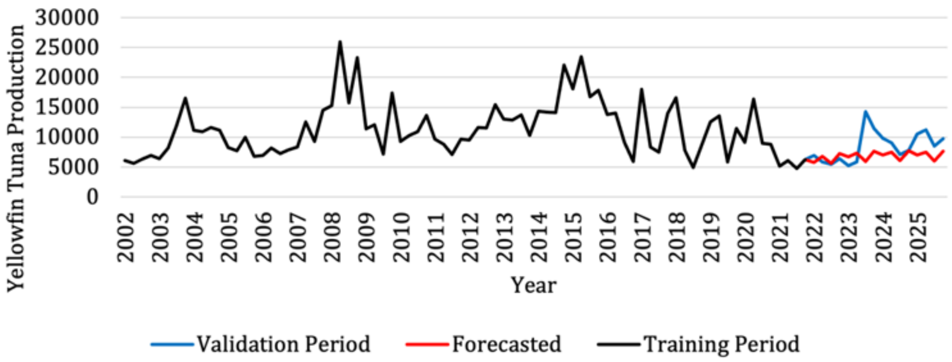

Figure 11. Forecast vs Actual Commercial Yellowfin Tuna Production Volume

On the whole, forecasts have demonstrated their capacity to describe the general level of commercial yellowfin tuna production and its directional path, especially during periods characterized by relatively low variability. However, significant deviations can be observed during abrupt changes in actual values that occur at different points, primarily in 2023Q3 and 2023Q4; in both cases, observed values present unexpected spikes that are not properly estimated by the forecasts. Similarly, the forecasts present relatively steady seasonality patterns compared to those of actual values in 2024 and 2025 quarters.

Table 6 below presents error statistics related to the evaluation of out-of-sample forecast accuracy.

Table 6. Error Statistics

ME	MSE	RMSE	MAE	MPE	MAPE	SMAPE
1,610.77	8,764,981	2,960.57	2,232.78	0.13	0.2345	0.2671

Based on the analysis above, the mean error of 1,610.77 shows a slight tendency of the forecast to overestimate commercial yellowfin tuna production during the validation period, which stands in contrast with the tendency to underestimate the value of the indicator during in-sample estimation and demonstrates a degree of unpredictability in terms of directional error.

As far as absolute measures are concerned, the mean absolute error of 2,232.78 metric tons shows that, on average, forecasts diverge by a relatively small number from actual figures and that out-of-sample MAE is lower than in-sample MAE. RMSE of 2,960.57 is an indicator of occasional relatively large forecast errors.

The MAPE of 0.2345 (23.45%) indicates that the average divergence of the forecast from the actual value equals one-fourth, which can be viewed as acceptable given the relatively high volatility of the data, whereas SMAPE of 0.2671 is a measure of proportional forecast error.

Finally, mean percentage error of 0.13 demonstrates the aforementioned tendency toward slight overestimation of the indicator during validation.

Thus, the overall out-of-sample evaluation of the model indicates that the SARIMA(1,1,1)(1,1,1)[4] model presents relatively good forecasting performance, especially in terms of capturing the general seasonal pattern and average production volume of commercial yellowfin tuna in South Cotabato.

Additionally, analysis of the in-sample and out-of-sample errors shows that the SARIMA(1,1,1)(1,1,1)[4] model is better at predicting the unseen series than replicating the training time-series. Indeed, according to the in-sample results, the MAE equals 3,042.85 and RMSE equals 3,856.60, while the out-of-sample estimates result in smaller errors in terms of MAE being equal to 2,232.78 and RMSE to 2,960.57, which indicates better prediction accuracy for validation samples. The percentage measures are also better in out-of-sample evaluation as MAPE drops from 28.98% to 23.45%, and SMAPE grows from 0.2526 to 0.2671. The lower out-of-sample error implies that there has been a relatively smooth path in the validation phase, unlike the huge volatilities which resulted in high errors in the training phase, for example, between the years 2016 and 2018. Thus, the errors remain relatively small and the forecasted values remain reasonable. In general, both estimates show rather low forecast errors; however, the in-sample estimate demonstrates the smoothing influence of the model on the historical extremes, while the out-of-sample estimation proves the stability of predictions for the near future, as well as growth of proportional deviation.

