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TEA PRODUCTION FORECASTING IN INDONESIA'S LARGE PLANTATION BY USING ARIMA MODELS

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ABSTRACT

Indonesia is known for its outstanding agricultural sector and natural wealth. Tea is one of the plantation sectors that are mostly consumed all over the world and has been one of Indonesia's mainstay commodities that has already been listed as one of the 10 export commodities with a big amount of production. Tea production data have a fluctuating pattern and characteristic. Therefore, it is really important to know the projection of tea production for planning and management purposes. The ARIMA (Autoregressive Integrated Moving Average) model is one of the methods that can be used to predict future productions. The ARIMA (4,1,0) is found to be the most suitable model to be used with a MAPE of 29.9%. The forecasting process shows the production will have an uptrend pattern for ten months from March 2018. The Tea production forecast data will be useful for future planning and production control.

Keywords: *Time series, Arima, Forecasting, Tea Production*.

1. Introduction

Indonesia is a country that is abundant in its natural wealth. The plantation sector is one of them. Rubber, palm oil, coffee, cocoa, tea, quinine, sugar cane, and tobacco are Indonesia's mainstay commodities. Tea plays an important role both in terms of income and foreign exchange, as well as in employment and regional development (Palupi, 2017). In general, tea is one of the most widely consumed natural products in the world. Tea is one of Indonesia's plantation products which is part of Indonesia's export commodities with a relatively large amount of production. As reported by the Plantation Office of East Kalimantan Province, tea, cocoa (cocoa), and coffee are Indonesian export commodities that have been recorded in the top 10 in the world in terms of production (Pemprov Kaltim, 2014). Indonesian tea is a tea known for its natural antioxidant content, namely catechins, with the highest concentration in the world (Anjarsari, 2016).

Research on tea production using ARIMA (Autoregressive Integrated Moving Average) modeling has been carried out in past research. Based on the research results of Wijaksono et al. on the green tea production data of PT. Rumpun Sari Medini in 2012-2016, tea production data fluctuates. Based on this research, the accepted model is ARIMA(1,0,0) with a Mean Square Error (MSE) of 0.03668 (Wijaksono and Sulistijanti, 2017)

As part of Indonesia's mainstay export commodity, the Indonesian government needs to know the projection of tea production in the future so that adjustments can be made, both in terms of the distribution of domestic and export sales volumes as well as in terms of increasing income. The tea itself is a natural product that has an expiration date and is affected by weather changes. Therefore, forecasting is necessary for production planning and control (Andriana and Susanto, 2017). The ARIMA Model is one of the data analysis methods with the Time Series concept in forecasting data that can be used to predict tea production at the Large Indonesian Plantation in the future.

2. Literature Review

A. Time Series Analysis

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Time Series data is a collection of observational data recorded in time sequence. Time Series analysis is a method used to extract information from the data to predict the output data by analyzing certain patterns in the data. In analyzing Time Series Data, there are two types of data that we must pay attention to, namely Stationary Data, and Non-stationary Data. Stationarity in Time Series Analysis itself is where the statistical properties or properties of the process of moving time series data do not change over time. A data can be said to be stationary if the data pattern is in equilibrium around a constant average value and the variance value around the average is constant over a certain period. The data to be used in the Time Series analysis must be stationary (Cryer, J. D., & Chan, K. S. 2008).

Differentiation, or Differencing is a method for converting Non-Stationary data into stationary. The differencing process is done by subtracting the current and previous observations. This helps in making the mean constant. And you can also use the Box-Cox method to make the variance constant. In general, the differencing process can be written as follows (Cryer, J. D., & Chan, K. S. 2008).

$$W_t = \nabla^d Y_t \tag{1}$$

where Y_t is the Value of the Variable at time t and ∇ is difference Operator.

B. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

The Covariance and Correlation between time series data Y_t and Y_{t-k} in the same process with different lag-time k are called The Autocovariance (γ_k) and autocorrelation (ρ_k). The Autocovarince formula is as follows (Cryer, J. D., & Chan, K. S. 2008).

$$\gamma_k = Cov(Y_t, Y_{t-k}) = E[(Y_t - \mu)(Y_{t-k} - \mu)] \tag{2}$$

As for the autocorrelation is as follows.

$$\rho_k = \frac{Cov(Y_t, Y_{t-k})}{\sqrt{Var(Y_t).Var(Y_{t-k})}} = \frac{\gamma_k}{\gamma_0} \tag{3}$$

If { Y_t } is a time series process with a normal distribution, then the Partial Autocorrelation Function can be written as follows.

$$\Phi_{kk} = Corr(Y_t, Y_{t-k} \mid Y_{t-1}, Y_{t-2}, \ \dots \ , Y_{t-k+1}) \tag{4}$$

It can also be approached using the Yule-Walker equations define as follows.

$$\rho_j = \Phi_{k1}\rho_{j-1} + \Phi_{k2}\rho_{j-2} + \Phi_{k3}\rho_{j-3} + \dots + \Phi_{kk}\rho_{j-k} \text{ , for j = 1, 2, ..., k} \tag{5}$$

The $\rho_1,\ \rho_2,\ ...,\ \rho_k$ above will be used to solve $\Phi_{k1},\ \Phi_{k2},\ ...,\ \Phi_{kk}$. The related problem could be solved recursively as follows (Cryer, J. D., & Chan, K. S. 2008).

$$\Phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \Phi_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \Phi_{k-1,j}\rho_j} \tag{6}$$

where $\Phi_{k,j} = \Phi_{k-1,j} - \Phi_{kk}\Phi_{k-1,k-j}$, for j = 1, 2, …, k-1.

C. Autoregressive Model (AR)

Autoregressive is a model that works with the concept of lag which is defined as forecasting a data series based on past values in the series [11] (Cryer, J. D., & Chan, K. S. 2008). The formula for the Autoregressive model is shown below.

$$Y_t = \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + e_t \tag{7}$$

where Y_t is The Value of the Variable at time t, ϕ_i is Autoregressive Coefficient, e_t is Error, p is Autoregressive Order.

D. Moving Average (MA)
Moving Average is a model of time series values that works based on elements of error in current and past data (Makridakis et al., 1999). The Moving Average formula is as follows.

$$Y_t = e_t - \theta_1 e_{t-1} - ... - \theta_q e_{t-q} \quad (8)$$

Where Y_t is the Value of the Variable at time t, θ_i is Moving Average Coefficient, e_t is Error, q is Moving Average Order.

E. Autoregressive Moving Average (ARMA) Model
The Autoregressive Moving Average model is a combination of the Autoregressive and Moving Average models, with the following formula.

$$Y_t = \Phi_1 Y_{t-1} + ... + \Phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - ... - \theta_q e_{t-q} \quad (9)$$

Where Y_t is The Value of the Variable at time t, ϕ_i is Autoregressive Coefficient, θ_i is Autoregressive Coefficient, e_t is Error at time t, p is Autoregressive Order
q = Moving Average Order

F. Autoregressive Integrated Moving Average (ARIMA)
The ARIMA model is an extension of the ARMA model where the data must be processed into stationary data before being used in model analysis which is carried out through a differencing process. ARIMA itself has 3 parameters, namely (p, d, q), where p is order AR , q is order MA, and d is order differencing (Cryer, J. D., & Chan, K. S. 2008).

$$W_t = \Phi_1 W_{t-1} + \Phi_2 W_{t-2} + ... + \Phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - ... - \theta_q e_{t-q} \quad (10)$$

Where $W_t = \nabla^d Y_t$.

G. Advantages and Disadvantages of Time Series Analysis
The advantage of Data Forecasting with Time Series Analysis is that it has a high level of accuracy and is easy to implement. Also it is a statistical technique that has been developed to analyze time series in such a way that the factors that influence the fluctuations of the series can be identified and treated and will produce good output with less variables.

