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Forecasting Farmers' Exchange Rates in North Sumatra Using the Arima Method

Yola Armita Nasution [a], Fibri Rakhmawati [b], Hendra Cipta [c]

[a,b,c] *Universitas Islam Negeri Sumatera Utara, Indonesia*

email: [a] yolaarmitanasution@gmail.com , fibri_rakhmawati@uinsu.ac.id [b] hendracipta@uinsu.ac.id [c]

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ABSTRACT

This study aims to forecast the farmer exchange rate (Nilai Tukar Petani, NTP) in North Sumatra in 2024 using the ARIMA method. The main objective of this study is to obtain a forecasting model that can be used to predict the farmer exchange rate over a certain time horizon and to measure the accuracy of the model through MAPE (Mean Absolute Percentage Error) analysis. The methodology used in this study is time series analysis using the ARIMA (Autoregressive Integrated Moving Average) approach. The data used in this study are secondary data obtained from the Central Statistics Agency (BPS) of North Sumatra for the period 2019 to 2023. The forecasting results show that the most effective ARIMA model for predicting the NTP of North Sumatra is the ARIMA (0,1,1) model with MA(1). This model provides accurate forecasting results with a MAPE value of 96.7%, which falls into the category of highly feasible forecasting. In general, the forecasting results indicate fluctuations in NTP from 2019 to 2023, with predicted NTP for 2024 showing a decrease in certain months but an increase in others. These results provide useful insights for the government and farmers in planning better agricultural policies in the future.

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1. Introduction

Indonesia is an agrarian country due to its location in a tropical climate, which facilitates complete rock weathering and results in fertile soil. In agrarian countries such as Indonesia, agriculture plays an important role both in the economy and in fulfilling the population's basic needs. This importance is further reinforced by continuous population growth, which leads to an increasing demand for basic necessities (Ayun et al., 2020). Indonesia has great potential due to its abundant natural resources in the agricultural sector. The agricultural sector in Indonesia encompasses a wide range of commodities supported by a diverse tropical climate. In terms of food crops, Indonesia has remarkable agricultural products, including rice, legumes, soybeans, peanuts, cassava, and many other crops (Prastowo, 2007). Agriculture is an important sector in the Indonesian economy. Indonesia is a country with extensive agricultural land. According to data from the Central Statistics Agency (Badan Pusat Statistik), in 2015 the total area of rice fields in Indonesia reached 8.087 million hectares (Badan Pusat Statistik, 2021).

The agricultural sector is chosen because it concerns the continuity of life and is a resource-based economic sector, making it relatively more resilient to external shocks. In broad terms, the role of the agricultural sector in each country's development includes providing basic food needs, absorbing labor, generating foreign exchange through exports, serving as a source of GDP formation, maintaining the national economic growth rate, controlling inflation, supplying raw materials for the industrial sector, preserving environmental sustainability, and increasing community income (Rachmat, 2020).

The agricultural sector also plays a significant role in absorbing labor in Indonesia compared to other economic sectors. Statistical data from May 2017 show that 31.86% of the total national workforce is employed in the agricultural sector (Maulana Surya, 2017). The agricultural sector consists of various subsectors, including the food crops and horticulture subsector, the plantation subsector, the forestry subsector, the livestock subsector, and the fisheries subsector. Horticultural commodities include fruits, vegetables, ornamental plants, and medicinal plants (Sofiatul Khadarisna, Agustono, 2022). Agriculture is one of the important sectors for the province of North Sumatra, with rice farming being one of the key areas continuously developed in the region (Elvin Desi Martauli, 2021). Even Deli Serdang, one of the regencies in North Sumatra, is known for its rice self-sufficiency. This is supported by a statement from one of the regents of Deli Serdang, who declared that the

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agricultural sector is a source of hope for the community in improving their living standards. This is further backed by the fact that Deli Serdang has fertile and vast land, along with farmers who love their work, are experienced, and have a deep understanding of agricultural issues.

Source: Central Statistics Agency

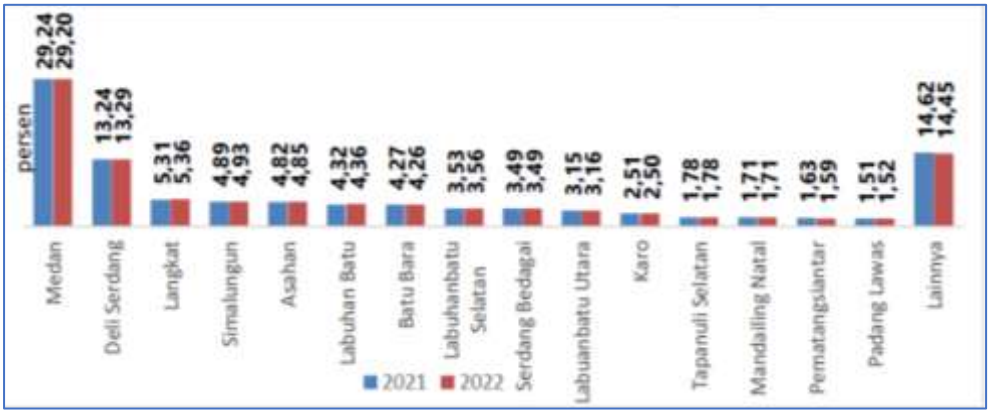


Figure 1: Contribution of GRDP to the Economy of North Sumatra in 2021-2022 (Percentage)

Based on the monitoring of rural prices in North Sumatra province in August 2022, the NTP (Farmer Exchange Rate) of North Sumatra Province increased by 8.22 percent compared to July 2022, from 108.85 to 117.80. This increase in the NTP for August 2022 was due to the rise in NTP across four subsectors: the NTP for the Food Crops subsector increased by 1.81 percent, the NTP for the People's Plantation subsector increased by 15.84 percent, the NTP for the Livestock subsector increased by 0.06 percent, and the NTP for the Fisheries subsector increased by 0.04 percent. Meanwhile, the NTP for the Horticulture subsector decreased by 3.83 percent (Badan Pusat Statistik, 2022).

