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Modeling and Predicting Galangal Production in Indonesia :ARIMA Approach

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ABSTRACT

This article aims to model and predict the Galangal production in Indonesia. As it is known, Galangal provides many benefits in the health sector as well as being a trading commodity both inside and outside of Indonesia. The model in this article is the ARIMA model (Auto Regressive Integrated Moving Average), that is one of the time series analysis used to model the dependent variable without including the exogenous/independent variables in the model. 23 data were used, namely the annual data of Galangal production in Indonesia from 1997 until 2019 which was published on the BPS website (Central Bureau of Statistic in Indonesia). The parameter tests, diagnostic tests, and AIC checks had been carried out on each model before. The best ARIMA model results for the transformation of natural algorithms data is the ARIMA model (0,2,1) and an exponential transformation is performed to obtain the customization and prediction data from the model. The MAPE from this model is 8% with the prediction results of Galangal production in Indonesia in 2021 is about 85478.035 ton.

1. Introduction

Indonesia is a country with the second richest biodiversity in the world after Brazil[1]. Therefore, Indonesia has enormous potential as a source and ingredient of natural or herbal medicine. Plants that are widely used as medicinal ingredients are called medicinal plants (biopharmaca). Indonesia has around 30,000 plant species, around 31.2% are known as medicinal plants and only around 3-4% are used and cultivated commercially as medicinal plants[2]. One of Biopharmaca plants is galangal. Galangal is a native of Indonesia although its exact origin is not known, but it has become naturalized in many parts of South and Southeast Asia. The oldest reports about its use and existence are from southern China and Java[3].

Galangal has three types: lesser galangal, greater galangal, and light galangal. The reddish-brown rhizomes are used as condiment and have an aromatic spicy odor and a pungent taste. The lesser galangal (*Alpinia officinarum Hance*.), a member of the family Zingiberaceae, is a native of southern China. The greater galangal (*Alpinia galanga (L.) Willd*.) is also a perennial herb with showy flowers and beautiful foliage. It is commonly found in Indonesia and Malaysia and is also cultivated in Bengal and southern parts of India. The light galangal (*Alpinia speciosa (Wendl.) K. Schum*) is a native of the Eastern Archipelago, off the Coromandel Coast of southeast India. Its rhizome is much larger and is generally used as a substitute for greater galangal, and even as a substitute for ginger in many preparations[4].

Aside of being used as cooking ingredients and herbal medicines, many studies have been conducted to find out more about the benefits of Galangal, and the results are; if Galangal extract is combined with amoxicillin, it will have an antibacterial activity and will be synergistic against Escherichia coli (AREC)[5], other than that A. galangal compounds showed a significant effect of inhibiting melanoma cell proliferation (which caused skin cancer) in cell viability test [6] and the other studies in the laboratory also proved that Galangal contains many bioactive compounds with pharmacological and medicinal properties that varies [7] and galangal showed the second best potency after *Citrus sp*. as the inhibitor of the development of SARS-CoV2 which can be consumed in everyday life as a prophylaxis (form of prevention) of COVID-19[8].

Galangal is also a commodity for both domestic and foreign trade. Based on the data from the Foor and Agriculture Organization (FAO) in 2016, Indonesia is on the fourth rank as a herb producer in the world with the total production about 113.649 tons and the total export value of 652,3 million US Dollar. Galangal is on the third place of herbs exported by Indonesia[9]. Galangal is exported to Shanghai[10], England[11], Eastern Europe[12], and to the rest of the world. Therefore, Galangal has many benefits in the health sector and helps the economy in Indonesia. One of the ways that can be done to assist the government in making policy is by modeling and predicting galangal production in Indonesia. Because there is the existence of predictive data, the adequacy of Galangal production can be compared to the demand of Galangal both for the development of the research and also health products; for the domestic trades as well as for the needs of Indonesian exports. In addition, this research is expected to provide benefits for the development of science and can be a reference for other practitioners. In this research, the ARIMA model is used (Auto Regressive Integrated Moving Average).

