A SARIMA-Based Time Series Analysis of Sugar Export Quantity and Price Trends in Thailand

Thitawan Insaad[1] and Peangtip Sribunrueang[2*]
[1]Faculty of Liberal Arts and Management Science,
Kasetsart University Chalermphrakiat Sakon Nakhon Province Campus, Thailand
[2*]Faculty of Business Administration and Information Technology,
Rajamangala University of Technology Suvarnabhumi Suphanburi, Thailand
(Received: March 17, 2025; Revised: June 13, 2025; Accepted: June 17, 2025)

Abstract

This study aims to forecast trends in Thailand's sugar export quantity and price. It uses secondary data, specifically monthly sugar export quantity and price data from January 2011 to December 2023, totaling 156 data points. The Box-Jenkins method was applied using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, denoted as SARIMA $(p,d,q)(P,D,Q)_s$.

Forecasting and data analysis were performed using Gretl software. The results indicate that the most appropriate forecasting models for Thailand's sugar export quantity and price are SARIMA $(1,1,1)(1,1,2)_{12}$ and SARIMA $(1,1,1)(2,1,1)_{12}$, respectively. The forecast suggests that during the 2024/25 sugarcane production season, sugar export quantity is likely to increase in the initial months (January – June 2024), which aligns with the harvesting and milling season. However, from July to December 2024, export quantity is projected to decline due to the end of the harvest and the closure of sugar mills.

In terms of pricing, the forecast indicates an upward trend between July and December 2024, primarily driven by reduced export volumes, which tend to raise market prices. These trends are consistent with historical patterns, reinforcing the reliability of the SARIMA model. The findings provide practical guidance for sugarcane farmers in planning cultivation, assist industry stakeholders in optimizing production schedules, and support policymakers in formulating export and pricing strategies.

Keywords: 1) Forecasting 2) Export Quantity 3) Export Price 4) Sugar

---

[1] Lecturer, Department of Business Administration; E-mail: thitawan.i@ku.th
[2*] Lecturer, Department of Finance and Economics; E-mail: paingtip.s@rmutsb.ac.th (Corresponding Author)

Introduction

Sugar is a critical agricultural commodity for many countries, including Thailand, which ranks among the world's top sugar exporters. The industry significantly contributes to national GDP, rural employment, food security, and international trade. As global demand fluctuates due to climate change, trade agreements, and post-COVID-19 recovery, accurate forecasting of export trends is increasingly essential. According to the Office of the Cane and Sugar Board (2023, pp. 5-6), Thailand's sugarcane cultivation area has expanded annually, reaching 4,502,034 acres (11,398,823 rai) in the 2022/2023 season—an increase of 3.42% from the previous year. This growth is attributed to favorable rainfall, improved water availability from the La Niña phenomenon, and rising sugar demand. The resumption of economic and tourism activities following the easing of COVID-19 restrictions has further boosted sugar demand both domestically and internationally (Office of the Cane and Sugar Board, 2022, p. 2).

In 2022, Thailand's sugar exports reached approximately 120 billion baht, highlighting the country's strategic role in the global sugar market. This performance reflects domestic production capacity and global trade dynamics. Moreover, while integration into global value chains benefits exports, domestic value-added is not strongly correlated with net-export earnings (Durongkaveroj, 2022, p. 703). Favorable climatic conditions and well-established farming practices support Thailand's sugarcane production and competitiveness.

In the same year, domestic sugar demand increased by 7.02%, driven by both end consumers and downstream industries, particularly within the food and beverage sector. The expansion of Thailand's sugar industry aligns with economic recovery and increasing demand from related sectors, such as food, beverages, and dairy products, which further stimulate sugarcane cultivation in the upcoming production cycles. Additionally, favorable climatic conditions have contributed to increased sugarcane and sugar production, along with a continuous expansion of sugarcane plantation areas in Thailand. The 2022/2023 crushing season further reflected these trends, reinforcing the industry's growth trajectory (Office of the Cane and Sugar Board, 2023, p. 20).

Despite the sector's significance, few Thai studies have applied SARIMA models to jointly forecast export quantity and price, making this integrated analysis a novel contribution to Thai research.

Sugar is recognized as a strategic industrial commodity crucial to economic and social development. The outlook for Thailand's sugar industry indicates sustained growth and strong potential in Production (Department of Trade Negotiations, 2021) Given this importance, forecasting sugar export volume and price is essential for effective production planning aligned with market demand. This study applies time series analysis using the Box-Jenkins methodology to predict export trends. The results aim to inform policy formulation and provide insights for sugar exporters, farmers, government agencies, and private sector stakeholders in developing future strategies.

Literature Review

Research on the Sugar Industry

Sugar is a crucial agricultural commodity in countries, like Thailand, which ranks among the world's top sugar exporters. The industry contributes significantly to national GDP, rural employment, food security, and international trade. As global demand for sugar fluctuates due to climate change, trade agreements, and economic recovery post-COVID-19, accurate forecasting of sugar export trends becomes increasingly essential.

According to the Office of the Cane and Sugar Board (2023, p. 5), Thailand's sugarcane cultivation area expanded during the 2022/2023 season, driven by favorable rainfall and higher global demand. The Department of Trade Negotiations (2021) has classified sugar and sugarcane as strategic economic crops for Thailand, influencing agricultural policy and trade strategies.

Research on sugar industry dynamics, particularly with respect to export forecasting, has been conducted extensively. For instance, Riansut (2022, p. 1) developed a forecasting model for sugar export volume employing seven statistical techniques, including Box-Jenkins, various exponential smoothing methods (Holt, Brown, Dam, Winter), and simple seasonal approaches (see Tuangkitkun and Suebpongsakorn, 2021, p. 6) Relying on monthly export data from January 2011 to November 2020, sourced from the Office of Agricultural Economics, the study utilized SPSS for analysis. Among the tested models, the Brown exponential smoothing method yielded the most accurate results, with a root mean square error (RMSE) of 15,350,934, indicating its suitability for short-term forecasting in the sugar sector.

