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Forecasting Monthly Rice Stock in the Philippines Using Time Series Models

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Abstract

This study investigated the status of rice stocks in the Philippines by analyzing data obtained from the Philippines Statistics Authority (PSA) spanning from January 2000 to March 2023. The exponential smoothing and Box-Jenkins methods were used to build a forecasting model for the rice stock in the Philippines. The different models for each method were evaluated in the training dataset using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and *Akaike's Information Criterion (AIC)*. The Holt-Winters(A, A, A) model and the $ARIMA(0, 1, 0) \times (0, 1, 1)_{12}$ model were the candidate models for the exponential smoothing method and Box-Jenkin method, respectively. The two candidate models performed closely during the training stage. However, the Holt-Winters(A, A, A) had smaller forecasting errors in the testing set. Thus, the final forecasting model was Holt-Winters(A, A, A). The forecast from the model suggests that Philippine rice stock may be enough to supply the country if there is no increase in the demand for rice until March 2024.

1 Introduction

Rice holds a special significance in the lives of Filipinos and other Asian countries. Despite the availability of essential foods like bread and noodles, rice remains the most preferred and cherished staple in the Philippines. It goes beyond being just a source of sustenance; locally known as "Palay" when unmilled, "Bigas" when milled, and "Kanin" when cooked, rice is deeply intertwined with the historical and cultural fabric of the nation. Throughout various regions in Luzon, Visayas, and Mindanao, it has become integral to traditions, ceremonies, and cultural activities [13]. Considering its immense importance to Filipino culture, nutrition, consumption, and economy, we should preserve its value and express gratitude to the hardworking farmers who toil to bring this essential grain to our tables.

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With its extensive importance to the Filipino diet, it is also important to ensure its supply stability to cater to the growing demand for more rice. According to PSA (Philippine Statistics Authority) data, a typical Filipino consumes 118.81 kilograms (kg) of rice each year [4]. This is equivalent to consuming around 325.5 grams of milled rice every day. Considering the total population of the Philippines at approximately 114, 189, 499 people [1], the total annual rice consumption in the Philippines would be approximately more than 12.3 million metric tons (MMT).

A time series is a sequence of observations arranged according to the time of their outcome [20]. Simply, it pertains to a series of data points ordered in time. A time series can be decomposed into four major components: trend T, season S, cycle C, and irregular pattern I. Trend T refers to the long-term upward or downward movement that characterizes a time series over a period of time. A seasonal variation S is a regular periodic fluctuation within a year. In contrast, cycle C refers to the up and down fluctuations that are observable over an extended period of time. Lastly, the irregular pattern I is an unpredictable random variation in the time series that the other three components (trend, cycle, seasonality) fail to account for.

Two common statistical methods exist in time series data: the exponential smoothing models [19] and the Box-Jenkins methods [8]. Through these methods, the study will build a forecasting model to estimate the monthly rice stock in the Philippines. This model will forecast rice stock inventory from April 2023 to March 2024.

This study thoroughly assesses the forecasting accuracy of both models by examining their performance on the given Philippine rice stock [16] data set. The evaluation will be based on how closely the model's forecast aligns with the observed values. The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) will be used to measure the accuracy of the model during model building and final evaluation [20]. The *Akaike's Information Criterion (AIC)* [11] will also be used for model comparison, especially for models with different numbers of parameters. By adopting this evaluation strategy, the research seeks to identify the model that exhibits the least error and demonstrates superior forecasting capabilities for the Philippine Rice Stock, aiding policymakers and stakeholders in making informed decisions about the nation's rice supply and demand dynamics.

2 Methodology

The monthly total stock inventory of rice in the Philippines from January 2000 to March 2023, expressed in kilo-metric tons (KMT), was used to produce a forecasting model using Exponential Smoothing [19] and Box-Jenkins models [8]. The data is then partitioned into training and testing sets. The training set is from January 2000 to July 2018, while the testing set is from August 2018 to March 2023. The trend, cycles, seasonality, and irregularities, as well as normality and variance assumptions, were determined to improve the accuracy of models further.

2.1 Exponential Smoothing Model

The exponential smoothing model forecasts the future by utilizing previous data as input. The essential idea of exponential smoothing is to give more weight to recent data and gradually reduce the weight when observations are made further in the past. As a result, the technique is more adaptable and sensitive to current data changes. Three basic variations of exponential smoothing are commonly used: simple exponential smoothing [18], trend-corrected exponential smoothing [2], and Holt–Winters' method [2, 14].

Simple exponential smoothing is suitable for forecasting data with no clear trend or seasonal pattern. The smoothing equation is given by

$$l_t = \alpha y_t + (1-\alpha)l_{t-1} \tag{1}$$

where l_t is the level at time t and $0 \leq \alpha \leq 1$ is the smoothing parameter. The h-ahead forecast is given by

$$y_{t+h|t} = l_t. \tag{2}$$

Holt's linear trend method [2] is an extended simple exponential smoothing to allow data forecasting with a trend. This method has equations for level and trend. The level and trend are given by

$$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1}), \tag{3}$$

and

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, \tag{4}$$

where b_t denotes an estimate of the trend (slope) of the series at time t, $0 \leq \beta^* \leq 1$ is the smoothing parameter for trend. The h-ahead forecast is then

$$y_{t+h|t} = l_t + hb_t. \tag{5}$$

This method may include a damping parameter $0 \leq \phi \leq 1$. In effect, equations (5),(3) and (4) are now in the form of

$$y_{t+h|t} = l_t + (\phi + \phi^2 + \cdots + \phi^h)b_t, \tag{6}$$

$$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + \phi b_{t-1}), \tag{7}$$

and

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)\phi b_{t-1}. \tag{8}$$

Holt [2] and Winters [14] extended Holt's method to capture seasonality. The Holt-Winters seasonal method comprises the forecast equation and three smoothing equations, one for the level l_t, one for the trend b_t, and one for the seasonal component s_t with corresponding smoothing parameters α, β^* and γ. Furthermore, it can be in the form of an additive or multiplicative model. The three smoothing equations in the additive model and its forecasting equation are given by

