International Journal of Advanced and Applied Sciences, 12(9) 2025, Pages: 169-179

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Modeling and forecasting Malaysian rice production: Insights from ARIMA, Exponential Smoothing, and LSTM models

Nur Amalina Shafie *, Ain Raziha Rosli, Wan Nur Syuhada Wan Azmi

College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Cawangan Negeri Sembilan, Kampus Seremban, Negeri Sembilan 72000, Malaysia

A R T I C L E I N F O

Article history:
Received 24 October 2024
Received in revised form
22 March 2025
Accepted 17 August 2025

Keywords:
Rice production
Forecasting models
Agricultural practices
Food security
Sustainability strategies

A B S T R A C T

This study aims to forecast future rice production in Malaysia concerning national targets by comparing the effectiveness of three models: Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, and Long Short-Term Memory (LSTM). Unlike ARIMA and Exponential Smoothing, which are based on predefined statistical assumptions, LSTM uses deep learning to detect complex, non-linear, and long-term patterns in time series data. The performance of these models, applied to Malaysia's annual rice production data from 1960 to 2023, was evaluated using error measures such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Results showed that Double Exponential Smoothing produced the lowest error rates, making it the most accurate method for predicting rice production. While LSTM is considered a more advanced technique, it did not perform better than Double Exponential Smoothing in this case. The study concludes that predicted rice production levels are likely to fall below government targets over the next five years. This finding emphasizes the need to focus on sustainability strategies, such as reducing reliance on imports and enhancing domestic rice production. The results can guide policymakers in addressing future challenges, promoting sustainable agricultural practices, and ensuring Malaysia's long-term food security. Future research could explore using hybrid models in a multivariate setting and expanding datasets to compare regional and global rice production trends.

1. Introduction

Rice is significant in Malaysia, ranking third as the most vital crop after rubber and palm oil. It plays a pivotal role in Malaysians' daily diet, being the country's most widely cultivated and consumed grain (Dorairaj and Govender, 2023). Nonetheless, according to the Malaysian Adult Nutrition Survey, the adult population in Malaysia eats two and a half plates of rice on average per day. Rice production is concentrated in the Peninsular and Borneo Islands, with approximately 300,500 hectares dedicated to cultivation in the Malaysian Peninsular and 190,000 hectares on Borneo Island. Malaysia has directed its self-sufficiency efforts toward the production of rice and paddy, crucial components of the nation's staple food and food crop. Over the Twelfth Malaysian Plan (2021–2025), the aim is to enhance the capacity of the Agro-food sector towards becoming more sustainable, resilient, and high-tech, ensuring national food security and driving economic growth.

Asia has been producing more than 90% of the world's rice, mostly in China, India, Indonesia, and Bangladesh, with smaller amounts remaining from Japan, Pakistan, and a few countries in Southeast Asia. In addition, there are areas of Europe, South America, North America, and Australia where rice is also cultivated. After wheat, rice is the second most significant crop in the world, and Asia is both its greatest producer and consumer. The Malaysian government's 2011–2012 National Agrofood Policy made it clear that more local rice production is necessary to meet the nation's projected demands. However, it has not yet been demonstrated empirically to what extent this guarantees Malaysia's food security.

Based on Abidin et al. (2018), the world has been facing the challenge of decreasing rice production, that influenced the increase in rice prices at the same

* Corresponding Author.
Email Address: amalina@uitm.edu.my (N. A. Shafie)
https://doi.org/10.21833/ijaas.2025.09.016
Corresponding author's ORCID profile:
https://orcid.org/0000-0003-4522-1758

time. Hence, Malaysia is among the nations that have had to deal with the issue of surging rice prices. The price and availability of white rice in Malaysia have been the subject of discussion since July 2020, when India, the world's largest supplier, declared it would immediately cease exporting any non-basmati rice to reduce the growing domestic rice price in their country. The price of rice soared, and people went into panicked buying out of worry that they would run out of this fundamental item. As a result, this created a fuss among the locals.

The rising cost of imported rice in Malaysia has led consumers to shift toward cheaper locally produced rice. This situation has placed additional pressure on households that already struggle with the increasing cost of food. Since only about 70% of the country's rice demand is met by domestic production, the Malaysian government has introduced plans to expand local cultivation. Recently, 5-kilogram and 10-kilogram bags of locally grown white rice have been purchased quickly, leaving many smaller shops and supermarkets with empty shelves.

According to the managing director of Mydin Mohamed Holdings Bhd, the growing price gap between local and imported rice is the main reason for these shortages. In the past, imported rice was generally more expensive than local rice. Most imported white rice came from Thailand, Vietnam, India, and Cambodia. However, after Padiberas Nasional (Bernas), Malaysia's main rice distributor, raised the retail price of imported rice by 36 percent on 1 September 2023, the difference became more noticeable, reflecting global price increases. As a result, demand for the cheaper local rice grew rapidly. At present, the price of 10 kilograms of white rice ranges between RM30 and RM70.

Fig. 1 demonstrates the Global Rice prices rising from August 2022 to August 2023. In August, the Food and Agriculture Organization's All Rice Price Index reached 142.4, up 31 percent from the previous year due to a global insufficiency of white rice and India's rice export ban, which had been in place since July. Furthermore, the Agriculture and Food Security Minister announced further intervention measures to address the nation's rice supply problem, namely giving the Federal Agricultural Marketing Authority (FAMA) orders to expand domestic white rice distribution to the countryside, including through retail establishments. In addition to that, the government had decided to subsidize imported white rice for Sabah and Sarawak by RM950 per metric ton starting on 5 October 2023. This would allow Beras perintah import (BPI) to be purchased at a market price of RM31 per 10 kg. Local private-sector rice producers and distributors who have been controlling the food chain should work with FAMA to expedite the rice supply remedy. This implies that whenever necessary, such as in situations where there is an excess of supply, FAMA will be prepared to assist in reducing the expenses and duties associated with transportation and warehousing on behalf of the private sector. Simultaneously, the government can also function as an independent last-resort stockpiler.