Forecasted Future Production of Commercial Yellowfin Tuna in South Cotabato (2026–2030)

Table 7 provides the forecasted values along with the respective 80% and 95% prediction intervals. It is evident that the predicted commercial yellowfin tuna production is expected to demonstrate stability in its seasonality pattern through the forecasted period, showing the same quarterly patterns seen before.

Table 7. Forecasts

Year	Quarter	Volume of Tuna Production	80% CI		95% CI	
			Lower	Upper	Lower	Upper
2026	Q1	10328.23	6855.29	15560.58	5521.10	19365.37
	Q2	10642.06	6592.13	17140.59	5117.12	22081.36
	Q3	8790.75	5309.16	14555.46	4064.68	19011.91
	Q4	10399.82	6194.78	17459.26	4710.05	22962.85
2027	Q1	9840.70	5585.03	17379.04	4130.72	23497.73
	Q2	10163.09	5623.75	18366.48	4121.22	25120.36
	Q3	8670.13	4742.70	15886.41	3443.70	21878.92
	Q4	10423.79	5636.71	19276.40	4064.68	26731.66
2028	Q1	9728.05	5152.59	18366.48	3673.04	25705.49
	Q2	10046.76	5260.49	19232.06	3724.14	27166.01
	Q3	8670.13	4487.72	16789.04	3162.47	23769.82
	Q4	10471.91	5370.64	20418.59	3767.26	29108.90
2029	Q1	9728.05	4909.37	19232.06	3420.00	27607.42
	Q2	10069.92	5023.72	20138.44	3483.58	29108.90
	Q3	8710.15	4305.52	17580.28	2971.84	25528.53
	Q4	10520.24	5164.47	21430.18	3540.18	31262.65
2030	Q1	9750.48	4720.91	20138.44	3213.85	29581.89
	Q2	10093.13	4842.01	21039.04	3281.15	31047.44
	Q3	8750.36	4149.79	18408.82	2799.15	27291.40
	Q4	10568.80	4977.67	22440.15	3342.15	33421.49

The forecasted production is expected to show maximum value in Quarter 4 of each year, which is followed by Quarters 1 and 2, whereas Quarter 3 is characterized by the minimum value in all forecasted periods. Such forecasted values confirm the seasonal structure observed during the analysis of decomposition and seasonality effects, as it demonstrates that Quarter 3 always showed the smallest production due to the negative seasonal deviation.

When it comes to the annual trend, it can be stated that the forecasts imply that there is no tendency of either growth or decline in the future production. Thus, it is expected that in the forecast period the same seasonal pattern of production will take place. Therefore, the model does not show any structural change of long-term deterministic tendencies.

In 2026, the production forecast is between 8,790.75 in Quarter 3 and 10,642.06 in Quarter 2. The similar picture is seen in 2027, when the values are between 8,670.13 and 10,423.79 metric tons. However, in 2028-2030 the forecasted values do not differ significantly from each other, suggesting that in the forecast period the system will continue showing stable seasonal changes.

Prediction intervals increase over time due to the increased forecast uncertainty. For example, in Quarter 1 of 2026 the 95% prediction interval ranges from 5,521.10 to 19,365.37, whereas in Quarter 4 of 2030 it ranges from 3,342.15 to 33,421.49 metric tons. Such an increase in prediction intervals fits into the theoretical framework of time-series forecasting, according to which the level of uncertainty rises as forecasts become longer in terms of time.

