Volume. 7 No 2 December (2024)

e-ISSN: **2615-3270**
p-ISSN: **2615-3599**

Eigen Mathematics Journal

Homepage jurnal: https://eigen.unram.ac.id/ index.php/eigen

Forecasting the Volatility of Tuna Fish Prices in North Sumatra using the ARCH Method in the Period January - April 2024

Riska Multiyaningrum[a], Ihsan Fathoni Amri [b]*, M. Al Haris [c], Havinka Angel Salsabilla[d], Heppy Nur Asavia Ginasputri[e], Salsabila Dhea Sintya[f]

[a] Department of Statistics, Universitas Muhammadiyah Semarang, Indonesia. E-mail: riskamultiya@gmail.com
[b] Department of Data Science, Universitas Muhammadiyah Semarang, Indonesia. E-mail: ihsanfathoni@unimus.ac.id
[c] Department of Statistics, Universitas Muhammadiyah Semarang, Indonesia. E-mail: alharis@unimus.ac.id
[d] Department of Statistics, Universitas Muhammadiyah Semarang, Indonesia. E-mail: havinkaangels@gmail.com
[e] Department of Statistics, Universitas Muhammadiyah Semarang, Indonesia. E-mail: heppynag23@gmail.com
[f] Department of Statistics, Universitas Muhammadiyah Semarang, Indonesia. E-mail: salsabiladheasintya2@gmail.com

ABSTRACT

Tuna (Euthynnus affinis) is one of the most important fisheries commodities in Indonesia with significant economic value, especially in its contribution to fisheries export revenue. However, the price of tuna experiences significant fluctuations that can affect local and national economic stability. This study analyzes the daily price fluctuations of tuna in the North Sumatra market from January 1, 2024 to April 29, 2024 using a time series analysis approach. Daily price data were collected and analyzed to identify existing price patterns and volatility. The Autoregressive Conditional Heteroskedasticity (ARCH) model was selected to address the heteroscedasticity in the data, which suggests that the volatility of tuna prices can be well predicted based on past price behavior. The analysis steps include identifying the optimal ARCH model using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), as well as testing parameter significance and normality assumptions to validate the model fit. The results show that the ARMA (1,0,0) model is the optimal one to model the price volatility of yellow tuna with the MAPE obtained of 2.382. compared to the ARMA-ARCH method with the MAPE value obtained of 2,747. Because it still contains heteroskedasticity effects, even though the results are good, the prediction results do not closely match the original data. The model is effective in improving price forecasting accuracy, which is important to support decision-making in risk management and economic planning in the fisheries sector. The findings contribute to understanding the dynamics of the yellowtail market and optimizing strategies for fisheries management.

Keywords: Tuna, Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroskedasticity (ARCH), North Sumatra, forecasting

Submitted: 08-07-2024; Accepted: 01-10- 2024;

Doi: https://doi.org/10.29303/emj.v7i2.236

1. Introduction

Indonesia, as an archipelago, has abundant natural resources, both on land and in the sea. These natural riches have great potential to improve the welfare of its people. According to the Republic of Indonesia's Ministry of Marine Affairs and Fisheries, the country has a lot of marine potential. Indonesian waters cover 5.8 million square kilometres, or about two-thirds of Indonesia's total area. With more than 17,000 islands and a coastline stretching 81,000 kilometres, the seas of Indonesia hold immense natural wealth (Nikawanti & Aca, 2021).

Indonesia's marine wealth has a huge potential and can be a source of food for the community. Even though Indonesia's sea area is wider than its land area, people still focus on food sources from land, such as rice and tubers. In fact, marine products can also be a source of food that is beneficial for people's welfare, both in terms of economics, nutrition and health (Nikawanti & Aca, 2021).

The waters in the archipelago are famous for their rich marine products. Various types of marine biota can be found in the waters of the archipelago, which stretch from Sabang to Merauke. Fish resources in Indonesian waters have a high

* Corresponding author.
Alamat e-mail: ihsanfathoni@unimus.ac.id

level of biodiversity, covering around 37% of the world's fish species (Office of the Minister of the Environment, 1994). In Indonesian sea waters, there are several types of fish with high economic value, such as tuna, skipjack, shrimp, mackerel, snapper, squid, coral fish (grouper, rabbitfish, barong shrimp/lobster), ornamental fish, and shellfish, including seaweed (Kusuma, 2017).

Tuna fish is a seafood product that is susceptible to quality degradation and short storage times. Tuna (Euthynnus affinis) is a fish that has high economic value. Tuna is a fish that is available every season and is very abundant. Tuna fish is the product that makes the largest contribution to the value of Indonesian fishery exports. Foreign exchange from exports will finance imports, particularly those of domestic raw materials and capital goods, thereby boosting national economic growth. Despite this, Indonesia's fish consumption is still very low (Andriyani & Syahputra, 2021).

Tuna fish (Euthynnus affinis) is a fish that is rich in nutrients, with nutritional content including water content of 71,00 percent-76,76 percent, protein 21,60 percent-26,30 percent, fat 1,30 percent 2,10 percent, minerals 1,20 percent-1,50 percent, and ash 1,45 percent-3,40 percent. Generally, people can consume a portion of fish ranging from 45 percent to 50 percent (Silfani, 2022).