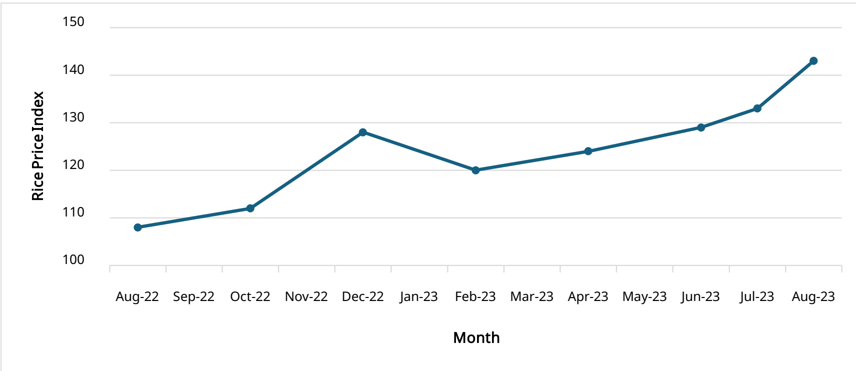

Fig. 1: Global rice prices are rising (FAO all rice price index)

Although rice is a major staple crop and a primary source of nutrition for the Malaysian population, the industry continues to face challenges that limit its growth and efficiency. The inconsistency of rice production can be linked to factors such as unpredictable weather conditions, poor soil fertility, nutrient imbalances, limited awareness, and insufficient knowledge among farmers. With a growing population, the demand for rice has steadily increased. In 2023, Malaysia produced only 1.75 million metric tons (MT) of rice, while national consumption reached 2.91 million MT. This gap highlights the inability of domestic production to fully meet local demand, forcing greater reliance on imported rice. To safeguard food security and maintain economic stability, it is necessary to strike a balance between imports and domestic supply. Proactive measures must therefore be implemented to strengthen local rice production and reduce dependence on imports.

Previous researchers have examined factors in agriculture such as meteorological parameters (Sharma et al., 2024), climate and soil conditions (Stetter and Cronauer, 2024), climate change (Habib-ur-Rahman et al., 2022), and climate change perception and adaptation among farmers (Sassi et al., 2024). Unlike previous research that analyzes various factors, this research limits its scope to univariate time series models to forecast agriculture, focusing on model selection and accuracy. Annamalai and Johnson (2023) explained a univariate time series analysis. A univariate analysis involves only one variable. A time series analysis examines a variable throughout time. Univariate time series analysis analyzes and forecasts a variable based on previous values and error factors. Example models that can be used to analyze univariate time series are ARIMA (Bezabih et al., 2023), Exponential Smoothing (Mgale et al., 2021; Nurviana et al., 2022; Bezabih et al., 2023), and Long Short-Term Memory (LSTM) (Banerjee et al., 2022; Saini et al., 2020; Wang et al., 2022). There are also numerous previous articles that compare models. For example, Annamalai and Johnson (2023) determined that the ARIMA model is the best model to use after comparing the ARIMA, Holt's exponential smoothing model, and Neural Network Autoregression (NNAR) model to analyze and forecast of area under cultivation of rice in India. Besides that, Nurviana et al. (2022) found that the Double Exponential Smoothing model is the best fit model after comparing ARIMA and Exponential Smoothing methods to forecast rice paddy production in Indonesia. In addition, Adiba et al. (2024) found that the LSTM-ARIMA hybrid is the best fit model after comparing it to the ARIMA, LSTM, and ARIMA-LSTM hybrid models to forecast rice production supplies in Indonesia.

This research uses forecasting techniques to look at past and future trends in rice production to ensure the long-term sustainability of rice production, focusing on Malaysia. Observing the trend helps to predict future time series data values and provides insights into underlying patterns and relationships within the data. Other than that, compared to most of the previous researchers in Malaysia, we used the ARIMA method to forecast rice production and compare it with exponential smoothing and LSTM. We employed the exponential smoothing method as it is relatively simple and easy to implement. Besides that, we chose ARIMA as another model to compare because it was capable of handling various patterns, including trends, seasonality, and non-stationary behavior. Both ARIMA and exponential smoothing methods often excel more in handling time series data, which is particularly suitable for univariate time series data with well-defined patterns, requiring less data pre-processing and being more interpretable due to their statistical foundations. In addition, one of the machine learning models is the LSTM model, which was also compared in this research. LSTM is a popular technique for time series data classification, processing, and prediction since its feedback connections and ability to accommodate any input sequences (Wang et al., 2022).

Hence, the research objective is to determine the best model to forecast the rice production in Malaysia between Box-Jenkins, Exponential Smoothing, and Long Short-Term Memory methods. Three models were examined to determine the best model. The model with the highest accuracy was chosen as the best model, as accuracy makes the result of forecasting the trend more precise. In addition, the objective of this research is to forecast the rice production in Malaysia five years ahead.

2. Methodology

In this study, two univariate time series methods were compared: the Box–Jenkins ARIMA model and the exponential smoothing method, which included both Single Exponential Smoothing and Double Exponential Smoothing. In addition, a machine learning approach, LSTM, was applied for comparison. The time series data on rice production were obtained from Index Mundi, a reliable commodity price index, and measured in MT. The secondary dataset consisted of annual rice production figures, covering 64 observations from 1960 to 2023.

2.1. ARIMA model

The Box-Jenkins methodology is also known as the time series modeling approach (Yasmin and Moniruzzaman, 2024). It is particularly associated with the ARIMA modeling. ARIMA is a commonly utilized time series analysis and forecasting method that merges autoregressive and moving average components through differencing to achieve stationarity. In this research, we choose ARIMA due to its suitability for predicting future trends in a time series by leveraging its historical patterns. A basic illustration of the model, described by ARIMA(p, d, q), could be expressed as Eq. 1.

$$Y_t' = \mu + \phi_1 Y_{t-1}' + \phi_2 Y_{t-2}' + \cdots + \phi_p Y_{t-p}' + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{1}$$

where, $Y_t' = Y_t - Y_{t-1}$ and μ is constant value. Based on Fig. 2, there are three main phases that characterize the essential procedure of Box-Jenkins modeling, which are:

1. Model Identification
2. Model Estimation and Validation
3. Model Application

Before continuing with those steps, data partitioning should be done to ensure that the models generated are accurate and can be implemented on new data, which is essential to developing, validating, and assessing models. The data partitioning was allocated into two sections, specifically 80% of estimation and 20% of evaluation. The Autocorrelation function (ACF), partial autocorrelation function (PACF), and the Unit Root Test using the Augmented Dickey-Fuller (ADF) test can all be used to evaluate stationarity. The ADF test is employed to examine the stationarity of a time series, which is an underlying assumption for many statistical models in time series forecasting. Stationarity implies that the statistical parameters of the series remain unchanged over time. The existence of a unit root in a time series indicates non-stationarity, and the data series should undergo differencing to make the series stationary.