George Box and Gwilym Jenskin were the founders of ARIMA model in 1976. Box and Jenkins used the ARIMA model for a one-variable time series (*univariate*). ARIMA (*p,d,q*) model, where *p* states the order of the *autoregressive* (AR) process, *d* states the differentiator (*differencing*) and *q* states the order of *moving average* (MA) process. The basis of the ARIMA model is carried out with four stages of modeling strategies that is model identification, parameter assessment, diagnostic examination, and prediction[13].

The reasons for choosing the ARIMA model as a model of the data are: First, this feature is advantageous for forecasting a large number of time series. Second, this avoids a problem that occurs sometimes with multivariate models. For example, consider a model including wages, prices and money. It is possible that a consistent money series is only available for a shorter period of time than the other two series, restricting the time period over which the model can be estimated. Third, with multivariate models, timeliness of data can be a problem. If one constructs a large structural model containing variables which are only published with a long lag, such as wage data, then forecasts using this model are conditional forecasts based on forecasts of the unavailable observations, adding an additional source of forecast uncertainty[14]. In addition, in previous research conducted by researchers, to make predictions, the ARIMA model shows that MAPE is classified as highly accurate [15].

2. Literature Review

2.1 Previous research that models and predicts the Galangal production

The researchers have not found the previous research that models and predicts the galangal production.

2.2 Theoretical Framework

a. *Auto Regressive Moving Average (ARMA)*

A time series $\{x_t; t = 0, \pm 1, \pm 2, \ldots\}$ is ARMA(p, q) if it is stationary and

$$x_t = \varphi_1 x_{t-1} + \cdots + \varphi_p x_{t-p} + w_t + \theta_1 w_{t-1} + \theta_q w_{t-q} \quad (1)$$

with $\varphi_p \neq 0, \theta_q \neq 0$ and $\sigma^2{}_w > 0$. The parameters p and q are called the autoregressive and the moving average orders, respectively. If x_t has a nonzero mean μ, we set $\alpha = \mu(1 - \varphi_1 - \cdots - \varphi_p)$ and write the model as

$$x_t = \alpha + \varphi_1 x_{t-1} + \cdots + \varphi_p x_{t-p} + w_t + \theta_1 x_{t-1} + \theta_q x_{t-q} \quad (2)$$

where $w_t \sim wn(0, \sigma^2{}_w)$.

As previously noted, when $q = 0$, the model is called an autoregressive model of order p, AR(p), and when $p = 0$, the model is called a moving average model of order q, MA(q)[16].

b. *Auto Regressive Integrated Moving Average (ARIMA)*

The general form of the ARIMA model equation:

$$\left(1 - \varphi_1 B - \cdots - \varphi_p B^p\right)(1 - B)^d x_t = \mu + w_t + \theta_1 w_{t-1} + \cdots + \theta_q w_{t-q}, w_t \sim IID(0, \sigma^2) \quad (3)$$

where B is the return operator (backward), that is $(B^j x)_t = x_{t-j}$

The equation above can also be written in the form of:

$$(1 - \varphi_1 B - \cdots - \varphi_p B^p)(1 - B)^d x_t = \mu + \left(1 + \theta_1 B + \cdots + \theta_q B^q\right) w_t, w_t \sim IID(0, \sigma^2) \quad (4)$$

[13].

c. *Steps of Time Series Modeling*

i. *Data Pre-processing*

Hypothesis testing which is often used to check the stationarity of time series data in an average is Augmented Dickey-Fuller (ADF) testing. This test is one of the most frequently used in testing the stationarity of the data, that is by looking at whether the model has a unit root or not[17]. Data that is not stationary in average can be stationary through a differencing process.

The test is done by testing the hypothesis $H_0: \rho = 0$ (there is unit root) in regression equation:

$$x_t = \alpha + \delta t + \rho x_{t-1} + \sum_{j=1}^{k} \varphi_j x_{t-j} + w_t \quad (5)$$

The null hypothesis is rejected if the statistical value of the ADF test has less (more negative) value than the critical area value. If the null hypothesis is rejected, then the data is stationary[13].

ii. Model Identification

As discussed earlier, the identification of ARMA models would require more care, as both the ACF and PACF will exhibit exponential decay and/or damped sinusoid behavior[18].