According to retail food price data from the National Food Agency (Bapanas), tuna prices in North Sumatra from January 1, 2024, to April 29, 2024 show a fluctuating pattern that is interesting to analyze. Not only is the pattern the reason why this research is important to analyze, but data on tuna prices can also support the economic sustainability of fishing communities that depend on tuna as their main source of income (Zakariya, 2020). Apart from that, this research can also help ensure the availability of tuna as an important source of protein, especially in coastal areas and developing countries.

On Monday, April 29, 2024, tuna prices in North Sumatra reached IDR 32,470 per kg. This price has decreased by Rp. 1,900 (5.53 percent) if you look at the price trend for the last 3 months. Throughout 2024, the average price for tuna will be the lowest at IDR 31,420 per kg, and the highest price will reach IDR 38,070 per kg. This also happens because of the population of Tuna, the higher the number of people consuming sea fish, the higher the demand for sea fish. Conversely, as the population decreases, the consumption of sea fish also decreases, leading to a decrease in the demand for sea fish (Jolianis et al., 2014).

The increase in food prices was triggered by minor disruptions in supply performance, although the government often emphasized that food supplies remained safe and under control. However, the reality on the ground shows that the production and distribution system for several types of food is experiencing obstacles due to the large amount of damage to transportation facilities and infrastructure (Kiha & Rindayati, 2013).

The price movement of tuna in Indonesia has a volatility classification, that is, within a certain period of time there are quite drastic increases and decreases in the data. This is called heteroskedasticity in time series data. Before discussing the ARCH (Autoregressive Conditional Heteroskedasticity) model, it is important to understand the role of the ARMA (AutoRegressive Moving Average) model in time series data analysis. ARMA is one of the models commonly used to model linear and stationary time series data. This model combines two components: autoregressive (AR), which predicts future values based on past values, and moving average (MA), which predicts based on past errors (Muslihin & Ruchjana, 2023). In the period January 2024 to April 2024, heteroscedasticity was detected in the tuna price data, which could not be addresses by the ARIMA model, so the ARCH (Autoregressive Conditional Heteroskedasticity) time series model was used, which is one method that can be used to forecast time series data that contains elements of heteroscedasticity. This model is applied to time series that show varying volatility and clustering patterns over time, where there are periods of fluctuation followed by periods of relative stability. ARCH models are often considered part of the family of stochastic volatility models, although this is not entirely true because at time t, volatility is determined deterministically based on previous values (Tarlan, 2020).

Forecasting is a predictive process that uses historical data to produce estimates about future states or values. It involves quantitative or qualitative analysis of available information from the past to make detailed projections about what may happen in the future. By leveraging patterns and trends identified in historical data, forecasting helps in planning and making better decisions in a variety of contexts, from business to science (Melyani et al., 2021).

The goal of forecasting is to make decisions based on past information with an effort to minimize errors as much as possible. This means that forecasting has the possibility of producing errors, and the smaller the error value that occurs in the forecast, the higher the level of accuracy of the forecast (Amri et al., 2024).

In the face of uncertainty and changes in market prices, forecasters have accurate estimates of fluctuations in order to reduce risks for sellers. Therefore, the application of forecasting techniques can make a significant contribution in improving the quality of decision making, with the aim ofreducing risks that may arise in the future (Amri et al., 2024).

In time series forecasting analysis, data often shows four types of patterns that can be identified. The first pattern is horizontal, where data fluctuations occur around a fixed or stable average value. The second pattern is a trend, which reflects the increase or decrease in data values over time. Seasonal patterns, the third, show regular recurring patterns over time. Finally, the fourth cyclical pattern is in the form of waves (cycles) that influence economic conditions for more than one year (Melyani et al., 2021). The primary purpose of this research is to develop a forecasting model that can estimate the price of tuna in Indonesia for the year 2024 using the ARCH method. This model is expected to serve as a foundation for making informed decisions regarding tuna price trends. By achieving this goal, the research aims to contribute to decision-making processes in various areas, particularly in predicting future tuna prices, thus supporting stakeholders in the fishery sector in their strategic planning.

Although the primary focus of this research is the use of the ARCH method to capture price volatility, the ARMA model also plays an important role. The ARMA (AutoRegressive Moving Average) model is used to identify short-term patterns in linear data. Combining ARMA with ARCH can yield better results because ARMA can capture seasonal or trend patterns in the data, while ARCH will capture the volatility aspect of unpredictable price fluctuations.

Therefore, in this study, ARMA will be used to detect seasonal patterns or short-term cycles in tuna price data, while ARCH will be applied to model fluctuating volatility over time. This combined approach aims to provide more comprehensive tuna price forecasts, both in terms of linear patterns and volatility.

2. Theoretical basis

2.1. Mackarel tuna

Tuna fish is a type of marine biological resource that has significant economic potential, making it one of the main targets in fishing activities carried out by fishermen. In other words, this fish is an important catch in the fisheries sector (Apriantari et al., 2017).

2.2. Data source

This research is a quantitative study that uses secondary data obtained from databoks. The data used is in the form of time series data covering the period from January 1, 2024 to April 29, 2024 processed daily with a total of 120 data per day to measure the level of price volatility. Table 1 contains an explanation of the definition of each variable used in this research.