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}), \tag{9}$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, \tag{10}$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}, \tag{11}$$

and

$$y_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)}, \tag{12}$$

respectively, where m is the seasonal frequency and $k = \text{int}((h-1)/m)$. On the other hand, the three smoothing equations in the multiplicative model and its forecasting equation are given by

$$l_t = \alpha\left(\frac{y_t}{s_{t-m}}\right) + (1-\alpha)(l_{t-1} + b_{t-1}), \tag{13}$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, \tag{14}$$

$$s_t = \gamma\left(\frac{y_t}{l_{t-1}+b_{t-1}}\right) + (1-\gamma)s_{t-m}, \tag{15}$$

and

$$y_{t+h|t} = (l_t + hb_t)s_{t+h-m(k+1)}, \tag{16}$$

respectively. According to Hyndman and Athanasopoulos (2021) [20], a method that often provides accurate and robust forecasts for seasonal data is the Holt-Winters method with a damped trend. The three smoothing equations in the damped multiplicative model and its forecasting equation are given by

$$l_t = \alpha\left(\frac{y_t}{s_{t-m}}\right) + (1-\alpha)(l_{t-1} + \phi b_{t-1}), \tag{17}$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)\phi b_{t-1}, \tag{18}$$

$$s_t = \gamma\left(\frac{y_t}{l_{t-1}+\phi b_{t-1}}\right) + (1-\gamma)s_{t-m}, \tag{19}$$

and

$$y_{t+h|t} = [l_t + (\phi + \phi^2 + \cdots + \phi^h)b_t]s_{t+h-m(k+1)}, \tag{20}$$

respectively.

The classification of the different exponential smoothing methods can be summarized using Table 1. Depending on the presence and type of components, one can use the entries in Table 1 as shorthand notation of these methods, e.g., simple exponential smoothing can be written as (N, N).

Table 1: Exponential smoothing methods classification based on trend and seasonal components.

Trend Component	Seasonal Component		
	N (None	A (Additive)	M (Multiplicative)
N (None)	(N, N)	(N, A)	(N, M)
A (Additive)	(A, N)	(A, A)	A,M
A_d (Additive dumped)	(A_d, N)	(A_d, A)	(A_d, M)
M (Multiplicative)	(M, N)	(M, A)	(M, M)
M_d (Multiplicative Dumped)	(M_d, N)	(M_d, A)	(M_d, M)

Exponential smoothing methods that were presented before generate only a point forecast. However, it can also generate interval forecasts by introducing errors in each method. Hence, each method can be extended into two models with either additive A or multiplicative M errors. ETS(Error, Trend, Seasonal) [19] is used as shorthand notation in distinguishing these models. For example, a simple exponential smoothing with additive errors can be written as ETS(A, N, N).

2.2 Autoregressive Integrated Moving Average Model

An Autoregressive Integrated Moving Average (ARIMA) model is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables [25]. An ARIMA model has three components: Autoregression (AR) which refers to a model that shows a changing variable that regresses on its own lagged or prior values; Integrated (I) represents the differencing of raw observations to allow the time series to become *stationary* where data values are replaced by the difference between the data values and the previous values; and Moving average (MA) which incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations [7]. For ARIMA models, a standard notation would be $ARIMA(p, d, q)$, where p, d, and q represents the order of autoregressive, differencing, and moving average, respectively. The model can be expressed as

$$\phi_p(B)(1-B)^d z_t = \theta_q(B)a_t \tag{21}$$

where

$$\begin{aligned} z_t &= y_t - \mu_y, \\ \phi_p(B) &= (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p), \\ \theta_p(B) &= (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q), \\ B^j z_t &= z_{t-j}, \end{aligned}$$

and a_t is from a white noise process, i.e.

$$a_t \sim WN(0, \sigma_a^2).$$

2.3 Modelling Procedure

Modeling time series data using ARIMA follows the Box-Jenkins methodology [8, 7]. The modeling approach involves checking stationarity conditions, order selection, estimation, and checking assumptions.

A stationary time series is one whose statistical features, such as mean and variance, are unaffected by the time the series is seen, and the correlation between observations is determined only by their temporal difference rather than by time itself [25]. Time series with trends or seasonality are not stationary since the trend and seasonality will affect the value of the time series. The study used *Augmented Dickey-Fuller (ADF) test* [3] to test the stationarity of the time series. *ADF test* tests the null hypothesis that the time series is not stationary. If the data is not stationary, the differencing technique is applied. The $k-$order differencing is the value from computing

$$(y_t - y_{t-1})^k.$$

The lowest k at which the differenced series becomes stationary will be the order of the differencing in the ARIMA model, i.e., $d = k$.

The autocorrelations and the partial-autocorrelations give the general idea of how to select the order of the AR and MA part in ARIMA model [25]. The nature of the autocorrelation function (ACF) and partial-autocorrelation function (PACF) of the difference times series with order d is summarized in Table 2. Once the order of the different parts of the ARIMA is identified, the parameters $\phi_1, \cdots, \phi_p, \theta_1, \cdots, \theta_q$ are estimated. The common method of estimating these parameters is using *maximum likelihood estimation (MLE)*. *MLE* finds the parameters' values that maximize the data's likelihood function. The *MLE* estimates are similar to *least square estimates*, obtained by minimizing the sum of squares of the residuals.