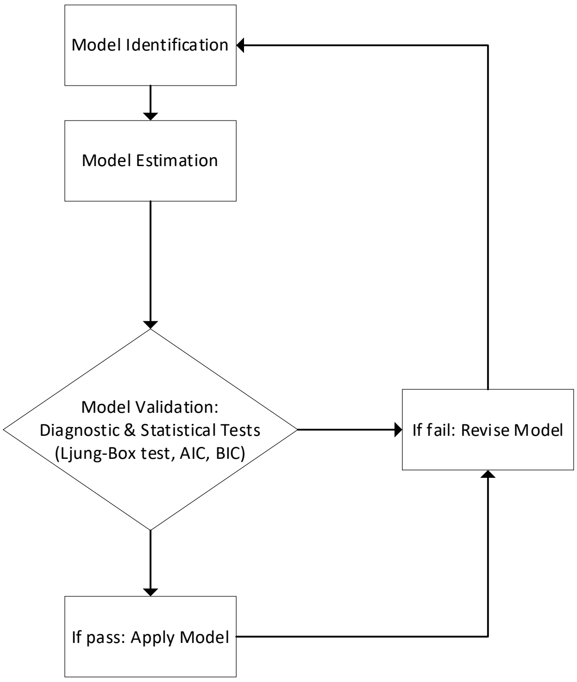

Fig. 2: General stages in ARIMA modeling (Lazim, 2000)

The hypothesis testing of the ADF test, and the decision rule of this test are provided below:

H_0: The production of rice yearly is not stationary
H_1: The production of rice yearly is stationary

2.1.1. Model identification

In this phase, the most appropriate model class was determined through the computation, analysis, and plotting of diverse metrics from past data, ensuring its suitability for application to the dataset. The level of differences necessary to accomplish stationarity in the time series was determined in this process. If the time series data is not stationary, a different process will take place. On the other hand, if the time series data is stationary, the procedure will proceed to the next step. Differencing is important as it helps to eliminate the trend component, remove seasonality, and remove autocorrelation. Therefore, making the data stationary. Listed below are the steps in the procedure of the process of model identification:

1. Difference (I): The initial stage involves examining whether differencing is necessary to make the time series stationary. If the series manifests a trend or seasonality, applying differencing can stabilize both the mean and variance. The order of differencing can be identified when the data becomes stationary, and it must be confirmed by the ADF test. Based on Solo (1984), typically, the second order of differencing suffices for most economic time series. Consequently, the first differencing order is articulated as Eq. 2.

$$\Delta y_t = y_t - y_{t-1} \quad (2)$$

First-order differencing is usually enough for handling time series data. However, second-order differencing can be required if the data shows erratic fluctuations or non-constant intervals.

2. ACF and PACF: After differencing, the ACF and PACF are examined to detect potential orders for the AR and MA components.

3. Identification of orders:

- Order of AR: The number of lag observations incorporated into the model
- Degree of differencing: The number of different computations performed on the data to get stationarity
- Order of MA: The window size of the moving average.

2.1.2. Model estimation and validation

In this phase, the primary goals are to achieve the best-fitting model and fulfill two essential objectives. The first one is that the predicted values should be nearly equivalent to the actual values. Then, the models should be parsimonious while providing a strong fit. When both objectives were successfully met, different statistical tests could be employed to evaluate the fitness and adequacy of the model. Several standard statistical measures, including Akaike's Information Criterion, known as AIC, the Bayesian Information Criterion, known as BIC, the Ljung-Box Statistic, the Root Mean Square Error (RMSE), and the Mean Absolute Percentage Error (MAPE), were employed for the validation of ARIMA models. A common statistic used to assess an ARIMA model's fitness is Akaike's Information Criterion (AIC). It calculates how each additional term introduced to the model affects the likelihood. Thus, if the additional term does not increase the likelihood by a factor larger than the penalty, it is not justified to include it in the model. An AIC score below that of every other competing model indicates a greater fit for the model. Eq. 3 can be used to determine AIC.

$$AIC = e^{\frac{2k}{T}} \frac{\sum_{t=1}^{T} e_t^2}{T} \quad (3)$$

where, k is the number of parameters estimated in the model; T is total number of observations in the data series.

The Bayesian Information Criterion (BIC) is used to decide the models that provide perfect accurate prediction accuracy by achieving an equilibrium trade-off between the complexity of the model and its fitting accuracy. Compared to the AIC, the BIC penalizes the degrees of freedom as illustrated by the factor much more sharply. Based on the concept that the best model is the one with the lowest BIC value, the AIC and BIC are similar. The BIC formula is provided as Eq. 4.

$$BIC = T^{\frac{k}{T}} \frac{\sum_{t=1}^{T} e_t^2}{T} \quad (4)$$

where, k is the number of parameters in the estimated model, including the constant; T is total number of observations in the data series.