While Riansut's study offers valuable insights into the efficacy of various statistical methods, it is limited to the forecasting export volume using univariate models and does not account for export price trends or the interaction between volume and price. This reveals a gap in the literature, as few studies (see also Phongphanich, et al., 2023, p. 4) in the Thai context integrate both variables using time series approaches that effectively According to the Office of the Cane and Sugar Board (2023, p. 20), Thailand's sugarcane cultivation area expanded during the 2022/2023 season, driven by favorable rainfall and higher global demand. The Department of Trade Negotiations (2021) has classified sugar and sugarcane as strategic economic crops for Thailand, influencing agricultural policy and trade strategies. address seasonal patterns, such as SARIMA.

Studies Using ARIMA/SARIMA Models

The ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) models are among the most widely employed statistical methods for time series forecasting in economic and agricultural contexts. These models are particularly suitable for datasets exhibiting temporal dependence and seasonal variation, making them ideal for predicting commodity prices and production quantities.

Several studies have demonstrated the effectiveness of these models. For example, Tuangkitkun and Suepphongsakorn (2021, p. 1) applied the ARIMA model to forecast the price of high-quality raw rubber sheets in Thailand, identifying ARIMA (1,1,0) as the most suitable model, with forecasts aligning closely with actual prices despite minor deviations due to economic fluctuations. Similarly, Pongprasert and Thepdaeng (2022, p. 22) used SARIMA to forecast cassava prices, identifying SARIMA(1,1,0)(0,1,1)$_{12}$ as optimal, offering valuable insights for cost estimation and revenue planning.

Internationally, Hassan et al. (2019, p. 27) utilized ARIMA (1,2,2) to project sugarcane production in Bangladesh, predicting a slight decline in future output. Kumar and Anand (2014, p. 84) also applied ARIMA models in India and reported a decreasing trend in sugarcane production due to land use shifts. In Brazil, Lemos, et al. (2023, p. 12) focused on forecasting sugar export volumes and prices using ARIMA, highlighting the high volatility influenced by global market forces and domestic policies.

These studies confirm that ARIMA and SARIMA are robust models for capturing agricultural trends, especially when dealing with seasonal patterns. However, much of the existing research has focused either on price forecasting or production volume, and often limited to single-variable models. In contrast, the present study employs SARIMA models to jointly forecast both export quantity and price in the Thai sugar industry — an approach that remains underexplored in the literature.

Agricultural Economic Forecasting

Agricultural economic forecasting is essential for production planning, market stability, and policymaking. Numerous studies, both in Thailand and internationally, have utilized time series models to predict agricultural trends such as crop yields, market prices, and export volumes. These studies illustrate how forecasting tools can assist farmers, agribusinesses, and governments in navigating economic fluctuations and seasonal cycles.

In Thailand, Tuangkitkun and Suepphongsakorn (2021, p. 10) employed the ARIMA model to forecast the price of high-quality raw rubber sheets, identifying ARIMA(1,1,0) as the most suitable option. Their model closely aligned with actual market prices, highlighting ARIMA's applicability to volatile agricultural commodities. Similarly, Pongprasert and Thepdaeng (2022, p. 31) applied a seasonal ARIMA model—SARIMA(1,1,0)(0,1,1)$_{12}$—to forecast cassava prices. Beyond price prediction, their study also provided valuable insights into cost estimation and revenue projections for farmers and agribusiness operators.

International research also supports the use of ARIMA-type models in agricultural contexts. Hassan, et al. (2019, p. 30) forecasted sugarcane production in Bangladesh using ARIMA(1,2,2), projecting a gradual decline due to production challenges. In India, Kumar and Anand (2014, pp. 93-94) used ARIMA(2,1,0) to analyze sugarcane trends, attributing decreased production to shifts in land use and industrial growth. Meanwhile, Lemos, et al. (2023, pp. 17-19) examined sugar exports in Brazil using ARIMA, noting high volatility in both price and volume caused by macroeconomic and policy factors.

These studies confirm that ARIMA and SARIMA models are widely used for agricultural economic forecasting due to their flexibility and reliability. However, while many studies focus on a single aspect—either production, price, or exports—few integrate multiple variables. Moreover, most Thai studies prioritize domestic commodity prices, while international research increasingly addresses broader market dynamics such as trade policy, sustainability, and global shocks.

This highlights a gap in the literature: there is limited research in the Thai context that simultaneously forecasts both export quantity and price using a seasonal model. The present study addresses this gap by applying SARIMA to forecast two interrelated economic indicators—sugar export volume and price—providing insights relevant to both producers and policymakers.

Time series analysis for export forecasting

The study of Rangkoonuwat (2013, pp. 4-5) 's refers time series analysis as a sequence of observations or data points collected at consistent intervals over time, such as daily, weekly, monthly, quarterly, or annually. This type of data exhibits temporal dependence, meaning that past values influence future trends. Time series analysis is widely used in economic forecasting, financial market predictions, and production planning. Particularly, the fundamental characteristic of time series data is its relationship with time. For accurate analysis, data must be collected over a sufficiently long period and at regular intervals. If data collection intervals are inconsistent, necessary adjustments must be made before conducting the analysis. Time series data consists of various components that contribute to fluctuations, which can be categorized into the following four main elements Rangkoonuwat (2013, p. 7).

1. Long-Term Trend (T): This reflects the overall direction of data over time, indicating either an upward or downward movement. For example, electricity usage and crude oil imports in Thailand often show consistent long-term growth.

2. Seasonal Variation (S): These are regular fluctuations within a year caused by climatic, economic, or social factors. For instance, rice production peaks early in the year, while retail sales rise during year-end holidays. These patterns are typically measured using a seasonal index.

