Forecasting sea surface temperature anomalies using the SARIMA ARCH/GARCH model

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Abstract. The areas that are close to the Indian Ocean can give a significant impact on climate change that caused by SSTA. Based on the records from NOAA website, there are data about points in the Indian Ocean. Moreover, climate change on earth is influenced by several parameters, one of them is called SSTA. Therefore, it is necessary to forecast SSTA in the future to minimize the impact of climate change. With a purpose to predict data that contains seasonal patterns, the method that can be used is SARIMA method with ARCH or GARCH. This study aims to determine the results of SSTA forecasting for the period from August to December 2018. This study uses the 4°N90°E point, which is a point located close to Aceh Province. The data used are daily data obtained from the NOAA website, from July 2010 to July 2018. Based on the research results, the best model for SSTA forecasting is the SARIMA model (2,1,1)(0,1,1) - GARCH(1,1) with forecasting accuracy values of 3.67% MAPE, 0.032 MAE, and 0.016 RMSE. The MAPE values that are smaller than 10% indicate that the SARIMA (2,1,1)(0,1,1) - GARCH(1,1) model is very good for forecasting SSTA in the future.

1. Introduction
Geographical location greatly affects climatic conditions in Indonesia, such as Sea Surface Temperature Anomalies (SSTA) conditions in the Indian Ocean. SSTA is a phenomenon of rising or decreased average Sea Surface Temperature (SST). Sea surface temperatures typically range from 27 - 29°C in the tropics and 15 - 20°C in subtropical areas. Temperatures will drop regularly according to their depth level. Sea water temperature is relatively constant between 2 - 4°C at depths of more than 1000 m [1]. Aceh province is a province located on the island of Sumatra and directly facing the Indian Ocean in the West, the Bay of Bengal to the North and the Strait of Malacca to the east. The Indian Ocean is a wider ocean than the Strait of Malacca. So Aceh Province which is close to the Indian Ocean will have a considerable impact on climate change caused by SSTA in the Indian Ocean [2].

SSTA changes will cause extreme climate change on earth. Climate change is a natural phenomenon that can have a considerable impact on life on earth. Future climate change impacts will occur such as floods, tropical storms, prolonged forest fires, and droughts in some regions. Therefore, SSTA forecasting is necessary to determine future climate change, so as to minimize the risk caused by SSTA. The study used the Seasonal Autoregressive Integrated Moving Average (SARIMA) Autoregressive Conditional Heteroskedasticity (ARCH) or Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method to predict the occurrence of SSTA. The application of SARIMA ARCH/GARCH...
method can be done on residual models of heteroskedastisity. The data used comes from the National Oceanic and Atmospheric Administration (NOAA) with the position of 4N90E. NOAA data is taken because the amount of missing data is small so that it can minimize forecasting inaccuracies and the position of 4N90E is one point that is very close to Sumatra Island, especially Aceh Province.

2. Method

2.1 Forecasting method
Forecasting is a situation that occurred in the past that is used for future estimation purposes. The forecast is essentially an estimate of an event that will occur in the future both quantitatively and qualitatively [3]. The method of forecasting can be divided into two qualitative methods and quantitative methods [4]. Qualitative forecasting methods will be obtained by inaccurate forecasting results. This is because qualitative data is based on individual and group opinions. Meanwhile, quantitative forecasting will be obtained accurate results with the help of data in the past [5].

2.2 Data stationary test
Data awareness indicates that there are no drastic changes in the distribution of data that fluctuate around average values and variances [3]. The data's specifics can be seen from the specifics of the mean, and the instasioneran to variance [6]. Data awareness of the mean can be done using the Dickey-Fuller Augmented Test (ADF) and the Phillips-Perron Test (PP). The ADF and PP Test hypotheses are as follows: \( H_0 \): data is not stationary; \( H_1 \): data is stationary. Meanwhile, data on variance can be seen using the Box-Cox Test. If the data is not stationary against variance then transformation can be performed using Box-Cox transformation. In general the equations in the Box-Cox transformation are following to equation (1) [6].

\[
T(X_t) = \begin{cases} 
\log x, & \lambda = 0 \\
\frac{x_t^{\lambda}-1}{\lambda}, & \lambda \neq 0
\end{cases}
\]

