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Time Series Analysis of Factors Affecting Coconut Price in the Philippines

Cristian T. Camañan*, Joy L. Picar
Professional School, University of Mindanao, Davao City, Philippines

*Corresponding Author Email: c.camanan.487160@umindanao.edu.ph

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Abstract. Coconut remains a fundamental agricultural product in the Philippines, widely used in food production, cosmetics, and bio-industries. Despite its importance, the price of copra, its dried kernel, has experienced substantial volatility due to environmental conditions, market dynamics, and production levels. This study aims to analyze and forecast the factors influencing copra prices in the country, utilizing time series data from 2013 to 2022. Specifically, it investigates the influence of rainfall, coconut production, and market demand. Utilizing a non-experimental quantitative approach, the study employed ARIMA and SARIMA models for trend analysis and forecasting. AIC, BIC, AICc, residual variance, and log-likelihood guided model selection. Results revealed that ARIMA(0,1,1) was optimal for forecasting coconut production, ARIMA(2,1,1) for copra prices, and SARIMA(2,0,1)(1,0,1)[12] for Philippine rainfall,SARIMA(0,0,1)(2,1,1)[12] was used for Luzon, SARIMA(1,0,0)(2,0,0)[12] for Visayas, ARIMA(1,1,1) for Mindanao. Regression results confirmed that rainfall did not significantly influence coconut production, and neither coconut production nor market demand had a statistically significant effect on copra prices. The forecast indicated a potential decline in coconut production and copra prices if current conditions persist. The study concludes that time series forecasting models are essential for agricultural stakeholders, enabling data-driven planning, risk management, and policy formulation. To improve predictive accuracy and policy relevance, future studies are encouraged to incorporate historical data points on market demand and coconut production, and to adopt multivariate time series models, such as ARIMAX or Vector Autoregression (VAR), which can account for external shocks and global economic indicators. These approaches could better capture the complex interactions within the Philippine coconut industry and support more effective decision-making.

Keywords: Coconut production; Copra price; Market demand; Rainfall variability; Time series analysis

1.0 Introduction

Cocos nucifera, commonly known as the coconut, is one of the most economically important crops grown in tropical regions for various purposes, including the food industry (e.g., water and bioproducts), cosmetics, pharmaceuticals, and renewable energy. Consumer preference for sustainable products as part of a plant-based and health-oriented lifestyle is increasing the global demand for coconut products, including copra, virgin coconut oil, coconut water, and desiccated coconut (Abeysekara & Waidyarathne, 2020). The uptrend in this space also suggests that more people acknowledge the uses and economic value of coconuts. Despite this, the world coconut industry remains an enigma, as it is confronted with a myriad of challenges, such as volatile prices, old coconut trees, pest infestations, and climate-change-induced disasters like typhoons and droughts (Zakia & Marifatullah, 2023). Insufficient supply chain infrastructure and competition from alternative oils, such as palm and soybean oil, exacerbate security challenges, which in turn show clear factors affecting its market dynamics (Girsang et al., 2018).

Indonesia, the Philippines, Vietnam, and Thailand are among the countries that control the world's coconut production and export sites, as well as other key players in ASEAN. Millions of smallholder farmers across these nations depend on their coconut farms as a significant source of livelihood. While the price of coconut has been drastically reduced, this reduction is mainly attributed to uncontrollable factors (natural events causing poor weather and pest infestations), lack of market access, as well as unsupportive government policies (Antonio et al., 2025). This volatility highlights the importance of data-driven strategies, particularly time series forecasting techniques, in efficiently predicting commodity prices and mitigating agricultural and economic risks (Senadheera et al., 2020).

On a global scale, the Philippines is currently the second-largest producer of coconuts. Inseparable from the Philippine economy, this vital industry is a top earner of agricultural exports and is critical for rural livelihoods, as around 2.5 million Filipinos rely on the Coconut Industry (Aguilar et al., 2023; Rodríguez et al., 2021). The coconut sector serves as a foundation for rural economic activities, interlinking with all livelihoods and being endemic to community life and sustainability. Provinces in the Philippines that produce coconuts, like Quezon, Davao Oriental, Zamboanga del Norte, and Leyte, are also examples of areas where coconut harvesting is a significant industry. Moreover, these regions often face acute price volatility. According to CEIC Data (2025), the price of copra has fluctuated widely between floor prices of ₱1,600 and attaining a ceiling level of over ₱9,150 per 100 kilograms. Volatility in markets poses a serious threat to the economic stability of coconut farmers, who are frequently in financial distress due to the high variation in their income, which is tied disproportionately not just to price information but to uncertain prices themselves, rather than predictable prices. The effects of climate change, pest attacks, and poor land management practices, which result in low crop yields, have only worsened this already tenuous situation (Alouw & Wulandari, 2020; Hadi, 2022; Zakia & Marifatullah, 2023). Additionally, the fluctuation of coconut prices may have dramatic economic consequences for farmers, particularly in areas where coconuts are a primary source of revenue. This scenario of economic disparities can create a sense of urgency for better policies regarding market interventions and empowerment programs to build farmers' resilience against market adversities (Panjaitan, 2024; Pujiharto & Wahyuni, 2023).

The situation is intensified by adverse weather conditions, such as typhoons, which are becoming more frequent due to climate change (Aguilar et al., 2023; Rodríguez et al., 2021), thereby increasing price instability. The rainfall influences the copra price since it directly affects coconut production. Such impacts will then negatively affect coconut growth through controls during the reproductive period of coconut trees (Flowering and Fruiting Cycles), which only begins after immaturity, similar to the tropical climate of the Philippines, whose primary factor is rain (Pulhin et al., 2016). Productivity rises and the supply of copra generally increases as well, resulting in a price-dampening effect due to favorable moisture levels during the rainy season (Boudreau et al., 2023). On the other hand, low rainfall during dry months contributes to reduced coconut production, resulting in supply shortages and likely price spikes (Pathmeswaran et al., 2018). Besides, rainfall variability affects not only the quantity but also the quality of copra. Impaired drying due to high ambient moisture in the rainy season decreases the quality and market value. An extended dry period, however, would increase drying efficiency, resulting in copra of better quality and higher prices. These patterns firmly establish the importance of rainfall in influencing both the supply and market value of coconut products in the Philippines.

Market demand, driven by both local consumption trends and shifts in the international market, is another significant factor influencing the copra price. The increasing consumer preference for health-oriented products and expanding industrial requirements for raw materials in food processing, cosmetics, and pharmaceuticals (Mulyadi et al., 2019; Prades et al., 2016) have driven this demand. Additionally, factors such as currency movements and trade policies significantly influence market demand and, consequently, copra pricing (Arapović & Karkin, 2015; Reddy et al., 2014). Copra prices fluctuate more when demand for copra is elastic, meaning consumers are highly responsive to changes in the price of copra. Elsewhere, inelastic demand helps to reduce the impact of price volatility and adds stability (Assa, 2016; Fujita, 2015). For farmers and market analysts to be conversant with this, demand elasticity provides a strong theoretical foundation for developing more revenue-generating strategies and market interventions (Kang et al., 2021; Mu'min et al., 2024).

The price of copra also depends on climatic factors, such as sufficient rainfall for growth, as well as market forces, including consumer demand. While these elements are undeniably influential, they represent only part of a larger picture. Equally important—if not more so—are the tangible realities surrounding copra production within the country, upon which the supply chain fundamentally rests. Consequently, even under presumably favorable conditions anticipated by many, price stabilization remains unattainable without a stable and sufficient output.

This highlights the crucial role of domestic supply dynamics in influencing copra price behavior. In this regard, local copra production data becomes an essential tool for managing market availability. Specifically, low levels of coconut production can result from adverse climatic conditions, leading to a scarcity of supply. This scarcity, in turn, drives prices upward in accordance with the principles of supply and demand. Notably, research indicates that regions with suboptimal weather conditions for coconut cultivation—such as insufficient rainfall or extreme temperatures—tend to report reduced yields, which contribute to higher market prices for coconuts and related products (Abeysekara & Waidyarathne, 2020; Zakia & Marifatullah, 2023). Moreover, the persistent gap between potential and actual coconut yields creates economic pressure within the industry, thereby amplifying price volatility whenever production falls short of meeting consumer demand (Descals et al., 2023).