3. Cyclical Variation (C): This involves long-term economic fluctuations beyond one year, such as inflation or recessions. Unlike seasonal patterns, cyclical variations are more irregular and harder to forecast.

4. Irregular Variation (I): These are unexpected changes caused by events like natural disasters, wars, or financial crises. They are non-systematic and considered random in time series models.

Forecasting Using the Box-Jenkins Method: The Box-Jenkins method is a highly accurate tool for short-term forecasting (Box, et al., 2015, pp. 179-180). It uses the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to identify patterns in stationary time series.

This study employs the SARIMA (p,d,q)(P,D,Q)$_s$ model, which integrates seasonal and non-seasonal components, making it suitable for capturing recurring trends in sugar exports. The non-seasonal part follows the ARIMA(p,d,q) model, where:

- p represents the order of the Autoregressive (AR) process, accounting for relationships between past and present values;
- d denotes the degree of differencing, applied to transform non-stationary data into a stationary form;
- q reflects the order of the Moving Average (MA) process, capturing dependencies in past forecast errors.

For time series with seasonal patterns, the model extends to SARIMA$(p,d,q)(P,D,Q)_s$, incorporating additional seasonal terms:

- P indicates the order of the seasonal AR component.
- D represents the number of seasonal differencing operations.
- Q denotes the order of the seasonal MA component.
- s represents the seasonal period, defining the frequency of recurring cycles.

By combining seasonal and non-seasonal components, the SARIMA model effectively captures both short-term variations and long-term seasonal dependencies, making it particularly useful for forecasting export trends and price fluctuations in sectors influenced by cyclical patterns, such as the sugar industry. The general multiplicative form of the SARIMA model is expressed as:

$$\varphi_p(B)\Phi_p\left(B^{\delta}\right)(1-B)^d\left(1-B^{\delta}\right)^D Y_t=\delta+\theta_q(B)\Theta_Q(B^{\delta})\alpha_t \quad (1)$$

where:

$$\Phi_p\left(B^{\delta}\right)=1-\Phi_{\delta}B^{\delta}-\Phi_{2\delta}B^{2\delta}-\ldots-\Phi_p B^{p\delta}$$
$$\Theta_Q\left(B^{\delta}\right)=1-\Theta_{\delta}B^{\delta}-\Theta_{2\delta}B^{2\delta}-\ldots-\Theta_{Q\delta}B^{Q\delta}$$

This model structure provides a systematic approach to forecasting in markets affected by seasonal fluctuations, ensuring accurate predictions for decision-making in agriculture, supply chain management, and policy formulation.

Box-Jenkins Methodology for Constructing the SARIMA $(p,d,q)(P,D,Q)_s$ Model

The Box-Jenkins methodology follows a four-step process to ensure accurate time series forecasting (Gujarati and Porter, 2011, pp. 837–840).

1. Model Identification:

Stationarity is tested using the Augmented Dickey-Fuller (ADF) unit root test, along with the time series plot, ACF, and PACF. If the series is non-stationary, differencing is applied until the p-value < 0.05, confirming stationarity.

2. Model Estimation:

Parameters for AR(p), MA(q), SAR(P), and SMA(Q) are estimated using the Maximum Likelihood (ML) method.
Statistically significant coefficients ($p < 0.05$ or 0.01) are retained. If any parameter is not significant, the model is adjusted accordingly (Keerativibool, 2014, pp. 37–38).

3. Model Validation:

The Ljung-Box Q-Statistic tests residual autocorrelation. A non-significant result ($p > 0.05$) confirms model adequacy (Farnum and Stanton, 1989, p. 573). When several models meet this criterion, selection is based on the lowest AIC, SIC, RMSE, and MAPE values.

4. Forecasting:

The final SARIMA model is used to project future values, supporting data-driven decisions in trade, planning, and policy.

Related Research

Thai studies confirm the Box-Jenkins method's utility in agriculture. Tuangkitkun and Suepphongsakorn (2021, p. 11) found ARIMA(1,1,0) effective for rubber price forecasts. Similarly, Pongprasert and Thepdaeng (2022, pp. 28-30) used ARIMA(1,1,0)$(0,1,1)_{12}$ to forecast cassava prices, supporting its application in both cost and revenue projections. These studies demonstrate ARIMA's flexibility across agricultural forecasting contexts.

International Studies

Beyond Thailand, time series forecasting of agricultural products has been widely studied internationally. Hassan et al. (2019, pp. 30-31) examined sugarcane production in Bangladesh and identified ARIMA(1,2,2) as the most suitable model, forecasting a slight production decline. Kumar and Anand (2014, p. 81) also applied ARIMA(2,1,0) in India, projecting a gradual decline due to economic growth and land-use shifts toward industrialization.

Lemos et al. (2023, p. 20) investigated sugar export volumes and prices in Brazil using ARIMA. Unlike production-focused studies, this research highlighted high volatility in export trends, driven by global economic changes, domestic policies, and macroeconomic conditions.

Methodologically, all studies utilized ARIMA-based models, affirming their robustness in agricultural forecasting. However, Thai studies tend to focus on price, whereas international research includes both production and trade dimensions. Notably, studies in Bangladesh and India reported declining trends, while Brazil's findings emphasized export volatility due to external factors.

These comparisons underscore that economic, environmental, and policy variables influence forecasting outcomes. Therefore, integrating both domestic and global market considerations is essential in forecasting research.

Overall, these studies validate the effectiveness of ARIMA models in agricultural contexts and reveal the complex interplay between market dynamics, policy interventions, and economic trends.

Methods

Forecasting trends in the quantity and price of sugar exports in Thailand through time-series analysis.

The following steps are followed in the time series analysis for the purpose of forecasting trends in the quantity and price of sugar exports in Thailand.