Table 1– Variable Definition.

Variable Name	Definition of Variables Used
y_t	Daily Price of Tuna Fish

2.3. Autoregressive Moving Average (ARMA)

The Autoregressive Moving Average (ARMA) model is one approach that is very commonly used in time series data analysis. The ARMA model combines an Autoregressive component, which assumes that current values are influenced by previous values, with a Moving Average, which assumes that current values are influenced by residual values from previous observations. Time series data itself is data that is regularly recorded based on the time sequence in which it was collected. The ARMA method was introduced by George *Edward Pelham Box and Gwily Meirion Jenkins*in 1976, so its formation is often known as the Box-Jenkins method in time series data analysis (Melyani et al., 2021).

In order for the ARMA model to produce optimal forecasts, the model must meet the residual white noise assumptions and be normally distributed. However, sometimes the data does not meet the assumptions in classical statistical analysis. As a result, statistical inference cannot be performed on the model parameters (Karomah & Hendikawati, 2014).

Autoregressive (AR) models use regression of past values of variables to predict future values. This model is denoted as AR(ρ), where p indicates the number of lags used in the model. The AR model uses the ρ lag order of the Autocorrelation Function (ACF). In this method, two indicators are used to measure model error and optimization, namely MAPE (Mean Absolute Percentage Error) and AIC (Akaike Information Criterion). The AR(ρ) model equation is:

$$y_t = b_0 + b_1 y_{t-1} + b_2 y_{t-2} + \cdots + b_n y_{t-n} + \varepsilon_t \tag{1}$$

The Moving Average (MA) model which is denoted by MA(q) is expressed as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_n \varepsilon_{t-n} + \varepsilon_t \tag{2}$$

where,

y_t	: sequence value that is stationary
y_{t-1}	: string light value
$\varepsilon_{t-1}, \varepsilon_{t-2} \dots \varepsilon_{t-n}, \varepsilon_t$	: residual
$\alpha_0, \alpha_1, \alpha_2 \dots \alpha_n$	: n MA coefficient constants
$b_0, b_1, b_2 \dots b_n$	: constant of the AR coefficient

2.4. AutoRegressive Conditional Heteroscedasticity (ARCH)

ARCH stands for AutoRegressive Conditional Heteroscedasticity which was later developed intoGARCH (Generilized AutoRegressive Conditional Heteroscedasticity). The GARCH model, which was introduced by Bollerslev in 1986 and 1994, is an evolution of the ARCH model first proposed by Engle in 1982. The ARCH model aims to overcome the problem of volatility in economic data, especially in the financial sector where forecasting models are often less accurate. In contrast, the GARCH model offers a more flexible structure with lags that can be adjusted to a greater extent. In the ARCH model, the variance of the residual time series data not only depends on the independent variables, but is also influenced by the residual values of the variables being studied (Sumiyati et al., 2022).

The ARCH model is used to model heteroscedasticity conditions, where the variance of the error term (residual) depends on past residual values. In this method, two indicators are used to measure model error and optimization, namely MAPE (Mean Absolute Percentage Error) and AIC (Akaike Information Criterion). The ARCH model equation is:

$$y_t = \beta_0 + \beta_1 X_{1t} + \varepsilon_t \tag{3}$$

$$\sigma_1^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{4}$$

where,

Y_t	: dependent variable at time t
β_0	: intercept
β_1	: regression coefficient
X_{1t}	: independent variable at time t
ε_t	: error term at time t

2.5. Data Stationarity Test

An important step in forecasting using the ARMA method is identifying data, where the data used must be stationary in terms of average and variance. To determine data stationarity, it can be done through a time series plot or by using the Augmented Dickey Fuller (ADF) test. The hypothesis used in the ADF test is as follows (Clarissa, Nisrina, Irfan, & Taqiyyuddin, 2021).

H_0: $\boldsymbol{\delta} = 0$ (The data is not stationary)

H_1: $\boldsymbol{\delta} < 0$ (The data is stationary).

The following are the test statistics used.

$$\Delta Z_t = \delta Z_{t-1} + u_t \tag{5}$$

$$\tau^* = \frac{\hat{\delta}}{se(\hat{\delta})} \tag{6}$$

where,

ΔZ_t : first difference of Z_t

δ : coefficient

Z_{t-1} : variable Z at the previous time"

u_t : error term at time t

τ^* : test statistic

$\hat{\delta}$: estimation of the coefficient δ

$se(\hat{\delta})$: standard error of the estimation of δ

2.6. Residual Assumption Testing

2.6.1 Normality Assumption Test

The Kolmogorov-Smirnov test (Chakravart, Laha, and Roy, 1967) is often used to determine whether a sample comes from a population with a certain distribution. This test measures the goodness of fit between the sample distribution and other distributions. This test compares sample data with anormal distribution that has the same mean and standard deviation. In short, this test is used to check whether the distribution of some data follows a normal distribution (Sintia et al., 2022).

$$H_0: F(a_t) = F_0(a_t) \tag{7}$$

(Residuals follow a normal distribution)

$$H_1: F(a_t) \neq F_0(a_t) \tag{8}$$

(Residuals do not follow a normal distribution)