To improve the welfare of farmers, calculations are made, and one of the measurement tools used is the calculation of the Farmer Exchange Rate (Aulia et al., 2021). NTP is a comparison between the price index received by farmers (It) and the price index paid by farmers (Ib). NTP serves as an indirect indicator of farmers' welfare, reflecting their purchasing power and ability in rural areas. To determine the level of farmers' welfare, one can look at the percentage calculation of what farmers have to pay. If the NTP ratio > 100, it means a surplus for farmers; if NTP = 100, it means farmers are breaking even; and if NTP < 100, it means a deficit for farmers. The Farmer Exchange Rate includes five subsectors: Food Crops, Horticulture, People's Plantations (TPR), Livestock, and Fisheries (B.P. Statistik, 2023).

The importance of the farmer exchange rate (NTP) to farmers' welfare has led to the development of a forecasting model to predict future NTP values. Forecasting is an activity aimed at anticipating future events based on past data. This NTP forecasting is expected to provide insights for the future and can serve as a benchmark or reference for the government in the development of agricultural policies. To assess the NTP values in the coming years, this research uses the ARIMA forecasting method to predict the NTP for 2023. ARIMA is suitable for data with a trend pattern.

Based on the explanation above, the author is interested in conducting a forecasting study for the future, along with calculating the MAPE value and the accuracy of the forecasting data using the ARIMA method with original data. The purpose of this research is to determine the results of the farmer exchange rate forecasting for North Sumatra from 2019 to 2023 using the ARIMA method and then evaluate the MAPE value and the accuracy of the forecast results. Other studies have been conducted, such as by Rahmawati et al. (2015), who concluded that the ARIMA method is the most effective approach for predicting cement sales in future periods. Additionally, another study by Rachmawati et al. (2020) found that the appropriate time series model to predict the spread of COVID-19 in Central Java was the ARIMA (1,1,1) model.

2. Literature Review

Analisis Time Series

Time Series Analysis (periodic series) is a forecasting method used to estimate future values based on past data. The goal of time series forecasting is to identify patterns in historical data and use these patterns to predict or estimate future outcomes (Markidakis, Wheelwright, & McGee, 1999). An important step in selecting a time series method is to observe the pattern of the data. The patterns in time series data are categorized into four types: horizontal pattern, seasonal pattern, cyclical pattern, and trend pattern.

ARIMA Box-Jenkins

ARIMA, also known as the Box-Jenkins method, is highly accurate for short-term forecasting, while its accuracy tends to decrease for long-term forecasts. Typically, for longer periods, the forecast will tend to flatten

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(remain constant) (Rakhmawati and Tripustikasari, 2018). The Box-Jenkins ARIMA model is a time series-based data analysis method used to forecast future data

Model Identification

Model identification is the first step to consider when performing forecasting. The model used in this analysis is ARIMA. Identifying an ARIMA model can be done by checking the stationarity of the data, as well as plotting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Through the identification process, the appropriate values for p, d, and q can be determined (Gujarati, 2004).

a. Data stationarity

Data stationarity is crucial in the formation of the ARIMA model. Stationarity means that there are no drastic changes in the data, and the data fluctuates around a constant mean value. Stationarity also implies that the variance is constant (Markidakis, Wheelwright, & McGee, 1999). The stationarity of the variance can be checked through a Box-Cox plot. If the data is found to be non-stationary in variance, it can be addressed using a Box-Cox transformation (Wei, 2006)..

$$T(Z_t) = \frac{Z_t^{\lambda} - 1}{\lambda}, \qquad dimana\ \lambda \neq 0$$

Based on the equation above, then for $\lambda = 0$ The following approach is taken.

$$\lim_{\lambda \to 0} \mathrm{T}(Z_t) = \lim_{\lambda \to 0} Z_t^{(\lambda)} = \lim_{\lambda \to 0} \frac{Z_t^{\lambda} - 1}{\lambda} = \ln(Z_t)$$

Overall value λ and the transformations used according to Wei (2006) are presented in the following table

Tabel 1 Transformasi

Value λ	**Transformations**
-1,0	$\frac{1}{Z_t}$
-0.5	$\frac{1}{\sqrt{Z_t}}$
0.0	$\ln Z_t$
0.5	$\sqrt{Z_t}$
1.0	Z_t (no transformation)

Parameter estimation λ on transformation *box cox* obtained by maximizing the probability function equation, so that for the value λ that has been determined, then the likelihood function is as follows.

$$L_{maks}(\lambda) = -\left(\frac{n}{2}\right) \ln \hat{\sigma}^2\,(\lambda) + (\lambda - 1) \sum_{t=1}^{n} Z_t$$

After examining the stationarity of the variance, the next step is to check the stationarity of the mean by observing the ACF plot. The data is considered stationary with respect to the mean if the lag in the ACF plot decreases rapidly in an exponential manner, or if the sinusoidal waves become progressively smaller. If the lag decreases slowly, the data is not stationary with respect to the mean. If the data is not stationary with respect to the mean, differencing is applied.

b. *Autocorrelation Function* (ACF) & *Partial Autocorrelation Function* (PACF)

Autocorrelation Function (ACF) It is a condition where there is a relationship between a time series and itself (Markidakis, Wheelwright, & McGee, 1999). The simple correlation coefficient between Y_t with Y_{t-1} can be searched as follows.

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k} (Z_t - \bar{Z})\,(Z_{t+k} - \bar{Z})}{\sum_{t=1}^{n-k} (Z_t - \bar{Z})^2}, k = 0,1,2, \ldots$$

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Partial Autocorrelation Function (PACF) used to measure the level of closeness (association) between Xt with $Xt - k$, if the influence of lag $1, 2, 3, \dots, k-1$ considered separate (Markidakis, Wheelwright, & McGee, 1999).

$$\hat{\phi}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k} \hat{\phi}_{kj} \hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k} \hat{\phi}_{kj}\, \bar{\rho}_j}$$

dimana

$$\phi_{k+1,j} = \phi_{kj} - \phi_{k+1,k+1}, \phi_{k,k+1-j}$$

Where $j = 1,2, \dots, k$

Estimation and Examiner Parameter

After determining a preliminary model in the model identification stage, the next step is to estimate the AR and MA parameters, both seasonal and non-seasonal, for the second stage. The desired estimation is one that provides the best values to match the time series being modeled (Markidakis, Wheelwright, & McGee, 1999). There are several parameter estimation methods, including the method of moments, the least squares method (Conditional Least Squares), the maximum likelihood method, the unconditional least squares method, and nonlinear estimation methods (Wei, 2006). One of the parameter estimation methods used in ARIMA is the Conditional Least Squares (CLS) method.).