(1)

where \( X_t \) is actual data in the period to \( t \), \( \lambda \) is transoration parameters, and \( T(X_t) \) is transformation results. Transformation can be done based on the value of \( \lambda \) obtained. Table 1 indicates transformation based on the value of \( \lambda \) according to Ref. [6].

| Value \( \lambda \) | Transformation Type |
|---------------------|---------------------|
| -2                  | \( \frac{1}{X_t^2} \) |
| -1                  | \( \frac{1}{X_t} \)  |
| -0.5                | \( \frac{1}{\sqrt{X_t}} \) |
| 0                   | \( \ln(X_t) \)       |
| 0.5                 | \( \sqrt{X_t} \)     |
| 1                   | \( X_t \) (no transformation performed) |
| 2                   | \( X_t^2 \)          |
2.3 Model determination

Autocorrelation Function (ACF) is a process to determine data awareness when the average value and variance of the possessed is constant. Auto correlates are used to view relationships between observations in a time series data. The Partial Autocorrelation Function (PACF) is used to identify how closely the lag measures on the Autoregressive model. ACF and PACF plots can identify the model to be used. But on the condition that the data used must be stationary. To find out if the data follows a specific model can be seen from the Table 2 [7].

| Model       | Pattern ACF                              | Pattern PACF                         |
|-------------|------------------------------------------|--------------------------------------|
| AR (p)      | Dies down (decreases exponentially to zero) | Cut off (disconnected after lag p)   |
| MA (q)      | Cut off (disconnected after lag q)        | Dies down (decreases exponentially to zero) |
| ARMA (p,q)  | Cut off (disconnected after lag q)        | Cut off (disconnected after lag p)   |
| ARIMA (p,d,q)| Dies down (decreases exponentially to zero) | Dies down (decreases exponentially to zero) |

Table 3. Seasonal models based on ACF and PACF.

| Model       | Pattern ACF                              | Pattern PACF                         |
|-------------|------------------------------------------|--------------------------------------|
| AR (P)      | Dies down (decreases exponentially at seasonal lag) | Cut off (disconnected after lag P) |
| MA (Q)      | Cut off (disconnected after lag Q)        | Dies down (decreases exponentially at seasonal lag) |
| ARMA (P, Q) | Cut off (disconnected at seasonal lag)    | Cut off (disconnected at seasonal lag) |
| ARIMA (P, D, Q) | Dies down (decreases exponentially at seasonal lag) | Dies down (decreases exponentially at seasonal lag) |

2.4 Autoregressive Conditional Heteroskedasticity (ARCH) model

The ARCH model is useful in addressing residual variance in time series data or often referred to as heteroskedastisity problems [8]. The ARCH model can be used when residual flavors are changed due to the influence of residual values in the previous period. Metamatically the ARCH(q) model can be written as following in equation (2).

$$
\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \cdots + \alpha_p e_{t-p}^2
$$  \hspace{1cm} (2)

where $\sigma_t^2$ is residual variety at t time, $\alpha_0$ is constants, $\alpha_p$ is ARCH parameters with p order, $e_t^2$ is squared residual at t time, and $e_{t-p}^2$ is residual square at t-p time. The test that can be done to find out if the model contains heteroskedastisity is to use the Lagrange Multiplier Test (LM) otherwise known as the ARCH-LM Test. The hypothesis of the ARCH-LM Test is as follows, if $H_0$: no heteroskedastic effect and if $H_1$: there is a heteroskedastic effect. Test statistics is following to equation (3).

$$
LM = nR^2
$$  \hspace{1cm} (3)

where n is number of observations, and $R^2$ is determination coefficient.
2.5 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model
The GARCH model is a development of the ARCH model developed by Tim Bollerslev in 1986. This model is used to avoid ordering too high on arch models based on simpler principles. The GARCH model can be written in equation (4).

\[
\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_p \epsilon_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2
\] (4)

where \(\sigma_t^2\) is residual variance at time \(t\), \(\alpha_0\) is constants, \(\epsilon_{t-p}^2\) is residual square at \(t-p\) time, \(\alpha_p\) is ARCH parameters period \(p\), \(\lambda_q\) is GARCH parameter \(q\) period, and \(\sigma_{t-q}^2\) is residual variance at \(t-q\) time.