Other than that, there also some major disadvantages of Time Series Analysis. Time Series models can be easily overfitted, leading to erroneous results. The analysis is sensitive to outlier data. If outliers are not handled properly they can lead to wrong predictions. The different elements that affect series fluctuations cannot be fully adjusted for Time Series analysis

3. Research Method

Data Forecasting Algorithm using ARIMA is illustrated at the following diagram.

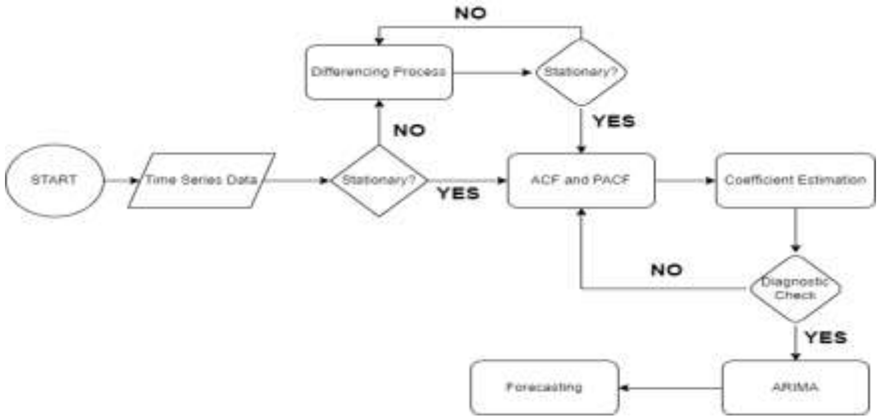

Figure 1. Box Jenkins Method

4. Results and Discussion

A. Data Preparation

The first thing we have to do is prepare the data and check the feasibility of the data before using it. The data that will be used is the Monthly Tea Production Data in Large Plantations in Tons with a time span from January 2009, to December 2018 (BPS, 2018).

Table 1. Monthly Tea Production 2009-2018

Year	Month	Production (Ton)	Year	Month	Production (Ton)
2009	January	8.8	2014	January	8.69
2009	February	7.9	2014	February	7.86
2009	March	8.5	2014	March	9.36
2009	April	9.3	2014	April	9.29
2009	May	10.3	2014	May	9.56
2009	June	8.5	2014	June	8.63
2009	July	8.4	2014	July	8.22
2009	August	8.1	2014	August	8.12
2009	September	7.9	2014	September	7.97
2009	October	10	2014	October	8.42
2009	November	9.7	2014	November	8.61
2009	December	10	2014	December	8.78
2010	January	8.2	2015	January	7.6
2010	February	7.4	2015	February	6.4
2010	March	9.7	2015	March	6.73
2010	April	9.1	2015	April	8.53
2010	May	9.7	2015	May	7.86
2010	June	8.8	2015	June	7.77
2010	July	7.7	2015	July	6.47
2010	August	7.6	2015	August	6.84
2010	September	7.7	2015	September	6.32
2010	October	8.4	2015	October	6.18
2010	November	7.8	2015	November	5.94
2010	December	7.9	2015	December	6.51
2011	January	7.78	2016	January	8.58
2011	February	6.89	2016	February	7.57
2011	March	8.86	2016	March	7.68
2011	April	8.42	2016	April	8.4
2011	May	8.66	2016	May	7.85
2011	June	8.54	2016	June	7.6
2011	July	7.38	2016	July	7.26
2011	August	6.92	2016	August	7.48
2011	September	7.69	2016	September	6.92
2011	October	7.81	2016	October	7.06
2011	November	7.77	2016	November	7.13
2011	December	8.4	2016	December	7.54
2012	January	7.7	2017	January	7.73