2.6.2 Residual Middle Value Assumption Test

The residual mean test aims to evaluate whether the average or median of the residuals from the regression model is equal to zero. This test is important because it indicates whether the model has effectively captured the data patterns. If the residual mean is not equal to zero, this may indicate the presence of bias in the model used (Irfan et al., 2021).

$$H_0: \rho_1 = \rho_2 = \rho_{..} = \rho_k = 0 \tag{9}$$

(The mean value of the residuals is equal to 0)

$$H_0: \rho_k \neq 0 \tag{10}$$

(The mean value of the residuals is not equal to 0)

2.6.3 Autocorrelation Assumption Test

The autocorrelation test aims to detect the level of correlation between observations in a data series. This assumption is defined as the existence of a correlation between two observations, where the appearance of data is influenced by previous data. If there is a correlation like this, then it is said that there is an autocorrelation problem (Magfiroh et al., 2018).

$H_0: \rho = 0$ (There is no autocorrelation) (11)

$H_0: \rho \neq 0$ (There is autocorrelation) (12)

3. Methodology

The steps in analyzing data in this research are represented in figure.

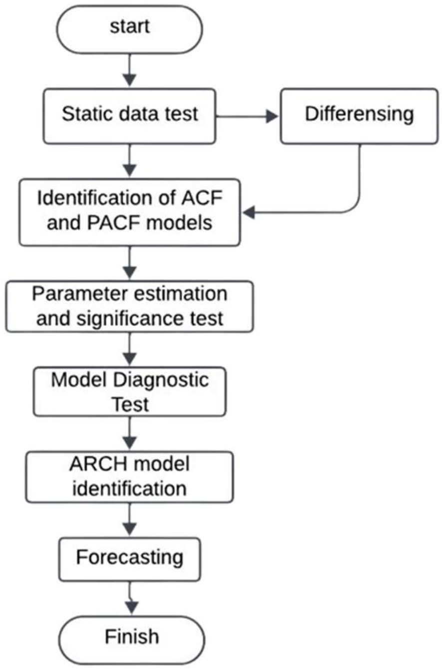

Figure 1 – ARCH flowchart.

In this study, data analysis is divided into two categories. First, stationarity testing on time series data using Augmented Dickey-Fuller (ADF) is conducted. Secondly, the ACF and PACF models are identified. If the time series data is not stationary at the zero level, the test can continue with iterations, such as using first differences if necessary. This process will continue until stationary data is obtained. This method is applied to test stationarity in this study. After that, the next step is to identify the ACF and PACF models, followed by parameter estimation and significance testing. If the significance and MAPE values are met, the model diagnostic test is conducted. Finally, forecasting will be determined based on the best model.

4. Discussion result

4.1. Descriptive Analysis

Descriptive analysis is a research method used to test the generalization of research results based on one data sample. This procedure involves descriptive hypothesis testing, which aims to determine whether the research results can be applied generally or not. If the null hypothesis is accepted, this indicates that the research results can be generalized. This descriptive analysis focuses on one or more variables separately, without making comparisons or exploring relationships between variables (Nasution, 2017).

The descriptive analysis used is maximum value, minimum value, standard deviation, average and median. The following are descriptive statistical values.

Table 2– Descriptive Analysis Value.

Statistics	Value
Maximum	38,07
Minimum	31,42
Standard Deviation	1,204
Average	34,36
Median	34,42

Table 2 – Descriptive Analysis Values shows that the maximum value obtained was 38,07, and the minimum value was 31,42. Meanwhile, the standard deviation value is 1,204, the average value of the tuna data is 34.36 and the median value is 34,42. Below is a graph of actual data on the price of tuna in North Sumatra.

4.2. Identify Plots on Actual Data

Data plotting is an important first step in time series analysis. The actual data plot is used to observe whether the data is stationary. Figure 2 displays a time series plot of daily tuna price data for the period January 1, 2024 to April 29, 2024.

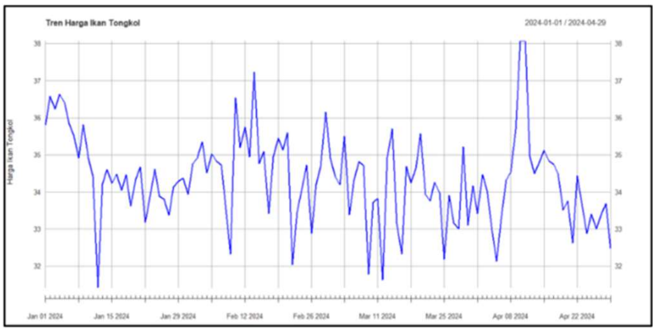

Figure 2– Data plot of tuna price in North Sumatra

From Figure 2, the data plot shows that the average and variance of tuna prices remain constant throughout the period January 1, 2024 to April 29, 2024. So the data can be visually considered stationary. This means there are no obvious trends or seasonal patterns visible in the data. However, this needs to be tested again using the Augmented Dickey-Fuller (ADF) test to ensure that the data is stationary.

4.3. Data Stationarity Test

Before proceeding with further analysis, it is important to ensure that the data used is stationary. Stationary data has a constant mean, variance, and autocorrelation over time, which is a prerequisite for many time series forecasting methods. With stationary data, the results of the analysis become more valid and accurate.