Based on the autocorrelation coefficients and on the partial correlation coefficients are determined the start autoregressive models for the analysis of the data series. At this stage we will determine the p and q parameters from the graph of the autocorrelation and partial autocorrelation functions of the stationary series[19].

Tabel 1. Bentuk plot sampel ACF/PACF dari model ARMA

Proses	ACF Sample	PACF Sample
White noise (random error)	None has crossed the interval limit on $lag > 0$	None has crossed the interval limit on $lag > 0$
AR(p)	Decays toward zero exponentially	Above the maximum interval limit until lag to p and below the limit on $lag > p$
MA(q)	Above the maximum interval limit until lag to q and below the limit on q	Decays toward zero exponentially
ARMA(p,q)	Decays toward zero exponentially	Decays toward zero exponentially

[13].

iii. Parameter Estimation

There are several methods such as methods of moments, maximum likelihood, and least squares that can be employed to estimate the parameters in the tentatively identified model[18].

iv. Diagnostic Checking

If the model is appropriate, then the residual sample autocorrelation function should have no structure to identify. That is, the autocorrelation should not differ significantly from zero for all lags greater than one[18] or by doing a serial correlation test, that is testing the hypothesis:

$H_0: \rho_1 = \rho_2 = \cdots = \rho_k, k < n$ (there is no serial correlation in the residual from $lag - k,\ k < n$)

This test can be done with the Box-Pierce test statistic:

$$Q = n \sum_{j=1}^{k} \hat{\rho}(j)^2 \tag{6}$$

Or Ljung-Box:

$$Q = n(n+2) \sum_{j=1}^{k} \hat{\rho}(j)^2/(n-j) \tag{7}$$

that will distribute $\chi^2\big(k - (p+q)\big), k > (p+q)$. In here, $\hat{\rho}(j)$ showed the ACF residual sample value on *lag-j*, whereas p and q showed the order of the ARMA (p,q) model. If the diagnostic check hypothesis is rejected, the model that has been identified above cannot be used and the model that may be suitable for the data can be identified again[13].

v. Best Model Selection

The best model selection is determined by measuring the quality of the predictive model. It can be done by using Akaike's Information Criterion (AIC) value[20]. The best model is those with the lowest AIC values. The formula for obtaining the AIC value is written as follows:

$$AIC = -2 \ln \ln (L) + 2u \tag{8}$$

with

n : sample size
L : Likelihood function value that obtained from parameter estimation

u : the number of parameters in the model that will be tested. Methodology

vi. Model Performance Measures

One way of measuring the goodness of conformity or forecasting is to use the MAPE (Mean Absolute Percentage Error) measurement[18].

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{w_t}{x_t}\right| \tag{9}$$

Table 2. A Scale of Judgment of Forecast Accuracy

MAPE Value	Judgment of Forecast Accuracy
$< 10\%$	Highly accurate
$11\% - 20\%$	Good forecast
$21\% - 50\%$	Reasonable forecast
$> 51\%$	Inaccurate forecast

[21].

3. Methodology

3.1 Data and Programming

This study analyzed the annual data of galangal production in Indonesia from 1997 until 2019. The data was taken from *Pertanian dan Pertambangan* (Agricultural and Mining) data *BPS* (*Badan Pusat Statistik*/Central Bureau of Statistic), *Hortikultura* (Horticulture) section with the title of the table *Produksi Tanaman Biofarmaka* (Biopharmaca Plant Production) and can be downloaded from the website BPS at https://www.bps.go.id/indicator/55/63/1/produksi-tanaman-biofarmaka-obat-.html. All of the analysis in this research was used R and R Studio software (R. Free Software Foundation's GNU General Public License., 2020)

3.2 Research Variable

This research consist of 1 variable i.e:
The galangal production (unit kilogram) in Indonesia from 1997 until 2019.