2012	February	7.17	2017	February	7.28
2012	March	8.53	2017	March	7.14
2012	April	8.12	2017	April	8.06
2012	May	8.47	2017	May	8.08
2012	June	8.03	2017	June	6.93
2012	July	6.96	2017	July	8.2
2012	August	6.62	2017	August	7.11
2012	September	6.92	2017	September	6.88
2012	October	7.35	2017	October	7.77
2012	November	7.94	2017	November	8.29
2012	December	7.85	2017	December	8.46
2013	January	7.51	2018	January	8.71
2013	February	6.54	2018	February	6.56
2013	March	6.31	2018	March	7.15
2013	April	8.93	2018	April	8.22
2013	May	8.93	2018	May	7.71
2013	June	8.47	2018	June	8
2013	July	9.09	2018	July	7.65
2013	August	8.13	2018	August	6.99
2013	September	8.1	2018	September	6.78
2013	October	8.07	2018	October	8.12
2013	November	8.04	2018	November	8.48
2013	December	8	2018	December	8.25

Source : BPS, 2018

The total production data is 120 data and has been sorted by time. We will divide the data into two parts, namely Training Data and Test Data. The last 10 data, the March 2018-December 2018 interval will be designated as Test Data while the rest as Training Data. In the data processing and analysis process, we will use Training Data and Test Data will be used to test forecast results. The data processing will be using software of RStudio. The following is a display of the Data Training plot.

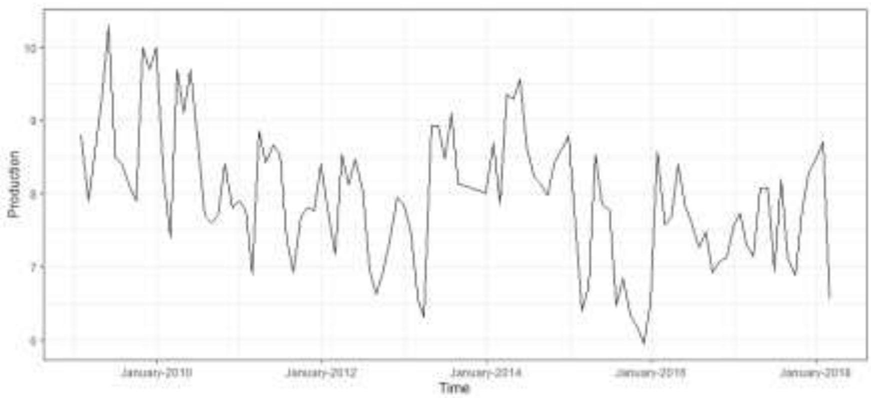

Figure 2. Training Data

B. Stationarity

Before applying Time Series analysis, we must check whether the data to be used is stationary or not by using the ADF Test.

```
        Augmented Dickey-Fuller Test

data:  Data_training$Production
Dickey-Fuller = -3.0973, Lag order = 4, p-value = 0.1214
alternative hypothesis: stationary
```

Figure 3. Augmented Dickey-Fuller Test

The ADF test results show a p-value of 0.1214, which is more than 0.05 which indicates that the Training Data is Non-Stationary. Therefore we have to do the differencing process. The data plot after the first differencing is shown in Figure 4.

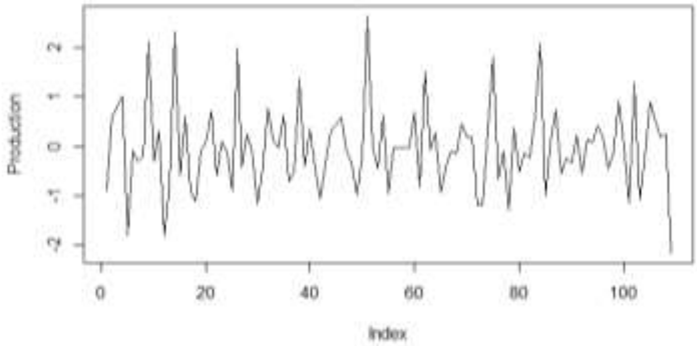

Figure 4. First Differencing Data

```
> prod=diff(Data_training$Production)
> adf.test(prod)

        Augmented Dickey-Fuller Test

data:  prod
Dickey-Fuller = -8.0444, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(prod) : p-value smaller than printed p-value
```

Figure 5. First Differencing ADF Test

After the first Differencing process, the p-value is less than 0.05, which means that the data is stationary and ready to be used.