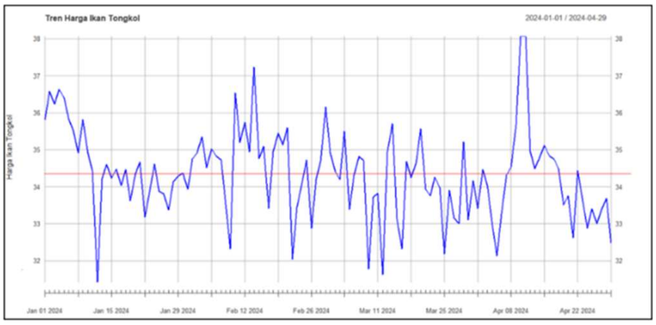

Figure 3– Data plot of tuna price in North Sumatra

In Figure 3, it can be seen that the data plot fluctuates around the zero point (constant). Therefore, it can be concluded that the data has shown stationary properties both in terms of average and variance.

Table 3 – Data Stationary Test

Test	*p-value*	Information
ADF Test	0,01	Stationary

Table 3 shows that the ADF test results have a p-value of 0,01, which is smaller than the significance level of 0,05. This shows that the price data for tuna is stationary and does not require differencing. Thus, the analysis can be continued at the next stage.

4.4. Model Identification

The selection of the optimal model is based on analysis of the Autocorrelation Function (ACF) plot and Partial Autocorrelation Function (PACF) plot. The MA(q) value is identified via the ACF plot, while the AR(p) value is identified via the PACF plot.

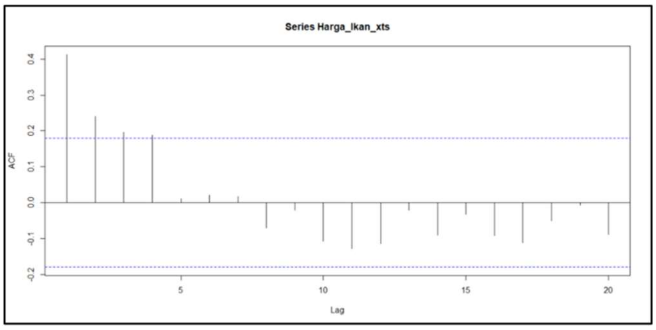

Figure 4– ACF plot

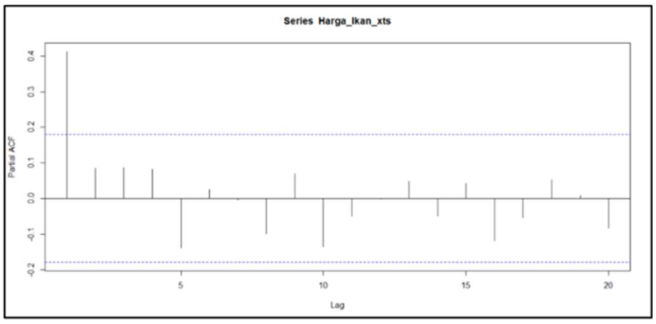

Figure 5– PACF plot

Based on Figure 4 and Figure 5, a tentative ARMA model can be formulated based on the results of ACF and PACF plot analysis. At the 4th lag, on the ACF plot and at the 1st lag, on the PACF plot, there are points that exceed the stationary limit. Therefore, several models can be generated, as shown in the following table.

Table 4– Best ARMA Model

ARMA MODELS	AIC
MODELS (1,0,4)	368,682
MODEL (1,0,3)	370,667
MODEL (1,0,2)	368,877
MODEL (1,0,1)	367,242
MODEL (1,0,0)	367,083

The AIC value resulting from each tentative model is used as a basis for selecting the most appropriate ARMA model. The ARMA model (1, 0, 0) has the lowest AIC value, namely 367,083, compared to the other models. Therefore, ARMA (1, 0, 0) is selected as the best model.

4.5. Parameter Significance Test

Table 5 – Significance of Model Parameters

No	Model	Parameter	*p-value*	Information
1	(1,0,4)	AR (1)	0,865	Not significant
		MA (1)	0,149	Not significant
		MA (2)	0,148	Not significant
		MA (3)	0,221	Not significant
		MA (4)	0,002	Significant
2	(1,0,3)	AR (1)	0,000	Significant
		MA (1)	0,097	Not significant
		MA (2)	0,636	Not significant
		MA (3)	0,645	Not significant
3	(1,0,2)	AR (1)	0,000	Significant
		MA (1)	0,034	Significant
		MA (2)	0,545	Not significant
4	(1,0,1)	AR (1)	0,000	Significant
		MA (1)	0,101	Not significant
5	(1,0,0)	AR (1)	0,000	Significant

Based on Table 5, the parameters in the ARMA model (1,0,0) have a p-value of less than 0,05. This leads to rejection of the null hypothesis, indicating that all parameters are significant. So the ARMA (1,0,0) model can be said to be the best model and can be used for forecasting

4.6. Normality Assumption Test

Before presenting the analysis results, we conducted a normality assumption test to evaluate whether the residuals from the model used follow a normal distribution. This test is important to ensure the validity of further analyses. We used the Kolmogorov-Smirnov test to assess the distribution of the residuals. Below are the results of the normality test that has been conducted.