Additionally, skewed socioeconomic factors of the coconut farmers, which form barriers to their productivity and marketing, are also significant determinants. Most farmers face systemic problems, including difficulties in accessing credit, inadequate technical training in farming practices, poor infrastructure for agricultural transport and marketing, and insecurity of land tenure. These constraints create heterogeneity in yield, which impedes the sustainability of farm convergence to market and hampers the environmentally friendly growth of the Coconut industry (Faried et al., 2023; Zakia & Marifatullah, 2023). Specifically, Zainol et al. (2023) address the complexities within the production landscape that coconut farmers navigate, including socioeconomic barriers that reflect systemic inequities in resource access. Likewise, the results of another study by Sportel and Véron (2016) highlight how high labor costs and low government support affect coconut production dynamics from a broader perspective, making life even more challenging for farmers. Furthermore, in discussing the inefficiencies within the coconut supply chain, Hadi (2022) also indicates how market dynamics affect procurement planning. Market risk is one of the factors that can significantly influence how farmers arrange and conduct aspects related to production, emphasizing the need for a systematic and permanent supply chain improvement to promote stability in both production and market prices (Hadi, 2022; Mulyadi et al., 2019). The study suggests that addressing these socioeconomic constraints is crucial to ensure a more consistent and stable supply of copra, as well as to stabilize market prices (Zakia & Marifatullah, 2023).

The coconut trade, particularly in terms of copra prices, has also received considerable attention in recent years. However, an important gap remains to be addressed in using sophisticated statistical methods for this purpose. Most work in the literature is descriptive or employs simple regression techniques, failing to capture the richness and time dependence of a system as complex as world copra prices. Abdullah et al. Inside the box, the use of sophisticated models, such as hybrid ARIMA methods, is necessary, suggesting that existing models were inadequate to handle the volatile prices of coconut products because they are too simple (Abdullah et al., 2023). The same sentiment is also shared in a study that explains the techniques used to estimate the interactive effects of factors such as rainfall, production levels, and market demand on price dynamics are limited (Mulyadi et al., 2019).

The isolated examination of factors affecting copra prices is another persistent theme identified within the literature. Researchers often compartmentalize variables such as rainfall and production levels, failing to construct models that synthesize these determinants into a cohesive forecasting framework. This oversight potentially constrains the understanding of their joint influence on price fluctuations. Studies implementing models that integrate various agricultural inputs have shown higher predictive efficacy, thereby demonstrating the need for comprehensive approaches that encompass market dynamics (ArunKumar et al., 2021; Sirisha et al., 2022; Wanjuki et al., 2021). In addition, the majority of previous studies have been conducted in specific regions or have had a limited geographic scope, which again limits generalization to a national context. Recent studies have shown that government datasets are primarily historical in nature, abundant, but do not always lend themselves to predictive analytics (Rahmawati et al., 2023). The absence of such capabilities undermines the abilities of a range of stakeholders, from farmers and policymakers to traders, who require forward-looking insights to operate effectively in the volatile coconut market.

Additionally, most studies have been conducted on a single-site basis and are therefore limited to local generalization, which creates discord in our overall understanding of nation-level scenarios. Recent studies have shown that many datasets produced by Governments are historical, vast, and limit predictive analytics (Rahmawati et al., 2023). This knowledge gap hinders key decision-makers, such as farmers, policymakers, and traders, from making informed decisions in a forward-looking manner in anticipation of the highly volatile coconut markets.

To address these gaps, a solution using national-level time series forecasting models with state-specific datasets, more aligned with predicting copra prices, is proposed in the current research. In this analysis, we employ ARIMA and SARIMA models to predict the official price of copra, aiming to develop a robust forecasting model that not only predicts the copra price but also incorporates key determinants such as coconut production and rainfall. The ARIMA family of models (e.g., SARIMA) is designed to be effective in time series data for two reasons: it can deal with seasonality and autocorrelation effects inherent in the time series data (Zheng et al., 2021). The application of such sophisticated statistical analysis will enable a more comprehensive, albeit fine-grained, understanding of price volatility and its associated features, which in turn could be translated into strategic interventions for the sustainable development of the coconut industry within the Philippines.

Specifically, the study seeks to:

1. Evaluate the performance of ARIMA and SARIMA models using appropriate statistical evaluation metrics (e.g., AIC, BIC, RMSE) to guide the selection of optimal forecasting models for coconut production, copra price, and rainfall.
2. Identify the best-fit forecasting models for the following variables based on model performance:
   a. Coconut production
   b. Copra price
   c. Rainfall
3. Generate approximate forecasts for:
   a. Coconut production
   b. Copra price
   c. Rainfall
   d. Coconut production as affected by rainfall
   e. Copra price as affected by coconut production
   f. Copra price as affected by market demand
4. Propose sound recommendations based on the forecasts, aimed at sustaining stable copra pricing and promoting long-term balance among coconut production, demand, and rainfall-related agricultural planning.

This research has important implications for a diverse range of coconut stakeholders in the Philippines, including smallholder farmers, cooperatives, policymakers, researchers, and planners involved in agricultural development. We propose a time series forecasting model that incorporates coconut production, market demand, and rainfall, enabling us to utilize it as an economic tool for predicting future copra price trends and responding to market and environmental changes. The results may be helpful in a data-driven governance framework for government agencies, such as the PSA, which can lead to strategic interventions, such as for PCA, allowing for well-timed introductions and stabilizing market prices to prevent extreme losses for coconut farmers. Local farmers can utilize more accurate price predictions to manage planting, harvesting, and marketing, enabling them to mitigate both market price volatility and climate risks. This work contributes to the overarching umbrella of the UN 2030 Agenda for Sustainable Development by addressing the core issues encountered in agricultural societies. Notably, it contributes to SDG 1 (poverty reduction) and SDG 2 (zero hunger) by facilitating strategies to improve the income risk exposure and food shock mitigation of smallholder coconut farmers. Additionally, by suggesting improvements throughout the coconut value chain, it supports SDG 12, which requires ensuring sustainable patterns of consumption and production in the management of natural resources and agricultural outputs (United Nations, 2015).

2.0 Methodology

2.1 Research Design

This research employs a non-experimental, quantitative design that utilizes multivariate mathematical modeling to analyze the factors influencing copra prices over time. Such a design aligns with established practices in social sciences research, where non-experimental methodologies are prevalent, as they can simultaneously explore multiple variables without manipulation of independent variables (Reio, 2016). The study explicitly considers rainfall, domestic coconut production, market demand for coconuts, and historical copra prices in the Philippines. As described in previous literature, employing non-experimental quantitative methodology enables the researcher to capture and analyze a multitude of types of evidence simultaneously in a context such as agricultural economics, where multiple external factors can influence market dynamics (Reddy et al., 2014).

This research utilizes historical data on copra prices in the Philippines to investigate these relationships and uncovers trends that may influence price movements. Time series analysis, using models such as the Autoregressive Integrated Moving Average (ARIMA) or its seasonal variant, SARIMA, is a crucial component of this methodology. Such models have been proven helpful for economic data analysis, particularly in capturing trends and periodic fluctuations in agricultural products, such as copra (Punzalan & Rosentrater, 2024). In this context, the versatility of the Box-Jenkins framework facilitates a disciplined approach to model validation and selection, thereby enhancing the robustness and accuracy of forecasts derived from historical data (M, 2025). The salient emphasis on critical variables, such as demand from coconut production, global markets, and rainfall, in this research highlights the intricate nature of copra pricing within an agricultural commodity context.

2.2 Research Instrument

The study utilized a database from the Philippines that encompasses rainfall, copra prices, copra production, and market demand over ten years (2013–2022). Ten years is also a reasonable choice of period when performing time series forecasting, as it allows for identifying trends and seasonality, or long-term patterns (Onkov & Tegos, 2014). Data were compiled from reputable institutions, such as PAGASA and UCAP, for monthly rainfall and copra prices, covering the period from production to demand, i.e., annual figures. The literature confirms that incorporating more historical data can facilitate more accurate model parameter estimation and reduce forecast error (Fisher et al., 2024). This duration also allows for some variability that can result from environmental factors, such as El Niño or La Niña events, which have an oscillating cycle that is enough to influence agricultural success. The data preprocessing involved validation and cleaning to ensure the data set remained intact (Fisher et al., 2024). Hence, the consistency of this dataset over a lengthy ten-year historical period supports the reliability of the modeling and provides valuable insights into the determinants of copra prices in a Philippine setting (Yan et al., 2024).