Residual Assumption Test

A time series model involves several procedures. The first stage is model identification, and the second stage is parameter estimation. After parameter estimation, it is important to check whether the model assumptions are met (Wei, 2006). There are two basic assumptions that must be fulfilled: the assumption of residual white noise and the normality test of the distribution.

a. White Noise Assumption

White noise is a process where there is no correlation in the residual series. Residuals that exhibit white noise behavior indicate that the model's residuals satisfy the assumptions of being identically distributed and independent. The assumption of white noise is tested using the Ljung-Box test. (Wei, 2006).

$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0$ (residuals meet the white noise assumption)

H_1 : there is at least one $\rho_k \neq 0$ for i=1,2,...,k (residuals do not meet the white noise assumption)

Test Statistics:

$$Q = n(n+2) \sum_{k=1}^{k} \frac{\hat{\rho}_{\alpha}^{2}}{(n-k)}$$

Where,

$$k = 1,2, \dots, K$$

Rejection Area: H0 rejected if $Q > X^2_{\alpha;(k-p-q)}$ or if value

$$P_{value} < \alpha$$

Information:

n = lots of observation data

$\hat{\rho}_{\alpha}^{2}$ = autocorrelation estimate at lag- k 2

p = lag plot PACF

q = lag plot ACF

K = maximum number of lags

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b. Normal Distribution Assumption

In addition, the assumption of normal distribution is also tested. The test can be done by creating a histogram of the standardized residuals and comparing it with the standard normal distribution using the chi-square goodness-of-fit test (Wei, 2006). The normality test is performed to determine whether the residuals of the data follow a normal distribution or not.

Normality can be tested using the Kolmogorov-Smirnov test. The hypothesis for the Kolmogorov-Smirnov test is as follows: (Daniel, 1989).

H_0: $F(a_t) = F_0(a_t)$ (Residual data is normally distributed)
H_1: $F(a_t) \neq F_0(a_t)$ (Residual data is not normally distributed)
Test Statistics:

$$KS = Sup \mid F_n(a_t) - F_0(a_t)\mid$$

Rejection Area: H0 rejected if $KS > D_{n;(1-\alpha)}$ or if value

$$P_{value} < \alpha$$

Information :
Sup = maximum value of $\mid F_n(a_t) - F_0(a_t)\mid$
$F_n(a_t)$ = cumulative probability function calculated from sample data
$F_0(a_t)$ = cumulative probability function of normal distribution or hypothesized distribution function
$F(a_t)$ = unknown distribution function

Selection of the Best Model

In time series analysis, the final step is model selection, which follows the identification, estimation, and parameter testing steps, as well as the residual assumption test (Diagnostic Checking). The best model is selected to determine the most suitable model for predicting future time periods. The model selection is based on the MAPE value criterion, choosing the model with the smallest MAPE value. The formula for the model selection criterion is as follows (Wei, 2006):

$$MAPE = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{e_t}{Z_{n+1}}\right| \times 100\%$$

3. Method

This research uses a quantitative research approach. Quantitative research is a method used to test certain theories by examining the relationships between variables. These variables are typically measured using research instruments, so the data, which consists of numerical values, can be analyzed based on statistical procedures (Creswell, J. W., & Creswell, 2018). This method is considered scientific because it adheres to scientific principles, such as being concrete/empirical, objective, measurable, rational, and systematic. It is called quantitative because the data in the research consists of numbers and uses statistical analysis (Sugiyono., 2019).

The type of data used in this research is secondary data, which is data obtained from existing sources. The data used in this study are from the Central Statistics Agency (BPS) of North Sumatra for the period 2019-2023. This technique is also an important stage in the research process. This study uses secondary data. The following are the two methods used for data collection:

a. Literature Study

At this stage, in addition to supporting information and obtaining theoretical support, we succeeded in collecting relevant data from the North Sumatra Agriculture Service.

b. Field Research

By observing the data obtained from the North Sumatra Agricultural Service Study Program, it will also become a joint encouragement to improve and resolve the problems being researched at this time

(1)

Where x = data of training, y = data of testing, n = total attributes, f = function of similarity between point x and point y, and w_i = weight given to attribute i.

4. Results and Discussion

In descriptive statistical analysis, the first step in this research is to perform a descriptive analysis of the variables used. One of the benefits of descriptive statistical analysis is to provide information about a dataset. In this study, the data used are the farmer exchange rate (NTP) and the price of urea fertilizer, which were obtained

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from the BPS of North Sumatra from January 2019 to December 2023. The results of the descriptive statistical analysis of these three variables can be presented in Table 4.1 as follows:

Table 2. Descriptive Statistics

	Fertilizer Prices	NTP
Mean	4.127,46	112,26
Median	3.333.000	11482.50
Maximum	9.250.000	130,38.00
Minimum	2.019.000	9.900.000
Std. Dev.	2.187.120	3.363.970
Skewness	0.867383	-1.995.586
Kurtosis	2.527.094	6.011.791
Jarque-Bera	7.813.213	6.041.749
Probability	0.020109	0.000000
Sum	243010.0	589621.0
Sum Sq. Dev.	2.73E+08	6.45E+08

Based on the table above, the price of fertilizer has a mean value of 4,127.46, while the farmer exchange rate (NTP) has a mean value of 112.26. The maximum price of fertilizer is 3,333,000, while the maximum value of the farmer exchange rate is 11,482.50. This continues until the value of Sum of Squares of Deviations (Sum sq. Dev.).

The formula for calculating the mean is as follows:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_1$$

1. Calculating the average Farmer's Exchange Rate:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_1$$

$$= \frac{1}{60}(98{,}57 + 99{,}33 + 98{,}54 + 99 + 98{,}14 + 96{,}52 + 96{,}68 + 96{,}96{,}83 + 97{,}43 + 98{,}08 + 98{,}91 + 99{,}08 + \cdots + 129{,}08)$$

$$= \frac{1}{60}(6735{,}61)$$

= 112,26

2. Calculating the average price of fertilizer :

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_1$$

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$$\frac{1}{60}(2200 + 2200 + 2200 + 2200 + 2200 + 2200 + 2200 + 2200 + 22000 + 2200 + 2200 + 2200 + 2200 \dots 4133)$$

=

$$= \frac{1}{60}(24.446)$$

= 4.127,46

Based on Table 2, it can be observed that the average value of the farmer exchange rate (NTP) for the years 2019-2023 is 112.26, with the highest value being 130.38 and the lowest value being 9.900. Meanwhile, the average price of urea fertilizer is 4,127.46, with the highest value being 9,250 and the lowest value being 2,019.