2.1.3. Model adequacy checking

Generally, a model is considered adequate if the residuals can improve projections. In other words, the residuals should be random, also known as white noise. The model is classified as inadequate if there are significant residual autocorrelations at low or seasonal lags, requiring the selection of a new or updated model. The Ljung-Box Q statistic provide the overall checking of model adequacy. The Q test statistics are represented as Eq. 5.

$$Q = n(n+2) \sum_{k=1}^{m} \frac{r_k^2(e)}{(n-k)} \quad (5)$$

where, $r_k^2(e)$ is the residual autocorrelation at lag k; n is the number of residuals; k is the time lag; m is the amount of time lags to be tested

It has $m-r$ degrees of freedom and is approximately distributed as a chi-square random variable. If the p-value for the Q statistic is modest, the model can be declared as inadequate. A new or modified model should be discovered and analyzed until a good model is found. Two simple competing models might be able to accurately represent the data, and a decision could be made based on the type of forecast. Therefore, the hypothesis tests for the Ljung-Box test are:

H_0: The errors are random (white noise)
H_1: The errors are non-random (not white noise)

2.1.4. Model application

The final step involves identifying the best model. Additionally, it involves creating a system capable of managing the generated forecast values. The final model is regarded as suitable when it demonstrates randomness, identical distribution, and independence, with no serial correlation present in the error term. At that point, the model is ready to produce value. In the application phase of the ARIMA model, the finalized model is used to generate forecasts, which are then employed for strategic decision-making.

The smallest value of AIC and BIC is frequently used to identify the best model among competing models. By weighing the model's complexity against goodness of fit, these criteria assist in avoiding overfitting and choosing the model that best describes the data.

The values between models are compared once the AIC and BIC for each model have been determined. In general, the model that exhibits the lowest AIC and BIC values is considered optimal since it represents the optimal balance between fit and complexity.

Furthermore, the application of the Box-Jenkins methodology assumes that it addresses concerns related to the attributes of the original data series. Fundamentally, the assumption is made that the data is stationary. A series is considered stationary when it exhibits no discernible evolution over time. In simpler terms, the data series does not show the existence of a trendy component.

2.2. Exponential smoothing

Based on Fig. 3, the Basic Steps in the Exponential Model are as follows:

1. Set the initial value: Firstly, assign the starting value of the exponential model. The initial value is a start-up value before the computation using the formula. Employ the first data point in the series as the initial value or the average of the first five data points as the starting point.
2. Select parameter value: Then, determine the parameter values that are the best to minimize the error.
3. Generate the error terms and error measures: Use statistical techniques to generate error terms and error measures.
4. Calculate the error terms and error measures: Next, calculate the error terms such as MSE, RMSE, and MAPE for each forecasted value by subtracting the actual observed value from the forecasted value. Then, compare the collected error measure to appropriate benchmarks or thresholds. More accurate forecasts are shown by lower values of MSE, RMSE, and MAPE.

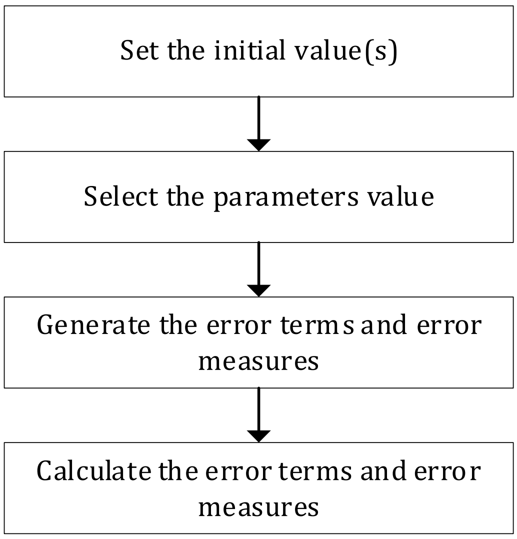

Fig. 3: General stages in exponential smoothing modelling (Lazim, 2000)

This research used 2 techniques of Exponential Smoothing:

1. Single Exponential Smoothing
2. Double Exponential Smoothing

2.2.1. Single exponential smoothing

A time series forecasting technique called Single Exponential Smoothing, also known as simple exponential smoothing, will forecast future values by utilizing a weighted average of historical observations. In modeling time series data, the most extensively utilized category of univariate methods is the exponential smoothing technique. This technique is particularly useful when the time series data shows a constant level with random fluctuations around that level. One of the advantages of using this technique is that it is easy to implement and computationally efficient. Single Exponential Smoothing is a simple yet effective technique for short-term forecasting when the time series data does not exhibit strong trends or seasonality. The single exponential smoothing equation can be derived by:

1. Set the initial forecast value
2. The forecast for the next period (t+1) is based on the current forecast F_t. The new forecast F_{t+1} can be computed as Eq. 6.

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t \tag{6}$$

3. For any period ($t+m$), the forecast can be formulated as Eq. 7.

$$F_{t+m} = \alpha Y_{t+m-1} + (1-\alpha)F_{t+m-1} \tag{7}$$

However, in practice, F_{t+m} for m > 1 is typically computed using the original equation. Therefore, the general equation for a single exponential smoothing method is given by Eq. 8.

$$F_{t+m} = \alpha Y_t + (1-\alpha)F_t \tag{8}$$

where, Y_t is the actual value for the period of t, alpha is the unknown smoothing constant to be determined with a value range between 0 to 1, or $0 \leq a \leq 1$ which is selected by the forecaster or determined by the data, and F_{t+m} is the single exponentially smoothed value in the period $t+m$, which is also defined as the forecast value when generated out of sample for m=1,2,3,...

2.2.2. Double exponential smoothing

Double Exponential Smoothing is a time series forecasting technique that extends basic exponential smoothing to address trends in data. It's particularly useful when the time series exhibits both a level (average) and a trend component. This method involves two smoothing formulas, one for the level `t and one for the trend b_t. When applying Double Exponential Smoothing for forecasting rice prices, historical rice price data will be used as the time series. The model would then update its estimates of the level and trend over time, thus providing forecasts for future periods.