Residuals are useful in checking whether a model has adequately captured the information in the data. A good model will yield residuals with the following properties [20]:

Table 2: Exponential smoothing methods classification based on trend and seasonal components.

Model	ACF	PACf
$ARIMA(p,d,0)$	Decaying exponentially and/or dumped sinusoid	Cuts off after lag p
$ARIMA(0,d,q)$	Cuts off after lag q	Decaying exponentially and/or dumped sinusoid
$ARIMA(p,d,q)$	Decaying exponentially and/or dumped sinusoid	Decaying exponentially and/or dumped sinusoid

1. The residuals are uncorrelated. If there are correlations between residuals, then information is left in the residuals that should be used in computing forecasts.

2. The residuals have zero mean. The forecasts are biased if the residuals have a mean other than zero.

3. The residuals have constant variance.

All these properties must be satisfied so the model will meet the assumption of white noise errors. To check the non-autocorrelated property of the residuals, the study used *Ljung-Box test*[9]. *Ljung-Box test* tests the null hypothesis that the errors are uncorrelated.

2.4 Seasonal ARIMA Model

SARIMA or Seasonal ARIMA is an extended algorithm that has a seasonal component along with the Autoregressive Integrated Moving Average method. The model has additional parameters and is written as $ARIMA(p,d,q) \times (P,D,Q)_m$, where m is the seasonal period, while P, D, and Q are the seasonal autoregressive, seasonal differencing and seasonal moving average orders, respectively [6]. The model is expressed as

$$\Phi_P(B)\phi_p(B)(1-B)^d(1-B^m)^D z_t = \Theta_Q(B)\theta_q(B)a_t \tag{22}$$

where

$$\Phi_P(B) = (1 - \Phi_1 B^m - \Phi_2 B^{2m} - \cdots - \Phi_P B^{Pm})$$

and

$$\Theta_p(B) = (1 - \Theta_1 B - \Theta_2 B^{2m} - \cdots - \Theta_q B^{Qm}).$$

The SARIMA modeling procedure is not very different from the (non-seasonal) ARIMA; only that the seasonal parts are identified separately.

The K-order seasonal differencing of a series y for time t is given by

$$(y_t - y_{t-m})^K.$$

The order of the seasonal differencing D in equation (22) can be identified in the combination of the non-seasonal differencing order d. The lowest K and k at which the differenced series becomes stationary will be the seasonal and non-seasonal differencing order, i.e., $D = K$ and $d = k$. Meanwhile, the seasonal lags of PACF and ACF will be used to determine the order of the seasonal autoregressive and seasonal moving average parts of the SARIMA.

2.5 Model Comparison and Selection

The general modeling procedure uses the ACF and PACF to identify the orders of the autoregressive and moving average parts in both ARIMA and SARIMA. However, there are times when it is not straightforward to identify the orders by just inspecting the ACF and PACF. Another way to select the order of the model is through a criterion. This study used *Akaike's Information Criterion (AIC)* [11] to choose the better model in the training phase. *AIC* both consider the likelihood and number of the parameters in the model. The *AIC* is given by

$$\mathrm{AIC} = -2\log(L) + 2N, \tag{23}$$

where L is the likelihood value and N is the total number of unknown parameters in the model. A model with a larger likelihood value is preferable when assessing two models with the same number of parameters. Furthermore, a model with fewer parameters is preferable when comparing two models with the same likelihood value. Thus, a model with a lesser *AIC* value is preferable. The study also utilized *Mean Absolute Error (MAE)*, *Mean Absolute Percentage Error (MAPE)*, and *(Root Mean Square Error (RMSE)* in selecting the better model.

The study's main objective is to build a forecasting model for the rice stock of the Philippines. Hence, the forecasting performance of the model needs to be measured. The test set is utilized to evaluate the forecasting performance of the model. The study used *Mean Absolute Error (MAE)*, *Mean Absolute Percentage Error (MAPE)*, and *(Root Mean Square Error (RMSE)* to assess the performance of the model in forecasting.

All the results are generated from **R** programming language [17]. The package used in generating the results is *forecast* [21, 22].

3 Results and Discussion

3.1 Philippine Rice Stock

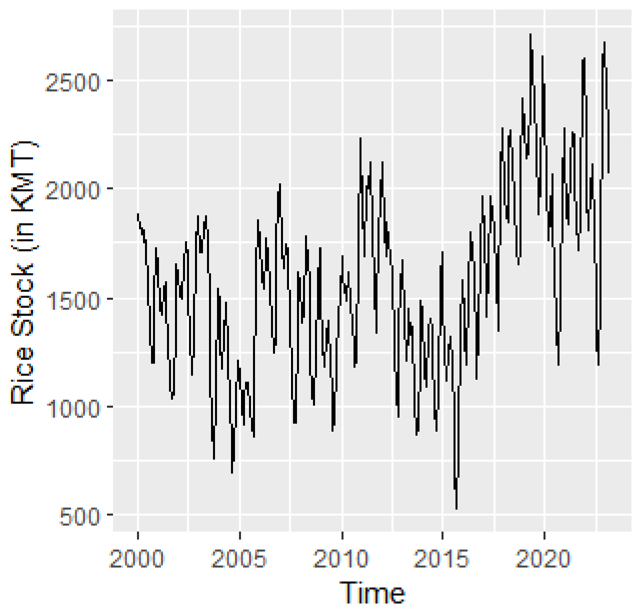

Figure 1: Plot of the monthly total number of rice stock (per kilo metric tonne) in the Philippines from January 2000 to March 2023

Figure 1 shows the monthly total number of rice stocks in the Philippines obtained from the OpenStat website utilized as the time series data [16]. The Philippine rice stock shows an overall gradual increasing trend. This trend is more apparent from 2016 to 2020. The study used the *Mann-Kendall Trend test* [12] to test formally whether the series has no monotonic trend. The test yielded $\tau = 0.264$ with $p - value < 0.0001$, implying evidence of a trend in the Philippine rice stock. The historical plot also suggests a cycle component in the series. The first cycle is from 2000-2008, and the second is from 2009 to 2022.