Table 6– Normality Assumption Test

Test	*p-value*	Information
Kolmogorov-Smirnov	0,488	Normally distributed

Based on Table 6, after carrying out the Normality Test using the Kolmogorov-Smirnov Test, the p-value was (0,488). It's greater than 0,05. Thus, it can be concluded that the ARMA model (1,0,0) has met the normality assumption. Next, a residual test was carried out on the median residual value of the best model and the following results were obtained.

4.7. Residual Middle Value Assumption Test

The residual mean test is conducted to evaluate whether the average of the residuals from the regression model is equal to zero.

Table 7– Residual Middle Value Assumption Test

Test	*p-value*	Information
t. test	0,956	the mean value of the residuals is equal to 0

Based on Table 7, after carrying out the t test using the t.test as shown in Table 7, the p-value was (0,956). It's greater than 0,05. Thus, it can be concluded that the ARMA model (1,0,0) has met the assumption, namely the median value of the residuals is equal to 0. Next, the residual autocorrelation test was carried out. on the best model and obtained the following results.

4.8. Autocorrelation Assumption Test

This test is important to ensure that each observation is not influenced by previous observations, so that the model used can provide valid results

Table 8– Autocorrelation Assumption Test

Test	*p-value*	Information
Box-Ljung test	0,586	There is no autocorrelation

After carrying out the Box-Ljung Test as shown in Table 8 the p-value was 0,586, so it can be concluded that ARMA model (1,0,0) meets the autocorrelation assumption. Because the ARMA (1,0,0) model has fulfilled all assumptions, the ARMA (1,0,0) model is then tested using the arch.test whether the (1,0,0) model has a heteroscedasticity effect.

4.9. Heteroscedasticity Test

The heteroscedasticity test is carried out to evaluate whether there is inequality in the variance of the residuals between observations in the regression model. If the variance of the residuals remains constant, then the condition is called homoscedasticity. A good regression model is one that is homoscedastic or does not experience heteroscedasticity (Ghozali, 2013). Detection of the presence of heteroscedasticity is carried out by looking at special patterns in the scatter plot between the predicted values of the related variables and their residuals, such as wave patterns, expansion and narrowing.(Magfiroh et al., 2018)

Table 9– ARCH Effect Test

Test	Orders	L.M	*p-value*
Lagrange-Multiplier	4	49,49	0,000
	8	21,98	0,003
	12	12,45	0,331
	16	6,25	0,975
	20	3,36	1
	24	2,28	1

After carrying out the Lagrange-Multiplier (LM) test as shown in Table 9, it can be seen that the p-value of the Lagrange Multiplier test is obtained based on the lag order when the lag is less than 8.

So a significant value is obtained or there is heteroscedasticity, but at a lag of more than 8 the value obtained is not significant or there is no heteroscedasticity. So it can be concluded that the data has heteroscedasticity even though the effect obtained is small, in other words, there is a strong indication of ARCH heteroscedasticity at low orders (4 and 8), which means there is conditional volatility in the tuna price data. Thus, the Autoregressive Conditional Heteroskedasticity (ARCH) method is used to handle conditional volatility in the tuna price data.

4.10. ARMA – ARCH

Results from the best ARMA (1,0,0) model combined with the ARCH (ρ) model. If the LM ARCH-TEST test applied to ARMA (1,0,0)-ARCH (1,0) shows a p-value greater than 0,05 or ρ > 0,05 for each lag. This indicates that there is insufficient evidence to state that there is a heteroscedasticity problem in the model.

Table 10– Fit ARCH Model

ARCH Lag	Statistics	Shapes	Scale	*p-value*
ARCH Lag [2]	4	1,609	2,000	0,205
ARCH Lag [4]	8	2,157	1,611	0,407
ARCH Lag [6]	12	2,927	1,500	0,485

Based on Table 10, after testing the ARCH effect, it was found that ARCH with lags 2, 4 and 6 had a p-value > 0,05 or greater than 0,05, thus we do not reject the null hypothesis that there is no ARCH heteroscedasticity is significant at this lag.

Thus, in the ARMA-ARCH (1,0) model there is no conditional volatility in the tuna price data. So to do forecasting or forecasting we can use the ARMA-ARCH (1,0) model as the best model for the next 20 periods. The ARMA-ARCH (1,0) model can be written as.

$$y_t = 34{,}304 + 0{,}416 + \varepsilon_t \tag{13}$$

ARCH Model Equation

$$\sigma_1^2 = 1{,}066 + 0{,}098\varepsilon_{t-1}^2 \tag{14}$$

AR+ARCH Model Combined Equation

$$y_t = 34{,}300 + 0{,}416Y_{t-1} + \sqrt{1{,}066 + 0{,}098\varepsilon_{t-1}^2} \times z_t \tag{15}$$

The model used is ARMA as the best model, however the residual variance is not constant and is handled with the arch model. For forecasting, the ARMA model is used, because if the arch model is used in the form of an average, forecasting fluctuations cannot be captured. The following forecasting plot is interpreted in figure 6.