This method consists of four main equations. The equations were listed in Eqs. 9-12 as follows. Eq. 9 represents the single exponentially smoothed value, while Eq. 10 evaluates the double exponentially smoothed value, which is denoted as S_t and S_t', respectively. Eq. 11 measures the difference between the smoothed values, a and b, while Eq. 12 calculates the adjustment factor.

$$S_t = \alpha y_t + (1-\alpha)S_{t-1} \tag{9}$$
$$S_t' = \alpha S_t + (1-\alpha)S_{t-1} \quad 10)$$
$$\alpha_t = 2S_t - S_t' \tag{11}$$
$$b_t = \frac{\alpha}{1-\alpha}S_t - S_t' \tag{12}$$

From Eqs. 9-12, for each time, t, let S_t be the exponentially smoothed value of Y_t, and S_t' be the double exponentially smoothed value of Y_t at the time, t. Determining the size of a constitutes an enormous difficulty when employing this technique. Thus, the solver is used to determine the value of a. Forecasts for m-step-ahead are calculated using Eq. 13 for forecasting purposes.

$$F_{t+1} = \alpha_t + b_t \times m \tag{13}$$

where, F_{t+1} is the forecast made period m made in period t, for m = 1,2,3,4, ... Therefore, for example, pf m=1, m=2, and so forth. When m initially starts with 1, the forecast value is

$$F_{t+1} = \alpha_t + \beta_t \times 1$$

while for m=2,

$$F_{t+1} = \alpha_t + \beta_t \times 2$$

2.3. LSTM

The LSTM model fully utilizes memory for forecasting time series data. The LSTM model's gated and feedback-based cell architecture enables long-term memory. Using autocorrelation in the time series allows for highly accurate and exact forecasts. LSTM is like Recurrent neural network (RNN) in that both use a feedback network to propagate information from past states, but their feedback networks differ. RNN processes all information recorded in previous memory cells, whereas LSTM prioritizes information depending on its importance for the next memory cell. There are three gates in the unit cell of LSTM, which are the input gate, output gate, and forget gate, along with one memory cell, as shown in Fig. 4.

All gates and memory cells work together to transmit information to the next LSTM cell. The input gate determines that the information from the current state input must be added to the memory cell.

The output gate selects useful information from the current memory state for the LSTM cell, while the forget gate selects relevant information from previous memory cells to keep in the current memory cell and discard unnecessary information.

The mathematical model describing the behavior of a single LSTM cell is shown in Eqs. 14-19.

$$f_t = \sigma\left(W_f . X_t + U_f . S_{t-1} + b_f\right) \quad (14)$$
$$i_t = \sigma(W_i . X_t + U_i . S_{t-1} + b_i) \quad (15)$$
$$\hat{C}_t = tanh(W_c . X_t + U_c . S_{t-1} + b_c) \quad (16)$$
$$C_t = (f_t \times C_{t-1})\left(i_t + \hat{C}_t\right) \quad (17)$$
$$O_t = \sigma(W_O . [S_{t-1}, X_t] + b_o) \quad (18)$$
$$S_t = O_t \times \tanh{(C_t)} \quad (19)$$

where, f_t, i_t, O_t represents the gate output of the LSTM cell; W_t, W_i, W_c, W_o represents the weights of the LSTM cell; b_t, b_i, b_c, b_o represents the biases of the LSTM cell; C_t represents the cell state; σ represent a sigmoid activation function which squeezes the values between [0,1].

The LSTM network's weights are changed during training to achieve optimal results and minimize training errors. LSTM can transmit sequential historical patterns by keeping crucial information from the data. This research was carried out in Google Colab using Python coding. The data was preprocessed by normalizing it with Min-Max scaling to ensure numerical stability and organizing it into overlapping 5-year sequences with the target year as the output. The model was trained on 80% of the data, and the remaining 20% was evaluated using RMSE and MAPE.

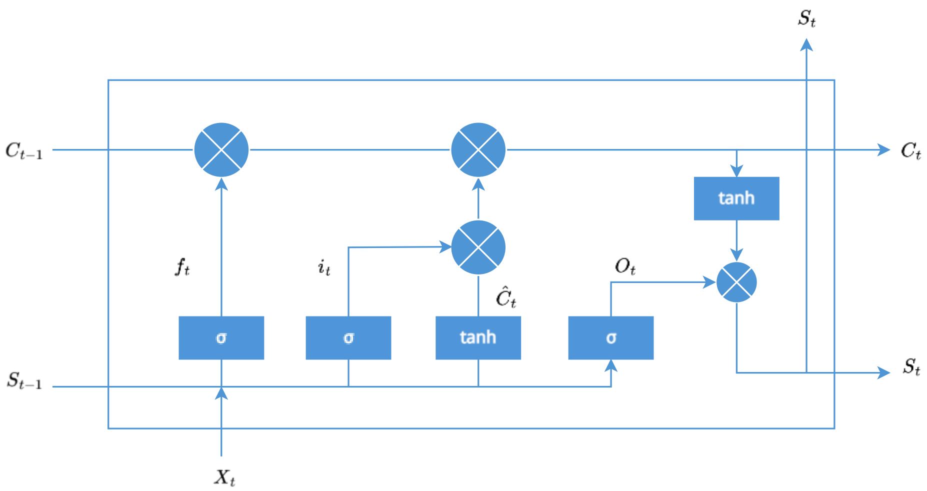

Fig. 4: LSTM cell architecture (Saini et al., 2020)

2.4. Model comparison

The assessment models will partition the data series into two segments. The initial segment, referred to as the estimation part, was employed for model estimation. The second segment is termed the validation segment, which is utilized to forecast the data series using the most accurately estimated model. One-fourth or twenty-five percent of the data is considered in the evaluation. The best-fitted model was found utilizing the RMSE and MAPE.

The magnitude of forecast errors is the standard criterion used to assess the performance of prediction accuracy. The discrepancy between the observed value and the forecasted value produced by the model is known as an error or residual. It is defined mathematically as Eq. 20.

$$e_t = Y_t - F_t \quad (20)$$

Error measures are employed to distinguish between a well-performing forecast and an inadequately modeled one. These metrics allocate a numerical evaluation of the model's precision by measuring the difference between expected values and actual results. A tighter match between forecasts and actual data is indicated by a smaller error measure, which denotes a more dependable and efficient forecasting algorithm. On the other hand, a larger error measure indicates possible weaknesses in the model's predictive ability by suggesting that the model's forecasts deviate noticeably from the observed values. Therefore, error measures are essential for analyzing the effectiveness and performance of forecasting models. Various types of error metrics exist; however, this research concentrated more on the two famous metrics, which are RMSE as Eq. 21 and MAPE as Eq. 22.

$$RMSE = \sqrt{\frac{\sum e_t^2}{n}} \quad (21)$$

where, $e = y_i - \hat{y}_t$; y_i is the actual measurement at time, t; $\hat{y}_t$ is the fitted value at time, t.

$$MAPE = \sum_{t=1}^{n} \frac{\left|\left(\frac{e_t}{y_t}\right) \times 100\right|}{n} \quad (22)$$

where, $\left|\left(\frac{e_t}{y_t}\right) \times 100\right|$ is described as the fitted value's absolute percentage error; n is the useful data points.

