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Forecasting Indonesia's Corn and Rice Production Using Box-Jenkins Approach: Implications for National Food Security

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ABSTRACT

Ensuring reliable the production of staple food is precondition to achieve food security, especially on the challenge of climate change and voaltile demands. Forecasting the production of food crops is essential for fabricating effective policies to maintain national food security in Indonesia. This study aims to forecast corn and rice productions using the Box-Jenkins methodology as additional information for supporting the decision tools for food security planning. Competing models were evaluated using information criteria and forecast accuracy measures such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The model specification used were: Corn production ARMA (2.0), while Rice production used SARIMA (0.1.4)(0.1.1)$_{12}$*. This model generate the forecast of both commodities from late 2025 to 2027. The result of this study can be a consideration for policymakers in making policy on food security in Indonesia.*

Keywords: *Food Security, Box-Jenkins, Forecasting*

Introduction

Food security constitutes a central pillar of national stability and sustainable development in Indonesia, where rice and corn function as the two most strategic staple commodities in terms of caloric intake, price formation, and rural economic resilience. Although Indonesia is classified as an upper-middle-income country and consistently ranks as one of the world's largest producers and consumers of rice, recent national food security indicators continue to signal structural vulnerability, particularly in terms of household food access and price stability. Based on the Global Food Security Index, Indonesia was ranked 83rd out of 113 countries in the Sustainability and Adaptation dimension, indicating that its food system remains relatively vulnerable compared with several neighboring Southeast Asian countries (Economist Impact, 2025). Meanwhile, data from Statistics Indonesia (BPS) indicate that average per capita expenditure on rice increased by 19.29% in 2024 compared to 2023, reflecting a substantial rise in the economic burden of staple food consumption for Indonesian households (Badan Pusat Statistik Indonesia, 2024). Episodes of food inflation, where rice prices surged by approximately 32.26% from 2021 to 2025, further indicate that Indonesia's food security system has not yet attained a fully stable equilibrium(Zakia, 2025). These vulnerabilities have elevated food security to the highest level of national policy priority, particularly since it was positioned as a core agenda in the early political vision of the current national leadership, emphasizing food sovereignty, domestic production strengthening, and the reduction of import dependence (Secretariat Cabinet of the Republic of Indonesia, 2025)

From the supply perspective, national rice and corn production exhibit long-term upward trends but remain characterized by significant interannual fluctuations. According to BPS, national unmilled rice production reached approximately 54.53 million tons, while corn production reached around 14.00 million tons during the January–August period of the latest year (Badan Pusat Statistik Indonesia, 2025). However, production growth has not been consistently stable, with notable declines occurring during climate anomaly years such as El Niño and La Niña, when rice and corn decreased(Ardiyansah et al., 2022). On the demand side, rice consumption remains structurally high at around 112,1 kg per capita per year (National food agency, 2024) while national corn demand continues to increase, driven by the livestock feed and agro-industry sectors, with approximately 87.83% of total national demand supplied by domestic production (Prasetyo et al., 2024). This widening pressure on domestic supply is exacerbated by persistent structural constraints in the agricultural sector, including climate variability, the increasing frequency of extreme weather events, land conversion estimated at 102 thousand hectares per year, rising fertilizer prices, and uneven yield performance across production regions (Inspectorate General of the Ministry of Agriculture, 2023).

The vulnerability of domestic food availability is further reflected in episodes of heightened import dependence during production shortfalls. During 2024, Indonesia imported approximately 4,52 million tons of rice and 1,5 million tons of corn to stabilize domestic availability and prices(Listiyorini, 2025; UkrAgroConsult, 2025). Even when imports represent a relatively small share of total national consumption, their sudden escalation during production shocks generates substantial fiscal pressure, political sensitivity, and market instability. Moreover, fluctuations in rice and corn prices during periods of supply stress directly affect household food access, particularly among low-income populations. Increases in retail rice prices and producer-level corn prices during such periods transmit production instability into broader socio-economic risks, including declining purchasing power and heightened food vulnerability.

Within this complex risk environment, reliable production forecasting becomes an indispensable instrument for evidence-based food security governance. Indonesia's medium-term development framework explicitly targets the dual objective of increasing staple food output while ensuring price affordability, including national production targets of 33,8 million tons of rice and 22,7 million tons of corn by 2026 (Xinhua, 2025). Achieving these targets requires a forward-looking production roadmap rather than reliance on retrospective trend evaluation. A two-year forecasting horizon is strategically critical because national planning for seed distribution, fertilizer allocation, planting area targets, food reserve management, and import regulation operates within multi-year budgetary cycles. Without credible short- to medium-term forecasts, policy instruments are likely to remain reactive, thereby weakening the state's capacity to anticipate supply shocks and stabilize domestic markets.

Based on these considerations, this study applies the Box–Jenkins time series approach to forecast rice and corn production in Indonesia as a quantitative foundation for strengthening food security planning. The central problem addressed in this research lies in the limited availability of accurate, statistically robust short-term production projections for Indonesia's two most vital staple commodities under conditions of high climatic and structural uncertainty. Accordingly, this study aims to generate reliable two-year production forecasts and to identify the most appropriate ARMA and SARIMA specifications based on rigorous statistical diagnostics and forecast accuracy measures. The results are expected to provide empirical support for more anticipatory, data-driven, and resilient food security policymaking in Indonesia.

Theoretical Framework And Hypothesis

The Autoregressive Integrated Moving Average (ARIMA) and its derivative variants are one of the time-series methods that are often used to perform non-stationary historical series analysis. This model works through a differentiating process to stabilize the variance and mean so that autocorrelation patterns can be clearly captured by the moving average and autoregressive components. This approach was introduced systematically through the Box-Jenkins framework which has been a major cornerstone in statistical forecasting for a long time.This method is also widely used in the agricultural sector because it can follow production patterns influenced by weather dynamics, price changes, planting cycles, and other external factors.

The ARIMA model remains relevant for various food commodities such as rice and corn as evidenced by previous studies. For example, in rice commodities, this trend can be seen from the many studies that use ARIMA to project production at the regional and national levels. According to research by Sultana & Khanam (2020) explained that the model provides good performance in short-term forecasting. The results of the study show that the Box-Jenkins approach is able to respond to production fluctuations due to variations in annual rainfall and seasonal shifts, two of which are the main factors that greatly affect rice production in Bangladesh.

The results are strengthened by a study conducted by Rosadi et al., (2024) that compared ARIMA for rice production in Sumatera. The researchers found ARIMA perform more accurately resulting the low MAPE in the model. Other study by Rosyid et al. (2019)which found that incorporating seasonal components through SARIMA significantly lower MAPEon forecasting the Indonesa import commodity.

Research on the seasonal model was also conducted by (Sulistijanti & Vayuanita, 2023)Widyaningrum et al. (2023) combining the SARIMA and Fuzzy Time Serious models to project rice production in Central Java Province. The combined model shows that it is able to improve the accuracy of predictions in the medium term with SARIMA's sharpness in capturing seasonal patterns and the FTS's superiority in adjusting for nonlinear trends. These findings show that rice is a commodity that requires a strong seasonal approach, especially in countries with regular planting patterns such as in Indonesia.