1. Data Collection

The complete SARIMA modeling procedure used in this study is summarized in Figure 1, which outlines each step from data acquisition to final forecasting. Monthly sugar export quantity and price data were collected from January 2011 to December 2023, totaling 156 data points. The dataset was divided into a training set (January 2011–December 2022; 144 data points) used to develop the forecasting model, and a testing set (January 2023–December 2023; 12 data points) for model validation (see Figure 2 and Figure 3).

Figure 1 Analytical Framework for SARIMA-Based Sugar Export

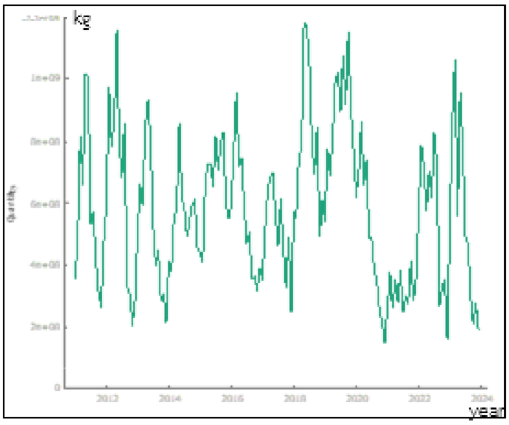

Figure 2 Thailand's Monthly Sugar Export Volume (2011–2023)

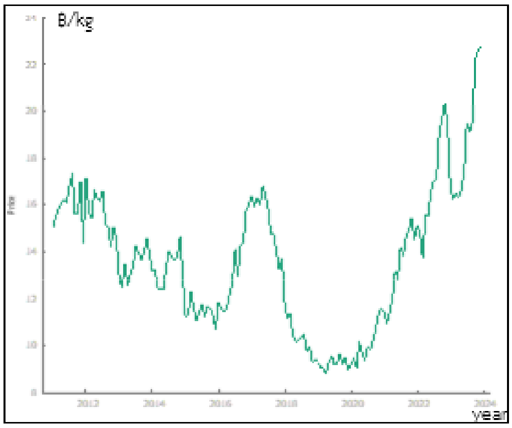

Figure 3 Thailand's Monthly Sugar Export Price (2011–2023)

2. SARIMA Model Specification

The Augmented Dickey-Fuller (ADF) test was used to evaluate the stationarity of the time series data. The subsequent hypotheses were examined: Null hypothesis (H_0): The data is non-stationary. Alternative hypothesis (H_1): Data that is stationary. Based on the p-value, the decision rule is used: If the p-value is greater than 0.05 or 0.01, the null hypothesis (H_0) should not be rejected (data is non-stationary). Reject H_0 and accept H_1 if the p-value is less than 0.05 or 0.01, indicating that the data is stationary. When the series is non-stationary, first-order or seasonal differencing is applied iteratively until stationarity is achieved, as indicated by the ADF test results. SARIMA allows for flexible specification of both seasonal and non-seasonal orders, supports multiplicative seasonality, and is grounded in the statistically rigorous Box-Jenkins methodology. Its parameter-rich structure makes it well-suited for modeling time series with pronounced, irregular, or evolving seasonal patterns—features observed in the sugar export and price data used in this study. This suitability, combined with SARIMA's strong track record in agricultural forecasting, supports its use as the primary model in this research.

3. Model Evaluation and Accuracy Metrics

Several performance metrics were used to evaluate model accuracy. The Mean Absolute Percentage Error (MAPE) measures forecasting accuracy by comparing the percentage difference between actual and predicted values. A lower MAPE indicates higher forecasting accuracy. The Root Mean Square Error (RMSE) quantifies the average magnitude of prediction errors, with lower values representing better fit. In addition, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare alternative models, with lower values suggesting better model parsimony.

4. Data Analysis

Model Identification

This study applies the Box-Jenkins method (Gujarati and Porter, 2011, pp. 837–840; Box, et al., 2015, pp. 179-180) to forecast sugar export trends using four key steps:

Step 1: Model Identification

Stationarity is tested using the ADF unit root test. If the series is non-stationary, differencing is applied. Seasonal patterns are confirmed through correlograms, and seasonal differencing is used where necessary. Residual autocorrelation is assessed using the Ljung-Box Q-Statistic.

Step 2: Parameter Estimation

Parameters for AR(p), MA(q), SAR(P), and SMA(Q) are estimated. Only statistically significant coefficients ($p < 0.05$ or 0.01) are retained. Alternative models are tested if required.

Step 3: Model Validation

Model adequacy is confirmed using the Ljung-Box test. The best-fitting model is selected based on the lowest AIC, SIC, RMSE, and MAPE values.

Step 4: Forecasting

The optimal SARIMA model is used to forecast sugar export volume and price from January to December 2024.

Results

Using 156 months of data (Jan 2011–Dec 2023), this study forecasts sugar export quantity and price using the Box-Jenkins method. The process includes model identification, parameter estimation, model validation, and forecasting via the SARIMA$(p,d,q)(P,D,Q)_s$ model.

1. Model Identification: SARIMA$(p,d,q)(P,D,Q)_s$

To identify the model, the Augmented Dickey-Fuller (ADF) test was used to assess stationarity. If the p-value > 0.05, the data is non-stationary; if $p < 0.05$, stationarity is confirmed. In cases of non-stationarity, first-order or seasonal differencing was applied until the data became stationary (see Table 1)

Table 1 Results of the Augmented Dickey-Fuller Unit Root Test for Export Quantity (Q) and Price (P)

Variable	I(d) = I(0)		I(d) = I(1)		I(D) = I(1)	
	t-statistics	p	t-statistics	p	t-statistics	p
Without α and T						
Q	-1.801	0	-14.777***	0	-18.840***	2
P	0.629	0	0.020**	0	-15.369***	12
Without α and on T						
Q	-4.835***	0	-14.730***	0	-18.779***	2
P	-0.436	0	-2.312	0	-1.244***	12
With α and T						
Q	-4.909***	0	-14.700***	0	-18.728***	2
P	-0.472	0	-2.920	0	-15.291***	12

Note: ** P-value < 0.05, *** P-value < 0.01, p: Lag length

The ADF unit root test was conducted to assess the stationarity of Thailand's sugar export quantity (Q) and price (P), as shown in Table 2. Three models were tested: (1) without constant and trend, (2) with constant only, and (3) with both constant and trend. The null hypothesis (H0) assumed non-stationarity. If the p-value > 0.01, H_0 was accepted; if p-value < 0.01, H_1 (stationarity) was accepted. When data was non-stationary, first-order or seasonal differencing was applied until stationarity was confirmed, ensuring valid time series forecasting.