2.3 Data Gathering Procedure

The researcher followed the traditional process of securing permission from UMERC before writing to any of our college colleagues to solicit information from personalities, including those in PAGASA and CUAP. After obtaining ethics approval, a request letter was written and provided to the authorities. It included a letter that was cosigned by the research advisor and the program coordinator to obtain institutional backing and authorization. We were informed later that the letter would only be sent by FBMP and signed by PASIG and UCAP if these compliances are met, in order to obtain what we needed. The researcher also adhered to the permissions and regulations of the institutions identified for the use, transmission, and duty of confidentiality concerning data received.

2.4 Data Analysis Procedure

After data collection and validation, the researcher applied time series modeling (ARIMA and SARIMA) and regression analysis to address the study's objectives. ARIMA was used to forecast coconut production and copra prices, while SARIMA was applied to rainfall data in Luzon and Visayas due to the presence of seasonality. For Mindanao, the ARIMA model was used, as no seasonal pattern was detected. Model development involved visual inspection, stationarity testing via the ADF test, and differencing as needed. ACF and PACF plots guided parameter selection, while AIC, AICc, and BIC informed model comparison. Residual analysis and the Ljung-Box test confirmed model adequacy. Forecast accuracy was evaluated using RMSE and MAPE. Regression analysis further examined the relationships among variables—specifically how rainfall influenced coconut production, which in turn affected copra prices and was shaped by demand—offering a clearer view of dynamics in the coconut industry.

2.5 Ethical Considerations

Benefits. This study offers valuable insights for researchers, policymakers, and market analysts involved in agricultural development. The identification of temporal patterns and key determinants of copra price movements provides actionable insights for agencies such as the Department of Agriculture (DA) and the Philippine Coconut Authority (PCA) in formulating data-driven, cost-effective policies for price stabilization. Local government units (LGUs), NGOs, and development agencies can use the findings for resource planning, rural livelihood programs, and targeted interventions to address price volatility. Coconut farmers, cooperatives, and agribusinesses may benefit through improved production planning, harvest timing, and marketing decisions. For traders, exporters, and supply chain managers, the research aids in anticipating price trends and optimizing pricing strategies. Academically, the study enriches the literature in agricultural economics by contributing empirical evidence on commodity price behavior in developing economies.

Plagiarism. The author has taken care to credit all sources, and this is not a duplication, misrepresentation, or other publication of other content not fully referenced. A Plagiarism Checker, such as Turnitin, Grammarly, or Plagiarism Detector, was used to verify the originality of the manuscript and detect plagiarism of published text. The cases of duplication (or text lifting) were corrected by respectfully citing or rewriting the relevant text. Adherence to these measures was closely monitored to ensure the integrity and ethical standards of the research.

Fabrication. There was no hint or indication that the study's result was intentionally misinterpreted. There was no deliberate presentation of erroneous conclusions or falsifications of data or results. The researcher has integrated ideas related to the data and other inferential notions.

Falsification. No evidence was found of purposely distorting the work to fit a model or theoretical expectation, nor of making excessive claims or exaggerating, in the study. Additionally, this study did not adhere to data manipulation, which entails fabricating claims, omitting crucial information, and altering tools, materials, or techniques to fool others.

Deceit. There was no evidence that the study misled the organizations (PCA, PAGASA) about potential harm. The rights of the organizations were extensively protected; therefore, fair and acceptable standards were adhered to.

Permission from the Organization/Location. The researcher proactively sought and obtained permission from the offices of the United Coconut Association of the Philippines (UCAP) and the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA), providing proper documentation and consulting with the research adviser.

Authorship. The researcher clearly defined authorship from the outset, ensuring that only individuals who have made substantial contributions to the conception, design, data collection, analysis, or interpretation were credited. All authors involved in drafting or critically revising the manuscript were asked for final approval before publication. No honorary or guest authorship was allowed. These provisions were strictly adhered to in order to uphold transparency and academic integrity throughout the publication process.

3.0 Results and Discussion

Stationarity Test of the Time Series Data

To assess the suitability of the coconut production data for time series modeling, an Augmented Dickey-Fuller (ADF) test was conducted. An augmented Dickey-Fuller test will reveal the presence of a unit root, indicating non-stationarity. The test statistic, lag order, and p-value from the procedure inform whether this conclusion is correct or not. Stationarity tests, such as the ADF test employed here, are among the most widely used tools in economic and financial studies to verify the reliability of a model (Acharya, 2024; Mathlouthi & Lebdi, 2021; Özdemir, 2022). Thus, using ADF test here is consistent with the traditional methods of forecasting in economics.

Table 1. *Augmented Dickey-Fuller Test Result for Stationarity of Coconut Production*

Test	Statistic	Lagged Order	p	H_0
Augmented Dickey-Fuller t	-19.76	0	0.010	Non-stationary

The Augmented Dickey-Fuller (ADF) test for coconut production has the following result: test statistic −19.76, lag order 0, and p-value 0.010. This p-value is smaller than the usual threshold level of 0.05, so the null hypothesis of non-stationarity is rejected. In other words, the time series of coconut production does not have a unit root and is stationary. This implies that the statistical properties of the series remain constant over time. So it is intuitive to consider this series for time series modeling without applying any further differencing. The small value of the test statistic provides strong evidence against non-stationarity, and the coconut production data remain steadfast for forecasting models, such as the ARIMA model, in their raw format.

ACF and PACF Analysis of Differenced Coconut Production Series

The ACF and PACF plots for the differenced coconut production series were plotted to gain an understanding of its inner structure, allowing for a suitable ARIMA model to be fitted. They are used to observe the autocorrelation at different lags and help identify appropriate orders for the autoregressive (AR) and moving average (MA) terms of your model.

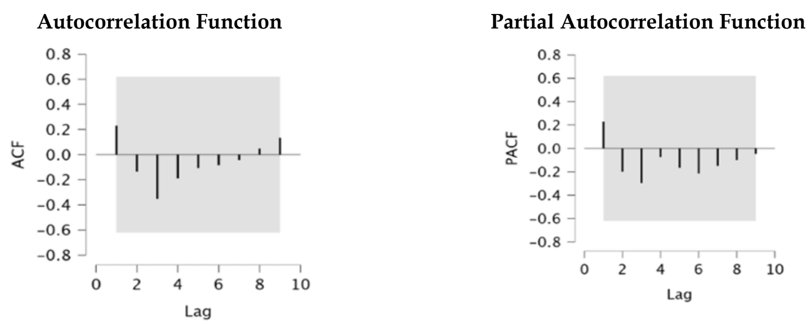

Figure 1. *ACF and PACF Plots of the Differenced Coconut Production Series*

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis for coconut production in the Philippines reveals specific patterns that can provide indications of time series processes underlying the deterministic fluctuations in production levels. The significant spikes at lags 1 and 2 in the ACF suggest a short-run dependence within the production series, as it indicates an increase in production during one period followed by a decrease in the next period, and vice versa (Abeysekara & Waidyarathne, 2020). The time-lagged sequence of the residuals indicates that this fluctuation pattern is somewhat similar to those found in a moving average (MA) process, especially MA(2), where ACF values decrease towards zero at lags higher than two, staying within the confidence interval, which suggests no sudden jumps or cut-offs in series dynamics (Abdullah et al., 2023).

Conversely, the PACF exhibits a spike at lag one and then tapers off, with small negative values for lags up to 6. A high spike shows that the latest observation affects the current observation a lot, showing autoregressive behavior akin to AR(1) processes (Ahalya et al., 2023). The decrease in the PACF indicates that more than one autoregressive term or possible seasonality is present in the production, as reported by numerous authors studying time series properties in agricultural commodities (Utomo et al., 2024). The behavior observed from both an ACF and PACF perspective suggests that a mixed model with autoregressive and moving average components is suitable for modeling coconut production data in the Philippines.