Meanwhile, the literature on corn commodities shows that ARIMA is often superior to seasonal models because corn production does not always follow the same rigorous cycle as rice. According to Badmus & Ariyo (2011), ARIMA is used to model maize production in Nigeria because the model is more effective in capturing short-term fluctuations. Studies in Indonesia also show a similar trend. This finding is also in line with research by Julyanti et al., (2025)) in West Nusa Tenggara Province which shows that the ARIMA model remains competitive by forecasting corn productions.

Overall, the existing studies show a consistent pattern. Commodities such as corn that do not have a dominant seasonal pattern tend to use ARIMA, while rice commodities with an annual pattern are more suitable to use SARIMA. The findings provide a strong methodological basis for selecting the ARIMA (2.0) model for corn and SARIMA (0.1.4)(0.1.1)12 for rice. This approach is theoretically consistent and aligned with empirical evidence from various international and national studies

Research Methods

Samples and Sampling Techniques

The data in this study is a time-series data consisting of Indonesia Rice Production and Corn Production. The rice production data consist of monthly observations from January 2018 to August 2025, while corn production from January 2020 to August 2025. The data were derived from the Badan Pusat Statistik Indonesia (BPS), each data series represent the monthly total production (in tons). The data is processed and analysed using Eviews 13 software, which provides built-in tools for time-series modelling.

Box-Jenkins methods is one of the traditional statistical model utilised to forecast timeseries data. In the Box-Jenkins method, it focuses on the Autoregressive Integrated Moving Average (ARIMA) models and the seasonal extensions. By the assumption that the past data is consistent with future data, the Box Jenkin Models assume the past and future data are linear(Chodakowska et al., 2021). The Box-Jenkins Method is an iterative process consisting model identification, estimations, and diagnostic checking to build the best fits for forecasting data.

In Model Identification, the data are examined for stationary and seasonality (if it has seasonality characteristics). Stationary check involves the graph check and statistical check. Most of the stationary check utilise the Augmented Dickey-Fuller (ADF) test to check for unit root. Plotting the autocorrelation function (ACF) and Partial autocorrelation function (PACF) are also analysed to look upon the possible model of autoregressive (AR) and moving average (MA).

Once the orders of models of ARIMA (p,d,q) or ARMA (p,q) and seasonal orders (P,D,Q) are acquired. The possible models are tested and estimated using maximum likelihood as implemented in the software. The best models amongst the selected possible models are determined by Akaike Information Criterion (AIC), Schwarz Criterion (SIC), and adjusted R-squared(Khan & Alghulaiakh, 2020).

Lastly, the residuals of the selected model are examined to ensure the model is behave white noise (no autocorrelation on the model) by utilising on the Ljung-box test on residual ACF and PACF to verify the models. If the diagnostic shows the model have autocorrelation, the other model is selected.

In the context of Box-Jenkins, ARIMA models are characterised by three parameters: p (AR order), d (differencing order), and q (MA order). The further model such as seasonal autoregressive moving average (SARIMA) models is utilised to identify seasons in yearly cycle in monthly or quarterly data.

Autoregressive (*p*) in ARMA and ARIMA is showing the dependence on the past value of data. The *p* is time series regression model of the Yt value predicted from linear combination of its observed past value (Wagner & Cleland, 2023). In other words, a higher autoregressive order p resepresent the productions level is influenced by longer past production value, following the amount of lag used. In equations, the p can be notated as follows:

$$Yt = \beta 0 + \beta 1Yt - 1 + \beta 2Yt - 2 + \cdots + \beta xYt - x + et$$

The moving average component (q) capture the influence of past disturbance on current value of series by using the residual of models as predictor(Royer-Carenzi & Hassani, 2025). The idea of this parameter q determine the impact of unexpected shock in the series. In equations, the q can be notated as follows:

$$Yt = \varepsilon t - \theta 1\varepsilon t - 1 - \theta 2\,\varepsilon t - 2 - \cdots.. - \theta x\varepsilon t - x$$

By combining the component of AR (p) and MA (q), the ARMA model can be achieved as notated below:

$$Yt = \beta 0 + \beta 1Yt - 1 + \beta 2Yt - 2 + \cdots + \beta xYt - x + \varepsilon t - \theta 1\varepsilon t - 1 - \theta 2\,\varepsilon t - 2 - \cdots.. - \theta x\varepsilon t - x$$

The differencing parameter d reflect the amount of original data need to be differenced to achieve stationary. By applying the differencing on the data, the data trend is eliminated, resulting the stationary data pattern. The number of d is based on the unit root test and visual obsverved of the data (Hanke & Wichern, 2014). An appropriate differencing order should render the data until it is stationary without over-differencing, which requires most of the data required one differencing before acquire the stationarity (Hanke & Wichern, 2014). The first order of the differencing can be notated as follows:

$$(Yt - Yt - 1) = \beta 0 + \beta 1(Yt - 1 - Yt - 2) \ldots. + et$$

By differencing the ARMA model, the ARIMA model has constructed as it consisted of AR (p), differencing (d), and MA (q). Hence, the model can be notated below:

$$\Delta Yt = \beta 0 + \beta 1\Delta Yt - 1 + \beta 2\Delta Yt - 2 + \cdots + \beta x\Delta Yt - x + \varepsilon t - \theta 1\varepsilon t - 1 - \theta 2\,\varepsilon t - 2 - \cdots.. - \theta x\varepsilon t - x$$

The further model of ARIMA to capture the seasonal behaviour is called Seasonal ARIMA or SARIMA (p,d,q)(P,D,Q)s model where the s is the length of the seasonal period. SARIMA model have an additional parameter on the seasonality, which also need to stationared. The stationaring the seasonality in SARIMA require the seasonal differencing following the amount of seasonality cycles (Hanke & Wichern, 2014). The equation of seasonal differencing can be notated below:

$$(Yt - Yt - 12) = \beta 0 + \beta 1(Yt - 1 - Yt - 13)$$

Subsequently, the seasonal differencing must be integrated with the non-seasonal differencing (normal differencing) to acquired the SARIMA model. The integrated differencing model can be notated as it follows:

$$(Yt - Yt - 1 - Yt - 12 + Yt - 13) = \beta 0 + \beta 1(Yt - 1 - Yt - 2 - Yt - 13 + Yt - 14)$$

or can be simplified as it follows:

$$\Delta(\Delta 12Yt) = \beta 0 + \beta 1(\Delta Yt - 1 - \Delta Yt - 13) + et$$

or

$$Wt = \Delta(\Delta 12Yt) = (Yt - Yt - 1 - Yt - 12 + Yt - 13)$$

more simplified as it integrated into SARIMA models:

$$Wt = \beta 0 + Wt - 1 + et - \theta 1\varepsilon t - 12 - x$$

The parameter of measuring the reliability of the model is observing the error rate of model. The smaller the model error, the greater accuracy acquired by the model. In order to measure the accuracy, several error measurement tools applied. The basic and convenient error measurement that can be represent the model accuracy are MAPE and RMSE(Khan & Alghulaiakh, 2020).

