PARAMETER
JURNAL MATEMATIKA, STATISTIKA DAN TERAPANNYA

e-ISSN. 2829-6303
Vol. 05 No. 2, September 2026
Page 373-388

Comparison of ARIMA and NNAR Model for Rice Production Forecasting

Mega Silfiani[1*], Primadina Hasanah[2,4], Irma Fitria[3]

[1,2,3]Department of Science and Data Analytics, Faculty of Science and Information Technology, Institut Teknologi Kalimantan, Balikpapan, 76127, East Kalimantan, Indonesia
[4]Department of Mathematical Sciences, Faculty of Science and Engineering, University of Liverpool, Liverpool, L693BX, United Kingdom

E-mail Correspondence Author: *megasilfiani@lecturer.itk.ac.id*

Abstract
Accurate forecasting of rice production is crucial for ensuring future food security in specific regions. This study aimed to compare the predictive capabilities of two distinct time series models, Autoregressive Integrated Moving Average (ARIMA) and Neural Network Autoregression (NNAR), in forecasting rice production. The selection of input variables for the NNAR model was aligned with the autoregressive components of the ARIMA model. Applying annual rice production data for the East Kalimantan Province from 1994 to 2023, this study evaluated forecasting accuracy through the Symmetric Mean Percentage Error (SMAPE). The results demonstrated the superior performance of the ARIMA ([2],0,0) model compared to the NNAR (2, 8) model. The advantage of the ARIMA ([2], 0, 0) model is attributed to the limited amount of data used, making simpler models like ARIMA more suitable for this case. Future research could develop more comprehensive forecasting models by incorporating additional factors such as weather data. Furthermore, the adopting of hybrid models combining ARIMA and NNAR, along with an increase in the quantity and diversity of data, could be potential steps towards enhancing the accuracy of rice production forecasting in the future.
Keywords: *ARIMA, forecasting NNAR, rice production, SMAPE.*

: https://doi.org/10.30598/parameterv5i2pp373-388
This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-ShareAlike 4.0 International License.

Copyright © 2026 The Author(s).
Research Ariticle ***Open Acces***
Email: jurnalparameter@gmail.com
Homepage: https://ojs3.unpatti.ac.id/index.php/parameter

Submitted: December 2026
Accepted: September 2026

1. INTRODUCTION

The relocation of Indonesia's capital city to Nusantara in East Kalimantan constitutes a transformative national project with far-reaching socio-economic implications. While the initiative is expected to accelerate urban development and population growth, it simultaneously poses challenges for the agricultural sector. A considerable portion of farmland is projected to be converted into urban and industrial areas, thereby reducing the land available for rice cultivation [1]. At the same time, the expected influx of migrants is likely to increase food demand, particularly for rice as the staple commodity [2], [3]. Anticipating these structural changes requires accurate forecasting of rice production to inform policies that safeguard food security under conditions of shrinking farmland and growing demand.

Time series forecasting has long been recognized as a reliable approach for predicting agricultural outputs based on historical patterns[4], [5]. Among existing methods, the Autoregressive Integrated Moving Average (ARIMA) model remains one of the most widely applied due to its ability to capture linear trends and temporal dependencies in time series data[6], [7]. ARIMA has demonstrated strong predictive performance across diverse fields, including stock markets [8], [9], macroeconomic indicators [10], energy demand [11], transportation systems [12], and agricultural production, particularly crop yield forecasting [4]. However, because ARIMA is fundamentally a linear model, its capacity to represent nonlinear or irregular fluctuations—such as those driven by climatic variability, technological change, or policy shocks in agriculture—may be limited.

To address these limitations, nonlinear approaches based on artificial neural networks have gained prominence. Neural Network Autoregression (NNAR), a neural network framework adapted for time series, leverages lagged inputs and hidden layers to capture nonlinear dynamics that linear models may fail to represent [13], [14]. Empirical studies have reported mixed results regarding the relative performance of NNAR and ARIMA. NNAR has been found to outperform ARIMA in forecasting sunspot activity [15] and hospital admissions [13], whereas ARIMA produced superior forecasts for rice and grain production in India [16], [17]. Other studies reported no statistically significant difference between the two models [14]. These inconsistencies indicate that the relative performance of ARIMA and NNAR is highly context-dependent, shaped by data length, variability, and underlying structural conditions.

Despite the extensive application of ARIMA- and NNAR-type models in agricultural forecasting, no previous study has evaluated their comparative performance for rice production in East Kalimantan. Existing empirical evidence is predominantly concentrated in South Asian settings, which differ from East Kalimantan in terms of agro-ecological characteristics, land-use dynamics, and policy environments. This geographical bias limits the transferability of previous findings to Indonesia, particularly under the structural changes induced by the national capital relocation. The present study addresses this gap by conducting a comparative assessment of ARIMA and NNAR models for forecasting rice production in East Kalimantan under conditions of anticipated land conversion and changing demand.

This study contributes to the time series forecasting literature in several ways. First, it provides empirical evidence on the relative performance of linear (ARIMA) and nonlinear (NNAR) models using a relatively short annual series in a region undergoing major structural transformation, thereby extending existing knowledge on model suitability under data and policy constraints. Second, it offers context-specific parameterization and validation of both models for rice production in East Kalimantan,

which has been underrepresented in prior agricultural forecasting research. Third, by linking forecasting results to the implications of capital relocation, the study generates insights relevant to food security planning and regional development. In addition to these theoretical contributions, the findings have practical significance for policymakers and stakeholders concerned with the sustainability agenda, particularly SDG 2 (Zero Hunger) through the strengthening of sustainable agricultural systems, SDG 11 (Sustainable Cities and Communities) by considering the agricultural consequences of urban expansion, and SDG 12 (Responsible Consumption and Production) through more efficient resource use in agricultural planning.