The stationarity test is used to determine whether the data is stationary or non-stationary. If the data is non-stationary, differencing is applied. In the stationarity testing process, the Augmented Dickey-Fuller (ADF) test is used. The data is considered stationary if the absolute value of the calculated ADF statistic is greater than the critical value at a significance level of $\alpha = 5\%$. If the data is non-stationary, the data will be differenced, and then stationarity testing will be conducted again. The results of the stationarity test are as follows:

The stationarity test is conducted using the unit root test with the Augmented Dickey-Fuller (ADF) method, performed using EViews software, with the following hypotheses:

H_0 : data is not stationary

H_1 : stationary data

a. Stationary Test on Farmer's Exchange Rate

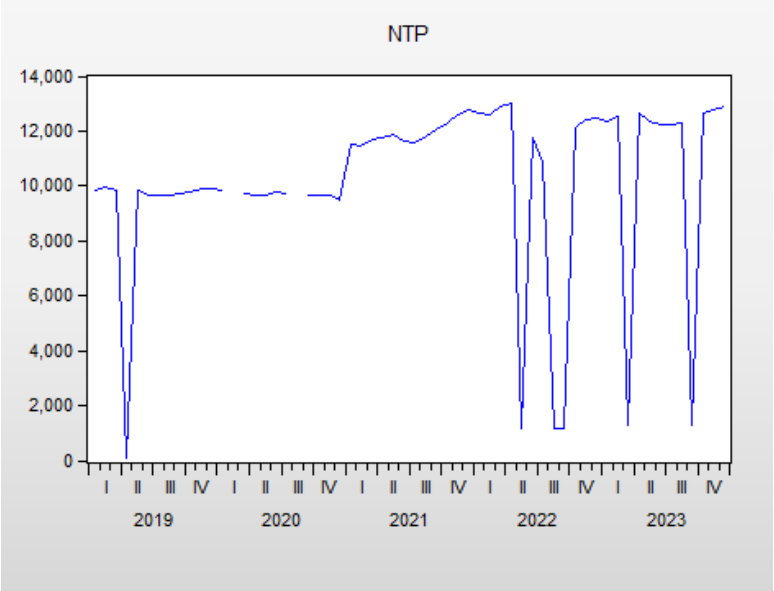


Figure 1 Stationarity of Data on Farmer's Exchange Rate

Table 3 Stationary Test of Data on Farmer's Exchange Rate

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.27.282	0.000
Test critical values:	1% level	-3.555.023	
	5% level	-2.915.522	
	10% level	-2.595.565	

In table 4.3, the p-value is <0.05, which is 0.000. In the ADF test, it is rejected if the p-value is <, so it can be concluded that the data is stationary.

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b. Stationary Test on Urea Fertilizer Prices

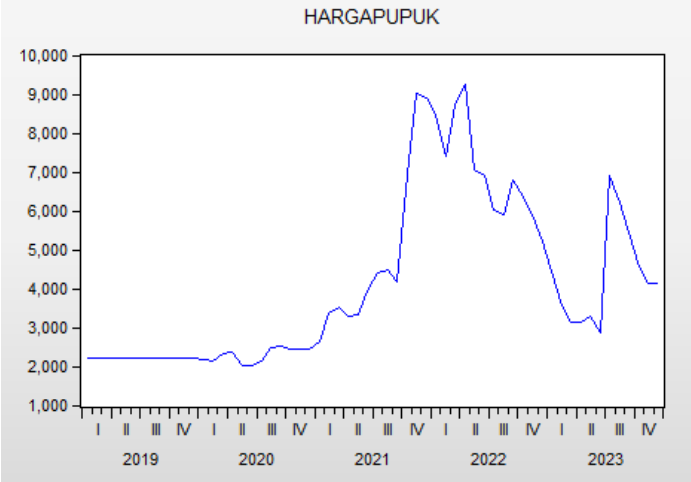


Figure 2 Stationarity of Data on Farmer's Exchange Rate

Table 4 Stationary Test of Data on Farmer's Exchange Rate

Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*
		-1.660.458	0.4458
Test critical values:	1% level	-3.546.099	
	5% level	-2.911.730	
	10% level	- 2.593.551	

In Table 4.4, the p-value is >0.05, which is 0.4458. The ADF test is rejected if the p-value is >0.05, thus concluding that the data is non-stationary, necessitating differencing.

This continues until December 2023..

After the data was differencing, it was tested again to determine its stationarity using the eViews application. The results of the first differencing data stationarity test are presented in Table 4.4 as follows:

Table 5 Data Stationarity Test after differencing

Variable	ADF test	Critical Value 5%	Probabilit y	Description
Fertilizer Price	- 7.446.75 6	-2.911.730	0.0000	Stasioner

Based on the data processing results in Table 4.4, it can be seen that the three ADF test values for the urea fertilizer price variable are smaller than the critical value, indicating that all three variables are stationary.

ARIMA Model Identification

To perform forecasting using ARIMA, the process involves a two-step approach: the AR (1) and MA (1) stages, and the model with the highest Adjusted value is selected as the model type. Before conducting the forecasting, a correlogram test is performed to determine the ARIMA (p, d, q), where:

P : Partial correlation

D : Differencial, yaitu 1

Q : Autocorellation

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Then, to determine (AR(p,q,r)), it can be observed based on the graph with the highest Autocorrelation and Partial Correlation values. In this case, the highest values are found in graphs 1 and 2. Therefore, with differencing = 1, p = 2, and q = 2, the models that can be formed are ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (0,1,1), ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (0,1,2), ARIMA (2,1,1), and ARIMA (2,1,2).