Mean absolute percentage error (MAPE) is the average percentage error of the actual value and the model predictions(Kumar & Vanajakshi, 2015). This assesment metrics express the percentage and can be defined as it follows:

$$MAPE = 100\% \times \sum_{t=1}^{n} \frac{|Yt - \hat{Y}|}{|Yt|}$$

Root Mean Squared Error (RMSE) is the square root of the mean square residual (Gilliland et al., 2016). This metric is used to evaluate the deviation of predictions from actual values in squares. Mathematically, RMSE is formulated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Yt - \hat{Y})}$$

Results And Discussion

Model Identification

In the Box-Jenkins methodology, the prerequisite before analysing the models is that the series must be stationary. A stationary process is characterised by the constant mean, variance, and autocovariance that depend on lag. Non-stationary series, rely on the trends and structural change in variance. Stationary can be assessed through the graphical and statistical approaches. Graphical approach involves the visual inspection by plotting the series and examining the fluctuation movement on the centered around the mean. However, the graphical approach is not solely adequate to determine the data pattern as it inherently subjective. A statistical method is used by analysing the unit root test as the Augmented Dickey-Fuller (ADF) are employed. A failure to reject the null hypothesis of a unit root in ADF test indicates the non-stationary data as the test based on the regression that includes the lagged difference term to high order autocorrelation on the data.

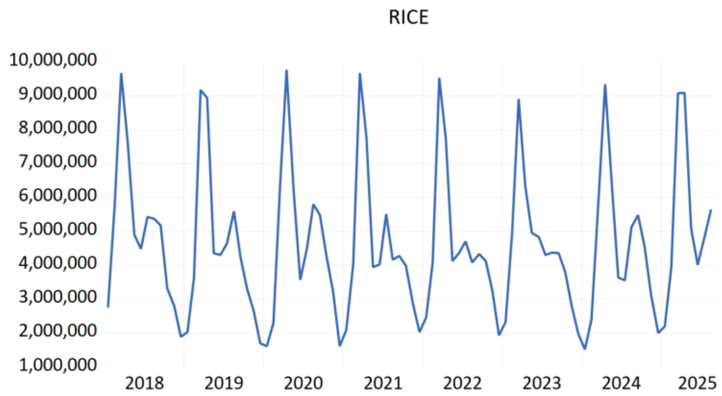


Figure 1
Indonesian Rice Production

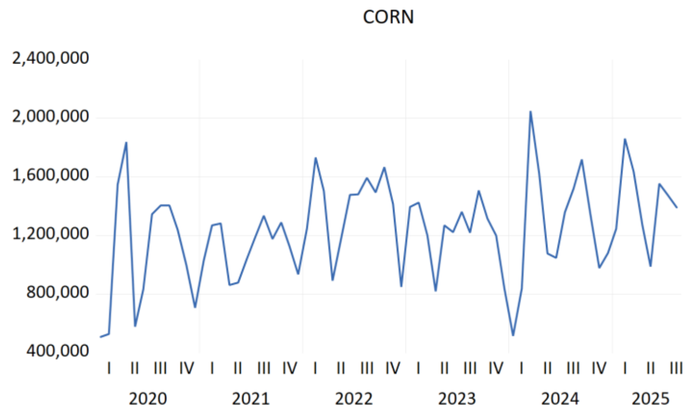


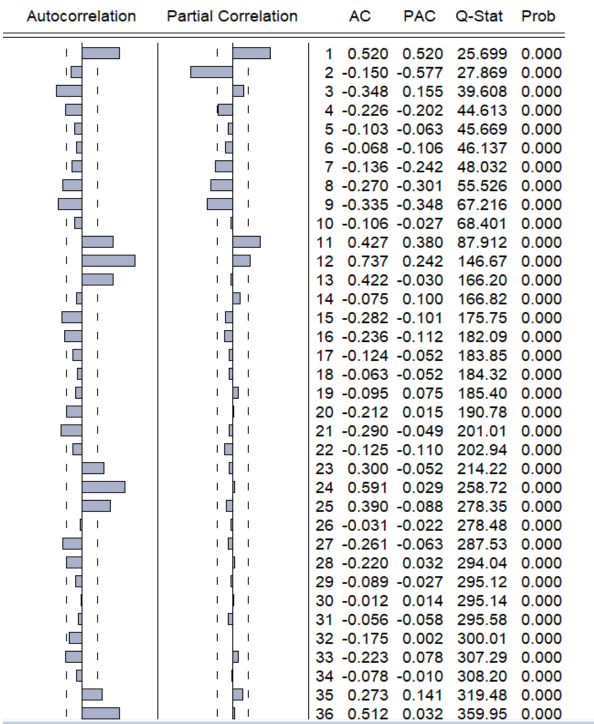
Figure 2
Indonesian Corn Production

The first datased is monthly Indonesia rice production from January 2018 to August 2025. A time series plotted in figure 1. By visual inspection, the data is fluctuate on the stable mean by the spanning timeline, suggesting the data might be stationary. The second series consist the monthly Indonesian corn production from January 2020 to August 2024, plotted in Figure 2, shows the corn production also appear fluctuative stable on the mean, suggesting the data might be stationary.

Table 1
Stationary Test Using ADF

Data	Level 0	Level 1
Rice Production Non-Seasonal	0.09741	0.0001
Rice Production Seasonal	0.09741	3.734614302813017e-07
Rice Production Final	-	1.036330338523242e-07
Corn Production	1.343971060988225e-10	-

Despite the visual interpretation, stationary cannot be assessed on the graphical plot. The ADF test is applied on each series to determine the unit root. The ADF test results are summarised on the table 1. In rice production dataset, the ADF p-value is 0.09741, which exceed the 5% significance level. As a result, the null hypothesis of unit root is cannot be rejected and can be assessed for the rice production is non-stationary at zero level. In order to achieve the non-seasonal stationary, first differencing is applied to the rice production series. After differencing, the ADF test result the p-value is 0.0001, less than 5% significance level. This findings indicating the first difference on the rice production reject the null hypothesis of unit root, thus the dataset is stationary at first level differencing.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.520	0.520	25.699	0.000
		2	-0.150	-0.577	27.869	0.000
		3	-0.348	0.155	39.608	0.000
		4	-0.226	-0.202	44.613	0.000
		5	-0.103	-0.063	45.669	0.000
		6	-0.068	-0.106	46.137	0.000
		7	-0.136	-0.242	48.032	0.000
		8	-0.270	-0.301	55.526	0.000
		9	-0.335	-0.348	67.216	0.000
		10	-0.106	-0.027	68.401	0.000
		11	0.427	0.380	87.912	0.000
		12	0.737	0.242	146.67	0.000
		13	0.422	-0.030	166.20	0.000
		14	-0.075	0.100	166.82	0.000
		15	-0.282	-0.101	175.75	0.000
		16	-0.236	-0.112	182.09	0.000
		17	-0.124	-0.052	183.85	0.000
		18	-0.063	-0.052	184.32	0.000
		19	-0.095	0.075	185.40	0.000
		20	-0.212	0.015	190.78	0.000
		21	-0.290	-0.049	201.01	0.000
		22	-0.125	-0.110	202.94	0.000
		23	0.300	-0.052	214.22	0.000
		24	0.591	0.029	258.72	0.000
		25	0.390	-0.088	278.35	0.000
		26	-0.031	-0.022	278.48	0.000
		27	-0.261	-0.063	287.53	0.000
		28	-0.220	0.032	294.04	0.000
		29	-0.089	-0.027	295.12	0.000
		30	-0.012	0.014	295.14	0.000
		31	-0.056	-0.058	295.58	0.000
		32	-0.175	0.002	300.01	0.000
		33	-0.223	0.078	307.29	0.000
		34	-0.078	-0.010	308.20	0.000
		35	0.273	0.141	319.48	0.000
		36	0.512	0.032	359.95	0.000