The remainder of this paper is structured as follows. The methodology section describes the dataset, model specification—including the non-seasonal and, where applicable, seasonal components of the ARIMA structure—and the evaluation metrics employed to assess forecasting accuracy. The results and discussion section presents the empirical findings, compares the predictive performance of ARIMA and NNAR, and interprets the outcomes in light of existing theory and policy considerations. The concluding section summarizes the key results, highlights the theoretical and practical contributions of the study, and outlines limitations and directions for future research.

2. METHOD

2.1. Dataset

Rice (Oryza sativa L.) is one of the vital cultivated crops, serving as a primary food source for the Indonesian population [18], [19]. This annual crop produces rice as its main product[18], [20]. Consequently, rice production plays a crucial role in meeting the basic demand for rice [21]. Given the increasing demand for rice each year, predicting rice production becomes essential for planning optimal cultivation to ensure sufficient rice supply [21].

Rice production is measured in tons of dry unpulled rice (GKG), obtained from the Statistics Indonesia (Central Bureau of Statistics—BPS). This data results from multiplying the harvested area by productivity (rice yield per hectare). Since 2018, the Area Sample Frame (KSA) method has been used to calculate the harvested area, replacing the previous method of estimation based on sample plots collected through Agricultural Statistics data reported by the Head of the Branch Office at the Subdistrict Level. Rice productivity is assessed through sample plot surveys using plots measuring 25 m x 25 m to measure the production of dry harvested rice (GKP), which is then converted to GKG using the conversion rate from the 2018 Grain to Rice Conversion Survey. The dataset in this study comprises annual rice production sourced from East Kalimantan province from 1993 to 2023. A total of 28 observations were used for training, while three observations were used for testing. In 2012, East Kalimantan province underwent a division where three districts, namely Malinau, Nunukan, and Tarakan, formed the North Kalimantan province. Therefore, in this study, data before 2012 includes rice production in both East Kalimantan and North Kalimantan provinces.

2.2. Data Partition

In this study, the rice production data from East Kalimantan province spanning the years 1993 to 2023 was divided into two distinct subsets: the training set and the testing set. The training set comprises observations from 1993 to 2020, accounting for 28 years of data, which were used to develop and calibrate the predictive models. This extensive period ensures that the model captures the underlying trends, seasonality, and

other temporal patterns present in the data. The remaining observations, from 2021 to 2023, form the testing set, which serves to evaluate the model's forecasting performance on unseen data. This partitioning approach is crucial as it allows for a rigorous assessment of the model's generalization capability. By evaluating the model on a separate testing set, the study aims to avoid overfitting, ensuring that the model's predictions are not only accurate on the training data but also robust when applied to future, unknown data points.

2.3. ARIMA Modeling

The ARIMA model, originally introduced in 1970 by American statisticians G.E.P. Box and G.M. Jenkins, is among the most widely utilized methods for forecasting time series data [10]. This model, widely known as the Box-Jenkins method [10]. The model is especially effective for non-stationary time series data. ARIMA consists of three components, as represented by its acronym [6], [10]:

- AR (Autoregressive): A regression that uses the dependency relationship between an observation and several previous observations (model parameter p).
- I (Integration): The process of calculating differences between observations at different time points, represented by the model parameter d, with the goal of making the time series stationary. The degree of differencing (d) indicates how many times this differencing process is applied to the data.
- MA (Moving Average): An approach that considers possible potential dependencies between an observation and the residuals produced when the moving average model is applied to lagged observations, denoted by the model parameter q

The ARIMA model assumes stationarity, which means that the time series maintains a constant mean and variance over time [7]. The d notation in ARIMA refers to differencing used to make a time series stationary if it was initially non-stationary [7]. This process involves converting the series into the differences between consecutive observations, such as, $Z_t - Z_{t-1}$ If the series remains non-stationary, differencing can be applied multiple times, as indicated by the d value in the ARIMA (p, d, q) model. The general form of ARIMA can be expressed as ARIMA (p, d, q), denoted as follows:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)N_t \quad (1)$$

where is the $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ non-seasonal Autoregressive component, is the non-seasonal $(1-B)^d$differencing, is the non-seasonal $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ moving average, and Z_t is the rice production in the t-period.

2.4. NNAR Modeling

Neural Network Autoregression (NNAR) is an approach in the deep learning category that simulates the neural networks of the human brain and can learn complex linear and non-linear relationships between input and output variables. NNAR uses lagged values in the time series data as inputs. This model is built from three layers of a feedforward neural network, consisting of an-input layer, a hidden layer, and an-output layer [17]. The architecture of NNAR can be illustrated as shown in **Figure 1**.