3.3 Analysis Steps

The steps to analyze data are listed in the followings:
1. Data Pre-processing
1a. Collecting the galangal production data in Indonesia from 1997 until 2019.
1b. Carrying out stationarity tests in average using the Augmented Dickey-Fuller Test. If the data are not stationary in the average, they are transformed
2. Model Identification
Identifying the ARMA model using ACF and PACF plots
3. Model Estimation
Performing parameter estimation and parameter significance test of the ARMA model
4. Diagnostik check
Verifying the ARMA model, which include residual independence test
5. Forecasting and Simulation with the Best Model
Forecasting galangal production for the next several periods 3. Measuring forecast accuracy using MAPE

The following is the methodology flowchart of the Box-Jenkins:

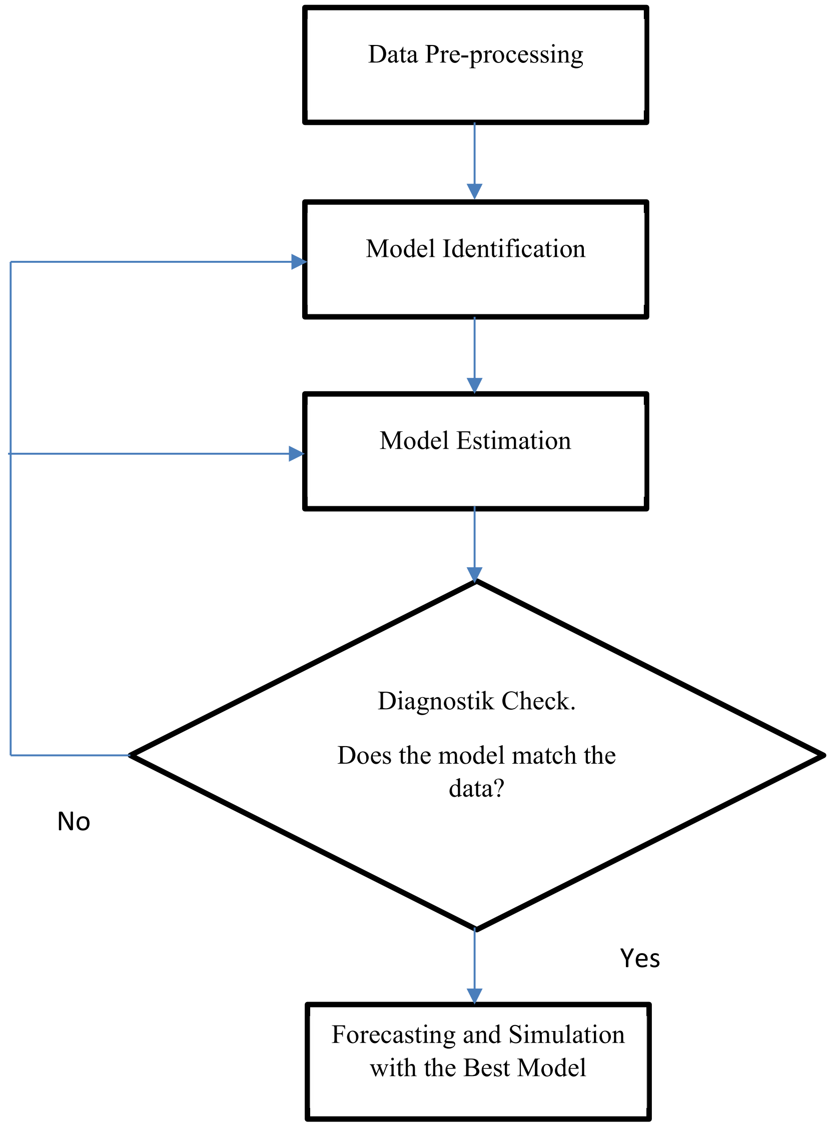

Figure 1. The Methodology Flowchart of the Box-Jenkins modeling

4. Results and Discussion

4.1 Data Description

This study analyzed the annual data of galangal production in Indonesia from 1997 until 2019. The data were divided into in-sample data from 1997 until 2019 which were used as training data and out sample data from 2020 until 2022 which were used to test the prediction accuracy. The plot of galangal production in Indonesia data movement can be seen in Figure 1.