Then to carry out model estimation, the following steps are carried out.:

1. The results of the ARIMA (1,1,0) test with AR (1) using D(NTP) C AR(1)

Table 6 Test Results with AR (1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.974.016	4.812.368	0.124139	0.9017
AR(1)	-0.389762	0.106538	-3.658.426	0.0006
SIGMASQ	17700732	2634804.	6.718.044	0.0000
R-squared	0.167539	Mean dependent var		5.807.273
Adjusted R-squared	0.135521	S.D. dependent var		4.653.697
S.E. of regression	4.326.884	Akaike info criterion		1.964.494
Sum squared resid	9.74E+08	Schwarz criterion		1.975.444
Log likelihood	-5.372.360	Hannan-Quinn criter.		1.968.729
F-statistic	5.232.691	Durbin-Watson stat		2.441.966
Prob(F-statistic)	0.008501			
Inverted AR Roots	-.39			

To assess the accuracy of the method and determine whether it is suitable for forecasting, a squared residual data test is conducted. The results of the residual test are presented in the following table:

Table 7 Results of AR Residual Test (1)

	AC	PAC	Q-Stat	Prob
1	-0.177	-0.177	18.110	
2	-0.379	-0.423	10.292	0.001
3	0.095	-0.094	10.840	0.004
4	0.026	-0.167	10.882	0.012
5	-0.255	-0.367	14.967	0.005
6	0.283	0.098	20.087	0.001
7	0.086	-0.059	20.565	0.002
8	-0.180	-0.019	22.733	0.002
9	-0.093	-0.154	23.327	0.003
10	0.147	-0.028	24.840	0.003
11	-0.151	-0.188	26.472	0.003
12	0.090	-0.002	27.066	0.004

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13	0.150	0.011	28.751	0.004
14	-0.120	-0.088	29.853	0.005
15	-0.102	-0.001	30.670	0.006
16	0.166	0.022	32.897	0.005
17	-0.049	0.031	33.092	0.007
18	-0.056	0.007	33.359	0.010
19	-0.009	-0.134	33.366	0.015
20	0.023	-0.064	33.414	0.022
21	0.008	0.037	33.420	0.030
22	-0.003	-0.086	33.421	0.042
23	-0.005	-0.031	33.423	0.056
24	-0.003	-0.059	33.425	0.074

Because the Prob value is < 0.05, AR (1) is not suitable to be used as a forecasting method.

2. ARIMA (2,1,0) Test Results with AR (1 to 2) using D(NTP) C AR(1 TO 2)

Table 8 Test Results with AR (1,2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.253.701	3.755.832	0.166506	0.8684
AR(1)	-0.547978	0.109882	-4.986.964	0.0000
AR(2)	-0.370457	0.111686	-3.316.958	0.0017
SIGMASQ	14861853	2484574.	5.981.651	0.0000
R-squared	0.301051	Mean dependent var		5.807.273
Adjusted R-squared	0.259936	S.D. dependent var		4.653.697
S.E. of regression	4.003.435	Akaike info criterion		1.952.098
Sum squared resid	8.17E+08	Schwarz criterion		1.966.697
Log likelihood	-5.328.269	Hannan-Quinn criter.		1.957.743
F-statistic	7.322.222	Durbin-Watson stat		2.292.031
Prob(F-statistic)	0.000357			
Inverted AR Roots	-.27+.54i	-.27-.54i		

To determine the accuracy of the method and whether it is suitable for use in forecasting, a squared residual data test was conducted. The results of the residual test are presented in the following table:

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Table 9 AR Residual Test Results (1 TO 2)

	AC	PAC	Q-Stat	Prob
1	-0.116	-0.116	0.7763	
2	-0.101	-0.116	13.819	
3	-0.274	-0.309	59.150	0.015
4	0.033	-0.073	59.803	0.050
5	-0.181	-0.299	80.330	0.045
6	0.297	0.148	13.661	0.008
7	-0.016	-0.046	13.679	0.018
8	-0.031	-0.102	13.743	0.033
9	-0.214	-0.152	16.853	0.018
10	0.104	-0.025	17.605	0.024
11	-0.108	-0.130	18.437	0.030
12	0.161	-0.013	20.323	0.026
13	0.057	0.041	20.564	0.038
14	-0.025	-0.101	20.611	0.056
15	-0.110	0.016	21.555	0.063
16	0.123	0.074	22.762	0.064
17	-0.066	-0.027	23.120	0.082
18	-0.014	-0.053	23.135	0.110
19	-0.060	-0.101	23.445	0.135
20	0.027	-0.058	23.512	0.172
21	0.012	0.057	23.525	0.215
22	0.004	-0.112	23.527	0.264
23	-0.008	-0.043	23.533	0.316
24	-0.014	-0.033	23.554	0.371

Because the Prob value is < 0.05 and Prob > 0.05, AR (1.2) is not suitable to be used as a forecasting method..

3. ARIMA (0,1,1) Test Results with MA(1) using D(NTP) C MA(1)

Table 10 MA(1) Test Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.524.475	9.282.678	-0.164228	0.8702
MA(1)	-1.000.000	1.687.898	-0.000592	0.9995
SIGMASQ	11265122	4.57E+08	0.024674	0.9804
R-squared	0.470204	Mean dependent var		5.807.273
Adjusted R-squared	0.449827	S.D. dependent var		4.653.697
S.E. of regression	3.451.816	Akaike info criterion		1.932.716
Sum squared resid	6.20E+08	Schwarz criterion		1.943.665
Log likelihood	-5.284.968	Hannan-Quinn criter.		1.936.950
F-statistic	2.307.550	Durbin-Watson stat		1.947.020
Prob(F-statistic)	0.000000			
Inverted MA Roots	1.00			

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To determine the accuracy of the method and whether it is suitable for use in forecasting, a squared residual data test was conducted. The results of the residual test are presented in the following table:

Table 11 MA Residual Test Results (1)

	AC	PAC	Q-Stat	Prob
1	0.055	0.055	0.1756	
2	-0.117	-0.120	0.9868	0.321
3	0.022	0.037	10.167	0.601
4	0.037	0.019	10.993	0.777
5	-0.180	-0.180	31.261	0.537
6	0.220	0.263	62.145	0.286
7	0.014	-0.083	62.266	0.398
8	-0.162	-0.105	79.807	0.334
9	-0.178	-0.164	10.146	0.255
10	0.080	0.034	10.591	0.305
11	-0.132	-0.101	11.830	0.297
12	0.073	0.072	12.215	0.348
13	0.077	0.015	12.660	0.394
14	-0.112	-0.130	13.616	0.401
15	-0.145	-0.014	15.260	0.361
16	0.074	-0.042	15.703	0.402
17	-0.066	-0.062	16.059	0.449
18	-0.057	-0.080	16.337	0.500
19	-0.050	-0.128	16.551	0.554
20	0.025	0.024	16.606	0.617
21	0.018	0.098	16.637	0.676
22	0.015	-0.070	16.657	0.732
23	0.010	-0.012	16.666	0.782
24	0.007	-0.023	16.671	0.825

Because the Prob value > 0.05, namely 0.258, AR (1) is suitable to be used as a forecasting method.