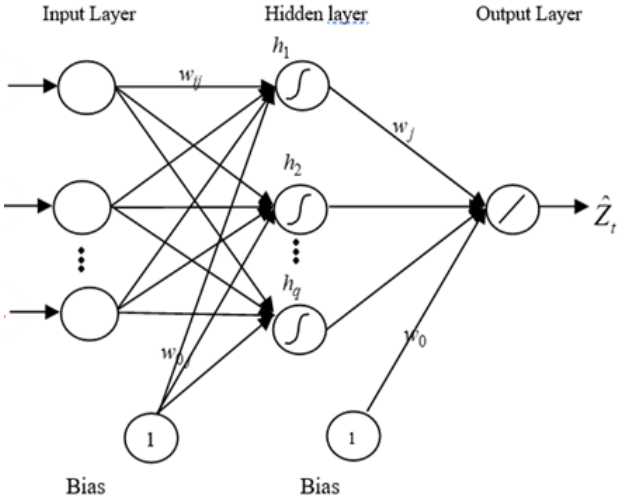


Figure 1. NNAR Architecture

In general, the relationship between the output variable (Z_t) and its lagged inputs $(Z_{t-1}, Z_{t-2}, \dots, , Z_{t-p})$ can be expressed mathematically following Zhang [22]. The functional form of the ANN with one hidden layer is given as:

$$Z_t = g^o\left[\alpha_0 + \sum_{j=1}^{q} \alpha_j g_j^h\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} Z_{t-i}\right)\right] + \varepsilon_t \quad (2)$$

where $\beta_{ij}(i = 0,1,2, \dots, p; j = 0,1,2, \dots, q)$ and β_0 are the input-to-hidden weights and bias parameters and $\alpha_j(j = 0,1,2, \dots, q)$ and α_0 are the hidden-to-output weights and bias parameters, p represents the number of input neurons (lags) and q denotes the number of neurons in the hidden layer. In practice, the logistic sigmoid function is commonly employed as the activation function in the hidden layer, defined as:

$$g(x) = \frac{1}{1+exp(-x)} \quad (3)$$

This nonlinear transformation enables the NNAR to capture complex relationships and nonlinear dependencies in time series data that cannot be effectively modeled by linear approaches such as ARIMA.

2.5. Model Evaluation

The evaluation of forecasting accuracy in this study employed the Symmetric Mean Absolute Percentage Error (SMAPE), which has been widely adopted in the forecasting area. SMAPE provides a normalized error metric by comparing the absolute difference between the actual and forecasted values relative to their average magnitude, thus reducing bias associated with large or small values. The mathematical formulation of SMAPE is expressed as follows [23]:

$$SMAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{2|Z_t - \hat{Z}_t|}{(Z_t + \hat{Z}_t)} \quad (4)$$

where Z_t denotes the actual value at time t, $\hat{Z}_t$ represents the forecasted value, and n is the number of observations in the evaluation set. A lower SMAPE value indicates a higher level of forecasting accuracy.

2.6. Research Prosedure

The research procedure of this study follows as:

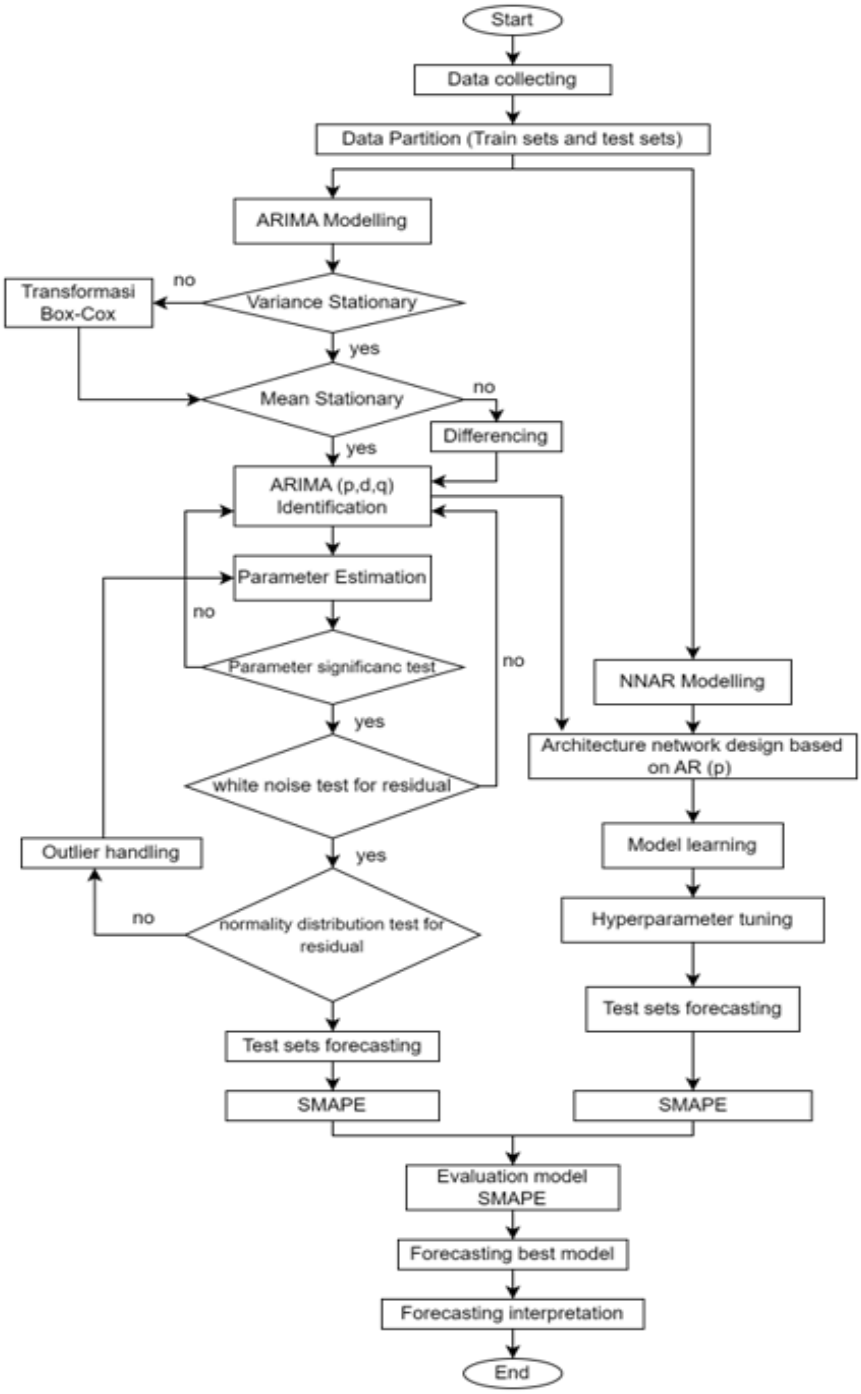


Figure 2. Research Procedure

1. The rice production data from East Kalimantan province from 1993 to 2023 was obtained from the Statistics Indonesia of East Kalimantan Province (BPS Kaltim—Badan Pusat Statistik Provinsi Kalimantan Timur)
2. The rice production data was divided into two sets: training data (1993-2020) and testing data (2021-2023). The training data was used to develop the models, while the testing data was used to evaluate forecasting performance.
3. Applying the training data to the ARIMA model. The procedure in ARIMA modeling is as follows:

a. Model Identification: The identification of the ARIMA model begins with assessing the stationarity of the time series in terms of both variance and mean. This study employs the Box–Cox transformation and autocorrelation function (ACF) plots to evaluate stationarity. If necessary, transformations or differencing are applied to achieve a stationary series. Once stationarity is ensured, the patterns of the ACF and partial autocorrelation function (PACF) plots are used to guide the selection of the ARIMA order (p, d, q). For instance, if differencing transforms the series into a white noise process, the model can be formally expressed as [5]

$$(1-B)^d Z_t = a_t \tag{5}$$

Differencing, however, can only be applied to achieve stationarity in homogeneous time series where nonstationarity arises from time dependence in the mean. In practice, many time series are not homogeneous, as nonstationarity may also result from time-varying variance or autocovariance structures. To address this issue, a variance-stabilizing transformation is often required. One widely used approach is the Box–Cox transformation, defined as [5].

$$Z_t^{(\lambda)} = \begin{cases} \frac{Z_t^{\lambda}-1}{\lambda}, \lambda \neq 0 \\ \ln Z_t, \ \lambda = 0 \end{cases} \tag{6}$$

This transformation normalizes the variance of the series, thereby facilitating subsequent differencing and ARIMA model identification.

b. Model Estimation: The estimation of ARIMA model parameters in this study was performed using the Conditional Least Squares (CLS) method, which minimizes the sum of squared residuals conditional on initial observations. To evaluate the statistical significance of the estimated parameters, a t-test was applied. Let θ denote a parameter in the Box–Jenkins model, $\hat{\theta}$ its point estimate of θ and $s_{\hat{\theta}}$ is the *standard error* of the estimate. The statistic test is defined as **[24]**

$$t = \frac{\hat{\theta}}{s_{\hat{\theta}}} \tag{7}$$

Under the null hypothesis $H_0: \theta = 0$ the statistic follows an approximate Student's t-distribution with n-p degrees of freedom where n is the number of observations and p is the number of estimated parameters. The decision rule is to reject H_0 if $|t| > t_{(\alpha/2, n-n_p)}$.

c. Diagnostic Checking: The Ljung-Box and Kolmogorov-Smirnov tests are used to check the white noise assumption and the normal distribution of model residuals. The hypotheses of the Ljung–Box Q test are defined as:

$H_0: \rho_k = 0, k = 1, 2, \ldots, K$
$H_1: at\ least\ one\ \rho_k \neq 0$

where ρ_k denotes the residual autocorrelation at lag k. The statistic test is given by:

$$Q = n(n+2)\sum_{k=1}^{K} \frac{\hat{\rho}_k^2}{n-k} \tag{8}$$

The statistic Q is approximately distributed as $\chi^2_{K-(p+q)}$ where p and q denote the AR and MA orders of the ARIMA (p, d, q) model. The decision rule is to reject H_0 if $Q > \chi^2_{K-(p+q)}$ indicating that the residuals are not independently distributed.

The normality of residuals was evaluated using the Kolmogorov–Smirnov (K–S) test. The hypotheses are:

H_0: residuals are normally distributed
H_1: residuals are not normally distributed

The K–S statistic test is defined as:

$$D = \sup_x |F_n(x) - F(x)|$$

$F_n(x)$ noted as cumulative distribution function (CDF) from the sample residuals and $F(x)$ is cumulative distribution function (CDF) of the normal distribution. The decision rule is to reject H_0 if $D > D_\alpha$ where D_α is the critical value from the Kolmogorov–Smirnov distribution table or equivalently if the p-value.

d. Forecasting with Test Data
e. Evaluating ARIMA Model Evaluation

4. Building the Neural Network Autoregression (NNAR) model. The steps to build the NNAR are as follows:
   a. Neural Network Architecture Design: This includes selecting the number of hidden layers, the number of neurons per layer, and the activation function.
   b. Model learning: The model is trained using training data and applying Backpropagation algorithm.
   c. Hyperparameter Tuning: Hyperparameter tuning was conducted to optimize the performance of the NNAR model by adjusting the architecture of the hidden layer. In this study, the tuning process was restricted to the number of neurons in the hidden layer, which was set to a maximum of $4p$, where p denotes the number of input neurons (lags) included in the model. This restriction follows common practices intime series neural network modeling, aiming to balance predictive accuracy and computational efficiency while avoiding overfitting.
   d. Forecasting with Test Data
   e. Evaluating NNAR Model Evaluation
5. Comparing the accuracy of the ARIMA and NNAR models. The model accuracy in this study is evaluated using the Symmetric Mean Absolute Percentage Error (SMAPE)
6. Forecasting the best model based on the smallest SMAPE.
7. Interpretation of the forecasting results.