3. Results and discussion

In Fig. 5, a trend line shows that rice production in Malaysia follows a positive linear trend. Thus, the trend analysis of rice production in Malaysia shows several distinct periods of change. The linear trend of average rice production in Malaysia from 1960 to 2023 is captured by the equation y =

15.734x+792.99. On average, Malaysia's rice production has increased by about 15.734 metric tons each year. The data is split into two parts, which are the estimation and evaluation parts. The first 80% of the data is used for estimation, and the 20% for evaluation. After that, the ACF, PACF, and the Dicky-Fuller stationary test were used to assess the stationarity condition (Fig. 5).

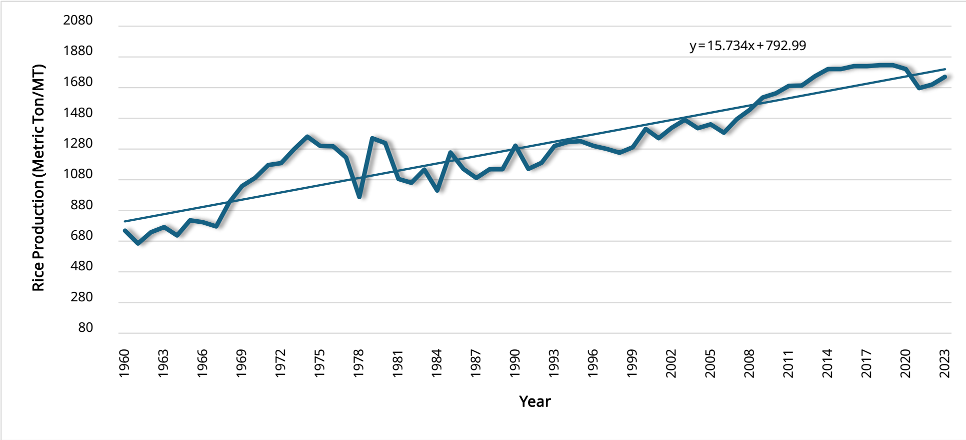

Fig. 5: Trend analysis for average production of rice in Malaysia

Based on Fig. 6, the ACF plot shows coefficients steadily fade to zero, indicating a potential non-stationary series. The PACF plot also suggests non-stationarity as the initial lags are significantly different from zero. Thus, Fig. 6 confirms non-stationarity. Hence, to address the non-stationarity, the initial differencing order known as d=1 was carried out to achieve stationarity. This process typically transforms the time series so that the mean and variance are constant over time, making it suitable for time series modeling techniques of ARIMA.

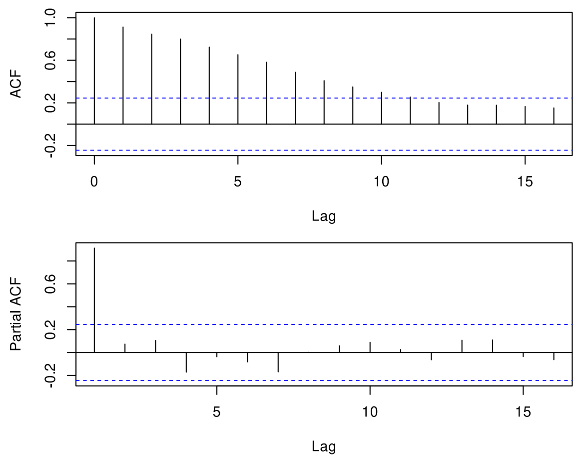

Fig. 6: ACF and PACF of the time series production of rice data

Fig. 7 shows the ACF and PACF results after the first order of differencing. The order of AR and MA was determined through a correlogram of ACF and PACF after the first order of differencing. The rice production fluctuates quickly at lag 1 for PACF, where the partial autocorrelation values turn negative, while for ACF, it fluctuates at lag 2, where the autocorrelation values turn negative.

The ACF shows 2 significant spikes at lag 1 and lag 2, while the PACF shows 3 spikes at lag 1, lag 2, and lag 3, where it exceeds the 2 standard error lines. Since the PACF shows 3 spikes, the p-value for AR for the ARMA model is AR(3), which is p = 3, while the q-value for MA for the ARMA model is MA(2), which is q = 2 since the ACF shows 2 spikes. Since the difference is done once before, the value of d is 1. The ordering of p and q for AR and MA might vary. We tested only 5 models out of 10 models of ARIMA that have the lowest AIC and BIC, which are ARIMA(0,1,1), ARIMA(1,1,0), ARIMA(1,1,1), ARIMA(2,1,1), ARIMA(2,1,2) ARIMA(2,1,3).