Figure 3
ACF and PACF Plot on Rice Production at Level

Monthly dataset mostly may contain the seasonality, especially on the agriculture dataset that typically associated with harvesting cycle and seasonal planting season. Investigating the presence of seasonality on the dataset is needed by plotting the autocorrelation fuction (ACF) and partial autocorrelation function (PACF) of the series. The correlogram in figure 3, shows the spikes at lag 12 and 24 in the ACF, which responding the annual seasonal in the data.

In order to remove the seasonal component, seasonal differencing is needed, by differencing the dataset with respect to the seasonal cycle which in this dataset is 12 months. The ADF test is performed on the seasonally differenced dataset. As it can be observed on the table 1, the p value of the differenced rice population is 0.000, which fall below 5% significance level. This result, reject the null hypothesis of unit root on the seasonality, indicating the the first order differencing remove the seasonality characteristic and alter the stationary on data.

Subsequently, the non-seasonal and seasonal differencing are combined to construct final form of rice production dataset that free from trend and seasonal component. The ADF test applied on the final transformed series in table 1, resulting the p-value of 0.000, confirming tat the data are stationary.

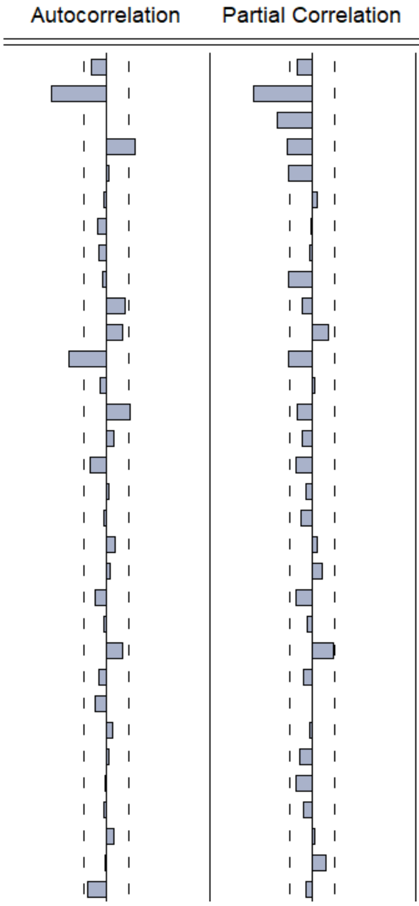
On the other hand, the corn production series shows the ADF test yield p-value 0.000 at zero level, below the 5% significance level. Therefore, the null hypothesis of unit root is rejected and the data is stationary at zero level. In addition, the correlogram of the corn series, as it shown on the figure 5, does not containt any spike at lag 12, suggesting there is no annual seasonal pattern on this series. The absent of seasonality characteristic and non-seasonal differencing in this series construct this series as ARMA model.

The next step in the Box-Jenksins Approach is model identification. This step utilised the ACF and PACF of the stationary series to detect the autoregressive (AR) and moving average (MA) component. Particularly, the the ARIMA (p,d,q) process the PACF is to imply the AR order as it cut off at lag p, while the ACF is used to identify the MA order at cutt off lag q. For SARIMA (p,d,q) (P,D,Q)s model, is applied throught the cut off at the seasonal lag.

According to the correlogram shown in figure 4. It shows the ACF has significant spike at lags 2 and 4, while the PACF decays gradually as the lag increase. This pattern where the ACF cut off at lag q while the PACF tails off indicating the characteristic of moving average process. Thus, the possible model for the non-seasonal component is on the between 2 and 4. Simultaneously, the significant spike also appears at lag 12 both in ACF and PACF, indicating the seasonality component on the seasonal AR and MA.

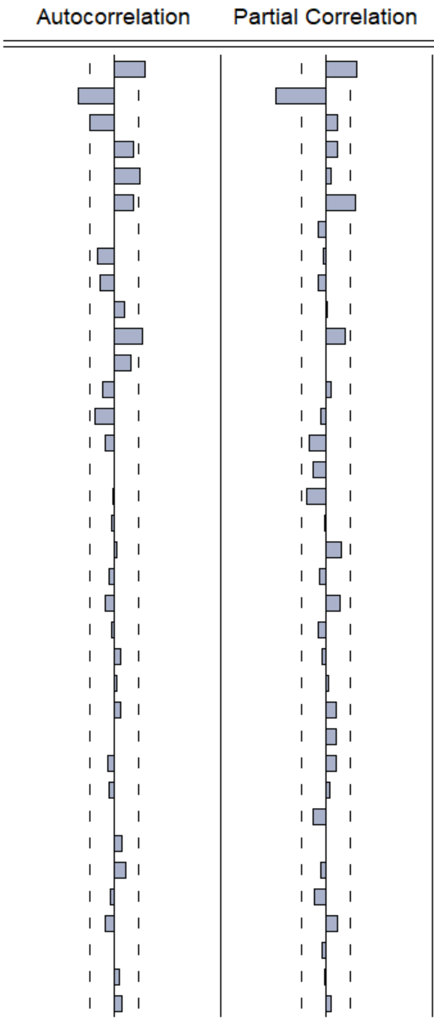
Based on correlogram, the candidate of SARIMA model of the rice production series, includes the seasonal differencing at order 1 and non-seasonal differencing of order 1. As it integrated based on the model identification of AR and MA on the non-seasonal and seasonal correlogram, the MA order q is between 2 and 4 and seasonal order of AR and MA are set either 1 or 0. Specifically the candidate can be listed: (0.1.4) (1.1.1)12, (0.1.4) (1.1.0)12, (0.1.4) (0.1.1)12, (0.1.3) (1.1.1)12. (0.1.3) (1.1.0)12, (0.1.3) (0.1.1)12, (0.1.2) (1.1.1)12, (0.1.2) (1.1.0)12, (0.1.2) (0.1.1)12.