C. AR(p) and MA(q)

Orders of AR and MA can be determined using PACF for Order p and ACF for Order q.

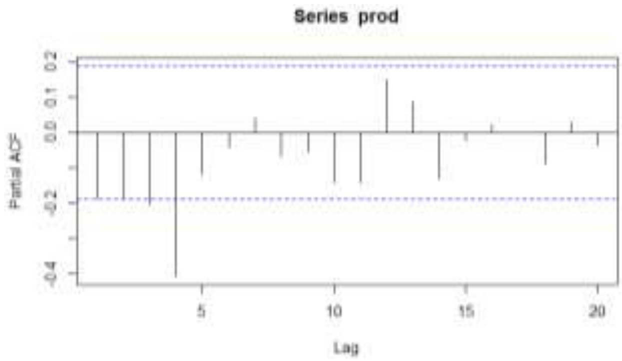

Figure 6. Partial ACF (PACF)

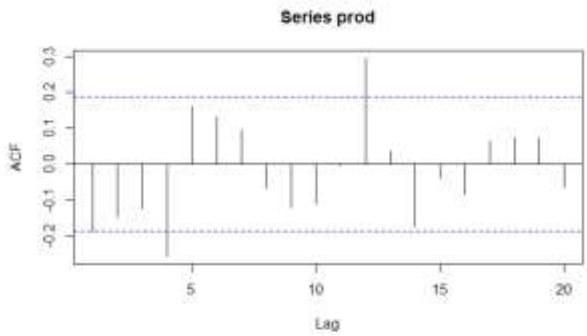

Figure 7. ACF

It can be seen that the cut off for PACF and ACF are both at lag time 4. Thus, the AR order, namely p, is 4 and the MA order, q, is 4.

D. Model Specification

With order p is 4, order differencing d is 1, and order q is 4, then the total ARIMA model that may be used is a total of 25 models. The following is a specification of the ARIMA Model that may be used.

Table 2. Arima Model Specification.

Model	ARIMA (p,d,q)	p	d	q	Model	ARIMA (p,d,q)	p	d	q
1	ARIMA(4,1,4)	4	1	4	14	ARIMA(2,1,1)	2	1	1
2	ARIMA(4,1,3)	4	1	3	15	ARIMA(2,1,0)	2	1	0
3	ARIMA(4,1,2)	4	1	2	16	ARIMA(1,1,4)	1	1	4
4	ARIMA(4,1,1)	4	1	1	17	ARIMA(1,1,3)	1	1	3
5	ARIMA(4,1,0)	4	1	0	18	ARIMA(1,1,2)	1	1	2
6	ARIMA(3,1,4)	3	1	4	19	ARIMA(1,1,1)	1	1	1
7	ARIMA(3,1,3)	3	1	3	20	ARIMA(1,1,0)	1	1	0
8	ARIMA(3,1,2)	3	1	2	21	ARIMA(0,1,4)	0	1	4
9	ARIMA(3,1,1)	3	1	1	22	ARIMA(0,1,3)	0	1	3
10	ARIMA(3,1,0)	3	1	0	23	ARIMA(0,1,2)	0	1	2
11	ARIMA(2,1,4)	2	1	4	24	ARIMA(0,1,1)	0	1	1
12	ARIMA(2,1,3)	2	1	3	25	ARIMA(0,1,0)	0	1	0
13	ARIMA(2,1,2)	2	1	2					

E. Parameter Estimation

In this section, we will perform parameter estimation for all possible models. The estimation includes the coefficients AR_1, AR_2, AR_3, AR_4, MA_1, MA_2, MA_3, MA_4, Log likelihood (LL). The result is shown in the following table.

Table 3. Parameter Estimation.