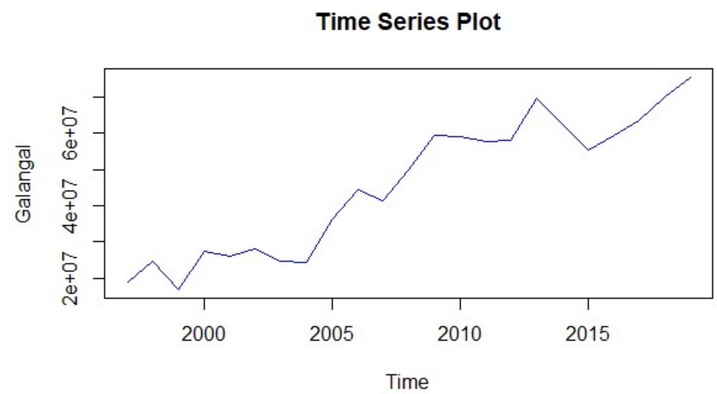

Figure 2. Time Series Plot of Galangal Production in Indonesia

Based on the time series plot, it can be seen that the value of galangal production data is not stationary. The data has an upward trend. Then, the descriptive statistics of galangal production value presented in Table 2.

Table 3.Descriptive Statistics	
Mean	45778760
Standard Deviation	18630330
Minimum Value	16886470
Maximal Value	75384910
Skewness	-0.11
Kurtosis	-1.57

The *kurtosis* value is -0,11, it can be said that the *Platikurtik* curve, is a distribution that has an almost horizontal peak (taper value $<$ 3), and the *skewness* showed a negative value -1,57 or the concentrated values on the left side (located to the left of the Modus), so that the curve had a tail extended to the left, the curve is skewed to the left or is skewed negatively for the period of 1997 until 2019.

4.2 Data Pre-processing

In Figure 1, it can be seen that the data has not been stationary which is confirmed by the unit root test with *Augmented Dickey-Fuller/ADF* (which denotes the existence of a unit root)or with the plot of ACF/PACF, as follows:

Hypothesis testing with *Augmented Dickey-Fuller/ADF* test

H_0: $\rho = 0$ (there is a unit root)

Table 4. The results of *Augmented Dickey-Fuller/ADF* test on galangal production data in Indonesia from 1997 until 2019

Value of test-statistic(τ)	$\tau_{\alpha;db}$			Decision
	$\tau_{0,01;17}$	$\tau_{0,05;17}$	$\tau_{0,1;17}$	
-2.4836	-4.38	-3.60	-3.24	Accepting H_0 (there is a unit root)

H_0 is rejected if τ has less (more negative) value than $\tau_{\alpha;db}$, but because the τ has more (less negative) value from $\tau_{\alpha;db}$, H_0 is accepted. There is a unit root that denotes the data is not yet stationary.

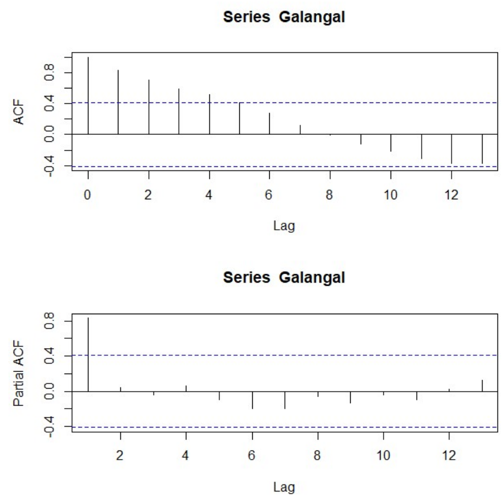

Figure 3. ACF and PACF Plots of Galangal Production in Indonesia

In Figure 2, it can be seen that the overall ACF value shows that the galangal production data is not stationary. The next step is to transform algorithms and differencing processes in order to produce stationary data. The data fulfills the stationary assumption after doing the algorithmic and differencing transformations twice (d=2). The following is the plot and the *Augmented Dickey-Fuller/ADF* test results from the transformation of galangal production data.