For the corn production series, the correlogram in figure 5,]shows the pattern that the PACF significant spike at lags 1 and 2, while the ACF decays to zero as it increasing its lag. This pattern where the PACF cutting of at low lag and ACF tailing of is an autoregressive process. It shows the non-seasonal component of the corn production series is captured by AR model. Since the ADF test of this series is stationary at zero level. Hence, the appropriate candidate for this model include the ARMA (1.0) and ARMA(2.0).



	AC	PAC	Q-Stat	Prob
1	-0.154	-0.154	1.9428	0.163
2	-0.550	-0.588	27.083	0.000
3	-0.005	-0.360	27.085	0.000
4	0.290	-0.251	34.245	0.000
5	0.018	-0.244	34.274	0.000
6	-0.017	0.041	34.298	0.000
7	-0.088	-0.015	34.980	0.000
8	-0.076	-0.030	35.494	0.000
9	-0.033	-0.235	35.595	0.000
10	0.192	-0.100	39.022	0.000
11	0.169	0.170	41.702	0.000
12	-0.378	-0.232	55.330	0.000
13	-0.059	0.024	55.673	0.000
14	0.237	-0.154	61.213	0.000
15	0.075	-0.104	61.780	0.000
16	-0.170	-0.165	64.713	0.000
17	0.028	-0.063	64.796	0.000
18	-0.026	-0.120	64.866	0.000
19	0.083	0.048	65.605	0.000
20	0.036	0.096	65.748	0.000
21	-0.114	-0.169	67.181	0.000
22	-0.025	-0.043	67.250	0.000
23	0.166	0.210	70.398	0.000
24	-0.071	-0.092	70.982	0.000
25	-0.108	-0.001	72.357	0.000
26	0.059	-0.031	72.776	0.000
27	0.029	-0.129	72.879	0.000
28	-0.012	-0.164	72.898	0.000
29	-0.019	-0.093	72.944	0.000
30	0.080	0.021	73.771	0.000
31	-0.013	0.132	73.794	0.000
32	-0.186	-0.062	78.511	0.000

Figure 4
ACF and PACF Plot on Rice Production at First Order non-seasonal and seasonal Differencing



	AC	PAC	Q-Stat	Prob
1	0.302	0.302	6.4850	0.011
2	-0.359	-0.496	15.782	0.000
3	-0.236	0.111	19.846	0.000
4	0.185	0.110	22.384	0.000
5	0.248	0.043	27.015	0.000
6	0.188	0.290	29.727	0.000
7	-0.005	-0.076	29.729	0.000
8	-0.158	-0.018	31.702	0.000
9	-0.134	-0.080	33.153	0.000
10	0.091	0.015	33.832	0.000
11	0.278	0.187	40.290	0.000
12	0.157	0.007	42.383	0.000
13	-0.107	0.043	43.366	0.000
14	-0.188	-0.054	46.487	0.000
15	-0.093	-0.157	47.259	0.000
16	-0.003	-0.124	47.260	0.000
17	-0.009	-0.192	47.267	0.000
18	-0.027	-0.013	47.335	0.000
19	0.024	0.149	47.391	0.000
20	-0.054	-0.058	47.684	0.000
21	-0.087	0.136	48.456	0.001
22	-0.017	-0.077	48.486	0.001
23	0.061	-0.038	48.877	0.001
24	0.032	0.033	48.987	0.002
25	0.058	0.096	49.362	0.003
26	0.001	0.091	49.362	0.004
27	-0.060	0.100	49.776	0.005
28	-0.043	0.040	49.991	0.006
29	-0.007	-0.131	49.997	0.009
30	0.072	0.001	50.651	0.011
31	0.108	-0.056	52.143	0.010
32	-0.035	-0.113	52.303	0.013
33	-0.097	0.109	53.573	0.013
34	-0.007	-0.037	53.580	0.018
35	0.053	-0.016	53.980	0.021
36	0.076	0.053	54.835	0.023

Figure 5.
ACF and PACF Plot on Corn Production at Level

Model Estimation

In the model selection process, several statistical criteria used to find the Box-Jenkins models. Specifically, the adjusted R-Squared, Akaike information criterion (AIC), and Schwaz criterion (SIC) were examined for each candidate models. These metrics collectively balance the goodness of fit. In practice, good model is indicated with higher adjusted R-squared, lower AIC, and SIC value to other models. These criteria wiedley recommended for model selections as it penelasie unnecassry complexity of extra parameters.

Based on the result presented in table 2. The optimal model for Rice production is SARIMA (0.1.4) (0.1.1)12. This specifications show the highest adjusted R-squared value (0.7614) while also having the lowest AIC (30.3375) and SIC (30.5474). On the other hand, ARMA(2.0) Corn production model is selected because have the highest adjusted R-square (0.3042), lowest AIC (27.9654), lowest SIC (28.09)

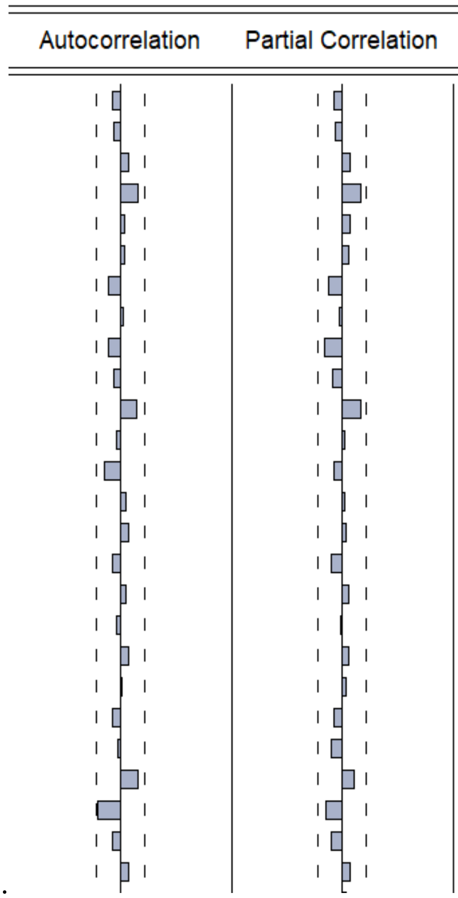
Table 2
Model Evaluation

Data	Model	Adjusted R-Square	AIC	SIC
Rice Production	(0.1.4) (1.1.1)12	0.757768837932816	30.362842712252	30.602786798578
	(0.1.4) (0.1.1)12	0.761492739266483	30.337526432319	30.547477507854
	(0.1.4) (1.1.0)12	0.575124485607388	30.616837759321	30.826788834856
	(0.1.3) (1.1.1)12	0.746013785522323	30.391113868267	30.601064943802
	(0.1.3) (0.1.1)12	0.750184807401785	30.365881926763	30.545839991508
	(0.1.3) (1.1.0)12	0.557512583131800	30.639122657176	30.819080721920
	(0.1.2) (1.1.1)12	0.729866144290382	30.430180340875	30.610138405619
	(0.1.2) (0.1.1)12	0.734497812746168	30.405025600349	30.554990654302
	(0.1.2) (1.1.0)12	0.529852274864292	30.678101417916	30.828066471870
	(0.1.1) (1.1.1)12	0.697255876175918	30.537614421400	30.687579475354
	(0.1.1) (0.1.1)12	0.702712905759576	30.512565592102	30.632537635265
	(0.1.1) (1.1.0)12	0.476316012677415	30.779353895054	30.899325938217
Corn Production	2.0	0.304226389564233	27.965474726800	28.096034003575
	1.0	0.07105455124778	28.2311823943418	28.3291018519231