4.11. Forecasting

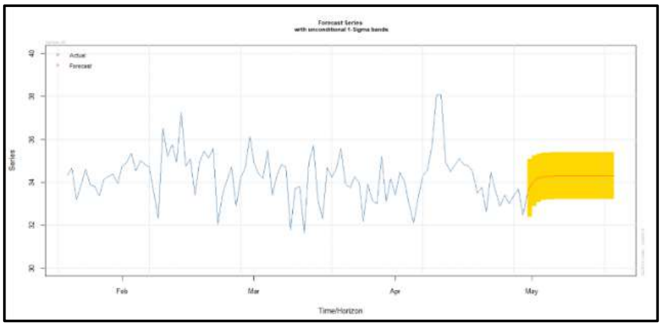

Figure 6– Forecasting Plots using the ARMA Method

The ARMA (1,0,0) model has shown a very good level of forecasting accuracy (MAPE) based on tuna price data in North Sumatra. This model is then applied to all data to forecast the daily price of tuna in the future. This model is used to project the price of tuna in the coming days and the results are shown in table 11.

Table11– Fit ARCH Model

Perioed	Series	Sigma
101	33,54	1,146
102	33,99	1,094
103	34,17	1,089
104	34,25	1,088
105	34,28	1,088
106	34,30	1,088
107	34.30	1,088
108	34,30	1,088
109	34,30	1,088
110	34,30	1,088
111	34,30	1,088
112	34,30	1,088
113	34,30	1,088
114	34,30	1,088
115	34,30	1,088
116	34,30	1,088
117	34,30	1,088
118	34,30	1,088
119	34,30	1,088
120	34,30	1,088

Based on Table 11, *Mean Absolute Percentage Error* (MAPE) is one of the methods used to calculate prediction error, or forecast error. This method measures the average absolute error as a percentage of the actual value (Putro et al., 2021).

Based on the results, it appears that the application of the ARMA method is able to predict the price of tuna in North Sumatra more accurately, with the MAPE value obtained being 2,382. This value is better compared to the ARMA-ARCH method, which produced a MAPE value of 2,747 This happens because, when using the ARMA-ARCH method, forecasting fluctuations cannot be captured optimally. Thus, it can be concluded that the best forecasting model to use is the ARMA (1,0,0) method, as it has better predictive capabilities in forecasting tuna prices.

5. Conclusion

Based on the results of the analysis and discussion that has been carried out, it can be concluded that the model for forecasting the price of tuna in North Sumatra using the ARCH method is the best model for forecasting the next 20 periods, namely using ARMA (1,0,0) or AR (1) with the MAPE error value amounting to 2,382. However, residual variance that is not constant must be overcome with an ARCH model. Because, if forecasting for the next 20 periods uses an ARCH model in the form of an average, forecasting fluctuations cannot be captured. This is also proven by the best ARMA model with an ARMA MAPE value smaller than the ARMA-ARCH MAPE value. With the smallest AIC value, namely 367,086 in the ARMA model (1,0,0) with the model equation:

$$y_t = 34{,}304 + 0{,}416 + \varepsilon_t$$

ARCH Model Equation

$$\sigma_1^2 = 1{,}066 + 0{,}098\varepsilon_{t-1}^2$$

AR+ARCH Model Combined Equation

$$y_t = 34{,}300 + 0{,}416Y_{t-1} + \sqrt{1{,}066 + 0{,}098\varepsilon_{t-1}^2} \times z_t$$

Implications of the Finding, these findings suggest that while ARMA models may offer better short-term accuracy, incorporating ARCH models is crucial for addressing variance fluctuations over longer periods. This implies that further attention should be given to the volatility and irregularities in price movements. Suggestions for Future Research, future studies should consider improving the ARCH component or exploring hybrid models to enhance forecasting accuracy, especially for capturing volatility. Moreover, additional variables or external factors, such as market trends and environmental factors, could be integrated into the model to improve its robustness and generalization.

Acknowledgment

We thank God Almighty for His blessings and mercy that made the completion of this article possible. We also express our thanks to Mr. Ihsan Fathoni Amri, S.Si., M.Stat., as supervisor who has provided direction and guidance during this research. We really appreciate the cooperation and dedication of all teammates who have contributed. We also express our thanks to our family and friends who always provide support and motivation. Hopefully this article can be useful and become a reference for future research.

REFERENCES

Amri, I. F., Sari, W., Widyasari, V. A., & Haris, M. A. (2024). The ARIMA-GARCH Method in Case Study Forecasting the Daily Stock Price Index of PT. Jasa Marga (Persero). *Eigen Mathematics Journal*, 25-33. https://doi.org/10.29303/emj.v7i1.174

Andriyani, D., & Syahputra, T. W. (2021). Pengaruh Ekspor Ikan Tongkol/Tuna Indonesia Ke Jepang Terhadap Pertumbuhan Ekonomi Di Indonesia Dengan Model Dinamis Regression. *Jurnal Ekonomi Regional Unimal*, 15-22. https://doi.org/10.29103/jeru.v4i1.4815

Apriantari, N. K., Dirgayusa, I. G., & As-syakur, A. R. (2017). Pengaruh Hasil Tangkapan Ikan Tongkol (Euthynnus sp) dan Pendapatan Keluarga Nelayan Terhadap Tingkat Pendidikan Anak Keluarga Nelayan di Desa Seraya Timur, Kecamatan Karangasem, Kabupaten Karangasem. *Journal of Marine and Aquatic Sciences*, 242-250. https://doi.org/10.24843/jmas.2017.v3.i02.242-250