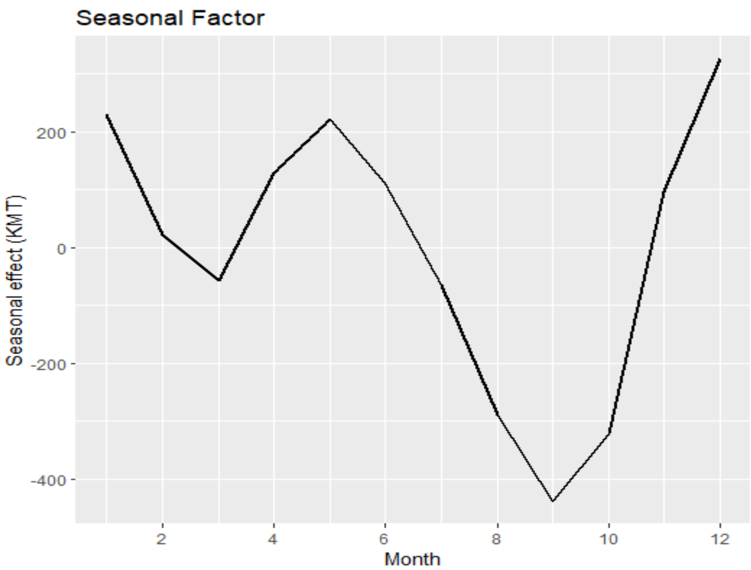

Figure 2: Seasonal factor of each month in the Philippine rice stock.

Regarding seasonality, the peak of the seasonality is constant and does not change much as it moves along with time. Figure 2 shows the seasonal effect of each month in the Philippine rice stock. From Figure 2, it can be observed that the Philippine rice stock seems higher every January, May, and December compared to other months of the year. In contrast, the months where the stock seems lower are from August to October. Furthermore, this seasonal effect seems unaffected by the trend since no apparent behavior shows that the increasing trend over time amplifies this pattern.

3.2 Exponential Smoothing Methods

The Philippine rice stock exhibits both trend and seasonality patterns. Hence, only Holt-Winters smoothing models will be considered candidates for exponential smoothing methods since they have a smoothing parameter for trend and seasonality. The study sets the trend component as an additive state since according to [20], it is better not to consider a multiplicative trend because it produces a poor forecast. Meanwhile, the seasonal component is also set to an additive state since the seasonal pattern's behavior seems unaffected by the trend, as shown in Figure 1.

There are four possible models of Holt-Winters smoothing with an additive trend and additive seasonality. Table 3 shows the training performance of these four models.

Upon assessing the Holt-Winters smoothing models, Holt-Winters with additive error performed better compared to those models with multiplicative errors in the training set since they have smaller values of *RMSE*, *MAE*, *MAPE*, and *AIC*. On the other hand, the performance of those models with additive errors is very close. Holt-Winters(A, A, A) has smaller *AIC*. This means that among the Holt-Winters models, Holt-Winters(A, A, A) is the better choice.

Table 3: ETS model performance comparison based on the training data.

Model	Training Performance			
	RMSE	MAE	MAPE	AIC
Holt-Winters(A, A, A)	98.77	74.72	5.4	3288.18
Holt-Winters(A, Ad, A)	98.58	74.67	5.39	3289.33
Holt-Winters(M, A, A)	105.30	81..42	5.89	3333.77
Holt-Winters(M, Ad, A)	102.71	78.8	5.69	3330.93

3.3 Box-Jenkins Methods

Before the model development process begins, the determination of the stationarity of the data is essential. As discussed, the Philippine rice stock has trend and seasonal components. These characteristics are indicative of non-stationary time series data. Observing also the ACF in Figure 3, the ACF is decaying quite slowly and also exhibiting a periodic pattern. This slow decaying pattern suggests non-stationary that may be attributed to either trend or seasonal components.

Meanwhile, PACF doesn't exhibit slow decay, but the periodic pattern is still apparent, as shown in Figure 3. This suggests that the non-stationarity of the data may be attributed greatly to seasonal components. The *ADF test* result in Table 4 for $d = 0$ and $D = 1$ confirms that the series is not stationary since the null hypothesis that the data is non-stationary is not rejected.