2.6 Model diagnostic test
After obtaining the best forecasting model, a further examination of the model is carried out to see if the model is feasible or not used in forecasting.

2.6.1 White noise test. Model feasibility can be measured using the Ljung-Box Test [6]. Where residual can be said to qualify for white noise when there is no auto correlation between residuals in the model. The hypothesis used is as follows; \(H_0: \hat{\rho}_k = 0\) (residual white noise qualified) and \(H_1: \hat{\rho}_k \neq 0\) (residual ineligible white noise). The test statistics is following to equation (5).

\[
Q = n(n + 2) \sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k}
\] (5)

where \(n\) is number of observations, \(k\) is lag to \(k\), \(h\) is maximum lag, and \(\hat{\rho}_k\) is residual autocorrelation at the \(k\) lag, with \(k = 1,2,...,h\).

2.6.2. Normalitas Test. One of the tests conducted to detect residual normality is the Jarque-Berra Test, with the following hypothesis: \(H_0:\) residual is normal distributed, \(H_1: \) residual is not normal distributed. The test statistics is following to equation (6).

\[
JB = \frac{n}{6} \left( S^2 + \frac{(K-3)^2}{4} \right)
\] (6)

where \(n\) is number of observations, \(S\) is skewness, and \(K\) is kurtosis.

2.7. Forecasting Model Selection
There are several criteria for selection of the best models based on residuals including Akaike’s Information Criterion (AIC) and Bayesian Information Criterion (BIC) which follow the Maximum Likelihood Estimation (MLE) method.

2.7.1. Akaike’s Information Criterion (AIC). AIC is a method used to determine the best model or distribution found by Akaike. The best distribution or model is the distribution and model that has the smallest AIC value. Mathematically, the AIC can be calculated by equation (7).

\[
AIC = -2 \left( \frac{L(\hat{\theta})}{n} \right) + \frac{2t_p}{n}
\] (7)

where \(AIC\) is Akaike Information Criterion, \(L(\theta)\) is likelihood log value, \(t_p\) is total model parameters, and \(n\) is number of observations.

2.7.2. Bayesian Information Criterion (BIC). Another selection of the best models introduced by Gideon E. Schwarz in 1978 was the Bayesian Information Criterion (BIC). The BIC is in equation (8)
\[ BIC = n \cdot \ln(\sigma_e^2) + k \ln(n) \]  

where \( \sigma_e^2 \) is residual variance, \( k \) is number of model parameters, and \( n \) is number of observations.

2.8. Accuracy of Forecasting Model

There are several indicators used to measure the accuracy of forecasting models [3]

2.8.1. Mean Square Error (MAE). The most commonly used way to measure the error rate of forecasting models is to use Mean Absolute Error (MAE). Mae values can be calculated with equation (9).

\[ MAE = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n} \]  

2.8.2. Root Mean Square Error (RMSE). The smaller the RMSE value produced, the better the forecasting results will be. RMSE values can be calculated with equations (10).

\[ RMSE = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}} \]  

2.8.3. Mean Absolute Percentage Error (MAPE). According to Makridakis et al. (1999), MAPE is one of the methods for measuring the suitability of forecasting models. A model can be said to be very good if the mape value obtained is less than 10% and it is said to be good if the MAPE value ranges from 10% to 20% [9] (eqs. (11).

\[ MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \]  

where \( y_t \) is actual value in time period \( t \), \( \hat{y}_t \) is the forecast value in the \( t \) time period, and \( n \) is the number of observations.

Figure 1. SSTA plot time series (°C).

3. Results and discussions

3.1. Plot Time Series

The initial step that needs to be done before doing forecasting is to divide the data into two parts, namely data training and data testing. Training data is used to estimate models from July 5, 2010 to July 18, 2014, while testing data is used at the forecasting stage from July 19, 2014 to July 31, 2018. Based on Figure 1 it can be seen that the actual data plot of SSTA visually has a stationary pattern and it is assumed that the data pattern is experiencing seasonal elements. This can be shown from the data patterns that are around the mean value and the variance is constant over time.
3.2. Data Stationary Test

3.2.1. Stationary Against Mean. Data analysis testing of mean can be done in two ways, visually and inference. Visually performed through ACF and PACF plots, while inference is performed using ADF and PP Tests. Figure 2 show the plot of ACF and PACF actual data without differencing data or I(0).