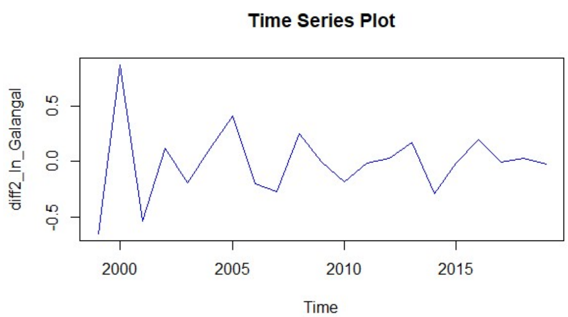

Figure 4. The result of two times natural algorithmic transformation and differencing of Galangal production data from 1997 until 2019.

In Figure 3, it can be seen that the confirmed stationary data from unit root *Augmented Dickey-Fuller/ADF* test (which denotes the existence of a unit root) or with the ACF/PACF plot, as follows:
Hypothesis of unit root test with *Augmented Dickey-Fuller/ADF* test
$H_0: \rho = 0$ (there is a unit root)

Table 5. The results of *Augmented Dickey-Fuller/ADF* test from two times natural algorithm transformation dan differencing Galangal production data in Indonesia from 1997 until 2019.

Value of test-statistic(τ)	$\tau_{\alpha;db}$			Decision
	$\tau_{0,01;17}$	$\tau_{0,05;17}$	$\tau_{0,1;17}$	
-5.4762	-4.38	-3.60	-3.24	Rejecting H_0 (there is no unit root)

H_0 is rejected if τ has less (more negative) value than $\tau_{\alpha;db}$, and because τ has less (more negative) value from $\tau_{\alpha;db}$ then H_0 is rejected. There is no unit root that indicates the data is stationary and fulfills the assumptions for the identification of the ARMA model.

4.3 Model Identification

The model identification process is done by checking ACF and PACF values on the stationary data.

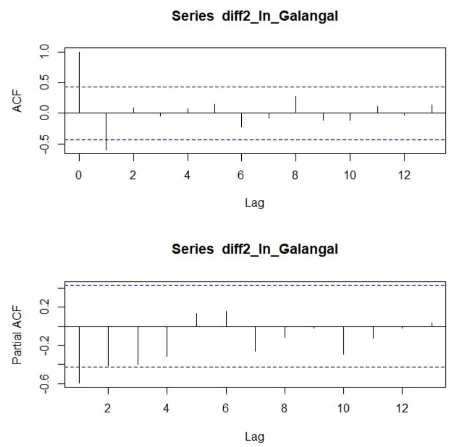

Figure 5. ACF and PACF plots from the two times transformation and differencing of Galangal Production data in Indonesia from 1997 until 2019.

In Figure 4, it can be seen that ACF *plot* is significant to the 1st and 2nd *lag* (the value of the order is possibly q=0 or q=1 or q=2) and Partial ACF(PACF) plot is also significant to the 1st *lag* (the value of the order is possibly p=0 or p=1 or p=2), so that the ARMA(p,q) model that was tried on the results of two times transformation and differencing data of Galangal production in Indonesia from 1997 until 2019 is ARMA(0,1), ARMA(1,1), ARMA(2,1), ARMA(0,2), ARMA(1,2), ARMA(2,2), ARMA(1,0), ARMA(2,0) or in the other words, ARIMA(p,d,q) from the natural algorithm of Galangal production data (two times differencing means d=2) is ARIMA(0,2,1), ARIMA(1,2,1), ARIMA(2,2,1), ARIMA(0,2,2), ARIMA(1,2,2), ARMA(2,2,2), ARMA(1,2,0), ARMA(2,2,0).

4.4 Parameter Estimation

Parameter estimation is carried out on the eight models and significant model are obtained in ARIMA(1,2,0) and ARIMA(0,2,1)

a. Parameter test on ARIMA(1,2,0) model
   Hypothesis for the order p=1
   $H_0 : \phi_1 = 0$
   $H_1 : \phi_1 \neq 0$
   H_0 is accepted if $-t_{table} \leq t_{count} \leq t_{table}$, otherwise if $t_{count} \leq -t_{table}$ atau $t_{count} \geq t_{table}$ then H_0 is rejected H_1 is accepted (significant parameter)..
   as for the calculation of the test statistics

$$t_{count} = t = (\widehat{\phi_i} - 0)/SE(\widehat{\phi_i}) \quad (8)$$

and the table statistics $t_{table} = t(df = n-1; \alpha = 2{,}5\%)$.