All three ADF test models—without constant and trend, with constant only, and with both constant and trend—initially indicated non-stationarity in Q (export quantity) and P (export price). First-order differencing (I(d) = I(1)) was applied. Q achieved stationarity across all models at the 0.01 level, while P became stationary only in the model without constant and trend at the 0.05 level. Due to seasonal effects, seasonal differencing was also applied. The final stationarity for both Q and P was confirmed at I(D) = I(1), leading to the SARIMA$(p,1,q)(P,1,Q)_{12}$ specification.

2. Model Identification

The complete SARIMA modeling procedure used in this study is summarized in Figure 1, which outlines each step from data acquisition to final forecasting. Monthly sugar export quantity and price data were collected from January 2011 to December 2023, totaling 156 data points. The dataset was divided into a training set (January 2011–December 2022; 144 data points) used to develop the forecasting model, and a testing set (January 2023–December 2023; 12 data points) for model validation.

Seasonal patterns were clearly observed in the raw time series data (see Figure 4 and Figure 5), supporting the decision to apply seasonal differencing and a SARIMA model. The Augmented Dickey-Fuller (ADF) test was conducted to confirm stationarity before proceeding with model specification, estimation, and evaluation using AIC, BIC, RMSE, and MAPE.

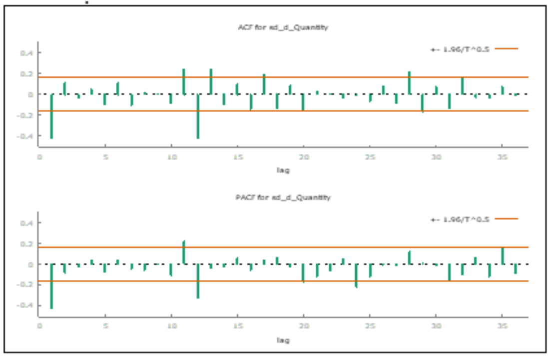

Figure 4 Correlogram of the Differenced Time Series ΔΔ12Q (Quantity)

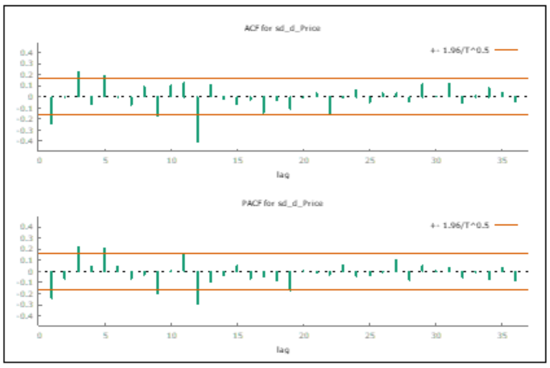

Figure 5 Correlogram of the Differenced Time Series ΔΔ12P (Price)

The selection of SARIMA$(1,1,1)(1,1,2)_{12}$ for export quantity and SARIMA$(1,1,1)(2,1,1)_{12}$ for export price reflects different adjustment patterns in Thailand's sugar export market. The seasonal MA(2) term for quantity suggests that current volumes are influenced by shocks from the previous two seasons, indicating a lagged response to disruptions in production or logistics. In contrast, the seasonal AR(2) term for price implies that current prices are shaped by patterns from earlier seasonal periods, highlighting the role of market expectations and cyclical pricing. These differences suggest that while export quantity reacts to operational shocks, price adjustments follow historical trends and trader behaviors.

The preliminary forecasting models were identified as follows from the correlograms of the time series ΔΔ12Q and ΔΔ12P in Figure 4 and Figure 5, respectively: SARIMA$(1,1,1)(2,1,3)_{12}$ for Q (Export Quantity). For P (Export Price): SARIMA$(1,1,1)(1,1,2)_{12}$.The maximum order specifications for AR(p), SAR(P), MA(q), and SMA(Q) are solely representations of these preliminary models. In order to identify the most suitable forecasting models, additional model selection and validation were implemented.

3. Parameter Estimation

Parameters were estimated using the Maximum Likelihood Estimation (MLE) method.

Statistically significant coefficients ($p < 0.05$) for AR(p), MA(q), SAR(P), and SMA(Q) were retained. The model with the lowest AIC, SIC, RMSE, and MAPE, along with a high correlation coefficient (r), was selected as optimal. Table 2 presents the evaluation of the selected SARIMA$(p,d,q)(P,D,Q)_s$ model.

Table 2 Model Identification Results for SARIMA$(p,d,q)(P,D,Q)_s$

Variable	Q			P		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
AR(1)	−0.385***	−0.393***	−0.403***	−0.313***	−0.302***	−0.695***

Variable	Q			P		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
SAR(1)			−0.941***	−0.537***	−0.633***	−0.504***
SAR(2)			−0.765***			
MA(1)	−1.000***	−1.000***	−0.999***	−0.844***	−0.858***	0.270***
SMA(1)	−1.812***	−1.794***	−0.651**	−1.000***	−0.999***	−0.999***
SMA(2)	0.999***	0.999***				
SMA(3)			−0.651**			
SMA(4)			0.999***			
AIC	5368.035	5369.492	5371.36	407.582	407.522	409.763
BIC	5388.108	5392.433	5400.035	424.787	427.595	432.703
RMSE	1.64E+08	1.62E+08	1.53E+08	0.929	0.907	0.929
MAPE	201.34	204.67	199.64	203.3	207.91	186.73

Source: The calculation

Note: ** P-value < 0.05, *** P-value < 0.01, E+08: Multiplication with the value

The results of the model suitability assessment for SARIMA(p,d,q)$(P,D,Q)_s$, as illustrated in Table 3, are as follows: SARIMA(1,1,1)$(1,1,2)_{12}$ is the most appropriate model for forecasting Q (Export Quantity) due to its lowest AIC value of 5368.035. SARIMA(1,1,1)$(2,1,1)_{12}$ is the most suitable model for forecasting P (Export Price) due to its lowest AIC value of 407.522.