4. Results of ARIMA (1,1,1) Model Estimation with AR(1) and MA(1) Using D(NTP) C AR(1) MA(1)

Table 12 AR(1) MA(1) Test Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.367.660	1.168.206	-0.117074	0.9073
AR(1)	0.098610	0.145133	0.679449	0.4999
MA(1)	-1.000.000	2.356.363	-0.000424	0.9997
SIGMASQ	11265441	5.87E+08	0.019196	0.9848
R-squared	0.470189	Mean dependent var		5.807.273
Adjusted R-squared	0.439024	S.D. dependent var		4.653.697
S.E. of regression	3.485.542	Akaike info criterion		1.935.394
Sum squared resid	6.20E+08	Schwarz criterion		1.949.992
Log likelihood	-5.282.333	Hannan-Quinn criter.		1.941.039
F-statistic	1.508.692	Durbin-Watson stat		2.125.980
Prob(F-statistic)	0.000000			

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Inverted AR Roots	.10			
Inverted MA Roots	1.00			

To determine the accuracy of the method and whether it is suitable for use in forecasting, a squared residual data test was conducted. The results of the residual test are presented in the following table:

Table 13. AR(1) MA(1) Residual Test Results

	AC	PAC	Q-Stat	Prob
1	-0.030	-0.030	0.0518	
2	-0.125	-0.126	0.9724	
3	0.032	0.025	10.358	0.309
4	0.049	0.036	11.839	0.553
5	-0.206	-0.200	38.397	0.279
6	0.239	0.252	74.999	0.112
7	0.009	-0.046	75.054	0.186
8	-0.146	-0.091	89.318	0.177
9	-0.169	-0.175	10.890	0.144
10	0.107	0.025	11.683	0.166
11	-0.147	-0.103	13.221	0.153
12	0.079	0.060	13.681	0.188
13	0.083	0.035	14.193	0.222
14	-0.105	-0.122	15.040	0.239
15	-0.141	-0.023	16.603	0.218
16	0.092	-0.037	17.290	0.241
17	-0.072	-0.061	17.719	0.278
18	-0.047	-0.074	17.906	0.329
19	-0.047	-0.139	18.095	0.383
20	0.024	-0.002	18.146	0.446
21	0.015	0.104	18.165	0.511
22	0.012	-0.058	18.178	0.576
23	0.007	-0.013	18.183	0.637
24	0.005	-0.026	18.186	0.695

Because the Prob Prob value is > 0.05, AR AR(1) MA(1) is suitable as a forecasting method.

4. ARIMA (0,1,2) Test Results with MA (1,2) using D(NTP) C MA(1 TO 2)

Table 14 MA(1,2) test results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.373.985	1.141.001	-0.120419	0.9046
MA(1)	-0.882131	7.493.466	-0.000118	0.9999
MA(2)	-0.117869	2.037.330	-5.79E-05	10.000
SIGMASQ	11250301	2.61E+09	0.004308	0.9966
R-squared	0.470901	Mean dependent var		5.807.273
Adjusted R-squared	0.439778	S.D. dependent var		4.653.697
S.E. of regression	3.483.199	Akaike info criterion		1.935.195
Sum squared resid	6.19E+08	Schwarz criterion		1.949.794

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Log likelihood	-5.281.787	Hannan-Quinn criter.		1.940.841
F-statistic	1.513.010	Durbin-Watson stat		2.161.485
Prob(F-statistic)	0.000000			
Inverted MA Roots	1.00	-.12		

To assess the accuracy of the method and determine whether it is suitable for forecasting, a squared residual data test is conducted. The results of the residual test are presented in the following table:

Table 15 Residual MA(1,2) Test Results

	AC	PAC	Q-Stat	Prob
1	-0.047	-0.047	0.1282	
2	-0.112	-0.115	0.8761	
3	0.031	0.020	0.9325	0.334
4	0.054	0.044	11.092	0.574
5	-0.211	-0.204	38.953	0.273
6	0.242	0.248	76.517	0.105
7	0.003	-0.040	76.521	0.176
8	-0.139	-0.091	89.431	0.177
9	-0.171	-0.179	10.933	0.142
10	0.112	0.025	11.802	0.160
11	-0.151	-0.101	13.432	0.144
12	0.081	0.055	13.910	0.177
13	0.080	0.039	14.387	0.212
14	-0.102	-0.122	15.185	0.231
15	-0.141	-0.026	16.745	0.211
16	0.095	-0.035	17.464	0.232
17	-0.075	-0.062	17.932	0.266
18	-0.043	-0.072	18.088	0.319
19	-0.047	-0.138	18.280	0.371
20	0.024	-0.007	18.330	0.434
21	0.014	0.107	18.348	0.499
22	0.012	-0.056	18.361	0.564
23	0.007	-0.015	18.366	0.626
24	0.005	-0.027	18.369	0.684

Because the Prob Prob value is > 0.05, AR AR(1) MA(1) is suitable as a forecasting method.

5. ARIMA Test Results (2,1,1) with MA(1) AR(1 TO 2) using D(NTP) C MA(1) AR(1 TO 2)

Table 16 MA(1) AR(1,2) Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.640.377	1.017.444	-0.161225	0.8726
AR(1)	0.096770	0.138077	0.700840	0.4867
AR(2)	-0.085660	0.295306	-0.290073	0.7730
MA(1)	-0.999996	5.437.703	-0.000184	0.9999
SIGMASQ	11086693	2.53E+09	0.004376	0.9965
R-squared	0.478596	Mean dependent var		5.807.273

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Adjusted R-squared	0.436883	S.D. dependent var		4.653.697
S.E. of regression	3.492.186	Akaike info criterion		1.938.294
Sum squared resid	6.10E+08	Schwarz criterion		1.956.542
Log likelihood	-5.280.308	Hannan-Quinn criter.		1.945.351
F-statistic	1.147.371	Durbin-Watson stat		2.126.504
Prob(F-statistic)	0.000001			
Inverted AR Roots	.05-.29i	.05+.29i		
Inverted MA Roots	1.00			