Based on this empirical evidence, an optimal model might be an ARIMA(1,0,2)(1,0,1)[12], which, in essence, considers the dynamics from the first two non-seasonal autoregressive and moving average terms, as well as potential seasonal influences arising from agricultural production (Abdullah et al., 2023). This is validated by the diagnostic checks of the model, which indicate the sufficient fit that it possesses in representing the temporal structure of Philippine coconut production data. This ensures its relevance not only in resilient economic projection, but also enables the reading of production tendencies with subtlety over the years.

Model Comparison and Selection Based on Goodness-of-Fit Criteria

When choosing an appropriate ARIMA (Autoregressive Integrated Moving Average) model for relapse prediction, several statistical measures have been employed to assess model fit: variance of residuals (σ^2), log-likelihood (high logs are more favorable), and information criteria like the Akaike Information Criterion, Bayesian Information Criterion, and corrected Akaike Information Criterion. Less residual variance is better, and AIC/BIC balances between model complexity/fit quality for parsimony in model selection. The outcomes of inspected models can be outlined in a table, providing a concise presentation for making a more straightforward decision in model selection to perform a prediction task (Sharma & Nigam, 2020; Adebiyi et al., 2014; Duan et al., 2024).

Table 2. *Summary of Goodness-of-Fit Metrics for ARIMA Models*

Model Summary	σ^2	Log-Likelihood	AICc	AIC	BIC
ARIMA(0,0,0)	185617.69	-74.32	154.35	152.64	153.25
ARIMA(0,0,1)	184526.25	-73.79	157.57	153.57	154.48
ARIMA(1,0,1)	210115.44	-73.77	163.55	155.55	156.76
ARIMA(1,1,1)	254171.19	-67.55	153.11	143.11	143.90
ARIMA(1,1,0)	273850.17	-67.98	146.77	141.97	142.56
ARIMA(0,1,1)	273189.57	-67.98	146.75	141.95	142.54

The ARIMA(0,1,1) model (ARIMA011) was identified as the best-fitted model among the examined models for coconut production in the Philippines, based on the described procedure of model comparison using AIC. This choice is supported by its results across the main tests conducted. Among all the models utilized, the ARIMA(0,1,1) model has a lower Akaike Information Criterion corrected (AICc) value of 146.75 and follows a similar pattern with forecasting data when comparing the AIC (141.95) and Bayesian Information Criterion (BIC) value of 142.54. This set of metrics is best explained by the idea that this model strikes a balance between model fit and complexity, making it the most efficient in representing the dynamics of coconut production time series (Burnham & Anderson, 2002).

In comparison, while ARIMA(1,1,1) also demonstrated strong performance with an AICc of 153.11, AIC of 143.11, and BIC of 143.90, it was slightly outperformed by ARIMA(0,1,1) across all three criteria. Other models, such as ARIMA(0,0,0) and ARIMA(0,0,1), showed relatively higher AIC and AICc values, indicating inferior performance. Furthermore, these two models lack differencing (d = 0), which limits their suitability for modeling the non-stationary nature of the coconut production series, as confirmed earlier by the stationarity tests. (Hyndman & Athanasopoulos, 2018) The variance (σ^2) further supports this selection, with ARIMA(0,1,1) yielding a relatively low value of 273,189.57, reinforcing its adequacy in capturing the variability within the series without overfitting. Overall, the ARIMA(0,1,1) model stands out as the most statistically robust and parsimonious for forecasting coconut production in the Philippines (Lim, 2015).

Forecast Analysis of Philippine Coconut Production Levels

To provide insights into the projected trend of coconut production in the Philippines, a time series forecast was generated using the selected ARIMA model. The graph below illustrates the forecasted values for the following ten time periods, along with the corresponding 80% and 95% confidence intervals. These intervals offer a visual representation of the uncertainty surrounding future values. The accompanying table presents the numerical forecast values with their respective lower and upper bounds, which help quantify the range within which future production levels are expected to fall.

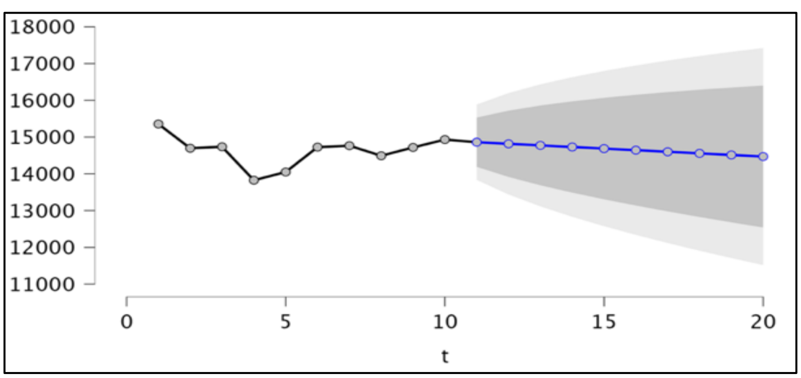

Figure 2. *Forecast Plot of Coconut Production in the Philippines with Confidence Intervals*

The ARIMA(0,1,1) model was used to forecast future values of coconut production in the Philippines, and the forecast plot presents both the predicted values and their associated uncertainty bounds. As shown in the graph, the point forecasts (represented by the blue line) indicate a gradual decline in coconut production over the next 10 years. The value at time point 11 is forecasted to be 14,859.89 units, and that at time point 20 is 14,469.73 units.

This consistent deceleration in position forecasts a negative projection for the country's coconut production if similar trends persist. It also presents 80% and 95% confidence intervals (CI) for each predicted value. As the length of the forecast horizon increases, these intervals widen, reflecting an increase in uncertainty over time. Thus, at time point 11, the 95% CI is 13,835.47 to 15,884.32, and at time point 20, it is 11,517.52 to 17,421.93 (downward). The pattern is something we often observe in time series forecasting, where the further we forecast into the future, the greater the uncertainty. The decreasing central forecast trajectory and increasing confidence intervals underscore the need for preparedness in the coconut sector.

Copra Price

Stationarity Assessment Using the Augmented Dickey-Fuller Test

To check if the time series is stationary, an important requirement for ARIMA models, the Augmented Dickey-Fuller (ADF) test was applied to different lag orders. The test statistics, lagged orders, and p-values are reported in the table below. A low p-value (generally $p < 0.05$) is indicative of the null hypothesis of non-stationarity being rejected, i.e., that the series is stationary at the specified lag (Hyndman & Athanasopoulos, 2018).

Table 3. *Augmented Dickey-Fuller Test Results for Stationarity of the Copra Price*

Test	Statistic	Lagged Order	p	H_0
Augmented Dickey-Fuller t	-2.46	0	0.385	Non-stationary
Augmented Dickey-Fuller t	-3.59	1	0.037	Non-stationary

The findings of the Augmented Dickey-Fuller (ADF) test provide significant insights into the nature of the time series data on copra prices. When the test was initially carried out at lag order 0, the test statistic was -2.46, and the p-value was 0.385. This high p-value suggests that our data fail to reject the null hypothesis of non-stationarity; the copra price series at this level still has trends or patterns that evolve. However, a significantly different result was obtained when the ADF test with a lag order of 1 was reused. We thus have a test statistic of -3.59, with a p-value that is significantly reduced to 0.037. This lower p-value is under the traditional threshold of 0.05, so the null hypothesis of non-stationarity can now be rejected. Alternatively, given a lag order that fulfils the autocorrelation of the data, our series seems to become stationary (an important requirement for a working ARIMA model). This suggests that even though the raw time series may initially be non-stationary, they become stationary after differencing or lag changes.

Identification of Model Components Using ACF and PACF

The following graphs show the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series data, which are key tools used in determining the parameters of our ARIMA model. The ACF is the correlation of a series with its lags; the PACF is that of a series with the effects of its previous lags removed. Large spikes outside the confidence bands indicate the presence of important autocorrelation that can inform the choice of autoregressive (AR) and moving average (MA) orders.