3. RESULTS AND DISCUSSION

This study focuses on rice production in East Kalimantan from 1993 to 2023. **Figure 3** illustrates the descriptive statistics visualized in a boxplot. The annual rice production in East Kalimantan province shows an average of 399,627 tons. The lowest production was recorded in 2023 at 170,256 tons, while the highest production was achieved in 2010 with a total of 588,879 tons. The line within the box represents the median rice

production, which is approximately 399,627 tons. There are no data points outside the whiskers, indicating that there are no significant outliers in this rice production data. With an understanding of the characteristics of the annual rice production in East Kalimantan, we can proceed with modeling using ARIMA (Autoregressive Integrated Moving Average) and NNAR (Neural Network Autoregressive) models.

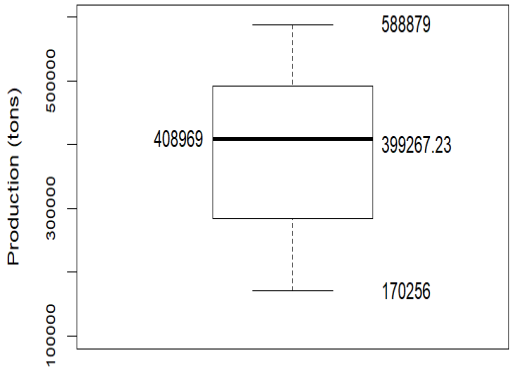


Figure 3. Box Plot Annual Rice Production

The ARIMA model is constructed through four stages: model identification, parameter estimation, diagnostic checking, and forecasting. In the identification stage, the stationarity of the annual rice production in East Kalimantan province is assessed. Stationarity identification is conducted to determine whether the variance and mean in the time series data are constant or not. If the time series data do not meet stationarity in variance, a transformation is required. Meanwhile, if the time series data do not meet stationarity in the mean, differencing needs to be applied. Variance stationarity can be identified using the Box-Cox Transformation. The transformation is performed on the Box-Cox Transformation parameter λ, which ranges between -1 and 1 **[5]**. Mean stationarity, on the other hand, can be identified from the ACF (Autocorrelation Function) plot. Differencing is performed if the lags in the ACF plot do not exhibit a "dies down" pattern (a rapid decrease). The time series data identification of the annual rice production in East Kalimantan province can be illustrated in **Figures 4(a)-(b).**

Figure 4(a) shows that the variance in the time series does not require transformation because the value of the λ parameter is outside the range of -1 to 1. Meanwhile, **Figure 4(b)** indicates that the time series data also do not require differencing as they follow a "dies down" pattern, with only lag 1 and lag 2 falling outside the upper control limit, while the rest are within the upper and lower control limits. After confirming that the data are stationary, an initial estimation of the order of ARIMA (p, d, q) can be made based on the lag patterns from the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) in **Figures 4(a)-(b).**