![Figure 2. Plot ACF and PACF actual data.](image)

Based on Figure 2 it can be seen that the data is not stationary against the mean. This can be seen from the slowly dying down ACF plot as well as the number of lag lines that cross the bartlett line. So it is necessary to differencing on the actual data.

![Figure 3. Plot ACF and PACF after Differencing=1.](image)

Based on Figure 3 it can be known that the data has been stationary. This is evident from the slightest lag that crosses the bartlett line on both the ACF and PACF plots. However, to better ascertain whether or not the data has been stationary against the mean can be measured using ADF and PP tests. The P-value of the ADF and PP tests can be seen in Table 4. ADF and PP tests shows the p-value (0.01) < α (0.05), thus rejects H₀. Thus it can be concluded that using both ADF and PP Tests, SSTA data has been stationary against the mean after one-time differencing or I(1).

| No | Measuring Instruments | P-value | Decision |
|----|-----------------------|---------|----------|
| 1  | ADF test              | 0.01    | Reject H₀ |
| 2  | PP test               | 0.01    | Reject H₀ |

3.2.2. Stationary Against Median. Data can be said to be stationary against variance if the lambda obtained is worth 1 or close to 1. Data can be said to be stationary when the data has been distributed normally. Based on the results of normality tests using the Jarque-Berra Test, it was obtained by a p-
value of $3.65 \times 10^5 < \alpha (0.05)$, so the decision that can be taken is reject $H_0$. This means that the data is not distributed normally and a transformation must be carried out. Figure 4 show a visualization of the normality test plot and the Box-Cox Test before in the transformation:

Figure 4a. Plot Q-Q before transformation.  
Figure 4b. Plot Box-Cox before transformation.

Once the $\lambda$ value is obtained, it is then seen the transformation criteria to be used in Table 1. Based on Table 1 the type of transformation used is the $\sqrt{X_t}$ transformation. However, in the actual data of SSTA there is data that is negative so that it cannot be transformed by using $\sqrt{X_t}$. Therefore, the transformation used is $\sqrt{X_t + 1.5}$. The addition of the number 1.5 is based on the lowest data on SSTA of -1.281. Figure 5 show a visualization of the normality test plot and Box-Cox after the transformation. After the data transformation, in Figure 5a and 5b it can be concluded that the data has been distributed normally and obtained a value of $\lambda=1$. This indicates that SSTA data has been stationary against variance after the transformation of $\sqrt{X_t + 1.5}$.

Figure 5a. Plot Q-Q after transformation.  
Figure 5b. Plot Box-Cox after transformation.

3.3. Determination of Forecasting Model
The ACF and PACF patterns have been stationary against mean but have not been stationary against seasonal factors. This is because both plots form a recurring pattern at a certain lag. Therefore, to overcome seasonal factors in the data needs to be done the process of seasonal differencing. Figure 6 show a seasonal ACF and PACF plot after differencing.
Figure 3 shows that the ACF Plot decreases drastically (cut off) at lag 1, while the PACF plot decreases exponentially (dies down). Based on the non-seasonal model criteria in Table 2 then the model is formed is an MA model with an order q after differencing once or I(1). Figure 6 is an ACF and PACF plot used to view seasonal models. Both plots show that the ACF plot decreases drastically (cut off) at lag 1, while the PACF plot decreases exponentially (dies down). Based on the criteria of the seasonal model in Table 3 then the model formed is the SMA model with order Q after differencing once or D(1).