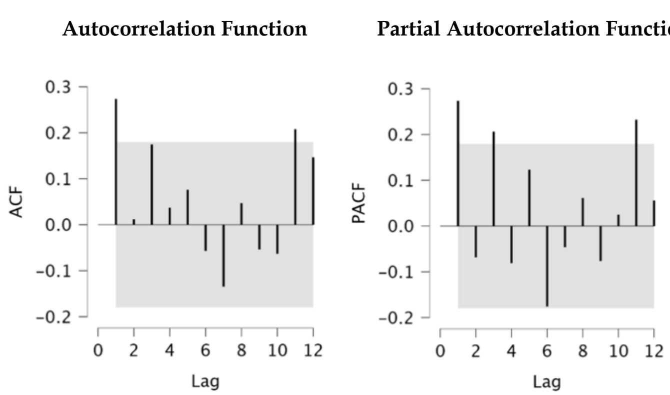

Figure 3. *Autocorrelation and Partial Autocorrelation Plots of the Copra Price*

Insights into the structure of the time series data for monthly copra prices can be gained by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. In the ACF plot, the decay is slow, except for some spikes at the lags 1, 2, and 10, which are above the significance level. This behavior is consistent with a series with short memory (higher) and (potentially) of autoregressive type, rather than that of a moving average of the process. The lack of a sharp oscillation in the ACF further indicates that the free lower limit value is also relatively close to zero, rather than being purely random or exhibiting white noise. In contrast, the PACF plot shows a significant spike at lag 1, followed by a sharp cutoff in partial autocorrelations for higher lags, many of which fall within the confidence interval. This sharp drop after lag 1 in the PACF indicates that this is a first-order autoregressive process, where the past value directly influences the current value of the series. The combination of the ACF slowly decreasing and the PACF sharply decreasing after the first lag makes an ARIMA(1,0,0) model a viable candidate for modeling the series. This structure models the immediate effect of the previous observation and accounts for the short-term covariance structure of the data.

Selection of the Best-Fitting ARIMA Model Based on Fit Statistics

The most appropriate ARIMA model for MFDS was identified by comparing several candidate models using key model selection statistics, including residual variance (σ^2), log-likelihood (LL), Akaike Information Criterion (AIC), AIC corrected for small sample sizes (AICc), and Bayesian Information Criterion (BIC). Smaller values of AIC, AICc, and BIC indicate better-fitting and more parsimonious models. Our new model evaluation comparison is summarized in the table below.

Table 4. *Model Evaluation Metrics for ARIMA Model Selection for Copra Price Forecasting*

Model Summary	σ^2	Log-Likelihood	AICc	AIC	BIC
ARIMA(1,0,1)	7.62	-292.05	592.44	592.09	603.24
ARIMA(0,0,0)	107.72	-450.51	905.18	905.08	910.66
ARIMA(2,1,0)	7.97	-290.90	590.15	589.80	600.92
ARIMA(2,1,1)	7.70	-288.35	582.23	586.70	600.60

The evaluation of ARIMA model performance for forecasting copra prices is summarized in Table 4. Among the four competing models—ARIMA(1,0,1), ARIMA(0,0,0), ARIMA(2,1,0), and ARIMA(2,1,1)—the ARIMA(2,1,1) model yielded the most favorable results based on key statistical criteria. It produced the lowest values for AICc (582.23), AIC (586.70), and BIC (600.60), indicating better overall model fit and parsimony. Although ARIMA(1,0,1) and ARIMA(2,1,0) also demonstrated relatively low values in terms of σ^2 and log-likelihood, their AIC-based metrics were consistently higher than those of ARIMA(2,1,1), making them comparatively less optimal. On the other hand, the baseline model ARIMA(0,0,0) performed poorly across all metrics, with the highest σ^2 (107.716), lowest log-likelihood (-450.51), and the largest AICc, AIC, and BIC values, confirming its inadequacy for capturing the underlying dynamics of copra price behavior. Hence, based on this model evaluation, ARIMA(2,1,1) is selected as the best-fitting model for forecasting monthly average copra prices in the Philippines.

Forecasting Copra Price Trends Using an ARIMA Model

To estimate future movements in copra prices, the finalized ARIMA model was employed to generate forecasts for the subsequent 60 time periods. The figure below illustrates the projected trend in copra prices, accompanied by 80% and 95% confidence intervals, which reflect the model's forecast uncertainty. The table that follows presents the exact forecasted values along with the corresponding upper and lower bounds at each confidence level, providing a detailed reference for evaluating expected price fluctuations.

Forecast Time Series Plot

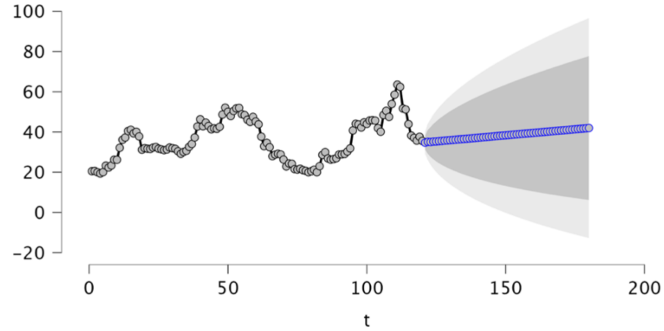

Figure 4. *Forecasted Copra Prices*

The five-year forecast of copra prices in the Philippines, generated using the ARIMA(2,1,1) model, shows a steady upward trend in price movement. Beginning at around ₱34.69 in the first forecasted month, the predicted price of copra gradually climbs to approximately ₱41.97 by the end of the forecast horizon (60 months later). This gradual rise, neither too hot nor too cold, is indicative of a stable market scenario with minimal fluctuations, which should provide a sense of hope for coconut farmers and other industry players to settle in and plan their future commercial endeavors. However, remember that the point forecasts see only a weak link from the lagged data to future data, which perhaps is not in itself a smoking gun; also, the prediction intervals, the range within which you think actual prices will come, get much broader as you go to the right. For example, the 95% confidence interval during the early months is narrower (₱29.25 to ₱40.13), indicating higher confidence in the forecast.

However, by the last month, the spread is significantly higher (from ₱−12.68 to ₱96.62), indicating a higher level of uncertainty over the years. This increasing ambiguity is common in time series prediction, especially when other external factors, such as climate impacts, global oil price changes, or international demand fluctuations, may affect the local copra market.

However, despite these limitations, the model's output provides useful findings. The prediction indicates an overall positive market sentiment, suggesting that prices will fluctuate and may experience slight increases. For farmers, processors, and policymakers, this may inform decision-making regarding planting, production, budgeting, and investment in postharvest technologies. However, they also need to be cautious and flexible, as real-world circumstances may not align with these projections. Overall, while the forecasted number does not provide the precise prices we will experience, it is pragmatic for us to anticipate where it will be applicable and adjust our expectations accordingly.

Rainfall

Stationarity Test of Rainfall Time Series Across Philippine Regions

To determine if the rainfall time series of the Philippines and its three primary island groups are stationary, allowing for ARIMA modeling, the Augmented Dickey–Fuller (ADF) test was applied to each series. Table 5 shows the implemented test statistics, lag orders, p-values, null hypotheses, and results of the decision. When the null hypothesis is rejected, it means there is stationarity.

Table 5. *Augmented Dickey-Fuller Test Results for Regional Rainfall Data*

Variable	ADF t-stat	Lagged	P-value	H_0	Decision
Philippines	-4.57	0	0.010	Non-stationary	Reject
Luzon	-7.30	0	0.010	Non-stationary	Reject
Visayas	-4.60	0	0.010	Non-stationary	Reject
Mindanao	-3.73	0	0.025	Non-stationary	Reject

Results from the Augmented Dickey-Fuller (ADF) testing for all four regions — namely, the Philippines, Luzon, Visayas, and Mindanao —indicate that the rainfall time series data belong to a stationary process. The ADF test shows p-values for all the variables lower than 0.05, whereby we reject the null hypothesis (H_0) of non-stationarity. Specifically, Luzon shows the most substantial evidence of stationarity with the most negative t-statistic (–7.29), followed by Visayas (–4.60), the Philippines (–4.57), and Mindanao (–3.73). While all p-values are within the threshold for rejecting non-stationarity, Mindanao's test statistic is relatively closer to the cutoff, suggesting weaker—but still sufficient—evidence. Overall, these findings confirm that the rainfall series in each region does not exhibit unit roots, making them suitable for time series modeling without differencing.