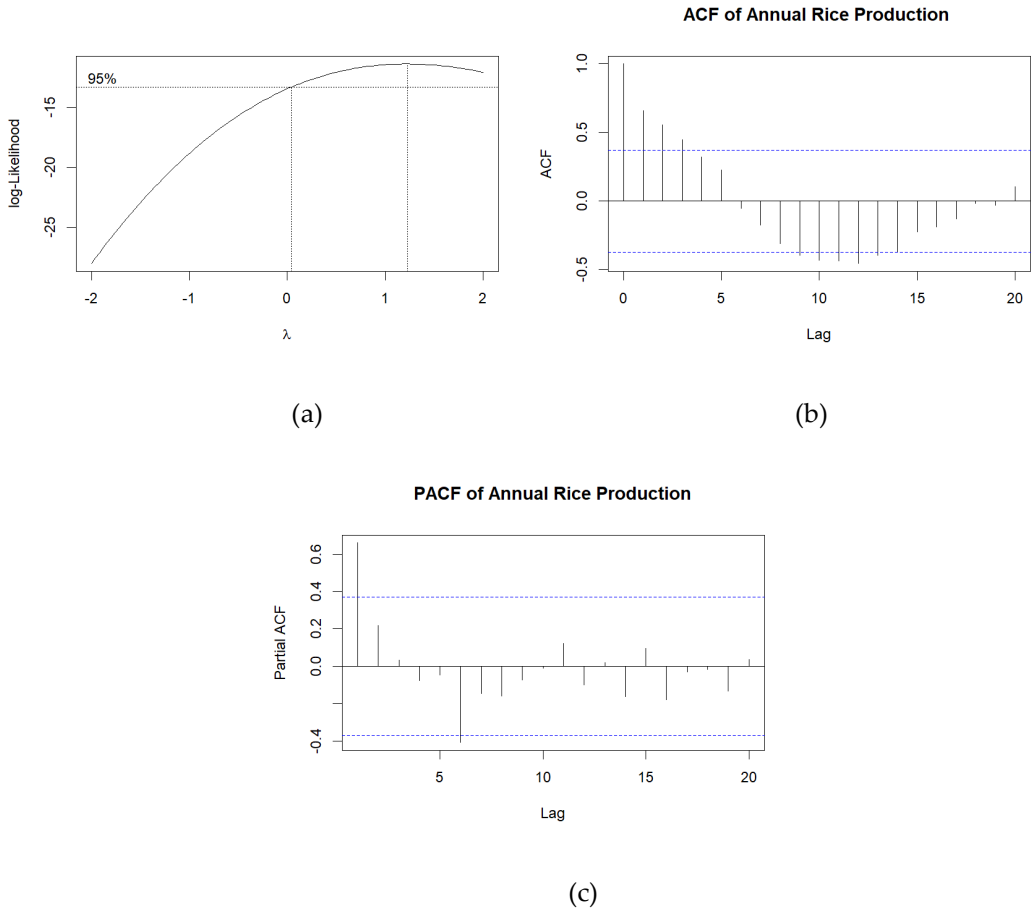


Figure 4. (a) Box-Cox Transformation, (b) ACF Plot and (c) PACF Plot

Figure 4(a) shows that lag 1 and lag 2 exceed the upper control limit, while no other lags exceed either the upper or lower control limits. In contrast, **Figure 4(b)** shows that lag 1 exceeds the upper control limit and lag six exceeds the lower control limit, with the remaining lags staying within the control limits. Based on the patterns observed in **Figures 4(a)-(b)**, the possible ARIMA (p, d, q) model estimations are ARIMA ([1,6], 0, [2]) or ARIMA ([6], 0, 2). Subsequently, model estimation is conducted based on the initial ARIMA (p, d, q) model estimation obtained. The final ARIMA (p, d, q) model obtained may differ from the initial estimation due to multiple trials during the parameter estimation stage, diagnostic checking with the Ljung-Box test, and normality testing on the residuals. A summary of the two final ARIMA (p, d, q) models, along with each parameter estimation and diagnostic checking stage, can be seen in **Table 1**.

Table 1 presents a comparison between two forecasting models for rice production in East Kalimantan, namely ARIMA (1, 0, 0) and ARIMA ([2], 0, 0). Both models exhibit significant parameters, as evidenced by p-values less than 0.05 for all parameters. The results of the diagnostic checks, including the Ljung-Box test and the normality test, indicate that both models satisfy the assumptions of white noise and normality in the residuals. Although both models demonstrate good performance, the ARIMA ([2], 0, 0) model slightly outperforms with a SMAPE value of 14.85%, compared to the ARIMA (1, 0, 0) model, which has a SMAPE value of 18.16%. This suggests that the ARIMA ([2], 0, 0) model has a slightly lower error rate in forecasting rice production in East Kalimantan.

Table 1. Summary of ARIMA Model

Model	Parameter Estimation			Diagnostic Checking			SMAPE (%)
	Parameter	Estimate	p-value	Ljung-Box Test		Normality	
				Until lag	p-value	p-value	
ARIMA (1,0,0)	M	332346.2	<0.0001	6	0.1003	0.0594	18.16
	ϕ_1	0.82311	<0.0001	12	0.5140		
				18	0.2762		
				24	0.1005		
ARIMA ([2],0,0)	M	328609.8	<0.0001	6	0.0988	>0.1500	14.85
	ϕ_2	0.80085	<0.0001	12	0.3794		
				18	0.4423		
				24	0.4037		

Following the identification of the final ARIMA model, the second modeling approach, the Neural Network Autoregression (NNAR) model, was developed. The NNAR model in this study was constructed using the R programming language. The input for the NNAR was determined based on the AR order obtained from the previous ARIMA model. Therefore, two experiments were conducted for the NNAR input in this study, i.e. NNAR with p = 1 and NNAR with p = 2. To determine the number of nodes in the hidden layer, experiments were conducted up to 4p nodes. Consequently, for NNAR with p = 1, the number of nodes in the hidden layer was tested up to 4, and for NNAR with p = 2, the number of nodes in the hidden layer was tested up to 8. The performance results of each model are illustrated in **Figure 3**.

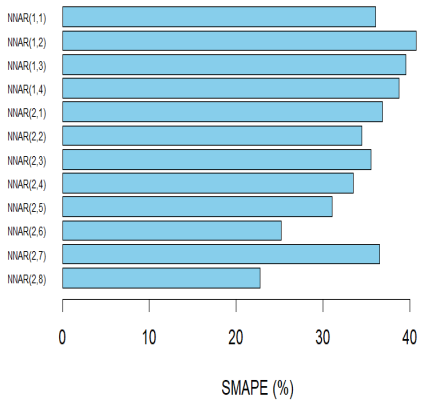


Figure 5. SMAPE of NNAR Model

Figure 5 illustrates the comparison of Symmetric Mean Absolute Percentage Error (SMAPE) for the Neural Network Autoregression (NNAR) model with different numbers of neurons in the input and hidden layers. The number of neurons in the hidden layer is a tunable parameter in the NNAR model. This hidden layer is responsible for learning complex patterns within the data. By varying the number of neurons, we can adjust the model's capacity to learn these patterns. **Figure 5** shows that the NNAR model with input p=2 performs better than with p = 1. In the case of NNAR with input p=2, the SMAPE initially decreases as the number of neurons increases. However, beyond a certain point, SMAPE begins to increase as the number of neurons continues to rise. This indicates that an excessive number of neurons can lead to overfitting, where the model becomes too closely tailored to the training data and fails to generalize well to new data. Therefore, it is crucial to select the appropriate

number of neurons in the hidden layer to achieve optimal forecasting performance. The NNAR (2,8) model was identified as the best-performing NNAR model for forecasting rice production in East Kalimantan province. Subsequently, the performance of each final model from ARIMA and NNAR will be compared as shown in **Figure 6**.