3.4. Estimation and Significance of SARIMA Model

Estimating sarima models is done using trial and error methods. Table 5 show some tentative models of SARIMA on SSTA variables.

| SARIMA Model | Coefficient | P-value | Conclusion | AIC     |
|--------------|-------------|---------|------------|---------|
| SARIMA (1,1,0)(0,1,2)[30] | AR(1) = -0.01, SMA(1) = -0.96, SMA(2) = 0.01 | 0.613, < 2 x 10^-16, 0.777 | Insignificant, Significant, Insignificant | -1669.1 |
| SARIMA (1,1,1)(0,1,1)[30] | AR(1) = 0.80, MA(1) = -0.92, SMA(1) = -0.96 | 2 x 10^-16, < 2 x 10^-16, < 2 x 10^-16 | Significant, Significant, Significant | -1696.8 |
| SARIMA (1,1,0)(0,1,1)[30] | AR(1) = -0.02, SMA(1) = -0.96, AR(1) = -0.57 | 0.596, < 2.2 x 10^-16, 0.596 | Insignificant, Significant, Insignificant | -1671.0 |
| SARIMA (1,1,1)(1,1,1)[30] | MA(1) = 0.59, SAR(1) = -0.01, SMA(1) = -0.94, AR(1) = 0.83 | 0.584, 0.701, < 2 x 10^-16, < 2 x 10^-16 | Insignificant, Insignificant, Significant, Significant | -1667.1 |
| SARIMA (2,1,1)(0,1,1)[30] | AR(2) = -0.08, MA(1) = -0.90, SMA(1) = -0.95 | 0.037, < 2 x 10^-16, < 2 x 10^-16 | Significant, Significant, Significant | -1699.0 |

Table 5 shows that the best model is the SARIMA model (2,1,1)(0,1,1)[30]. The model is derived from the smallest AIC value of -1699.07 and has significant model parameters. Here's the SARIMA model equation (2,1,1)(0,1,1)[30] on the SSTA variable:

\[
Z_t = \frac{(1 - \theta_1 B^{30} - \theta_1 B + \theta_1 B B^{30})a_t}{(1 - (1 + \phi_1) B + (\phi_1 - \phi_2) B^2 + \phi_2 B^3 - B^{30} + (1 + \phi_1) B^{31} - (\phi_1 - \phi_2) B^{32} - \phi_2 B^{32})}
\]

\[
Z_t = 1.839Z_{t-1} - 0.921Z_{t-2} + 0.082Z_{t-3} + Z_{t-30} - 1.839Z_{t-31} + 0.921Z_{t-32} - 0.082Z_{t-33} + a_t + 0.902a_{t-1}
\]

+ 0.958a_{t-30} + 1.864a_{t-31}
3.5. **SARIMA Model Diagnostic Test**

3.5.1. **White Noise Test.** A model can be said to be white noise eligible if the residual on the model has been homogeneous and independent. The test results showed that p-value (0.997) > α (0.05). This means that by using α 5% of the decisions that can be taken are unable to reject H0. So it can be concluded that the residuals on the SARIMA model (2,1,1)(0,1,1)[30] have qualified for white noise.

3.5.2. **Residual Normality Test.** Residual normality tests on SARIMA models (2,1,1)(0,1,1)[30] were conducted using the Jarque-Bera Test. Based on the test results obtained a p-value of less than 2.2 x 10^-16. This indicates that using α for 5% of the decisions that can be taken is H0 reject. Thus it can be concluded that the residuals on the SARIMA model (2,1,1)(0,1,1)[30] are not distributed normally. So it is suspected that there is a heteroskedastisity problem in the model.

3.6. **Testing Heteroskedastisity**

Heteroskedastisity testing or ARCH effect testing is performed using the ARCH-lagrange mutiplier (ARCH-LM) Test which refers to equation (3). Based on Table 6, the p-value (0.0002) value is less than α (0.05). This indicates that using α for 5% of the decisions that can be taken is to reject H0. Thus it can be inferred that the SARIMA model (2,1,1)(0,1,1)[30] contains elements of heteroskedastisity. Since the model contains elements of heteroskedastisity, the model must continue to be an ARCH or GARCH model with the smallest AIC value comparison.

| Model | Chi-Square | df | P-value |
|-------|------------|----|---------|
| SARIMA (2,1,1) (0,1,1)[30] | 36.515 | 12 | 0.0002 |

3.7. **Identification of ARCH or GARCH Models**

One way to determine the best ARCH or GARCH model is to use the trial and error method based on the smallest AIC value. The selection of the best ARCH or GARCH models can be seen in Table 7.