Model Evaluations

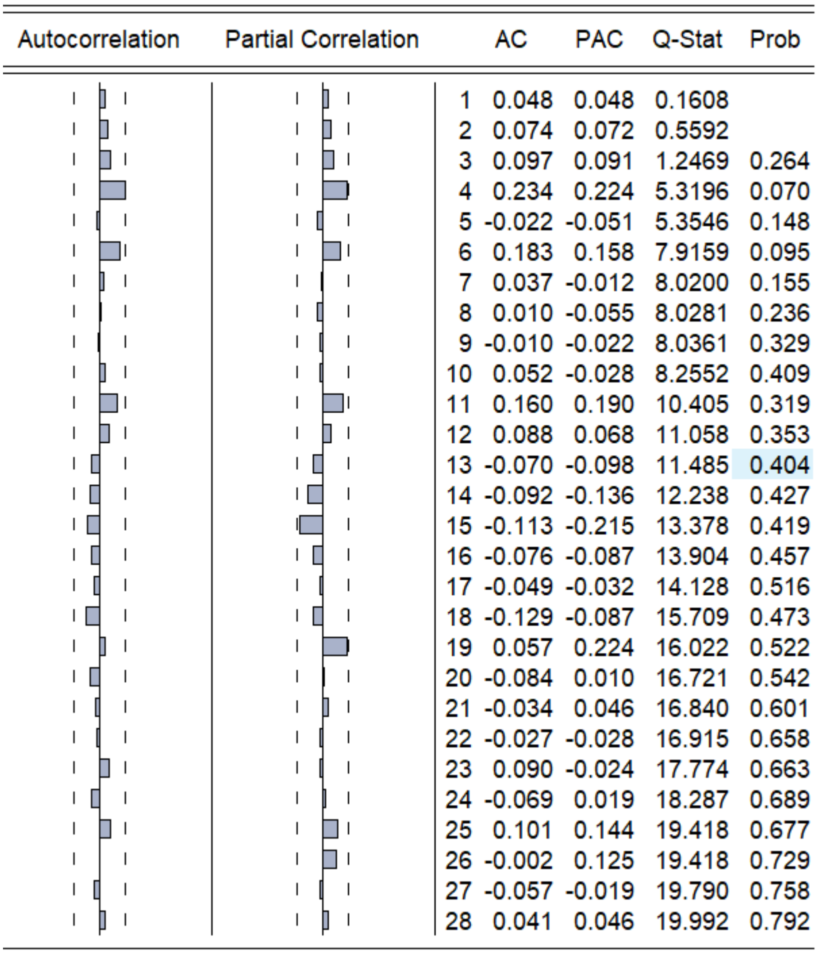
After the model have been selected, the next step in Box-Jenkin is to evaluate the model through diagnostic checking. The objective of this step is to verify wheter the residual of models behave white noise. Ideally, the residual should uncorrelate not correlate each other, because the residual error should not correlating with other residual error as it the error need to be random(Gujarati & Porter, 2009).

Diagnostic tool to detect the autocorrelation on residual must be examined on the autocorrelation function and partial autocorrelation of the residual. By applying the correlograms as it stated on the figure 6 and 7, the ideal Box-Jenkins model should avoid the autocorrelation or in other word, the correlogram of residual both in ACF and PACF should not statistically significant on spikes. The autocorrelations should fall within the confidence bonds. In addition, the formal examination through the Ljung-Box Q statistic employed to test the hypothesis. Figure 6 and 7 represent the p-value of the given lags for selected models. For both series, p-values of the Ljung-Box Q -statistics shows the lags are greater than the 5% significance leter. It is indicating the null hypothesis of no autocorrelation cannot be rejected, hence the both models shows it is white noise and can be regarded as adequate to take on further step of forecasting



	AC	PAC	Q-Stat	Prob
1	-0.066	-0.066	0.3555	
2	-0.061	-0.065	0.6628	
3	0.074	0.066	1.1269	
4	0.166	0.174	3.4808	
5	0.038	0.074	3.6059	
6	0.034	0.060	3.7100	0.054
7	-0.107	-0.126	4.7343	0.094
8	0.024	-0.032	4.7847	0.188
9	-0.108	-0.159	5.8437	0.211
10	-0.065	-0.095	6.2377	0.284
11	0.149	0.173	8.3267	0.215
12	-0.039	0.026	8.4696	0.293
13	-0.152	-0.067	10.710	0.219
14	0.042	0.024	10.887	0.284
15	0.080	0.037	11.525	0.318
16	-0.079	-0.100	12.158	0.352
17	0.054	0.058	12.459	0.410
18	-0.035	-0.015	12.588	0.480
19	0.070	0.058	13.108	0.518
20	0.009	0.037	13.117	0.593
21	-0.080	-0.073	13.819	0.612
22	-0.032	-0.099	13.934	0.672
23	0.161	0.112	16.912	0.529
24	-0.210	-0.154	22.047	0.282
25	-0.071	-0.101	22.637	0.307
26	0.076	0.075	23.335	0.326

Figure 6
ACF and PACF Plot on Residual of Rice Production Model



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.048	0.048	0.1608	
		2	0.074	0.072	0.5592	
		3	0.097	0.091	1.2469	0.264
		4	0.234	0.224	5.3196	0.070
		5	-0.022	-0.051	5.3546	0.148
		6	0.183	0.158	7.9159	0.095
		7	0.037	-0.012	8.0200	0.155
		8	0.010	-0.055	8.0281	0.236
		9	-0.010	-0.022	8.0361	0.329
		10	0.052	-0.028	8.2552	0.409
		11	0.160	0.190	10.405	0.319
		12	0.088	0.068	11.058	0.353
		13	-0.070	-0.098	11.485	0.404
		14	-0.092	-0.136	12.238	0.427
		15	-0.113	-0.215	13.378	0.419
		16	-0.076	-0.087	13.904	0.457
		17	-0.049	-0.032	14.128	0.516
		18	-0.129	-0.087	15.709	0.473
		19	0.057	0.224	16.022	0.522
		20	-0.084	0.010	16.721	0.542
		21	-0.034	0.046	16.840	0.601
		22	-0.027	-0.028	16.915	0.658
		23	0.090	-0.024	17.774	0.663
		24	-0.069	0.019	18.287	0.689
		25	0.101	0.144	19.418	0.677
		26	-0.002	0.125	19.418	0.729
		27	-0.057	-0.019	19.790	0.758
		28	0.041	0.046	19.992	0.792