To determine the accuracy of the method and whether it is suitable for use in forecasting, a squared residual data test was conducted. The results of the residual test are presented in the following table:

Table 17 Residual Test Results MA(1) AR(1,2)

	AC	PAC	Q-Stat	Prob
1	0.103	0.103	0.6214	0.431
2	-0.138	-0.150	17.443	0.418
3	0.153	0.191	31.598	0.368
4	0.092	0.028	36.842	0.450
5	-0.057	-0.023	38.866	0.566
6	0.232	0.251	73.295	0.291
7	0.145	0.049	86.942	0.275
8	-0.082	-0.029	91.438	0.330
9	-0.089	-0.119	96.816	0.377
10	0.154	0.111	11.325	0.333
11	-0.044	-0.098	11.465	0.405
12	0.040	0.100	11.584	0.480
13	0.112	0.006	12.524	0.485
14	-0.078	-0.083	12.991	0.527
15	-0.089	0.016	13.610	0.555
16	0.170	0.099	15.928	0.458
17	-0.027	-0.074	15.989	0.525
18	-0.083	-0.027	16.575	0.552
19	-0.069	-0.141	16.988	0.591
20	-0.029	-0.029	17.062	0.649
21	-0.029	0.059	17.141	0.703
22	-0.066	-0.139	17.559	0.732
23	-0.042	-0.022	17.732	0.772
24	-0.024	0.006	17.790	0.813

Since the Prob value is > 0.05, AR AR(1) MA(1) is suitable as a forecasting method.

Based on the test results, to determine the best model, each model must meet the following criteri :

1. Small Schwarz criterion value
2. Small AIC value
3. The SSE value is small

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4. The largest Adjusted R-squared value and the Akaike info criterion value must be smaller.

Table 18 Comparison of Models for Forecasting

Method	Schwarz criterion value	Akaike info criterion value	SSE value	Adjusted R-squared	Significant
AR (1)	1.975.444	1.964.494	4.326884	0.167539	Not Significant
AR(1,2)	1.966.697	1.952.098	4.003.435	0.259936	Not Significant
MA (1)	1.943.665	1.932.716	3.451.816	0.449827	Significant
AR(1) MA(1)	1.949.992	1.935.394	3.485.542	0.439024	Significant
MA(1,2)	1.949.794	1.935.195	3.483.199	0.439778	Significant
MA(1) AR(1,2)	1.956.542	1.938.294	3.492.186	0.478596	Significant

Based on the table above, the model that meets the criteria is the ARIMA (0,1,1) model with MA(1) so that for the next forecast, the model used is MA (1) with the model:

$$NTP = 15.24475 - 1$$

Parameter Significance Test

The results of the model estimation on the parameters are then tested for parameter significance with the assumption that if the p-value is <0.05 then the parameter has a significant effect on the model.

Table 19 Parameter Significance Test

Parameter	t_hitung	Probabilitas	Information
NTP	23,03567	0,000	Significant parameters
HP	1,374065	0,1749	Parameters are not significant

In Table 19, it can be seen that there are no parameters that significantly affect the model. Although the parameters are not significant, the forecasting can still proceed because, in forecasting, the most important aspect is the ability of the MA(1) model to predict the data.

White Noise Test

In time series models, the residuals must have constant variance (white noise). The purpose of the white noise residual assumption test is to determine whether there is any correlation between the residual vectors of the MA(1) model that has been formed. This white noise residual assumption test is conducted using the Portmanteau test in EViews, where the p-value is compared with a significance level of 0.05. The Portmanteau test aims to check whether the residuals meet the condition of no autocorrelation. Below are the results of the Portmanteau test.

Table 20 White Noise Test Results with Portmanteau

F-statistic	1.529.378	Prob. F(2,55)	0.2257
Obs*R-squared	3.055.661	Prob. Chi-Square(2)	0.2170
Scaled explained SS	6.833.533	Prob. Chi-Square(2)	0.0328

Based on table 4.19, the Prob. value is > 0.05, meaning there is no heteroscedasticity in the ARIMA modeling or the residuals test the white noise assumption, meaning the model (ARIMA) is suitable for use.

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Forecasting

To forecast the Farmer Exchange Rate (NTP) in Medan City, North Sumatra, the estimation model obtained is the ARIMA (AR(1)) model.

$$NTP = -1{,}524 - 1(x - 1)$$

Forecasting is done for farming results for January 2019-December 2023

1. Forecast in February 2019, with x-1 being January 2019
   $NTP = -1{,}524 - 1(x - 1)$

   $NTP = -1{,}524 - 1(98{,}57)$

   $NTP = -100{,}09$, because NTP cannot be negative then NTP = 100,09.

2. Forecast in March 2019 with x-1 is February 2019
   $NTP = -1{,}524 - 1(x - 1)$

   $NTP = -1{,}524 - 1(100{,}90)$

   $NTP = -100{,}85$, because NTP cannot be negative then NTP = 100,85

3. Forecast in April 2019 with x-1 is March 2019
   $NTP = -1{,}524 - 1(x - 1)$

   $NTP = -1{,}524 - 1(100{,}85)$

   $NTP = -100{,}06$, because NTP cannot be negative then NTP = 100,06

4. The forecast for May 2019 with x-1 is April 2019
   $NTP = -1{,}524 - 1(x - 1)$

   $NTP = -1{,}524 - 1(100{,}06)$

   $NTP = -100{,}52$, because NTP cannot be negative then NTP = 100,52

5. The forecast for June 2019 with x-1 is May 2019
   $NTP = -1{,}524 - 1(x - 1)$

   $NTP = -1{,}524 - 1(100{,}52)$

   $NTP = -100{,}66$, because NTP cannot be negative then NTP = 100,66.

   And so on until December 2023.