4. Diagnostic Checking of the Model

Preliminary SARIMA models for Q and P were tested using the Ljung-Box Q-Statistic to check for autocorrelation. The model is considered valid if no autocorrelation is found at lag 12, indicated by a p-value > 0.05. Table 3 presents the diagnostic results confirming the models' statistical adequacy.

Table 3 The parameter estimation of the SARIMA(p,d,q)(P,D,Q)s forecasting model for the variables Q and P.

Variable	Q			P		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Q-Statistic 1						
Q-Statistic 2						
Q-Statistic 3						
Q-Statistic 4						
Q-Statistic 5				2.907^{ns}		
Q-Statistic 6	3.787^{ns}			2.943^{ns}	2.993^{ns}	
Q-Statistic 7	5.252^{ns}	5.569^{ns}		3.623^{ns}	3.809^{ns}	2.766^{ns}

Variable	Q			P		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Q-Statistic 8	7.013^{ns}	7.012^{ns}		3.683^{ns}	3.882^{ns}	2.980^{ns}
Q-Statistic 9	7.117^{ns}	7.117^{ns}	8.261^{ns}	4.928^{ns}	5.146^{ns}	4.548^{ns}
Q-Statistic 10	7.262^{ns}	7.286^{ns}	8.457^{ns}	5.070^{ns}	5.199^{ns}	4.784^{ns}
Q-Statistic 11	7.496^{ns}	7.633^{ns}	8.728^{ns}	5.070^{ns}	5.243^{ns}	4.785^{ns}
Q-Statistic 12	7.572^{ns}	7.641^{ns}	8.945^{ns}	5.347^{ns}	6.417^{ns}	5.105^{ns}

Source: The calculation

Note: ^{ns} :P-value > 0.05

The Ljung-Box Q-Statistic was used to assess model suitability, based on parameter estimates in Table 3. The results confirm that all SARIMA models for Q (Export Quantity) show no autocorrelation issues, supporting their forecasting reliability:

1. SARIMA$(1,1,1)(1,1,2)_{12}$
2. SARIMA$(1,1,1)(2,1,2)_{12}$
3. SARIMA$(1,1,1)(2,1,4)_{12}$

Similarly, all models for P (Export Price) are also appropriate:

1. SARIMA$(1,1,1)(1,1,1)_{12}$
2. SARIMA$(1,1,1)(2,1,1)_{12}$
3. SARIMA$(1,1,3)(1,1,1)_{12}$

5. Forecasting

For forecasting Thailand's sugar export trends, the most suitable models were selected:

SARIMA(1,1,1)(1,1,2)12 for quantity (Q) and SARIMA(1,1,1)(2,1,1)12 for price (P). A 12-month forecast (January–December 2024) was conducted, with results shown in Figures 6–7 and Table 4.

The forecasted volume from 2011 to 2023 shows high volatility, which continues into 2024. The widened 95% confidence interval reflects growing uncertainty due to seasonal and environmental factors. In contrast, export price trends remain more stable, though future price forecasts also show uncertainty, likely influenced by global trade dynamics and macroeconomic conditions. The results are presented in Figures 6 and 7 and Table 4.

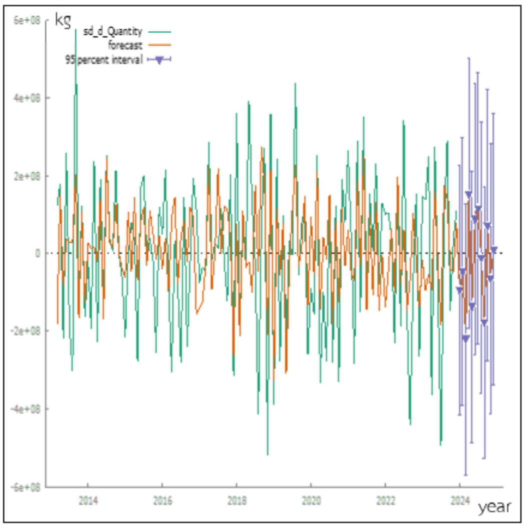

Figure 6 Forecast of Monthly Sugar Export Volume in Thailand for 2024

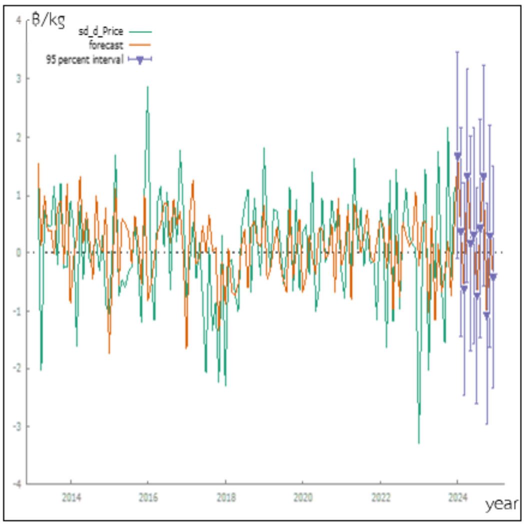

Figure 7 Forecast of Monthly Sugar Export Price in Thailand for 2024

Table 4 Forecast Results for Thailand's Sugar Export Quantity and Price (January–December 2024)