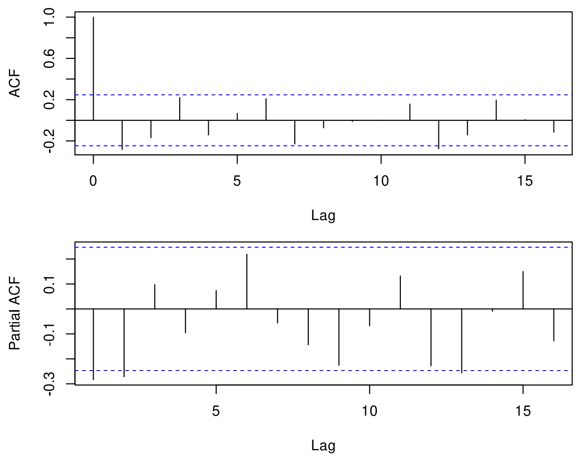

Fig. 7: ACF and PACF of time series production of rice data, 1st order differencing

The Ljung-Box Q statistic are used to check whether there is any serial correlation among the residuals for each model based on the 5% level of significance. It is assumed that the residuals from a well-fitted model exhibit white noise properties. If the residuals are white noise, there should be no significant ACF and no significant PACF. As a result, in Table 1, the residuals satisfy the stationarity condition. The best model is selected from the lowest AIC and BIC values. From Table 1, ARIMA(0,1,1) shows the lowest AIC and BIC values compared to the other models. Therefore, ARIMA(0,1,1) is selected as the best model for fitting the rice production with AIC and BIC of 566.0447 and 562.49, respectively. Table 2 shows that Double Exponential Smoothing has the smallest value of MSE and RMSE when compared with Single Exponential Smoothing and ARIMA(0,1,1). Despite having the biggest MAPE value, the MAPE value for Double Exponential Smoothing is still relatively close to the other two methods, resulting in only a small difference. Therefore, Double Exponential Smoothing was chosen as the best model as it has the lowest overall error measures when compared with the other two models.

Table 1: Summary of Ljung-Box, error, AIC, and BIC values

Number	Ljung-Box (p-value)	Errors	AIC	BIC
ARIMA(0,1,1)	0.19	White noise	566.04	562.39
ARIMA(1,1,0)	0.08	White noise	567.67	564.01
ARIMA(1,1,1)	0.13	White noise	569.87	565.31
ARIMA(2,1,1)	0.20	White noise	570.79	563.47
ARIMA(2,1,2)	0.09	White noise	792.29	808.01
ARIMA(2,1,3)	0.25	White noise	576.55	565.58

Table 2: Comparison of error measures between Box-Jenkins and exponential smoothing

Model	RMSE	MAPE
Single exponential	24.61	60543.65
Double exponential	22.3746	0.43
ARIMA(0,1,1)	359.63	9.26
LSTM	105.62	6.71

The value and the plot of actual and forecasted yearly rice production in Malaysia using the Double Exponential Smoothing technique are stated in Table 3 and Fig. 8. As we can see, the actual and the forecasted value of rice production do not much differ, and they were quite close to each other indicating that double exponential smoothing is an effective method for predicting the future trend of rice production. Nurviana et al. (2022) applied Exponential Smoothing and the ARIMA Box-Jenkins method to analyze rice paddy production in Aceh, Indonesia. The research found that the Double Exponential Smoothing model provided the best fit for the data pattern and was used to calculate Aceh's rice paddy productivity. Therefore, Double exponential smoothing's ability to account for trends makes it a powerful tool for forecasting in contexts where data exhibit clear trends, such as rice production in Aceh, Indonesia. The research supports this by demonstrating that this method best fits their data, leading to more accurate and reliable forecasts. Hence, the result is equivalent to supporting our result, as we get Double Exponential Smoothing as the best model. LSTM is not the best model for this data since the data is not large. Based on Staudemeyer and Morris (2019), LSTM can handle long time-dependent data with more than 1000 time steps.

Table 3: Forecast values for rice production in five years

Year	Forecast (MT)
2024	1735.82
2025	1740.69
2026	1745.57
2027	1750.45
2028	1755.32

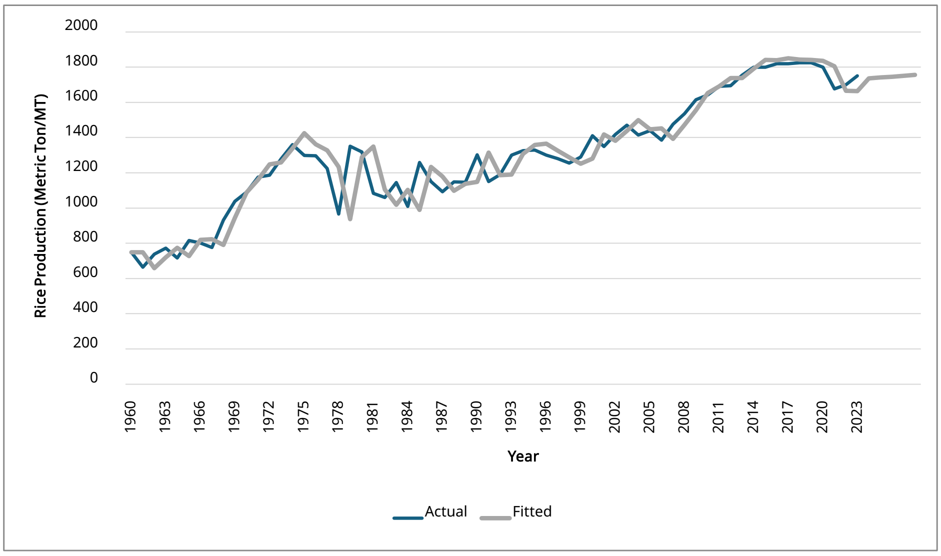

Fig. 8: Time series plot of the actual values and the forecasted values (2024 – 2028) by using double exponential smoothing

This research projects the values through 2028 because the Ministry of Agriculture and Food Security stated the desired value in that year. The Agriculture and Food Security Ministry has established specific production targets for white rice, with a gradual increase expected to reach 2,224,229 metric tons by 2028. However, the model forecasts indicate a lower production output than the ministry's targets. This suggests that potential obstacles such as inefficiency in agricultural techniques, climate variability, or resource limits may impede the attainment of these goals. This will enable better planning and resource allocation, helping to increase production and reduce reliance on imported rice. To overcome the inconsistencies and ensure sustainable rice production, this model offers accurate projections that aid in understanding and anticipating future rice production.

The projected developments have important ramifications for stakeholders. Farmers can use these projections to enhance planting schedules and implement new techniques, while governments can use them to steer investments and reforms. Furthermore, agricultural supply chain participants can use forecasts to optimize operations, resulting in efficient distribution and market stability. By incorporating these findings, this study helps to promote sustainable agriculture methods and supports Malaysia's long-term food security goals.