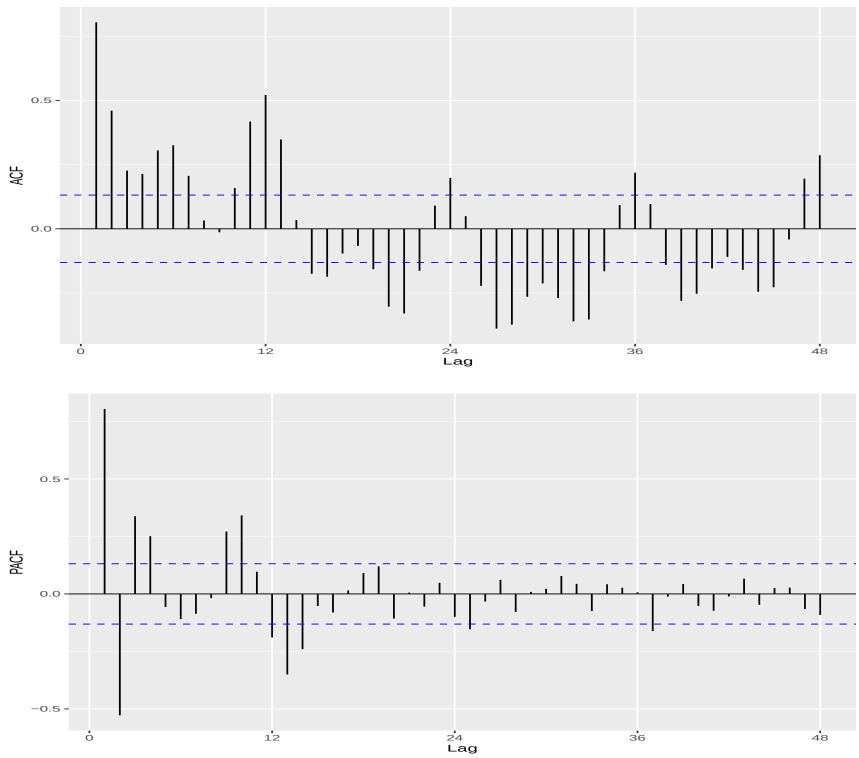

Figure 3: The autocorrelations and partial-autocorrelations of the training set.

The study tested the stationarity condition of the differenced series when *(i)* $d = 1$ but $D = 0$, *(ii)* $d = 0$ but $D = 1$, and *(iii)* both $d = 1$ and $D = 1$. From Table 4, the differenced

Table 4: Augmented Dickey-Fuller Test results for different lags.

Dickey-Fuller Statistics	Non-seasonal Differencing Order d	Seasonal Differencing Order D
-1.5683	0	0
-14.8244*	1	0
-3.3205*	0	1
-11.1356*	1	1

*Significant at 5% level of significance

series satisfy the stationary condition for each combination of non-seasonal and seasonal order of differencing.

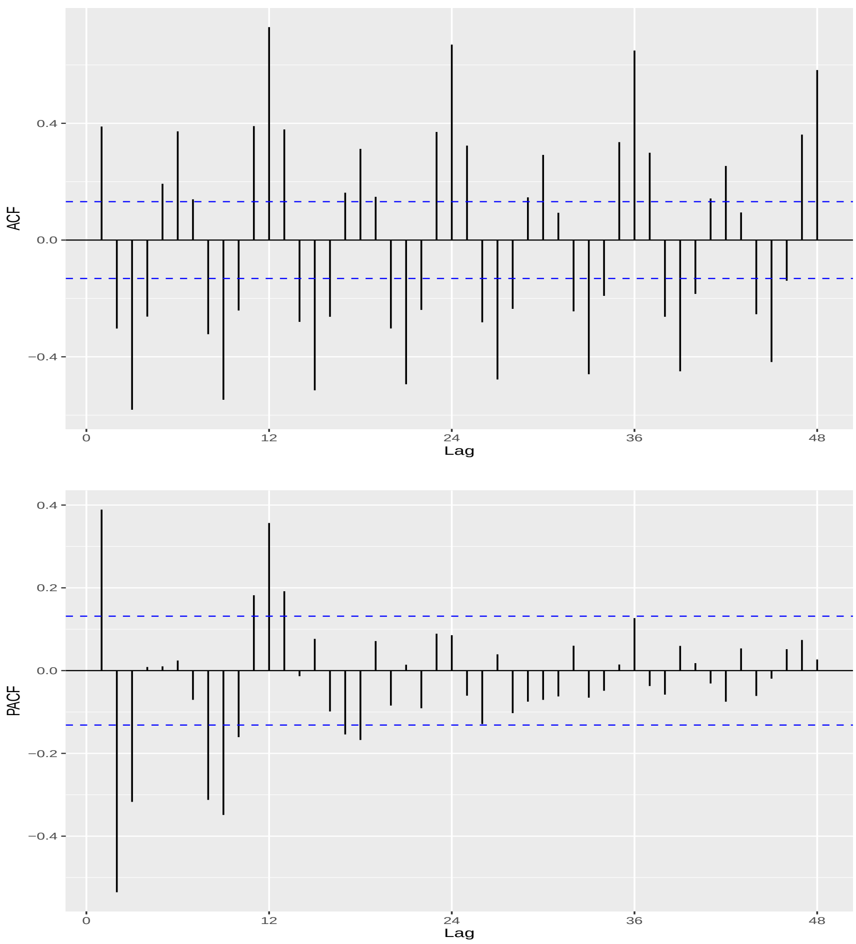

Figure 4: The autocorrelations and partial-autocorrelations of the first difference ($d = 1$) training set.