ACF and PACF Plots for Philippine Rainfall Series

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are fundamental tools in identifying the structure of time series models, particularly in determining the appropriate autoregressive (AR) and moving average (MA) terms for ARIMA and SARIMA models. These plots reveal the persistence and lag patterns within the rainfall time series across the Philippines and its three major island groups—Luzon, Visayas, and Mindanao—thereby aiding in the development of region-specific forecasting models.

For the entire Philippines, the ACF plot exhibits a significant spike at lag 1, followed by a slow decay, and another prominent spike at lag 12, indicating both short-term dependence and annual seasonality. Likewise, the PACF exhibits a significant drop after lag 1, and other notable spikes occur around lag 12, indicating the presence of a seasonal AR component. These attributes all indicate a model that is capable of handling non-seasonal and seasonal dynamics. Thus, the SARIMA(1,1,1)(1,1,0)[12] model is the most suitable because it well accommodates the short-term memory, the regular differencing for stationarity, and the seasonal effect to the annual cycle.

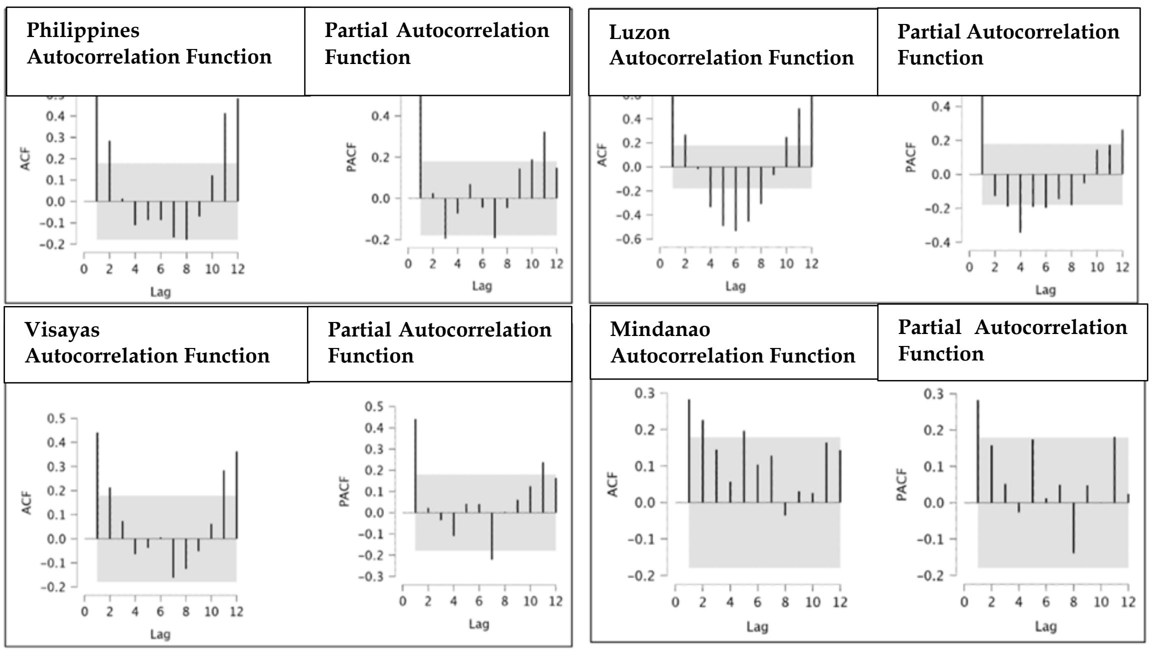

Figure 5. *Autocorrelation and Partial Autocorrelation Plots of the Rainfall in the Philippines and the Other Three Regions*

For Luzon, the ACF exhibits significant periodicity, with a prominent peak at lag 12, whereas the PACF displays a peak at lag one and then a rapid decay thereafter. This feature indicates the presence of a non-seasonal AR(1) term, as well as both seasonal AR and MA components. The observed seasonality pattern corresponds to the known monsoon cycles, and hence, SARIMA(1,1,0)(1,1,1)[12] appears to be the most appropriate model. This model represents the seasonal pattern of rainfall observed on Luzon and accounts for the relationship between regular differencing and seasonality over one year.

For the Visayas, a significant positive spike at lag one and a decaying ACF structure with another strong peak at lag 12 are displayed in the ACF plot, indicating short-term persistence and a seasonal component, respectively. The PACF shows a sharp drop off after lag one and a seasonal spike, supporting the existence of a non-seasonal AR(1) and seasonal terms. Thus, the SARIMA(1,1,0)(1,1,1)[12] model is suggested, which characterizes the irregular yet seasonally patterned nature of the rain in the Visayas region, taking into consideration both regular and seasonal differencing.

Mindanao, on the other hand, is non-seasonal primarily in ACF and PACF plots. As for the ACF, it decays slowly and exhibits a significant spike at lag 10, with some signal also present at lag 12, suggesting mild or irregular seasonality. The PACF, on the other hand, shows a spike at lag one but then tails off for bigger lags. Unlike in the other regions, the signal of an apparent strong annual seasonality is less than clear. Thus, here the model ARIMA(1,0,0) is less complex. This specification reflects the weak short-term autoregressive nature of the data, excluding spurious seasonal terms that could introduce noise to the estimates. Continued validation — check residuals and test out-of-sample to confirm ongoing robustness

In general, the ACF and PACF diagnostics reveal regional features in the rainfall behavior of the Philippines. These findings underscore the importance of region-specific time series models that capture the climatological characteristics of each region, thereby enhancing the contextually accurate forecasting of rainfall.

Comparative Evaluation of Regional SARIMA and ARIMA Models

The most suitable time series models for predicting rainfall in the Philippines and for its major island groups were selected using various SARIMA and ARIMA models. Models were compared and assessed based on selection criteria, including residual variance (σ^2), log-likelihood, corrected Akaike Information Criterion (AICc), AIC, and Bayesian Information Criterion (BIC). For each population, the model with the lowest AICc and BIC values was considered the best fitting. The comparative results table for model performance in the Philippines, including Luzon, Visayas, and Mindanao, is presented below.

Table 6. Model Selection Summary for the Philippine, Luzon, Visayas, and Mindanao Rainfall Forecasting

	σ^2	Log-Likelihood	AICc	AIC	BIC
Model (Philippines)					
SARIMA(2,0,0)(1,0,0)[12]	5794.89	-689.50	1389.53	1389.01	1402.94
SARIMA(2,0,1)(1,0,1)[12]	5072.78	-683.46	1381.93	1380.93	1400.44
SARIMA(2,0,1)(1,0,1)[12]	6854.36	-697.85	1408.44	1407.69	1424.42
Model (Luzon)					
SARIMA(0,0,1)(2,1,1)[12]	5741.20	-629.28	1269.15	1269.15	1281.98
SARIMA(1,0,1)(1,0,1)[12]	11690.93	-729.91	1472.57	1472.57	1488.55
SARIMA(0,0,1)(0,0,1)[12]	9513.16	-720.29	1448.92	1448.92	1459.73
SARIMA(0,0,1)(2,0,1)[12]	11763.19	-730.27	1473.28	1473.28	1489.26
Model (Visayas)					
SARIMA(1,0,0)(2,0,0)[12]	14481.80	-743.91	1498.36	1497.83	1511.77
SARIMA(1,0,1)(2,0,1)[12]	16145.63	-748.69	1512.37	1511.37	1530.88
SARIMA(1,1,1)(2,0,1)[12]	15133.99	-742.91	1500.83	1499.82	1519.27
Model (Mindanao)					
ARIMA(0,1,1)	8008.00	-703.67	1411.45	1411.35	1416.90
ARIMA(1,1,1)	8023.66	-702.94	1414.24	1413.89	1425.00
ARIMA(1,1,0)	9087.49	-710.32	1426.85	1426.64	1434.98

From comparative model validation in terms of AICc and likelihood measures, the most suitable time series models that capture the dynamical features of monthly rainfall are presented for Luzon, Visayas, Mindanao, and the entire Philippines.