| Order ARCH | α₀ | α₁ | α₂ | α₃ | α₄ | α₅ | AIC |
|------------|----|----|----|----|----|----|-----|
| c(0,1)     | 4x10^-3 | 9.66x10^-2 | 2.63x10^-1 | 1.79x10^-1 | 7.88x10^-1 | 1.15x10^-1 | -1945.13 |
| c(0,2)     | 2.90x10^-3 | 1.08x10^-1 | 1.79x10^-1 | 7.88x10^-1 | 1.15x10^-1 | -1942.66 |
| c(0,3)     | 2.13x10^-3 | 1.38x10^-1 | 2.62x10^-1 | 1.79x10^-1 | 7.88x10^-1 | -1942.66 |
| c(0,4)     | 2.00x10^-3 | 1.09x10^-1 | 2.48x10^-1 | 1.66x10^-1 | 7.88x10^-1 | -1942.66 |
| c(0,5)     | 1.64x10^-3 | 1.15x10^-1 | 2.17x10^-1 | 1.76x10^-1 | 7.96x10^-1 | -1945.13 |

Test results using the trial and error method found that the ARCH model(5) is the best model based on the smallest AIC value of -1945.13. The ARCH model equation (5) can be seen as equation (13).

\[
\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \cdots + \alpha_p e_{t-p}^2
\]
\[
\sigma_t^2 = 1.64x10^{-3} + 1.15x10^{-1}(e_{t-4}^2) + 2.17x10^{-1}(e_{t-2}^2) + 1.76x10^{-1}(e_{t-3}^2) + 7.96x10^{-2}(e_{t-4}^2) + 1.15x10^{-1}(e_{t-5}^2)
\]

(13)
Furthermore, the selection of the best GARCH(p,q) model is carried out using a similar method. The selection of GARCH models(p,q) can be seen in Table 8. Based on the table, it can be noted that the GARCH model(1.1) is the best model with the smallest AIC value of -2030.49. Furthermore, parameter significance testing was carried out on ARCH(5) and GARCH(1.1) models. The hypothesis on the parameter significance test is as follows: $H_0$: $\Phi=0$ (insignificant parameter to model), $H_1$: $\Phi\neq0$ (significant parameter to the model).

### Table 8. Determination of GARCH model(p,q).

| Order GARCH | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $b_1$ | $b_2$ | AIC  |
|-------------|-------------|-------------|-------------|-------------|-------|-------|------|
| c(1,1)      | 6.34x $10^{-5}$ | 1.65x | $10^{-3}$ | 8.54 x $10^{-2}$ | 8.41x | -2030.49 |
| c(1,2)      | 7.18x $10^{-3}$ | 9.77x | $10^{-2}$ | 8.24x | 1.07x | -2020.99 |
| c(1,3)      | 9.26x $10^{-3}$ | 4.74x | $10^{-2}$ | 7.39x | 1.01x | -1986.95 |
| c(2,1)      | 6.88x $10^{-3}$ | 1.61x | $10^{-2}$ | 8.42x | 2.95x | -2028.17 |
| c(2,2)      | 8.39x $10^{-3}$ | 1.00x | $10^{-2}$ | 6.30x | 1.64x | -2019.22 |

The results of the parameter significance test show that there is one insignificant parameter to the model. This is because the p-value obtained is greater than $\alpha = 0.05$. So it can be concluded that the ARCH model (5) with the smallest AIC criteria is not significant with an error rate of 5%. Furthermore, a test of the significance of the parameters was carried out on the GARCH model (1.1). The test results of the significance of parameters on the GARCH model (1,1) are as follows:

### Table 9. Test the significance of model parameters ARCH(5).

| Parameters | Coefficient | Standard error | P-value | Conclusion |
|------------|-------------|----------------|---------|------------|
| $\alpha_0$ | 1.64x $10^{-3}$ | 2x $10^{-4}$ | 2.2x $10^{-16}$ | Significant |
| $\alpha_1$ | 1.15x $10^{-1}$ | 5.03x $10^{-2}$ | 0.022 | Significant |
| $\alpha_2$ | 2.17x $10^{-1}$ | 4.08x $10^{-2}$ | 1.02x $10^{-7}$ | Significant |
| $\alpha_3$ | 1.76x $10^{-1}$ | 3.89x $10^{-2}$ | 5.83x $10^{-6}$ | Significant |
| $\alpha_4$ | 7.96x $10^{-1}$ | 4.26x $10^{-2}$ | 0.061 | Insignificant |
| $\alpha_5$ | 1.50x $10^{-1}$ | 3.84x $10^{-2}$ | 0.002 | Significant |