To gain insights into the possible order of non-seasonal and seasonal parts of the ARIMA, the correlograms of cases $d = 1, D = 0$, $d = 0, D = 1$, and $d = 1, D = 1$ presented in the Figure 4, Figure 5, and Figure 6, respectively, were investigated. Based on Figure 4, there is no sign that

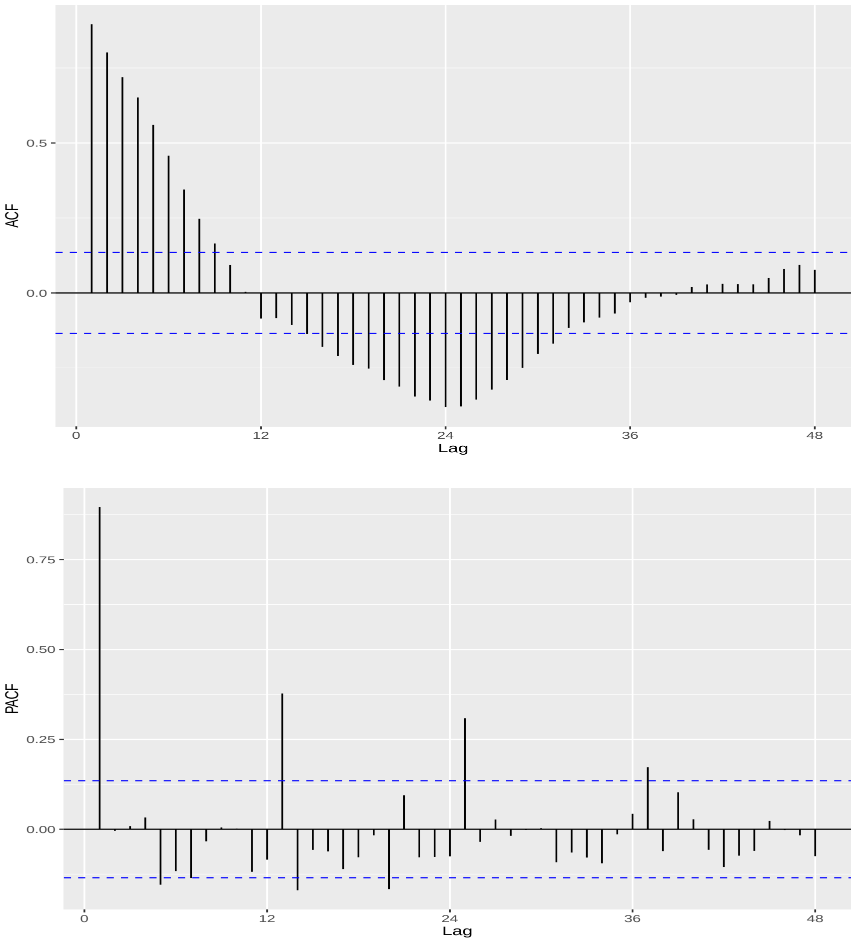

Figure 5: The autocorrelations and partial-autocorrelations of the first seasonal difference ($D = 1$) training set.

the ACF cuts off at a particular lag. Meanwhile, the PACF shows significant values only within two seasons. The significant PACF value at lag 12 suggests that the seasonal AR order is $P = 1$. Significant values can be observed within a season for different lags, such as at lags 1, 2, 3, or even at lags 8 to 11. This observation may suggest non-seasonal AR orders $p = 1, 2, 3$ or higher orders such as $p = 8, 9, 10, 11$. However, higher non-seasonal AR orders may lead to complex models and, hence, less desirable. Thus, based on these observations, the first-order difference series may follow models such as $ARIMA(1, 1, 0) \times (1, 0, 0)_{12}$, $ARIMA(2, 1, 0) \times (1, 0, 0)_{12}$, or $ARIMA(3, 1, 0) \times (1, 0, 0)_{12}$.

The ACF decays in a sign-wave fashion for the first-order seasonally difference series, suggesting a possible zero-order MA in both non-seasonal and seasonal components (see Figure 5). Meanwhile, significant PACF values can be observed for up to three seasons. The spikes at lags 13, 25, and 37 may suggest a seasonal AR order $P = 3$. In addition, the largest spike at lag one may be a signal for non-seasonal AR order $p = 1$. The presence of some significant PACF values, such as at lags 5, 14, or 20, may also suggest higher non-seasonal AR orders but are less desirable since they lead to very complex models. Thus, the first-order seasonally difference series may follow a $ARIMA(3, 0, 0) \times (1, 1, 0)_{12}$ model.

In the case of the series, which has undergone both first-order and first-order seasonal differencing, only ACF values at lag 12 and lag 33 are significant at a 5% significance level (see

Figure 6). This suggests a possible non-seasonal MA order of $q = 0$ and seasonal MA order of $Q = 1$. Meanwhile, significant PACF values can be observed for every 12 lags until lag 48. This suggests a possible seasonal AR order of $P = 4$. Thus, a possible model for the series with $d = 1$ and $D = 1$ is $ARIMA(0, 1, 0) \times (4, 1, 1)_{12}$.