For Luzon, the best-fitting model is SARIMA(0,0,1)(2,1,1)[12], with the lowest AICc value of 1269.15 and the highest log-likelihood of -629.28 among the candidate models. This model includes seasonal differencing and multiple seasonal components, indicating a strong and consistent annual seasonality in rainfall. The non-seasonal part consists only of a moving average component, indicating that short-term noise is effectively captured without the need for autoregressive terms. At the same time, the seasonal structure accounts for repeated patterns over a 12-month cycle.

For Visayas, the most appropriate model is SARIMA(1,0,0)(2,0,0)[12], which yields the lowest AICc value of 1498.355. This model includes one non-seasonal autoregressive term and two seasonal autoregressive terms, without any differencing. The presence of autoregressive components points to a strong dependence on past observations, both short-term and annual, which aligns with the structure observed in the ACF and PACF plots. The absence of differencing indicates that the rainfall data is stationary in level, while the autoregressive terms account for the persistence in rainfall values (Hyndman & Athanasopoulos, 2018).

For Mindanao, while ARIMA(0,1,1) is simpler, ARIMA(1,1,1) offers a marginally better log-likelihood (-702.94 vs. -703.67) and a competitive AICc (1414.23 vs. 1411.45), suggesting comparable performance. The inclusion of an AR(1) term, though not statistically significant (p=0.364), may capture subtle short-term dynamics that a pure MA(1) model misses. Forecasts from ARIMA(1,1,1) indicate slight adjustments before stabilizing, potentially providing a more accurate reflection of recent trends. Residual diagnostics are similar for both models, indicating that neither is inferior in terms of fit. If the data exhibits weak autoregressive behavior, ARIMA(1,1,1) provides a more flexible structure without significantly overfitting, making it a justifiable alternative when slight short-term responsiveness is preferred.

Lastly, for the entire Philippines, the most suitable model is SARIMA(2,0,1)(1,0,1)[12], with the lowest AICc value of 1381.93 and the highest log-likelihood of -683.46 among the national-level models. This model integrates both autoregressive and moving average components in its non-seasonal and seasonal parts, effectively capturing the complex structure of the aggregated rainfall data across all regions. The inclusion of seasonal components at lag 12 reflects a clear annual cycle, supported by the ACF and PACF plots. This model is particularly suitable given the diverse climatic influences from Luzon, Visayas, and Mindanao, which contribute to the national rainfall pattern.

Forecast of Monthly Rainfall in the Philippines and the Islands Using SARIMA and ARIMA Models
Seasonal Autoregressive Integrated Moving Average (SARIMA) models were used to generate forecasts of future rainfall for Luzon, Visayas, Mindanao, and the entire country, utilizing monthly historical rainfall data. The forecasts from January 2023 to December 2025 are presented, along with the uncertainty boundaries as 80% and 95% confidence intervals per model.

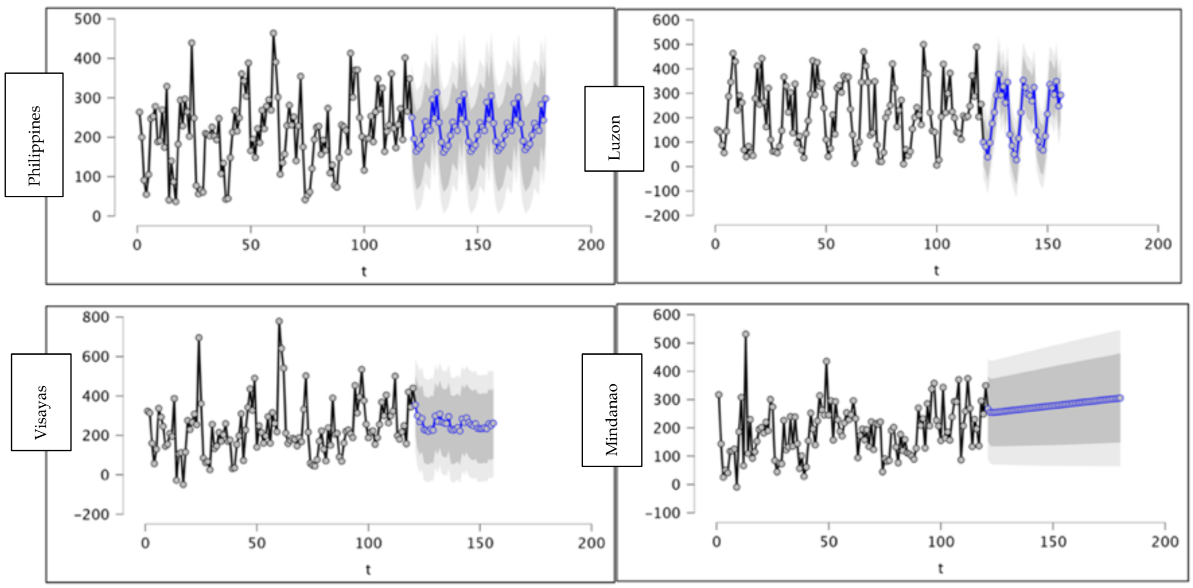

Figure 6. *Forecasted Rainfall of the Philippines and the Islands*

The SARIMA(0,0,1)(2,1,1)[12] model provided the best fit for Luzon, with the lowest corrected Akaike Information Criterion (AICc) and diagnostic accuracy. The model effectively captured both non-seasonal and seasonal raids, a crucial aspect in regions influenced by the Northeast and Southwest monsoons. Recurrent seasonal variations are reflected in the forecasted distribution of annual rainfall, with peaks centered on mid-year and year-end (Fig. 6). Rainfall estimates by month range from approximately 27 mm to 377 mm, with August 2023 expected to feature the highest rainfall. The widening confidence intervals over time indicate an increasing level of forecast uncertainty. However, the model's alignment with Luzon's climatological cycles makes it a valuable tool for anticipating weather extremes and informing decisions related to agriculture, water resource allocation, and infrastructure resilience.

In the Visayas, the SARIMA(1,0,0)(2,0,0)[12] model best reflected the region's rainfall characteristics, capturing both autoregressive lags and seasonal dependencies without the need for differencing. Forecast results suggest a relatively stable trend, with monthly rainfall ranging between 220 mm and 300 mm, showing regular seasonal peaks. January 2023 is forecasted to be the month with the highest rainfall at 354.61 mm, while July 2023 is projected to be the driest, with rainfall expected at 220.43 mm. These projections correspond to typical precipitation cycles caused by prevailing monsoon winds. The model's ability to track the Visayas' cyclical rainfall behavior supports its relevance in guiding climate-responsive agricultural calendars, water conservation strategies, and early warning systems for communities prone to drought or flooding.

The one for Mindanao is simpler, as it is derived using the ARIMA model without strong seasonal factors. The trend line showed an accretionary trend in precipitation along the forecast horizon. Monthly estimates increase from about 267 mm in January 2023 to some 306 mm in December 2025. Notably, the model revealed minimal variation between months, suggesting that Mindanao experiences a more consistent rainfall regime compared to other regions. The lowest predicted value is in February 2023 (255.36 mm), while December 2025 reflects the highest (305.44 mm). Despite the absence of strong seasonality, the forecast remains instrumental for strategic planning in agriculture, irrigation, and flood control in the region.

For the Philippines, the SARIMA(2, 0, 1)(1, 0, 1)[12] model was used to predict total monthly cumulative rainfall at the national scale. This model reproduces the overall seasonal character of the country's historic rainfall, characterized by dry periods in the January–March interval and peak rains around October during the wet season—the predicted quantities of precipitation range from approximately 160 mm to over 300 mm per month. By January 2023, for example, there would be a rainfall of 249.33 mm, and one of up to 295.50 mm for October 2023, which is usually the peak of the rains. The 95% confidence intervals are wider towards the end of the forecast horizon, due to the larger uncertainty that typically characterizes long-range forecasts. However, despite this, the SARIMA model can still capture the underlying seasonal dynamics and therefore provides a valuable foundation for policy formulation at a national scale, infrastructure development, and climate risk analysis.