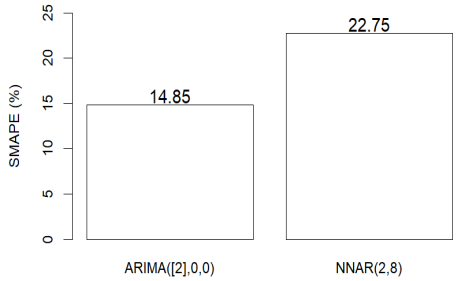


Figure 6. Comparison SMAPE of ARIMA and NNAR Model

Figure 6 presents the comparison of Symmetric Mean Absolute Percentage Error (SMAPE) values between the ARIMA and NNAR models in forecasting rice production. As a measure of forecasting accuracy, lower SMAPE values indicate better model performance. The results show that the ARIMA(2,0,0) model achieved a lower SMAPE compared to the NNAR(2,8) model, suggesting that the ARIMA specification provided more accurate forecasts of rice production in East Kalimantan. This outcome implies that the relatively simple ARIMA model is better suited for capturing the linear patterns in the data, whereas the NNAR model, which is designed to exploit nonlinear dynamics, may have been disadvantaged by the limited dataset.

The superior performance of the ARIMA(2,0,0) model should be interpreted with caution. The training dataset consisted of only 28 observations, which may have been insufficient to adequately train the more complex NNAR model. Neural networks generally require larger and more diverse datasets to fully capture nonlinear dependencies, and the limited sample size in this study may have led to overfitting and, consequently, reduced forecasting accuracy. These findings are consistent with previous studies in the agricultural domain, such as Vijayalakshmi, Pushpanjali, and Babu [16]and Ahmar et al.[17], which also reported that ARIMA outperformed NNAR in forecasting crop yields. From a practical perspective, the results suggest that ARIMA remains a reliable and interpretable tool for rice production forecasting in East Kalimantan, particularly under conditions of limited data availability. This finding is relevant for policymakers and agricultural stakeholders seeking to develop evidence-based strategies for food security planning amidst the structural changes associated with the relocation of the national capital.

Nevertheless, there is scope for further improvement. Future research should incorporate additional explanatory variables such as climatic factors and cultivated land area to enhance forecasting accuracy. Moreover, the exploration of hybrid models that combine ARIMA and NNAR may offer a promising avenue to integrate the strengths of linear and nonlinear approaches. Expanding the dataset in both temporal length and variable diversity would also be beneficial, particularly for improving the performance of neural network-based models, which are inherently data-intensive.

4. CONCLUSION

This study shows that the ARIMA model ([2], 0, 0) is superior in predicting rice production in East Kalimantan Province compared to the NNAR model (2, 8). This is likely due to the limited amount of data and the complexity of the NNAR model. Therefore, the ARIMA model ([2], 0, 0) is recommended for forecasting rice production in East Kalimantan Province. Further research can develop a more comprehensive forecasting model by considering other factors such as weather data, planting area, fertilizer use, and pest and disease attacks. In addition, the use of a hybrid model that combines ARIMA and NNAR, as well as an increase in the number and diversity of data, can be a potential step to improve the accuracy of rice production forecasting in the future.

Acknowledgments

The author gratefully acknowledges the financial support provided by the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia through the BIMA Research Grant under the Penelitian Dosen Pemula scheme in 2024.

Funding Information

This research is funded by BIMA Research Grant under the Penelitian Dosen Pemula scheme in 2024.

Author Contributions Statement

M.S: Conceptualization, methodology, writing-original draft, software, validation, writing-review & editing. P.D: Data curation, resources, draft preparation. I.F: Formal analysis, validation. All authors discussed the results and contributed to the final manuscript.

Conflict of Interest Statement

Authors state no conflict of interest.

Data Availability

Derived data supporting the findings of this study are available from the corresponding author M.S on request.

REFERENCES

[1] P. S. Gita, "Pembatasan Alih Fungsi Lahan Pertanian Terhadap Rencana Pemindahan Ibu Kota Negara," *Ganaya: Jurnal Ilmu Sosial Dan Humaniora*, vol. 2, no. 2, pp. 41–48, 2019, Accessed: Jul. 26, 2024. [Online]. Available: https://jayapanguspress.penerbit.org/index.php/ganaya/article/view/370

[2] K. N. Gunawan, "Analisis Pengaruh Jumlah Penduduk, Harga Beras Dalam Negeri, Dan Produksi Beras Terhadap Impor Beras Di Tahun 2000-2019," Universitas Muhammadiyah Surakarta, Surakarta, 2021.

[3] R. Khairati and R. Syahni, "Respons Permintaan Pangan Terhadap Pertambahan Penduduk Di Sumatera Barat," *Jurnal Pembangunan Nagari*, vol. 1, no. 2, pp. 19–36, 2016.

[4] N. Annamalai and A. Johnson, "Analysis and Forecasting of Area Under Cultivation of Rice in India: Univariate Time Series Approach," *SN Comput Sci*, vol. 4, no. 2, Mar. 2023, doi: 10.1007/s42979-022-01604-0.