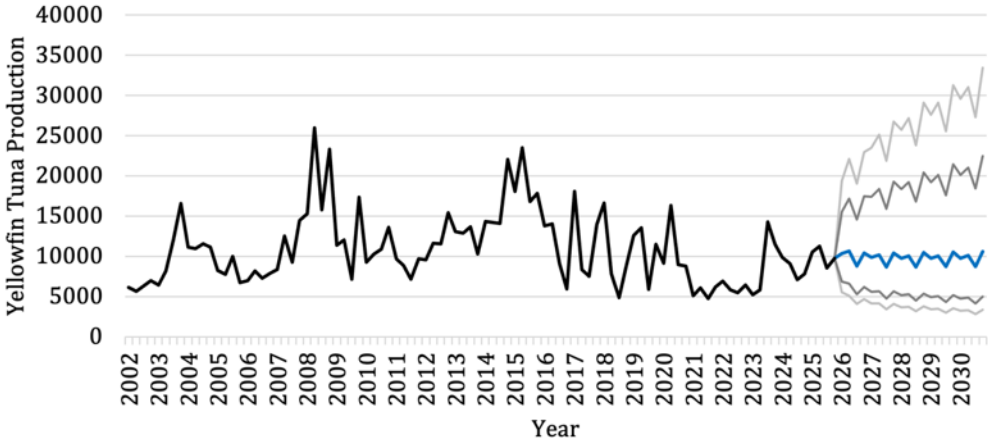

Figure 12. Forecast Time Series Plot

Figure 12 represents the forecasted time series from 2026 to 2030. As it is clearly seen from the visual representation, there is the pattern that shows a cyclic behavior with stable seasonal oscillations. Nevertheless, the confidence bands show a growing trend, confirming that the uncertainty increases over time. Longer-range forecasts should be taken with some caution since the assumptions of SARIMA include the continued existence of the historical patterns in the future.

To sum up, it should be admitted that according to the results obtained in this study, commercial yellowfin tuna production is expected to be stable in its seasonal behavior in the medium term. As far as the SARIMA model used predicts the values of the time series, it implies that the major driving force in future production will be the seasonal effects occurring quarterly.

Conclusion

This study employed stochastic time series analysis through the application of the SARIMA method to explain, analyze, and forecast the production of commercial yellowfin tuna (Thunnus albacares) on a quarterly basis from 2002 to 2021 in South Cotabato, Philippines. The findings reveal considerable variation in production along with a clear cyclical trend and seasonality where there were recurring quarterly patterns showing that the output was generally at its minimum level in the third quarter but relatively higher in the second and fourth quarters. From among the various candidate models, the SARIMA(1,1,1)(1,1,1)[4] was found to be most appropriate based on the information criteria and statistical tests, capable of adequately accounting for the non-seasonal and seasonal properties of the series. While the estimated model had a relatively good fit, the tendency of the fitted values towards smoothing the extreme deviations was observed. Nevertheless, it performed well in forecasting with moderate errors and very slight biases. The forecasts up to 2030 indicated stable seasonal pattern with no noticeable trends toward increase or decrease although uncertainty became more pronounced as the forecasted periods became farther.

Recommendation

The need for consideration of seasonality becomes evident in terms of the production drop in the third quarter (Q3) while at the same time having peaks in production in the second and fourth quarters (Q2 and Q4). Stable production forecast until 2030 allows one to have an essential period for strategic planning of the industry activities in General Santos City. For example, local canneries will be able to take advantage of this forecast by managing inventory effectively. It means that canneries will stockpile raw materials in the periods of high yield (Q2 and Q4) to maintain processing in the period of low production (Q3). In addition, the logistics in cold chain should be managed in terms of high yield in order to avoid post-harvest losses. Seasonal forecast can help local authorities of General Santos City in terms of regulation in the low production period of Q3. The

SARIMA(1,1,1)(1,1,1)[4] model may be considered as a baseline forecasting model for shorter periods ahead; nonetheless, caution must be taken when interpreting the forecasts for long periods ahead due to greater prediction uncertainties.

For future studies, there is a need to improve forecasting performance through the inclusion of pertinent predictor variables such as environmental factors and climate phenomena using SARIMAX or similar multivariate models. Regular update of the model with new data and evaluation with other forecasting methods (e.g., machine learning techniques and hybrid time series models) should also be pursued.

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