Month	Export volume (kg.)	Price (฿/kg.)
January	424,893,973.00	18.47
February	834,308,648.00	16.63
March	845,564,777.00	15.90
April	713,415,888.00	17.68
May	824,227,650.00	16.85
June	867,548,613.00	17.68
July	611,334,315.00	18.79
August	459,521,657.00	19.58
September	118,318,500.00	20.87
October	280,426,697.00	21.20
November	212,317,178.00	22.84
December	200,677,190.00	22.38

Source: The calculation

The forecast for January to December 2024 indicates that sugar export quantities will increase from January to June, aligning with the sugarcane harvesting season. From July to December, exports are projected to decline due to the end of the harvest and mill closures. This seasonal pattern reflects typical supply surges during harvest and drops post-harvest. As a result, sugar prices are expected to rise in the latter half of the year, driven by reduced supply. The inverse relationship between quantity and price highlights the seasonal impact on Thailand's sugar export trends.

Conclusion and Discussion

This study applied the SARIMA model using the Box-Jenkins methodology to forecast Thailand's sugar export quantity and price from January 2011 to December 2023 (156 data points). Data were sourced from the Office of Agricultural Economics and processed using Gretl software. The best-fit models identified were SARIMA$(1,1,1)(1,1,2)_{12}$ for quantity and SARIMA$(1,1,1)(2,1,1)_{12}$ for price. These align with previous models used for palm oil (Cumroon, et al., 2021, p. 315) and crude rubber (Tuangkitkun and Suepphongsakorn, 2021, pp. 11-12) confirming SARIMA's robustness.

Export quantities showed cyclical patterns influenced by economic conditions and agricultural policies. This study contributes to agricultural forecasting, reinforcing the effectiveness of time series models. Comparable research by Cumroon et al. (2021, pp. 325-327) found SARIMA effective for predicting crude palm oil trends, where export volumes and prices fluctuated year to year. These findings highlight SARIMA's applicability in capturing seasonal and economic dynamics in agricultural trade forecasting.

Internationally, Lirio, et al. (2020, pp. 15-16) forecasted Brazil's sugar exports using SARIMA (1,1,1)(1,0,1)6, effectively capturing seasonal trends linked to sugarcane harvest cycles. Notably, export volumes were higher in October 2012 and February 2016. In contrast, Lemos et al., (2023, p. 20-21) also used ARIMA to forecast Brazil's sugar exports but focused on forecast errors, revealing that price volatility and economic policy shifts impacted forecast accuracy.

Other studies examined sugarcane production. Mehmood, et al. (2019, p. 1396) applied ARIMA to forecast sugarcane production in Pakistan, finding a slight decline from 1972 to 2017. Similarly, Hassan, et al. (2019, p. 24) used ARIMA(1,2,2) in Bangladesh and projected a future decline. Meanwhile, Hazarika and Phukon (2025, p. 968) used ARIMA(1,2,1) to forecast sugarcane production in Assam, India, predicting an upward trend.

These findings confirm ARIMA's effectiveness in capturing seasonal and economic dynamics across various countries and highlight its flexibility for both export and production forecasting.

While this study's findings align with earlier research that supports the use of SARIMA models in agricultural forecasting, some differences emerge when compared with international studies. For example, unlike the gradual decline in sugarcane production observed by Hassan, et al. (2019, p.31) in Bangladesh or Mehmood, et al. (2019, p. 1400) in Pakistan, Thailand's sugar export volume exhibited more frequent fluctuations rather than a long-term downward trend. This could be attributed to Thailand's government support programs, crop zoning policies, and relatively advanced irrigation systems, which may mitigate the impact of climate variability. Moreover, the time frame of this study (2011–2023) includes significant global and regional disruptions—particularly the COVID-19 pandemic, which affected trade routes and labor availability, and fluctuating oil prices, which influenced global food markets. These events likely contributed to the widening confidence intervals observed in the forecasts, particularly for sugar export volume. In contrast to Brazil (as in Lemos, et al., 2023, pp.20-21), where political and economic volatility was a central driver of export variation, Thailand's patterns appear to be more strongly influenced by seasonal production cycles and global demand trends for sugar.

These contextual differences highlight the importance of interpreting forecasting models not only through statistical fit, but also through local agricultural, economic, and political lenses.

While the SARIMA model demonstrates strong statistical performance, it also has limitations. Forecast accuracy may decline during periods of major market disruption, such as abrupt policy changes, natural disasters, or global trade shocks. Additionally, SARIMA does not account for external explanatory variables like weather patterns, input costs, or geopolitical events, which may also influence sugar export volumes and prices. These limitations should be considered when applying the results for policy or planning purposes.

This study advances previous research by jointly forecasting both export quantity and price using SARIMA models, whereas most earlier Thai studies have analyzed only a single variable in isolation. Additionally, this study uses a longer post-pandemic dataset, capturing economic shifts and trade disruptions between 2011 and 2023. These elements distinguish the study's contribution by offering a more integrated and context-responsive forecasting approach for Thailand's sugar export sector.

This study highlights the effectiveness of the SARIMA model for forecasting seasonal trends in Thailand's agricultural exports. The results provide new insights into the dynamics of sugar export fluctuations, supporting the model's suitability for handling complex seasonality and irregularities in time series data. Furthermore, it can be applied to other commodities with strong seasonal patterns, such as rice, cassava, and palm oil, making it a practical tool for agricultural economic forecasting.

Implications and Recommendations

This study provides both academic and managerial contributions in the following ways:

1. For Farmers: The forecasting data can assist farmers in planning the procurement of production inputs, such as fertilizers and labor, to minimize costs. Additionally, this information can support the adoption of sustainable production practices, including reducing chemical usage, implementing proper soil and water management, and utilizing crop rotation systems. These strategies help mitigate environmental impacts and enhance the long-term sustainability of the agricultural sector.