Model	Estimation								
	AR_1	AR_2	AR_3	AR_4	MA_1	MA_2	MA_3	MA_4	LL
1	0.4774	-0.2037	-0.7895	0.2473	-0.9596	0.1692	0.8330	-0.7322	-112.81
2	-0.0429	-0.3387	-0.6354	-0.4084	-0.3521	0.2752	0.6143	-	-116.16
3	-0.0734	-0.3389	-0.2833	-0.3847	-0.3523	0.0798	-	-	-117.48
4	-0.1261	-0.2931	-0.2824	-0.3848	-0.2989	-	-	-	-117.49
5	-0.3649	-0.3616	-0.3451	-0.4397	-	-	-	-	-118.43
6	0.3089	-0.2832	-0.6978	-	-0.8221	0.2124	0.6902	-0.5522	-113.48
7	1.3805	-1.3686	0.3636	-	-1.8905	1.8815	-0.8475	-	-113.32
8	0.5867	-0.2802	-0.2044	-	-1.0260	0.2910	-	-	-120.5
9	0.3352	-0.1249	-0.1858	-	-0.7678	-	-	-	-121.2
10	-0.2777	-0.2514	-0.2194	-	-	-	-	-	-129.34
11	-0.4320	-0.7158	-	-	0.0469	0.3454	-0.5738	-0.4456	-117.81

12	1.0090	-0.9911	-	-	-1.5908	1.5264	-0.5998	-	-114.97
13	-0.3736	0.3005	-	-	-0.0504	-0.7909	-	-	-122.18
14	0.4536	-0.1416	-	-	-0.874	-	-	-	-122.38
15	-0.2359	-0.2008	-	-	-	-	-	-	-131.89
16	-0.5195	-	-	-	0.1405	-0.4279	-0.2349	-0.2773	-120.67
17	-0.8280	-	-	-	0.3800	-0.7525	-0.2692	-	-122.7
18	0.2605	-	-	-	-0.6936	-0.1896	-	-	-122.64
19	0.4560	-	-	-	-0.9274	-	-	-	-123.12
20	-0.1983	-	-	-	-	-	-	-	-134
21	-	-	-	-	-0.3717	-0.2426	-0.1118	-0.1527	-122
22	-	-	-	-	-0.4453	-0.2729	-0.1164	-	-122.62
23	-	-	-	-	-0.4502	-0.3588	-	-	-122.99
24	-	-	-	-	-0.7022	-	-	-	-130.01
25	-	-	-	-	-	-	-	-	-136.05

F. Residual Analysis

A good and acceptable model is a model whose p-value from Saphiro and Ljung-Box Test is above 0.05. After done this test, we provide the accepted models and rejected model at Table 4.

Table 4. Residual Analysis

MODEL	P-VALUE		Description	MODEL	P-VALUE		Description
	Saphiro	Ljung-Box			Saphiro	Ljung-Box	
1	0.01872	0.7066	Reject	14	0.2637	0.8003	Accept
2	0.01175	0.7675	Reject	15	0.1301	0.6484	Accept
3	0.02242	0.9357	Reject	16	0.2177	0.7092	Accept
4	0.02242	0.928	Reject	17	0.4586	0.8225	Accept
5	0.06291	0.5037	Accept	18	0.2878	0.9405	Accept
6	0.02887	0.8049	Reject	19	0.2431	0.739	Accept
7	0.00765	0.7371	Reject	20	0.01191	0.6889	Reject
8	0.007372	0.8256	Reject	21	0.1391	0.6043	Accept
9	0.03359	0.7278	Reject	22	0.2529	0.9914	Accept
10	0.135	0.3229	Accept	23	0.3445	0.8902	Accept
11	0.1866	0.7469	Accept	24	0.8525	0.00742	Reject
12	0.00466	0.4605	Reject	25	0.005704	0.04744	Reject
13	0.4823	0.9817	Accept	-	-	-	-

According to Table 4, the models that pass the test are models 5, 10, 11, 13, 14, 15, 16, 17, 18, 19, 21, 22, and 23.

G. Best Model Evaluation

Among the acceptable models in the previous section, we will determine the best model by doing an AIC comparison. The model that passes the residual test which has the smallest AIC value is the best model.