Forecasting Accuracy

Based on the forecasting results of the Farmer Exchange Rate (NTP) in North Sumatra for the years 2019-2023, using predicted data from January 2019 to December 2023, with actual data from dragon fruit farming from January 2019 to December 2023, the obtained MAPE is as follows:

Table 21. Comparison of Actual and Predicted Data

Year	Month	Farmer Exchange Rate (NTP)	
		Actual	Forecasting
2019	January	98,57	-
	February	99,33	100,0945
	March	98,54	100,8545

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	April	99	100,0645
	May	98,14	100,5245
	June	96,52	99,66448
	July	96,68	98,04448
	August	96,83	98,20448
	September	97,34	98,35448
	October	98,08	98,86448
	November	98,91	99,60448
	December	99,08	100,4345
2020	January	98,23	100,6045
	February	98,1	99,75448
	March	96,95	99,62448
	April	96,44	98,47448
	May	96,92	97,96448
	June	97,56	98,44448
	July	96,95	99,08448
	August	96,9	98,47448
	September	96,76	98,42448
	October	96,61	98,28448
	November	96,38	98,13448
	December	94,98	97,90448
2021	January	114,96	96,50448
	February	114,69	116,4845
	March	117,05	116,2145
	April	117,53	118,5745
	May	118,58	119,0545
	June	116,56	120,1045
	July	115,78	118,0845
	August	117,92	117,3045
	September	120,61	119,4445
	October	123,21	122,1345
	November	125,75	124,7345
	December	127,95	127,2745
2022	January	126,75	129,4745
	February	125,83	128,2745
	March	128,65	127,3545
	April	130,38	130,1745
	May	116,4	131,9045
	June	117,31	117,9245
	July	108,85	118,8345
	August	117,8	110,3745
	September	119,3	119,3245
	October	121,22	120,8245
	November	124,37	122,7445
	December	124,56	125,8945
2023	January	123,78	126,0845
	February	125,34	125,3045

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	March	127,4	126,8645
	April	126,42	128,9245
	May	123,51	127,9445
	June	122,19	125,0345
	July	122,33	123,7145
	August	122,99	123,8545
	September	126,2	124,5145
	October	126,79	127,7245
	November	127,81	128,3145
	December	129,04	129,3345
Total		6735,61	6696,514

To calculate the MAPE value of the forecast results, the following equation is used:

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Z_i - \hat{Z}_i}{Z_i} \right|}{n} \times 100\%$$

$$MAPE = \frac{6735,61 - 6696,514}{\frac{6735,61}{60}}$$

$$MAPE_{nagabesar} = \frac{0,005804}{60}$$

$$MAPE_{nagabesar} = 0,96739X100\%$$

$$MAPE_{nagabesar} = 96,7\%$$

Based on the forecasting results using the ARIMA model, the MAPE value obtained for the prediction of the farmer's exchange rate was 96.7% so that based on Chang et al (2007) the MAPE value >50% is included in the very reasonable forecasting category so that based on this decision it can be concluded that modeling using the ARIMA method to predict the farmer's exchange rate in North Sumatra is very good to use.

Exchange rate forecast per year 2024

To predict the farmer's exchange rate in 2024, the same thing is done using the ARIMA model (AR(1) .

$NTP = -1,524 - 1(x - 1)$

Forecasting is done for agricultural business results for January-December 2024.

1. Forecast in January 2024, with x-1 being December 2023

   $NTP = -1,524 - 1(x - 1)$

   $NTP = -1,524 - 1(129,04)$

   $NTP = -130,56$, because NTP cannot be negative then NTP =130,56.

2. Forecast in February 2024, where x-1 is January 2024

   $NTP = -1,524 - 1(x - 1)$

   $NTP = -1,524 - 1(130,56)$

   $NTP = -129,04$, because NTP cannot be negative then NTP =129,04.

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3. Forecast in March 2024, where x-1 is February 2024

$NTP = -1{,}524 - 1(x - 1)$

$NTP = -1{,}524 - 1(129{,}04)$

$NTP = -130{,}56$, because NTP cannot be negative then NTP =130,56.

So the rivalry continues until December 2024.

Table 22 NTP Forecast Values for 2024

Month	NTP Forecasting
January	130,564
February	129,04
March	130,564
April	129,04
May	130,564
June	129,04
July	130,564
August	129,04
September	130,564
October	129,04
November	130,564
December	129,04

Based on Table 4.23 above, it can be concluded that the Farmer Exchange Rate (NTP) in 2024 will experience a decline in February, April, June, August, October, and December, while it will increase in January, March, May, July, September, and November. The Farmer Exchange Rate (NTP) is the ratio between the price index received by farmers and the price index paid by farmers, expressed as a percentage. NTP is one of the indicators used to determine the level of farmers' welfare. From the research results obtained, forecasting the NTP using the best model provides farmers with insights into the future exchange rate. If NTP > 100, it means farmers are experiencing a surplus. Production prices increase more than the increase in consumption prices. Farmers' income increases more than their expenses. If NTP = 100, it means farmers are breaking even. The increase/decrease in production prices equals the percentage increase/decrease in consumption prices. Farmers' income equals their expenses. If NTP < 100, it means farmers are experiencing a deficit. The increase in production prices is relatively smaller compared to the increase in consumption prices. Farmers' income decreases, being smaller than their expenses.

The usefulness and benefits of the Price Index Received by Farmers (It) can be seen in the price fluctuations of goods produced by farmers. This index is also used as supporting data in calculating agricultural sector income. From the Price Index Paid by Farmers (Ib), the price fluctuations of goods consumed by farmers—who represent the largest segment of rural society—can be observed, as well as the fluctuations in the prices of goods needed for agricultural production. The development of Ib can also reflect the development of inflation in rural areas. NTP is useful for measuring the exchange ability of products sold by farmers in relation to the products they need for production and household consumption. The NTP value indicates the competitiveness of agricultural products compared to other products. Based on this, efforts to specialize in and improve the quality of agricultural products can be carried out

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7. Conclusions

The ARIMA model for forecasting the Farmer Exchange Rate in North Sumatra in 2023 is the Farmer Exchange Rate . The prediction for the farmer exchange rate (NTP) is 96.7%, and according to Chang et al. (2007), a MAPE value > 50% falls into the category of highly accurate forecasting. Based on this conclusion, it can be stated that using the ARIMA method to forecast the farmer exchange rate in North Sumatra is highly suitable. The forecasting results for the farmer exchange rate in North Sumatra from 2019 to 2023 show fluctuations with ups and downs each year. Based on the forecast using the ARIMA model, it was found that the farmer exchange rate in North Sumatra in 2024 will experience a decline in February, April, June, August, October, and December. It will increase in January, March, May, July, September, and November. NTP is useful for measuring the exchange ability of products sold by farmers in relation to the products they need for production and household consumption. The NTP value indicates the competitiveness of agricultural products compared to other products. Based on this, efforts to specialize in and improve the quality of agricultural products can be carried out

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