Table 6.Parameter estimation of ARIMA(1,2,0) model

Model	Parameter	SE Parameter	t_{count}	t_{table}= $t(df = n-1; \alpha = 2{,}5\%)$	Decision
ARIMA (1,2,0) with the constant	$\widehat{\phi}_1 = -0.7022$	0.1674	-4.194743	-2.308 (used -t_{table} as comparison)	Rejecting H_0

b. Parameter test of ARIMA(0,2,1) model
   Hypothesis of the order q=1
   $H_0 : \theta_1 = 0$
   $H_1 : \theta_i \neq 0$
   H_0 is accepted if $-t_{table} \leq t_{count} \leq t_{table}$, otherwise if $t_{count} \leq -t_{table}$ atau $t_{count} \geq t_{table}$ then H_0 is rejected and H_1 is accepted (significant parameter).
   As for the calculation of the statistic test

$$t_{count} = t = (\widehat{\phi_i} - 0)/SE(\widehat{\phi_i}) \quad (8)$$

and the statistic table $t_{table} = t(df = n-1; \alpha = 2{,}5\%)$.

Table 7. Parameter estimation of ARIMA(0,2,1) model

Model	Parameter	SE Parameter	t_{count}	t_{table}= $t(df = n-1; \alpha = 2{,}5\%)$	Decision
ARIMA (0,2,1) with the constant	$\hat{\theta}_1 = -1.0000$	0.1331	-7.513148	-2.308 (used -t_{table} as the comparison)	Rejecting H_0

4.5 Diagnostic Checking

Diagnostic Checking is including white noise testing on residual.