Figure 7
ACF and PACF Plot on Residuals of Corn Production Model

Forecasting

According to the selected model. The SARIMA (0.1.4) (0.1.1)12 and ARMA (2.0) are utilised to project the result forecasting to 2027. The result can be observed as the figure 8 and 9 below:

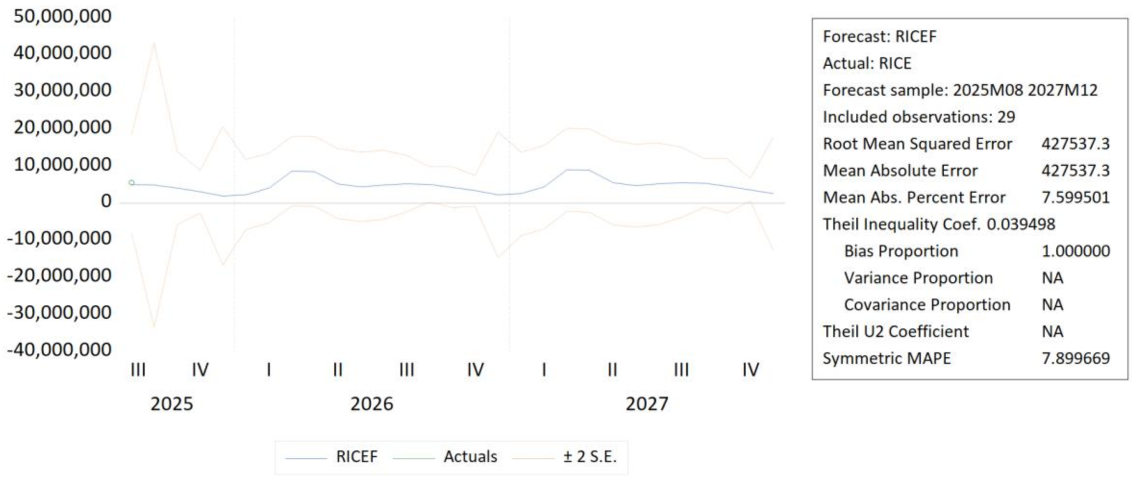


Figure 8
Rice Production Forecasted

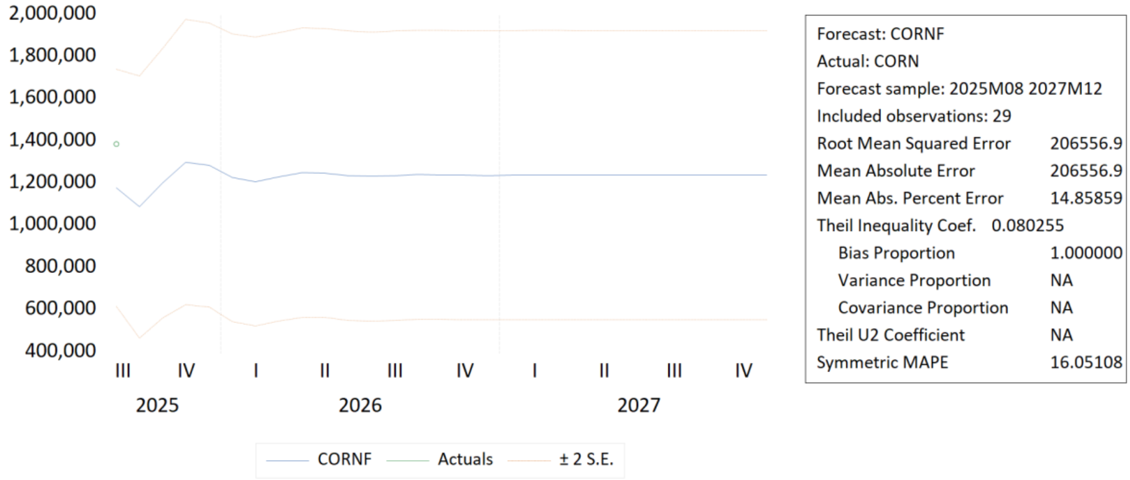


Figure 9
Corn Production Forecasted

Based on the figure 8, the SARIMA model (0.1.4) (0.1.1)12 for Indonesian rice production shows high accuracy. The model RMSE set of 427537 and MAPE 7.50%. The RMSE shows by average the forecast error are approximately around 427573 tonnes. On the other hand, MAPE value shows the average forecast error is 7.5%. In terms of accuracy, with margin error around 7.5% is generally considered as highly accurate model, which capture the 9.25% of the accuracy in rice production forecast. This model, suggest that the model provide a robust and reliable forecast for rice productions.

Based on the figure 9, the forecasting performance of ARMA (2.0) of Indonesian corn production shows the RMSE around 206556 and MAPE 14.85%. The RMSE shows the average forecast error in the original scale data is around 206556 tonnes, while MAPE forecast error around 14.85% of the actual corn production value. Although MAPE for corn production is considerably higher than the rice production model, 14.85% error result the good level of accuracy on forecasting. In other word, the average accuracy for this model is about 85.15%.