[5] W. W. S. Wei, *Time Series Analysis - Univariate and Multivariate Methods*, Second edi. Boston: Pearson Addison Wesley, 2006.

[6] V. I. Kontopoulou, A. D. Panagopoulos, I. Kakkos, and G. K. Matsopoulos, "A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks," Aug. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/fi15080255.

[7] R. Ospina, J. A. M. Gondim, V. Leiva, and C. Castro, "An Overview of Forecast Analysis with ARIMA Models during the COVID-19 Pandemic: Methodology and Case Study in Brazil," Jul. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/math11143069.

[8] Z. Sun, "Comparison of Trend Forecast Using ARIMA and ETS Models for S&P500 Close Price," *ACM International Conference Proceeding Series*, pp. 57–60, 2020, doi: 10.1145/3436209.3436894.

[9] S. S. Wulandari, Sufri, and S. Yurinanda, "Penerapan Metode ARIMA Dalam Memprediksi Fluktuasi Harga Saham PT Bank Central Asia Tbk," *BUANA Matematika: Jurnal Ilmiah Matematika dan Pendidikan Matematika*, vol. 11, no. 1, pp. 53–68, 2021.

[10] Y. Ma, "Analysis and Forecasting of GDP Using the ARIMA Model," *Information Systems and Economics*, vol. 5, no. 1, 2024, doi: 10.23977/infse.2024.050112.

[11] W. Li and Z. G. Zhang, "Based on time sequence of ARIMA model in the application of short-term electricity load forecasting," *ICRCCS 2009 - 2009 International Conference on Research Challenges in Computer Science*, pp. 11–14, 2009, doi: 10.1109/ICRCCS.2009.12.

[12] A. Pratiwi, D. Safitri, and B. Warsito, "Peramalan Penumpang Pelayaran Dalam Negeri Di Pelabuhan Tanjung Priok Dengan Metode ARIMA Box-Jenkins Dan Metode Variasi Kalender Arimax," *Jurnal Statistika* , vol. 6, no. 1, pp. 56–64, 2018, [Online]. Available: www.bps.co.id.

[13] G. Perone, "Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy," *European Journal of Health Economics*, vol. 23, no. 6, pp. 917–940, 2022, doi: 10.1007/s10198-021-01347-4.

[14] M. Kalantari, "Forecasting COVID-19 pandemic using optimal singular spectrum analysis," *Chaos Solitons Fractals*, vol. 142, Jan. 2021, doi: 10.1016/j.chaos.2020.110547.

[15] Z. Pala and R. Atici, "Forecasting Sunspot Time Series Using Deep Learning Methods," *Sol Phys*, vol. 294, no. 5, p. 50, 2019, doi: 10.1007/s11207-019-1434-6.

[16] G. Vijayalakshmi, K. Pushpanjali, and Dr. A. M. Babu, "A comparison of ARIMA and NNAR models for production of rice in the state of Andhra Pradesh," *International Journal of Statistics and Applied Mathematics*, vol. 8, no. 3, pp. 251–257, Jul. 2023, doi: 10.22271/maths.2023.v8.i3c.1041.

[17] A. S. Ahmar, P. K. Singh, R. Ruliana, A. K. Pandey, and S. Gupta, "Comparison of ARIMA, SutteARIMA, and Holt-Winters, and NNAR Models to Predict Food Grain in India," *Forecasting*, vol. 5, no. 1, pp. 138–152, Mar. 2023, doi: 10.3390/forecast5010006.

[18] W. Jannah, "Invigorasi Beberapa Benih Padi (Oryza Sativa L.) Varietas Lokal Kadaluarsa Menggunakan Ekstrak Tauge," Universitas Islam Negeri Sultan Syarif Kasim Riau Pekanbaru, Pekanbaru, 2024.

[19] M. N. Fawaiq, A. Jazuli, and M. M. Hakim, "Prediksi Hasil Pertanian Padi Di Kabupaten Kudus Dengan Metode Brown's Double Exponential Smoothing," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 4, no. 2, pp. 78–87, 2019, doi: https://doi.org/10.29100/jipi.v4i2.1421.

[20] M. A. P. Hutabarat, M. Julham, and A. Wanto, "Penerapan Algoritma Backpropagation Dalam Memprediksi Produksi Tanaman Padi Sawah Menurut Kabupaten/Kota Di Sumatera Utara," *Jurnal semanTIK*, vol. 4, no. 1, pp. 77–86, 2018.

[21] H. W. Herwanto, T. Widiyaningtyas, and P. Indriana, "Penerapan Algoritme Linear Regression untuk Prediksi Hasil Panen Tanaman Padi," *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, vol. 8, no. 4, pp. 364–370, 2019, Accessed: Jul. 28, 2024. [Online]. Available: https://journal.ugm.ac.id/v3/JNTETI/article/view/2563

[22] P. G. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, 2003, doi: 10.1016/S0925-2312(01)00702-0.

[23] J. G. De Gooijer and R. J. Hyndman, "25 years of time series forecasting," *Int J Forecast*, vol. 22, no. 3, pp. 443–473, 2006, doi: 10.1016/j.ijforecast.2006.01.001.

[24] B. L. Bowerman, R. T. O'Connell, and A. B. Koehler, *Forecasting, Time Series, and Regression: An Applied Approach. 4th Edition*, . Duxbury Press, 2005.