4. Conclusions

The main objective of the research was to determine the best model to forecast the rice production in Malaysia between ARIMA, Exponential Smoothing method, and Long Short-Term Memory Techniques throughout the year. Therefore, the models were fitted, and their performance was assessed via several error measures. Double Exponential Smoothing was found to outperform the other models in fitting rice production in Malaysia, compared to the other three models, since it has the smallest error measure value of RMSE and MAPE. This research also manages to forecast the future values of the production of rice for the next five years ahead using the best model obtained, which is Double Exponential Smoothing. The forecasted steady increase in rice production from 2024 to 2028, rising from around 1800 metric tons to close to 1950 metric tons, provides significant benefits for investors, entrepreneurs, farmers, policymakers, consumers, and companies. By using both historical data and forecasts for the future, these stakeholders may maximize their operations and make well-informed decisions. This research recommends analyzing using hybrid models and expanding the dataset to include regional and global rice production data.

List of abbreviations

ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller
AIC	Akaike's information criterion
ARIMA	Autoregressive integrated moving average
BIC	Bayesian information criterion
BPI	Beras perintah import
FAMA	Federal agricultural marketing authority
FAO	Food and agriculture organization
LSTM	Long short-term memory
MAPE	Mean absolute percentage error
MSE	Mean squared error
MT	Metric tons
NNAR	Neural network autoregression
PACF	Partial autocorrelation function
RMSE	Root mean squared error
RNN	Recurrent neural network

Acknowledgment

We would like to thank Universiti Teknologi MARA for their financial support through (600-RMC/GPM LPHD 5/3 (136/2021)).

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Abidin Z, Destiarni RP, and Septya F (2018). Reviewing government policy on rice price: Study through rice price in East Java market. In the Proceedings of the International Conference on Science and Technology (ICST 2018), Atlantis Press, Kuala Lumpur, Malaysia: 614-619. https://doi.org/10.2991/icst-18.2018.126

Adiba JIQ, Slamet J, Teguh AM, Septiyanto AF, and Sarno R (2024). Advanced deep learning and hybrid models for forecasting rice production in Indonesia. In the 11th International Conference on Information Technology, Computer, and Electrical Engineering, IEEE, Semarang, Indonesia: 302-307. https://doi.org/10.1109/ICITACEE62763.2024.10762812

Annamalai N and Johnson A (2023). Analysis and forecasting of area under cultivation of rice in India: Univariate time series approach. SN Computer Science, 4: 193. https://doi.org/10.1007/s42979-022-01604-0 **PMid:36778724 PMCid:PMC9897162**

Banerjee T, Sinha S, and Choudhury P (2022). Long term and short term forecasting of horticultural produce based on the LSTM network model. Applied Intelligence, 52: 9117–9147. https://doi.org/10.1007/s10489-021-02845-x

Bezabih G, Wale M, Satheesh N, Fanta SW, and Atlabachew M (2023). Forecasting cereal crops production using time series analysis in Ethiopia. Journal of the Saudi Society of Agricultural Sciences, 22(8): 546-559. https://doi.org/10.1016/j.jssas.2023.07.001

Dorairaj D and Govender NT (2023). Rice and paddy industry in Malaysia: Governance and policies, research trends, technology adoption and resilience. Frontiers in Sustainable Food Systems, 7: 1093605. https://doi.org/10.3389/fsufs.2023.1093605

Habib-ur-Rahman M, Ahmad A, Raza A, Hasnain MU et al. (2022). Impact of climate change on agricultural production; issues, challenges, and opportunities in Asia. Frontiers in Plant Science, 13: 925548. https://doi.org/10.3389/fpls.2022.925548 **PMid:36325567 PMCid:PMC9621323**

Lazim MA (2000). Introductory business forecasting: A practical approach. Univision Press, Los Angeles, USA.

Mgale YJ, Yan Y, and Timothy S (2021). A comparative study of Arima and holt-winters exponential smoothing models for rice price forecasting in Tanzania. Open Access Library Journal, 8(5): 1-9. https://doi.org/10.4236/oalib.1107381

Nurviana N, Amelia A, Sari RPSRP, Nabilla UNU, and Talib T (2022). Forecasting rice paddy production in Aceh using Arima and exponential smoothing models. CAUCHY: Jurnal Matematika Murni dan Aplikasi, 7(2): 281-292. https://doi.org/10.18860/ca.v7i2.13701

Saini U, Kumar R, Jain V, and Krishnajith MU (2020). Univariant time series forecasting of agriculture load by using LSTM and GRU RNNS. In the IEEE Students Conference on Engineering and Systems, IEEE, Prayagraj, India: 1-6. https://doi.org/10.1109/SCES50439.2020.9236695

Sassi M, Ali Y, and Ali I (2024). Climate change perception and adaptation among farmers in the mountains of western Karakoram, Pakistan. Development in Practice, 35(1): 3–20. https://doi.org/10.1080/09614524.2024.2417249

Sharma A, Kumar J, Redhu M, Kumar P, Godara M, Ghiyal P, Fu P, and Rahimi M (2024). Estimation of rice yield using multivariate analysis techniques based on meteorological parameters. Scientific Reports, 14: 12626. https://doi.org/10.1038/s41598-024-63596-6 **PMid:38824223 PMCid:PMC11637069**

Staudemeyer RC and Morris ER (2019). Understanding LSTM–A tutorial into long short-term memory recurrent neural networks. Arxiv Preprint Arxiv:1909.09586. https://doi.org/10.48550/arXiv.1909.09586

Stetter C and Cronauer C (2024). Climate and soil conditions shape farmers' climate change adaptation preferences. Agricultural Economics, 56: 165–187. https://doi.org/10.1111/agec.12870

Wang J, Si H, Gao Z, and Shi L (2022). Winter wheat yield prediction using an LSTM model from MODIS LAI products. Agriculture, 12(10): 1707. https://doi.org/10.3390/agriculture12101707

Yasmin S and Moniruzzaman M (2024). Forecasting of area, production, and yield of jute in Bangladesh using Box-Jenkins ARIMA model. Journal of Agriculture and Food Research, 16: 101203. https://doi.org/10.1016/j.jafr.2024.101203