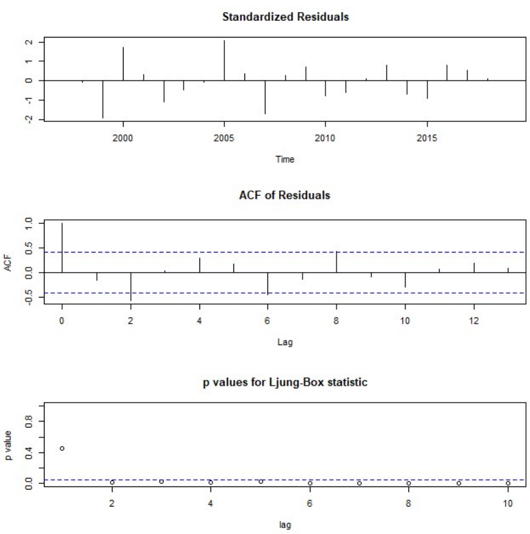

Figure 6. Diagnostic Plot from the (1,2,0) model

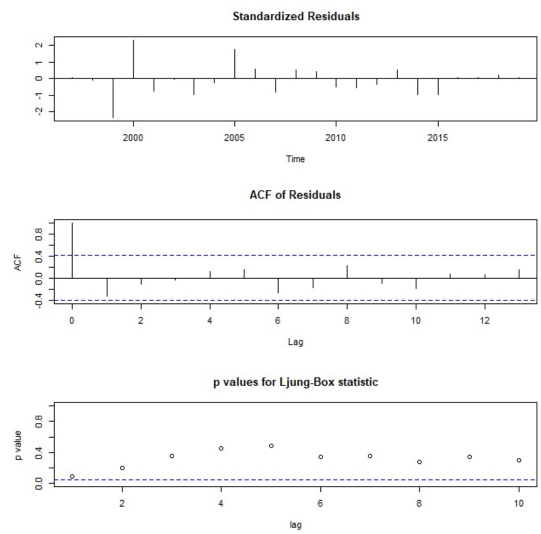

Figure 7. Diagnostic plot from the (0,2,1) model

In Figure 5, it can be seen from the results of diagnostic check that residual from ARIMA(1,2,0) model on the ACF plot does not meet the assumption of the white noise model, it can be seen from the lag that that comes out (≥ 1) from the interval limit and the p-value of the Ljung-Box statistic is also below the 5%, which indicates that the null residual hypothesis does not contains serial correlations is rejected, whereas in Figure 6 shows the results of diagnostic check that the residual from the ARIMA(0,2,1) model has meet the assumptions of the white noise model, characterized by the significant residual ACF values only in the first lag, and the p-value of the Ljung-Box statistic is above the 5% threshold, which indicates that the null residual hypothesis does not contains serial correlations is accepted. Only the ARIMA(0,2,1) model satisfies the assumptions of the residual white noise model.

As for the AIC value from ARIMA(1,2,0) and ARIMA(0,2,1) models in sequence are 3.192645 and -3.398891. Because the ARIMA(0,2,1) model fulfills the assumptions of the residual white noise model and and has the smaller AIC, it can be concluded that the ARIMA(0,2,1) model is the best model that modeled natural algorithms from Galangal production data in Indonesia from 1997 until 2019.

4.6 Forecasting and Simulation with the Best Model

Based on table 5, if written in the equation, will be obtained ARIMA(0,2,1) model as follows:

$$(1-B)^2\hat{Y}_t = -1.0000\varepsilon_{t-1}$$

where $\hat{Y}_t = ln\ ln\ \hat{Z}_t$
so that the calculation of the prediction value for Z_t is

$$\hat{Z}_t = exp\ (\hat{Y}_t)$$

Annotation:

$\hat{Z}_t$: the prediction of Galangal production

This following is the results of calculating the prediction value using the ARIMA(0,2,1) model for *in-sample* and *out-sample* data.

Table 8. The comparison between Actual Data with the Prediction Data of Galangal Production in Indonesia *In-Sample* (confidence interval 95%)

Time (year)	Galangal Production in Indonesia (kg)	
	Actual Data	Prediction Data
2014	62520835	75222608
2015	55149830	66705175
2016	59453023	58550842
2017	63536065	63155023
2018	70014973	67562059
2019	75384910	74535400

The MAPE obtained based on the table above is 8,00 %.

Table 9. Prediction *Out-Sample* Data of Galangal Production in Indonesia (confidence interval 95%)

Time (year)	Galangal Production in Indonesia (kg)		
	Prediction	Lowest Prediction	Highest Prediction
2020	80272688	54501566	118230894
2021	85478035	48856598	149549799
2022	91020016	45234924	183148892

The following is a plot of Galangal production data, *in sample* value adjustment, and the prediction value of the lowest and the highest production with the ARIMA(0,2,1) model above. The table 7 shows the prediction results of Galangal production in Indonesia (kg)from 2020 to 2022, with an increase in the production of about 5373664 kg or 5373,7 ton in average every year.

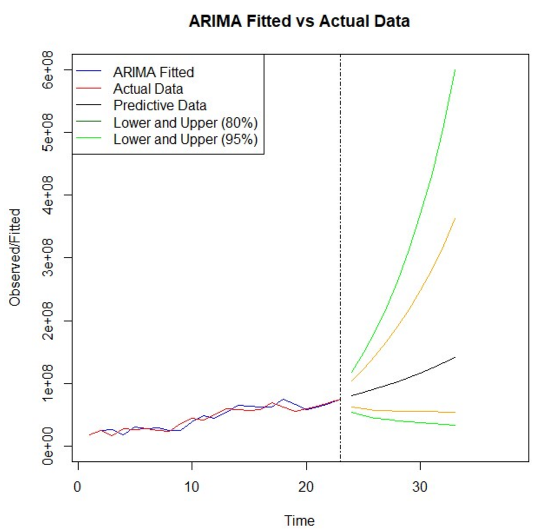

Image 6. The plot data of Galangal Production in Indonesia (kg),customized series and prediction of galangal production in Indonesia (kg)

5. Conclusion
Based on the results and discussion, it is conclusive that the best model for modelling and forecast Galangal Production in Indonesia is the ARIMA (0,2,1) model.

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