Table 5. The value of Akaike's Information Criterion

Model	AIC
5	244.87
10	264.69
11	247.63
13	252.36
14	250.76
15	267.77
16	251.34
17	253.39
18	251.28
19	250.23
21	252.01
22	251.24
23	249.99

Based on the comparison results, Model 5 and Model 11 are 2 models that have the smallest AIC value, and have a relatively small difference between the two. Next, we will compare the MSE, RMSE, MAE, and MAPE errors from the forecasting projections of the two models.

Table 6. The Error of The Model 5.

Time	Actual Data (y)	Prediction Data (y)	$\mid \hat{y} - y \mid$	$(\hat{y} - y)^2$	$\frac{(\hat{y} - y)^2}{y}$
March 2018	7.15	6.966875	0.183125	0.033534766	0.5%
April 2018	8.22	7.434899	0.785101	0.61638358	7.5%
May 2018	7.71	7.749037	0.039037	0.001523887	0.0%
June 2018	8	8.2701	0.2701	0.07295401	0.9%
July 2018	7.65	7.625908	0.024092	0.000580424	0.0%
August 2018	6.99	7.358344	0.368344	0.135677302	1.9%
September 2018	6.78	7.370996	0.590996	0.349276272	5.2%
October 2018	8.12	7.456348	0.663652	0.440433977	5.4%
November 2018	8.48	7.796225	0.683775	0.467548251	5.5%
December 2018	8.25	7.75461	0.49539	0.245411252	3.0%

Table 7. The Error of The Model 11.

Time	Actual Data (y)	Prediction Data (y)	$\lvert \hat{y} - y \rvert$	$(\hat{y}-y)^2$	$\frac{(\hat{y}-y)^2}{y}$
March 2018	7.15	7.025219	0.124781	0.015570298	0.2%
April 2018	8.22	7.612433	0.607567	0.369137659	4.5%
May 2018	7.71	7.422092	0.287908	0.082891016	1.1%
June 2018	8	7.591348	0.408652	0.166996457	2.1%
July 2018	7.65	7.65447	0.00447	1.99809E-05	0.0%
August 2018	6.99	7.506051	0.516051	0.266308635	3.8%
September 2018	6.78	7.524988	0.744988	0.55500712	8.2%
October 2018	8.12	7.623042	0.496958	0.246967254	3.0%
November 2018	8.48	7.567127	0.912873	0.833337114	9.8%
December 2018	8.25	7.521098	0.728902	0.531298126	6.4%

Table 8. The Error Comparison of Model 5 and Model 11.

Error	Model 5	Model 11
MSE	0.2363324	0.306753
RMSE	0.0558530	0.553853
MAE	0.4103612	0.483315
MAPE	29.9%	39.2%

Based on the comparison results, overall, Model 5 has a smaller error value than Model 11. Therefore, the best model that we can use is Model 5. The ARIMA formula for model 5 is as follows.

$$Y_t = -0.3649Y_{t-1} - 0.3616Y_{t-2} - 0.3451Y_{t-3} - 0.4397Y_{t-4} + e_t \tag{11}$$