2. For Sugar Industry Stakeholders (including exporters and entrepreneurs): Forecast data can be used to optimize production cycles, manage supply chain logistics, and plan exports in line with market demand. This helps minimize excess inventory and strengthens Thailand's position in the global sugar market.

3. For policymakers: Government agencies can use this information to formulate international trade policies, such as implementing support measures that help businesses adapt to global market trends and allocating export quotas to ensure a stable and competitive

sugar industry.

Recommendations for Future Research

Based on the findings of this study, the following recommendations are proposed for future research:

1. Macroeconomic Variables: Future studies should examine the impact of macroeconomic factors, such as exchange rates and inflation, on sugar export quantity and price to enhance the understanding of economic influences on the industry.

2. Comparative Forecasting Methods: Future research should explore alternative forecasting methods, such as linear regression, exponential smoothing methods, and hybrid BRNN-ARIMA models, SARIMAX model to compare forecasting accuracy and identify the most suitable model for sugar export predictions.

3. Comparisons with Sugar market in ASEAN: Future studies should incorporate comparisons with Sugar market in ASEAN trends to enhance international relevance international relevance. Examining trade policies, price fluctuations, and production cycles in major sugar-exporting countries could provide a broader perspective on market dynamics, improving the accuracy and applicability of forecasting models for Thailand's sugar industry.

4. Impact of Sustainability Regulations: Further studies should analyze the effects of emerging sustainability regulations on international trade in the sugarcane and sugar industry, particularly concerning concerns about carbon footprints and the increasing global demand for environmentally friendly agricultural practices.

Acknowledgments

The researchers extend sincere gratitude to the Faculty of Liberal Arts and Management Science, Kasetsart University, Chalermphrakiat Sakon Nakhon Province Campus, for its generous research funding support for this study.

Bibliography

Box, G. E., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2015). **Time series analysis: Forecasting and control** (5^{th} ed). USA: John Wiley & Sons.

Cumroon, C., Jatuporn, C., Suvanvihok, V. and Seerasarn, N. (2021). Forecasting export volume and export price of crude palm oil in Thailand: A case study of time series analysis. **Journal of Modern Learning Development,** 6(4), 315–329.

Department of Trade Negotiations. (2021). **Sugarcane and sugar.** Retrieved May 5, 2024, from https://www.dtn.go.th/th/content/category/detail/id/983/iid/12389

Durongkaveroj, W. (2022). Emphasis on domestic value added in export in the era of global value chain: Evidence from Thailand. **Economia e Politica Industriale: Journal of Industrial and Business Economics,** 50(3), 703–729.

Farnum, N. R. and Stanton, L. W. (1989). **Quantitative forecasting methods.** USA: PWS-Kent Publishing Company.

Gujarati, D. N. and Porter, D. C. (2011). **Basic econometrics** (5^{th} ed.). USA: McGraw-Hill.

Hassan, M. Z., Siraj-Ud-Doulah, M. and Hasan, M. K. (2019). Forecasting the production of sugar cane based on time series models in Bangladesh. **Bull. Math. & Stat. Res,** 7(4), 77-89.

Hazarika, M. and Phukon, K. K. (2025). Development of ARIMA model for forecasting sugarcane production in Assam. **Indian Journal of Agricultural Research,** 59(6), 968-973.

Keerativibool, W. (2014). A comparison of egg price forecasting methods using the Box-Jenkins approach and Holt's exponential smoothing method. **Thaksin University Journal,** 17(2), 35-43.

Kumar, M. and Anand, M. (2014). An application of time series ARIMA forecasting model for predicting sugarcane production in India. **Studies in Business Economics,** 9(1), 81-94.

Lemos, J. D. J. S., Cruz, M. P. M. D., Costa Filho, J. D., Paiva, E. C. D., Sousa, E. C. and Monteiro, A. P. (2023). Evolution of sugar exports in two centuries. **International Journal of Business, Economics and Management,** 10(2), 12-22.

Lirio, V. W., Ueda, R. M., Reichert, B. and Souza, A. M. (2020). Brazilian sugar export forecast by means of residual control charts. **Ciência e Natura**, 42, e39.

Mehmood, Q., Sial, M. H., Riaz, M. and Shaheen, N. (2019). Forecasting the production of sugarcane in Pakistan for the year 2018-2030, using Box-Jenkin's Methodology. **The Journal of Animal and Plant Sciences,** 29(5), 1396-1401.

Office of The Cane and Sugar Board. (2022). **Summary of the sugar situation in various countrie.** Retrieved June 16, 2024, from https://www.ocsb.go.th/wp-content/up loads/2023/03/14387-7430.pdf

Office of The Cane and Sugar Board. (2023). **Sugarcane growing situation report.** Retrieved June 26, 2024, from https://www.ocsb.go.th/2023/reportsticles/area-yield/21623/

Phongphanich, B., Chairit, S., Sitthiphon, T. and Suwanvijit, W. (2023). Forecasting the export quantity of Thai fresh durian: Box-Jenkins method and Winters' additive exponential smoothing method. **Economics and Business Administration Journal Thaksin University,** 15(3), 1-16.

Pongprasert, R. and Thepdaeng, S. (2022). Cassava price forecasting using the Box-Jenkins method. **Rattanakosin Journal of Science and Technology,** 4(1), 22-33.

Rangkoonuwat, P. (2013). **Time series analysis for economics and business.** Bangkok: Chulalongkron University Pess.

Riansut, W. (2022). Forecasting model of sugar export quantity via the use of statistical methods. **PBRU Science Journal.** 19(1), 1-12.

Tuangkitkun, P. and Suepphongsakorn, A. (2021). Forecasting high-quality raw rubber sheet prices using the Box-Jenkins method. **The Journal of Faculty of Applied Arts,** 14(1), 1-13.