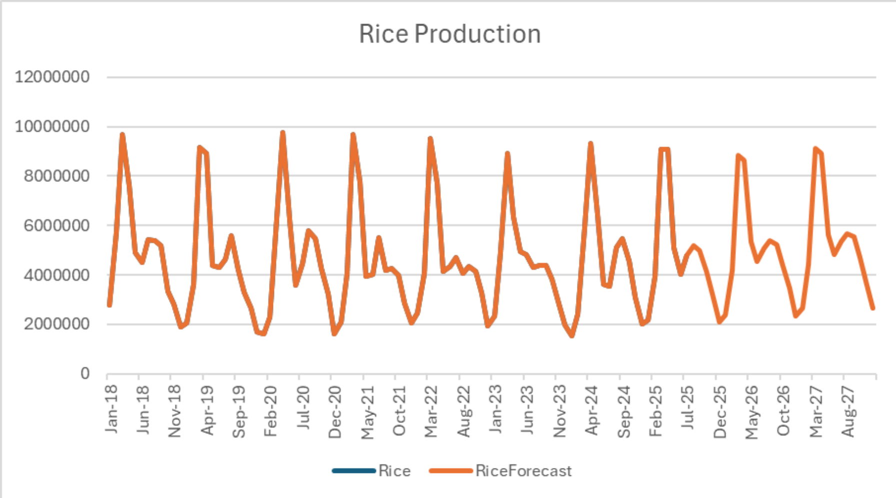


Figure 10
Rice Production Projection to 2027

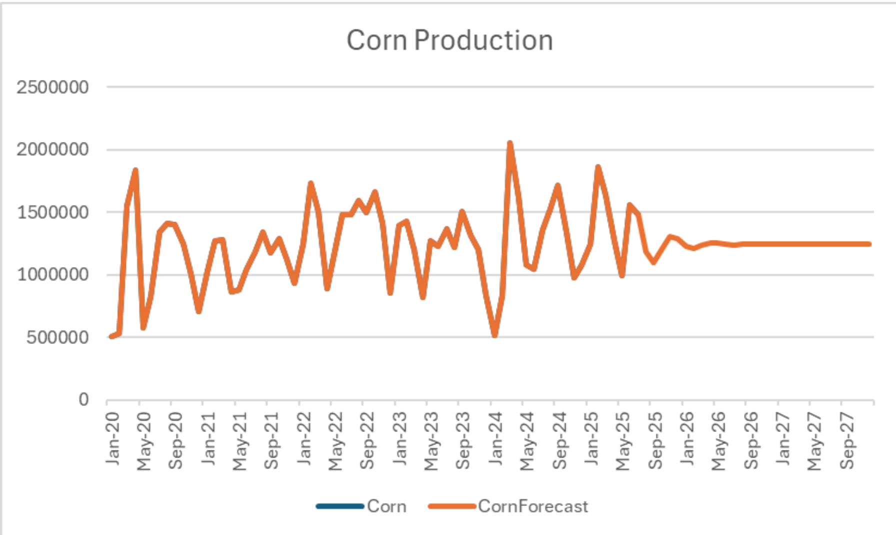


Figure 11
Corn Production Projection to 2027

Based on the figure 10. The rice production forecast generated by SARIMA (0.1.4) (0.1.1)12 model shows the monthly production continue fluctuate between high peak and low season through annual cycle. The peak production month are projected rach level close to the historical data. The seasonal peak of the forecasted and observed historical data oriented on the march and april, then gradually decrease until it reaches the lowest season at december and january. The forecasted shows the peak season at March 2026 reach 8850468 ton rice produced and by the March 2027 it reach 9115031, increase around 264562 tons by the one year gap. On the other hand, by december 2026 as the lowest season on the 2026 reach 2356243 ton rice produced, increased from 2106334 in december 2025 with year to year comparison. Additionally, by December 2027, the monthly production hit 2664768. In conclusion, based on the forecasted model, the forecasted rice production remain similar to previous year, but the low season shows the better production than historical production on the same month.

Similar to our findings, the study by Ruslan & Prasetyo (2023) shows that rice production in Indonesia has strong seasonal fluctuation, In March and April as the peak seasona while the December and January as low season, typically affected by the rainfall and planting cycle. Forecasting model by utilising SARIMA and Holt-winters have been conducted and shown an effecty capture on the seasonal trend and provide reliable projection. A research by Salamah et al., (2025) shows the Holt-Winters Exponential Smoothing may capture the seasonal characteristic in the rice production and forecast it From January 2024 until December 2025 with forecasting accuray about 75%. Another research conducted by Kusuma et al., (2024) shows the SARIMA model may applied to conduct the rice production forecasting in Nusa Tenggara Barat Province with MSE is 0,0006714. Lastly, Research conducted by E. Parreño (2023) on comparing the SARIMA and Holt-Winters Model on Rice and Corn production shows the Holt-Winters Model perform better for both Rice and Corn with only MAPE around 5.9% and 7.31% while SARIMA with MAPE around 8.70% and 11.53%.

The ARMA model (2.0) for corn production provides different result. The historial segment shows monthly volatility. However, on the forecast period, the projected forecast moving toward the mean around 1.2 million tonnes per month. This projected model indicated in the longterm, the corn production may not variety and become stable on the 1.2 million tones per month. However, in the agriculture scenario, the corn production morelikely to produce fluctuated on each month as it affected by planting season. But, model identification cannot depict the seasonality on the data, hence the result of the forecast may steady on the mean in the long run. This findings shows the models predict the stable average output at the long run. Similar findings by Syaharuddin (2024) shows the corn planting area will be hit the stable mean after it hit the longrun.

Both rice and corn forecast pin point on the broadly stable outlook for Indonesia staple commodity in the near term. For rice, the continuation of the current production level may result on supply remain identical with historical production but there is a growth of production in lowest season in future. For corn, the forecast shows remain steady on the 1.2 million tones monthly in spans of 2026 to 2027.

Stability aggregate output does not guarante the secure access for all population group. Several risk remain exist over coming two years. In seasonal rice production, the model predict the growth in the productions, especially in the lowest season, but population growth may also increase that allow the growth consumption rate. In addition, the both rice and corn production are vulnerable on the exogenous shock such as climate event, pest, and disruption in input agribusiness supply chain. The forecast reassuring the near-term supply stability both in two main staple commodity but risk on securing the food security is remain exist.

As policy maker, the forecasting evidence may suggest the rice production is heavily depends on the seasonality in production, the government should focus on the robust stockholding and buffer-stock management on preparing the low season production on facing the market demand. It also, regulating the agency that responsible on the market stock, the agency may use the short-term forecast to anticipate the low production month and build reserves during high peak. By releasing stocks during predicted shortages, the government may mitigate the price volatility.

At the farm level, the seasonal pattern also suggest the local government and local farmer on the investment on irrigation infrastructure and water management to reduce the volatility on the seasonal fluctuation by stabilising the yield during the productions. Government may also develop the risk-management instrument to help the farmer to cope with variability of production and also providing the information that allow the farmer to observe the bulk stock moment, avoiding the over supply and low price commodities in these moment.

For corn, the forecast relatively stable on the 1.2 million tones and shows no rapid growing production level. Although the result of the forecast is likely not possible happens in the real case, the policy maker should taking the consider of increasing the corn production to secure a secure level of corn production. The policy that may be conducted is improvig the irrigation, water, post harvest handling, and storage.

Furthermore, the forecast result support and serve as the earling warning and planning system to construct the food security in Indonesia. The policy maker should focus more on the stock-holding and bulk stock management on managing the supply commodity in the market, while also encouraging and improving the agriculture infrastructure to support the staple commodity.

Conclusion, Suggestions, and Limitations

This study applied the Box-Jenkins approach to model Inodnesia monthly rice and corn production to forecast the shorterm production for food security aspect. After determining the stationary with ADF test and differencing, SARIMA (0.1.4) (0.1.1)12 was selected as preferred model for rice and ARMA (2.0) for corn production, based on the adjusted R square, AIC, and SIC. Residual diagnostic showed there is no autocorrelation on the models, indicating the models is ready to be forecasted. The forecast evaluation shows high accuracy for rice with RMSE 427.537 and MAPE 7.5% while corn with RMSE 206.556 and MAPE 14.85%, The forecast shows the stable rice and corn production over the next two year with rice maintaining strong seasonality.

This study has limitation on relies on national monthly aggregate data, which may hide the regional productions. Also, the Box-Jenkins models are heavy reliance on the historical data which not incorporate with exogenous variables such as weather, temperature, price, etc. Lastly, the study is only focus on the production while ignoring the implication of prices, stock, consumption,a dn access to food.

Further study may extend the models by applying the ARIMAX or SARIMAX model by including the variables that incorporate with agriculture such as weather, input price, and etc. Lastly, the alternative models such as machine learning approach may construct the better prediciton interval and scenario analysis.

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