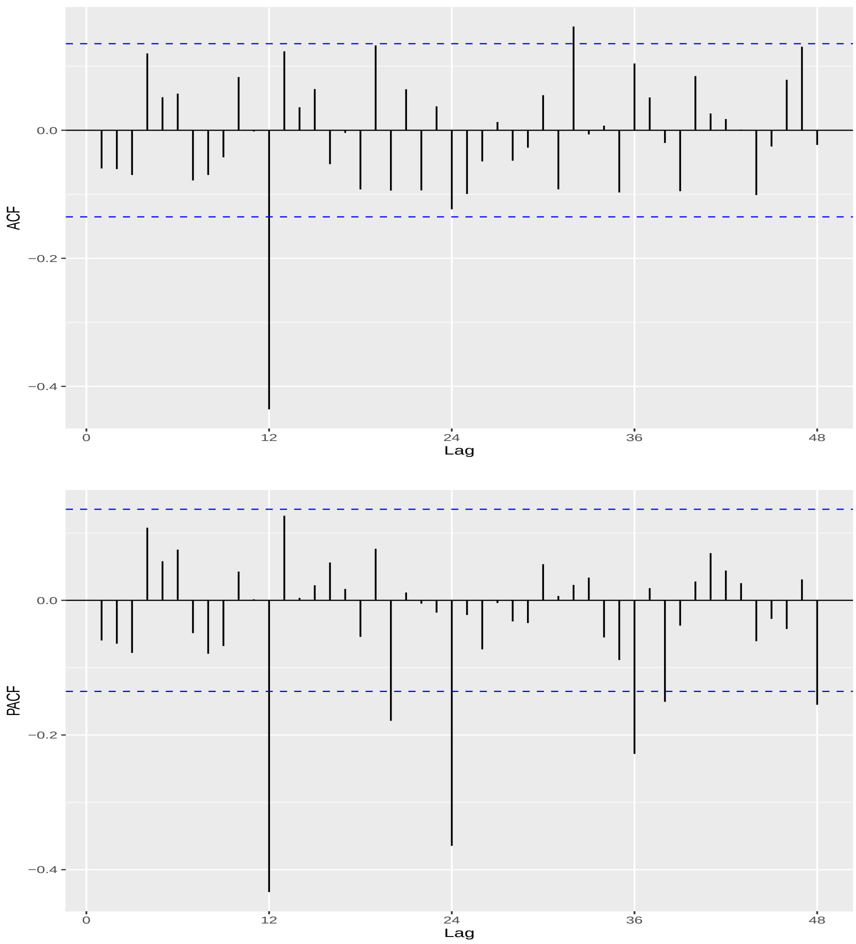

Figure 6: The autocorrelations and partial-autocorrelations of the first seasonal ($D = 1$) and non-sesaonal ($d = 1$) difference training set.

Based on the investigation on the ACF and PACF of different cases for differencing, the study considered $ARIMA(p, d, q) \times (P, D, Q)_{12}$ models with $d = \{0, 1\}$, $D = \{0, 1\}$, $p = \{0, 1, 2, 3\}$, $q = \{0, 1\}$, $P = \{0, 1, 2, 3, 4\}$, and $Q = \{0, 1\}$. The inclusion of lower-order models is due to the rule of parsimony in modelling. The rule of parsimony in modelling states that an adequate model with fewer parameters is expected to generalize better than another adequate but more complex model. Each time series model has undergone diagnostic checking and checking the stationarity and invertibility conditions. The summary of the training performance of the top five SARIMA models according to AIC that satisfy the assumptions is presented in Table 5.

Upon comparing different SARIMA models, $ARIMA(0, 1, 0) \times (0, 1, 1)_{12}$ performed the best based on AIC. It also has a very close value of MAE, MAPE, and RSME with other models. From Table 3 and Table 5, the $ARIMA(0, 1, 0) \times (0, 1, 1)_{12}$ generally outperformed the Holt-Winters(A, A, A) on training performance based on the AIC values. However, the Holt-Winters(A, A, A) exhibits slightly lower RMSE, MAE, and MAPE values.

Table 5: Performance comparison based on the training data of the SARIMA models.

Model	Training Performance			
	RMSE	MAE	MAPE	AIC
$ARIMA(0,1,0) \times (0,1,1)_{12}$	102.3535	76.5844	5.5266	2571.58
$ARIMA(3,1,0) \times (2,1,1)_{12}$	100.1835	75.9157	5.5228	2572.74
$ARIMA(3,1,0) \times (0,1,1)_{12}$	100.9787	76.2664	5.5270	2573.10
$ARIMA(0,1,0) \times (1,1,1)_{12}$	102.3668	76.6074	5.5338	2573.42
$ARIMA(0,1,1) \times (0,1,1)_{12}$	102.3579	76.5921	5.5298	2573.56

3.4 Forecasting Model

The main objective of this study is to build a forecasting model for the Philippine rice stock. Between $ARIMA(0,1,0) \times (0,1,1)_{12}$ and Holt-Winters(A, A, A) , the latter shows better performance in the testing phase as shown in Table 6. It has lower RMSE, MAE, and MAPE than the $ARIMA(0,1,0) \times (0,1,1)_{12}$.

Table 6: Test performance of Holt-Winters(A, A, A) and $ARIMA(0,1,0) \times (0,1,1)_{12}$.

Model	Testing Performance		
	RMSE	MAE	MAPE
Holt-Winters(A, A, A)	264.1482	216.6350	11.0792
$ARIMA(0,1,0) \times (0,1,1)_{12}$	308.7103	252.2658	13.9021

The description of the errors of Holt-Winters(A, A, A) is shown in Figure 7. The residuals fluctuate around 0 based on its line plot and the histogram. This suggests that the residuals may have zero mean. To formally check this, the study tested the null hypothesis that the mean residual is zero using *t-test*. The *t-test* yielded a $t = 0.19082$ with p-value $= 0.8488$. This means the null hypothesis is not rejected at a 5% significance level. Furthermore, the ACF plot of the residuals shows very minimal significant lags. This suggests a possible non-autocorrelations of the residuals and is further supported by the *Ljung-Box test*, which yielded a $Q^* = 34.94$ with p-value $= 0.07958$. Thus, the hypothesis of having unautocorrelated residuals cannot be rejected at a 5% level of significance. These observations imply that it is safe to assume that the residuals of Holt-Winters(A, A, A) do not deviate from a white noise process.

After inspection, the final forecasting model for Philippine rice stock is the Holt-Winters(A, A, A). Its estimated parameters are shown in Table 7. The large value of α suggests that the current value has more weight than the past values in forecasting the future level of rice stock. In addition, the small values of β^* and γ imply that the slope of the trend component and seasonal components' slopes hardly change over time, respectively.