In conclusion, predictions for all four domains highlight spatial differences as well as a temporal signal that characterizes Philippine precipitation. The SARIMA and ARIMA models employed in this study effectively modeled historical patterns and provided realistic future scenarios. Such predictions provide useful decision-support information for different sectors (government, farmers, urban planners, and disaster risk managers) to adapt to climate variability and to achieve sustainable resource management.

Coconut Production as Affected by Rainfall

To investigate the relationship between environmental factors and agricultural output, a regression analysis was conducted to determine whether rainfall has a significant impact on coconut production in the Philippines. This objective sought to quantify the extent to which variations in rainfall could explain fluctuations in coconut yield, providing insights into the potential impact of climatic conditions on the agricultural sector.

Table 7. *Regression Analysis on Coconut Production as Affected by Rainfall*

ANOVA[a]						
	Model	**Sum of Squares**	**Df**	**MS**	**F**	**Sig.**
1	Regression	3841.99	1	3841.99	.018	.895[b]
	Residual	1666702.20	8	208337.78		
	Total	**1670544.18**	**9**			

a. **Dependent Variable**: Production b. **Predictors**: (Constant), Rainfall

The analysis results, as presented in the ANOVA table, revealed an F-statistic of 0.018 with a corresponding p-value of 0.895. This high significance value greatly exceeds the conventional threshold of 0.05, indicating that the regression model is not statistically significant. In other words, there is insufficient evidence to support the claim that rainfall meaningfully influences coconut production within the scope of the data analyzed (Mialhe et al., 2013). The negligible F-value suggests that only a tiny portion of the variation in coconut production can be attributed to rainfall. This finding suggests that coconut output may be influenced more strongly by other factors, such as farm management practices, input utilization, market demand, or policy interventions, than by rainfall alone. Consequently, while rainfall is a crucial environmental variable, it may not serve as a reliable standalone predictor of coconut production trends in the Philippine context.

Copra Price as Affected by Coconut Production

To examine the influence of coconut production on market dynamics, a regression analysis was performed to determine whether variations in coconut production significantly affect the price of copra in the Philippines. This investigation is crucial for policymakers and agricultural stakeholders seeking to stabilize farm incomes and anticipate price movements in response to supply-side changes.

The ANOVA summary of the regression model shows an F-statistic of 2.813 with a significance level (p-value) of 0.132. While this indicates a moderate degree of association between coconut production and copra price, the result does not reach the commonly accepted threshold for statistical significance ($p < 0.05$). This suggests that the influence of coconut production on copra price is not strong enough to be considered statistically significant based on the dataset used. Given this outcome, it may be inferred that additional or alternative factors beyond production volume alone influence copra price. These could include export demand, processing costs, international price trends, or government pricing interventions. Although production plays a role in the overall market mechanism, its isolated effect on price may be insufficient for robust forecasting or policy-making without considering other variables (Dawe, 2008).

Table 8. *Regression Analysis on Coconut Price as Affected by Coconut Production*

ANOVA[a]						
	Model	**Sum of Squares**	**Df**	**MS**	**F**	**Sig.**
1	Regression	215.41	1	215.41	2.813	.132[b]
	Residual	612.55	8	76.57		
	Total	**827.96**	**9**			

a. **Dependent Variable**: Price b. **Predictors**: (Constant), Production

Copra Price as Affected by Market Demand

To evaluate whether market demand significantly influences the price of copra in the Philippines, a regression analysis was conducted using demand as the independent variable and price as the dependent variable. Understanding this relationship is crucial for both market analysts and agricultural policymakers who aim to ensure stable incomes for coconut farmers and balance supply and demand dynamics.

Table 9. Regression Analysis on Coconut Price as Affected by Market Demand

ANOVA[a]						
	Model	**Sum of Squares**	**Df**	**MS**	**F**	**Sig.**
1	Regression	57.82	1	57.82	.601	.461[b]
	Residual	770.14	8	96.27		
	Total	827.96	9			

a. **Dependent Variable**: Price b. **Predictors**: (Constant), Demand

The ANOVA results reveal an F-value of 0.601 with a corresponding significance level (p-value) of 0.461. This p-value is considerably higher than the conventional alpha level of 0.05, indicating that the effect of market demand on copra price is statistically insignificant in the context of the current dataset. The Regression Sum of Squares is 57.82 over 827.96, which means demand explains a relatively small proportion of variability in price (Fernando & Samarasinghe, 2019). When assessing the complexity of copra price fluctuations, it is evident that demand alone cannot fully explain the market's irregularities. However, numerous factors have a significant impact on the outlook, including production variability, global price fluctuations, input costs, and government interventions. While global prices are an important external source of volatility, it has been found that a significant portion of Turkey's price fluctuations stems from supply-side shocks and the production dynamics (Ahn et al., 2016; Keintjem et al., 2023). A multidimensional model that incorporates these various impacts is crucial for accurately predicting and analyzing copra price movements (Mardiyati et al., 2023). Therefore, it is essential to consider all the factors for a better understanding of the copra market over the last decade.

4.0 Conclusion

This paper develops ARIMA and SARIMA models to assess and predict coconut production, copra prices, and rainfall in the Philippines, aiming to provide empirical evidence to support agricultural and economic policies. The dependence of coconut (ARIMA(0,1,1)) is compatible with a sustainable long-run upward trend and the absence of any seasonal pattern. This evidence suggests that coconut cultivation has a steady outlook with considerable scope, particularly in the years to come. The regression analysis, on the other hand, indicated that rainfall did not have a statistically significant effect on coconut production in the short run, and the direct linear relationships between rainfall, production, and copra prices were generally weak. Such a study suggests that value-add is relatively mundane, or at least that getting value-add with contemporaneous regressions is reasonably practical (It turns out forecast ability at the individual level is quite different, and adding value seems to most reliably come from a long history of out-of-sample successes on new data sets). Thus, policymakers are advised to focus on long-term solutions, such as irrigation development, replanting programs, and soil conservation, to maintain stable and resilient production in provinces that heavily rely on coconut output.

The suitable model for price projection of copra was ARIMA(2,1,1), due to its lower AIC and BIC, as well as the smaller residual variance. The 5-year forecast showed the market price from the first month to the sixtieth month of forecast as: a declining trend from ₱34.69 to ₱41.97 (a relatively constant market). This kind of stability can help farmers, traders, and policymakers make more informed financial, farming, and investment decisions. Moreover, to harness these positive impacts, institutions such as PCA and DTI should strengthen support functions—farmer trainings on cooperative marketing, provision of post-harvest facilities, and price advisory services. In reality, these can act as shock absorbers for smallholders against volatility, and hybrid models such as ARIMAX, GARCH, or machine learning can be applied in the future to incorporate external shocks (such as oil prices, exchange rates, and trade policies) into the model.

Variations in rainfall SARIMA(0,0,1)(2,1,1)[12] for Luzon, SARIMA(1,0,0)(2,0,0)[12] for Visayas, ARIMA(1,1,1) for Mindanao, and SARIMA(2,0,1)(1,0,1)[12] for national. Luzon and Visayas exhibited fairly distinct seasonal patterns, whereas Mindanao had a steadier linear trend. These findings imply that to develop an effective adaptation strategy, DA and LGUs may need to design their own planting calendar, early warning systems, and crop diversification strategies. In practice, incorporating seasonal climate forecasts into farm-level planning can minimize risks. At the research level, applying SARIMA to other crops or integrating it with remote sensing and geospatial technologies may improve the predictive performance of forecasts. However, with the convergence of big data analytics, climate modeling, and artificial intelligence, the future appears to hold something better in store, making the coconut industry climate-smart and economically resilient.

5.0 Contribution of Authors

Author 1: The lead author conceptualized the study and was responsible for the overall development of its content.
Author 2: The secondary author contributed by polishing the manuscript, offering feedback, corrections, and recommendations to strengthen the paper.

6.0 Funding

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7.0 Conflict of Interests

There is no indication of a conflict of interest in the study, as shown by the disclosure of COI, which is a set of situations in which a professional's judgement about a primary good, like the welfare of participants or the validity of the research, is influenced by a secondary interest, like monetary or academic gains or recognitions. Additionally, the researcher is not familiar with PCA and PAGASA firsthand.

8.0 Acknowledgment

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