Clarissa, N., Nisrina, N., Irfan, M., & Taqiyyuddin, T. A. (2021). Penerapan Model ARCH-GARCH dalam Prediksi Harga Saham The Walt Disney. *Jurnal Sains Matematika dan Statistika*,, 108-120. http://dx.doi.org/10.24014/jsms.v7i2.13175

Karomah, Y., & Hendikawati, P. (2014). Estimasi Parameter Bootstrap pada Proses ARMA dan aplikasinya pada harga saham. *UNNES Journal of Mathematics*. https://journal.unnes.ac.id/sju/ujm/article/view/4343

Kiha, E. K., & Rindayati, W. (2013). Konvergensi Harga Pangan Pokok Antar Wilayah di Indonesia. *Jurnal Ekonomi dan Kebijakan Pembangunan*, 30-46. https://doi.org/10.29244/jekp.2.1.2013.30-46

Kusuma, Y. B. (2017). Proses Produksi Hasil Laut Dalam Upaya Memperoleh Produk Unggulan (Studi Kasus Pada UD Yanis Di Kelurahan Sukolilo Baru). *Aplikasi Administrasi: Media Analisa Masalah Administrasi*, 139-154. https://doi.org/10.30649/aamama.v20i2.78

Magfiroh, S., Sunarmo, A., & Primasari, D. (2018). Profesional Audit Dan Etika Kerja Terhadap Tindakan Whistleblowing. *Jurnal Analisis Bisnis Ekonomi*, 103-116. https://doi.org/10.31603/bisnisekonomi.v16i2.2619

Melyani, C. A., Nurtsabita, A., Shafa, G. Z., & Widodo, E. (2021). Peramalan inflasi di Indonesia menggunakan metode Autoregressive Moving Average (ARMA). *Mathematics Education and Science*, 67-74. https://doi.org/10.32665/james.v4i2.231

Muslihin, K. R., & Ruchjana, B. N. (2023). Model Autoregressive Moving Average (ARMA) untuk peramalan tingkat inflasi di Indonesia. *Limits: Journal of Mathematics and Its Applications*. http://dx.doi.org/10.12962/limits.v20i2.15098

Nasution, L. M. (2017). Statistik deskriptif. *Hikmah*, 49-55. https://e-jurnal.staisumatera-medan.ac.id/index.php/hikmah/article/view/16

Nikawanti, G., & Aca, R. (2021). Ecoliteracy: Membangun Ketahanan Pangan Dari Kekayaan Maritim Indonesia. *Jurnal Kemaritiman: Indonesian Journal of Maritime*, 149-166. https://doi.org/10.17509/ijom.v2i2.37603

Putro, E. A., Rimawati, E., & Vulandari, R. T. (2021). Prediksi Penjualan Kertas Menggunakan Metode Double Exponential Smoothing. *Jurnal Teknologi Informasi dan Komunikasi (TIKomSiN)*, 60-68. http://dx.doi.org/10.30646/tikomsin.v9i1.548

Silfani, D. (2022). Suplementasi Ikan Tongkol (Euthynnus Affinis) Terhadap Mutu Organoleptik, Kadar Protein Serta Daya Terima Risoles Sebagai Makanan Jajanan Anak Sekolah. http://repositoryperpustakaanpoltekkespadang.site/id/eprint/1328

Sintia, I., Pasarella, M. D., & Nohe, D. A. (2022). Perbandingan Tingkat konsistensi uji distribusi normalitas pada kasus tingkat pengangguran di Jawa. *In Prosiding Seminar Nasional Matematika dan Statistika (Vol. 2)*. https://jurnal.fmipa.unmul.ac.id/index.php/SNMSA/article/view/844

Sitilamsyari, B., Asrizal, & Jolianis. (2014). Faktor-Faktor Yang Mempengaruhipermintaankonsumen Terhadap Ikan Tongkoldi Tiku Kecamatan Tanjung Mutiara Kabupatenagam. *Pendidikan Ekonomi*. https://www.neliti.com/publications/29858/efaktor-faktor-yang-mempengaruhipermintaankonsumen-terhadap-ikan-tongkoldi-tiku#cite

Sumiyati, Sandy, B. D., & Wilujeng, P. R. (2022). Metode Arch/Garch untuk memprediksi hubungan Economic Uncertainty akibat Pandemi Covid 19 dan Volatilitas Saham. *Jurnal Bisnis dan Akuntansi*, 117-130. https://doi.org/10.34208/jba.v24i1.1152

Tarlan, S. (2020). Analisis volatilitas dan value at risk pada sukuk indonesia dengan menggunakan model arch/garch (Bachelor's thesis, Jakarta. *Fakultas Ekonomi dan Bisnis UIN Syarif Hidayatullah Jakarta*. https://repository.uinjkt.ac.id/dspace/handle/123456789/38750?mode=full

Zakariya, F. (2020). Pemberdayaan Nelayan dalam Mambangun Kekuatan Ekonomi Melalui Pengolahan Ikan Di Desa Karangagung. *Islamic Management and Empowerment Journal*, 133-148. https://doi.org/10.18326/imej.v2i2.133-150