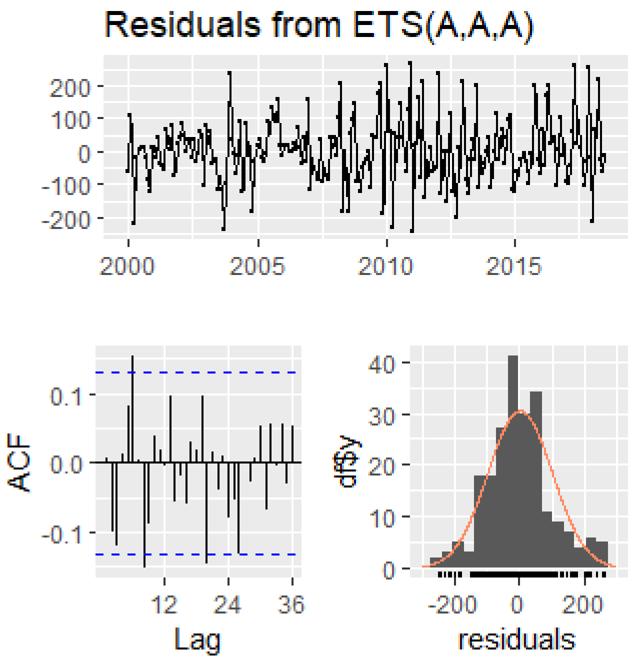

Figure 7: The residuals line plot (upper panel), autocorrelations (lower left), and histogram (lower right) if the Holt-Winters(A, A, A).

Table 7: Parameters of Holt-Winters(A, A, A).

Parameter	Value
α	0.9908
β^*	0.0002
γ	0.0003

3.5 Philippine Rice Stock Forecast

As Figure 8 shows, the Holt-Winters(A, A, A) forecasted a minimal decrease in rice stock from April 2023 to March 2024. Despite the gradually decreasing trend, a visible annual seasonal pattern was observed. Based on the forecasts, rice stock is expected to be highest in December 2023 with 2469.521 KMT and lowest in September 2003 with 1706.940 KMT. Furthermore, the total forecast for April 2023 to March 2024 is 25669.86 KMT or 25.66986 MMT. The historical rice consumption for 108.66 million Filipinos as of 2022 is around 12.9 MMT annually. If the rice consumption of the Filipinos will not drastically increase, then it is safe to say that there will be enough supply to demand in rice based on the forecasted values.

4 Conclusion

This study compares exponential smoothing and Box-Jenkins to forecast the Philippine monthly rice stocks (per kilo metric tonne) from January 2000 to March 2023. Among the exponential smoothing models, Holt-Winters(A, A, A) had a better overall performance in the training stage. Meanwhile, $ARIMA(0, 1, 0) \times (0, 1, 1)_{12}$ was the best among the trained SARIMA models. Be-

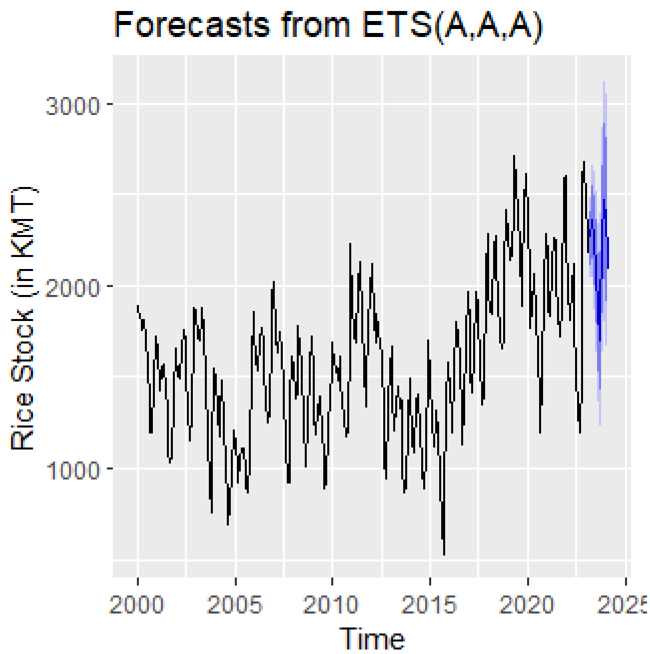

Figure 8: Historical plot with the one-year forecast (blue line) of monthly rice stock from April 2023 to March 2024 (blue line) using Holt-Winters(A, A, A).

tween the Holt-Winters(A, A, A) and $ARIMA(0,1,0) \times (0,1,1)_{12}$, the former had lower RMSE, MAE, and MAPE. However, the difference in these metrics was small, especially in the MAPE, where the difference was less than 0.2%. Using the AIC, the $ARIMA(0,1,0) \times (0,1,1)_{12}$ had a lower value suggesting a better fit in the training set.

The study evaluated the two candidate models using the forecasting errors to choose the final forecasting model. The data used as a testing set was the values from August 2018 to March 2023. Upon comparison, the Holt-Winters(A, A, A) was selected as the forecasting model for Philippine rice stock since it had lower forecasting errors.

Based on the Holt-Winters(A, A, A) forecasts, the Philippine rice stock may be enough to supply the country if there is no increase in the demand for rice until March 2024. However, it does not guarantee the rice stock stability in the succeeding years due to the extreme effects of climate change and increasing demand for rice, which is estimated to rise around 16 MMT by 2023-2024[15].

The study only used univariate time series models to forecast the Philippine rice stock. Because of this limitation, the researchers recommend investigating multivariate models. This may give better insights into understanding factors that affect the rice stock in the Philippines. Another worth studying is the spatiotemporal models. These models will help to model the rice stock for different locations simultaneously.

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