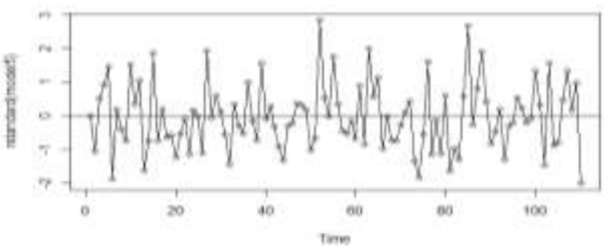

Figure 8. Model 5 Standardised Residual Plot

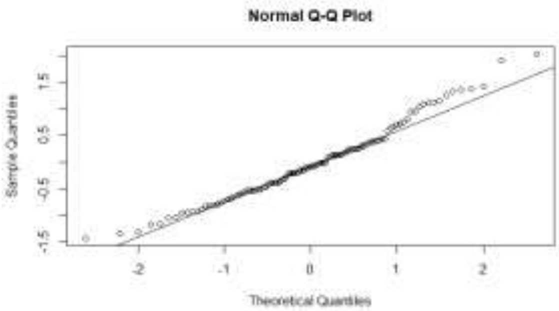

Figure 9. Model 5 Residual Plot

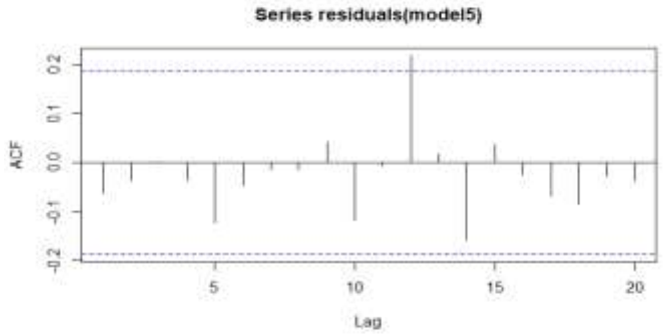

Figure 10. Model 5 ACF Residual

H. Forecasting

The forecasting data process will use model 5, namely ARIMA(4,1,0) with a 95% confidence interval. By using R, the forecasting results are as follows. The black line represents the actual data, the blue line represents the forecast data, and the gray area indicates the error area.

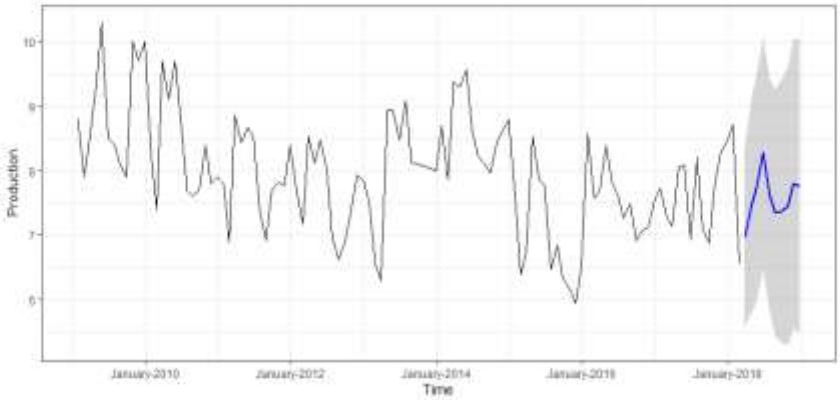

Figure 11. *Forecast*

I. Comparison Between Actual and Forecast Data

The following is a comparison table for Forecast Data Training with Test Data which contain 10 actual observation.

Table 9. The Comparison of actual and forecast data in 2018.

Time	Actual Data	Prediction Data	Lower Boundary	Upper Boundary
March	7.15	7.858702	5.568499	8.365250
April	8.22	7.474120	5.778364	9.091433
May	7.71	7.705067	5.997642	9.500432
June	8	7.984195	6.476433	10.063767
July	7.65	8.055627	5.827528	9.424287
August	6.99	7.992499	5.454724	9.261963
September	6.78	7.813460	5.328630	9.413362
October	8.12	7.775885	5.301373	9.611322
November	8.48	7.854141	5.557323	10.035128
December	8.25	7.919646	5.480553	10.028668

5. Conclusion and Implications

Based on the results of forecasting data on tea production at the Indonesian Large Plantation in the period 2009-2018, the best ARIMA model that can be used in the forecasting process is the ARIMA Model (4,1,0) with Errors: MSE 0.236332372, RMSE 0.05585299, MAE is 0.41035612 , and MAPE by 29.9%. The formula of the model used is as follows.

$$Y_t = -0.3649Y_{t-1} - 0.3616Y_{t-2} - 0.3451Y_{t-3} - 0.4397Y_{t-4} + e_t$$

Forecasting results show a fluctuating pattern of tea production data, with a 95% confidence level. It is predicted that tea production will increase in the March 2018 interval until a turning point in July 2018. As part of the Commodities of the Indonesian plantation sub-sector, it is very important for the management party to know the projections of tea production, so that the export volumes and domestic sales can be adjusted properly. The ARIMA model is able to assist the management party in predicting the tea production of Indonesian plantations in a certain period of time in the future.

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