The test results of parameter significance on the GARCH model(1,1) indicate that the p-value of each parameter is smaller than $\alpha = 0.05$. So it can be concluded that the parameters of the GARCH model(1,1) with the smallest AIC criteria have been significant. Therefore, the best model in forecasting SSTA is the GARCH model(1,1).
3.8. GARCH Model Diagnostic Test

Once obtained the best model, the next step is to conduct a diagnostic test of the model consisting of:

3.8.1. White Noise Test. The white noise test was conducted on the GARCH model(1,1) using the Ljung-Box Test which refers to Equation 5. Based on Table 11 obtained p-value value (0.268) >\( \alpha \) (0.05). This indicates that by using \( \alpha = 5\% \) the decision that can be taken is unable to reject \( H_0 \). So it can be concluded that the residual model GARCH(1,1) on the SSTA variable has qualified white noise.

| Variable | GARCH Model | \( X^2 \) | \( P \) – value |
|----------|-------------|-----------|----------------|
| SSTA     | c(1,1)      | 0.550     | 0.268          |

3.8.2. Residual Normality Test. Normality tests are performed to determine whether or not garch models(1,1) have been distributed normally. The results of normality testing using the Jarque-Berra Test are tabulated in Table 12.

| Variable | GARCH Model | \( X^2 \) | \( P \) – value |
|----------|-------------|-----------|----------------|
| SSTA     | c(1,1)      | 41.675    | 8.92x10^{-10} |

Based on the test results obtained p-value of 8.92x10^{-10}. This indicates that using \( \alpha \) for 5% of decisions that can be taken is reject. \( H_0 \). So it can be concluded that the residuals on the GARCH model(1,1) are not distributed normally. Although the assumption of normality towards residuals has not been met, the GARCH model(1,1) is the best model in forecasting SSTA. Here are the similarities of the GARCH model(1,1) used in SSTA forecasting:

\[
\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2 \tag{14}
\]

\[
\sigma_t^2 = 6.34 \times 10^{-5} + 1.65 \times 10^{-1} e_{t-1}^2 + 8.41 \times 10^{-1} \sigma_{t-1}^2 \tag{15}
\]

GARCH model forecasting is done by combining sarima model and the best GARCH model that has been obtained previously namely SARIMA model (2,1,1)(0,1,1)\(^{30}\)-GARCH(1,1). The SARIMA equation (2,1,1)(0,1,1)\(^{30}\)-GARCH(1,1) to forecast SSTA can be written as follows:

\[
Z_t = 1.839Z_{t-1} - 0.921Z_{t-2} + 0.082Z_{t-3} + Z_{t-30} - 1.839Z_{t-31} + 0.921Z_{t-32} - 0.082Z_{t-33} + a_t + 0.902a_{t-1} + 0.958a_{t-30} + 1.864a_{t-31} + 6.34 \times 10^{-5} + 1.65 \times 10^{-1} e_{t-1}^2 + 8.41 \times 10^{-1} \sigma_{t-1}^2 \tag{16}
\]

3.9. SARIMA and SARIMA-GARCH Forecasting

After obtaining the best SARIMA-GARCH model, SSTA forecasting for the next few months is the period August to December 2018. However, before proceeding with SSTA forecasting for the period August to December 2018, the forecasting accuracy check will be conducted by comparing the actual data with the forecast data in the period May to June 2016 using complete data without any missing data from December 1, 2014 to May 20, 2016. Figure 7 is the forecast results for the period May to June 2016. Based on the figure, it can be seen that the forecast data pattern is almost similar to the actual data pattern, only that the forecast data pattern does not reach the peak point as in the actual data. SSTA’s forecasting akuation rate was measured using MAE, RMSE, and MAPE values of 0.061, 0.022, and 6.215%. Therefore, the model can be used to forecast SSTA for the upcoming period of August to December 2018.
The forecast was conducted using data testing from July 19, 2014 to July 31, 2018. The results of forecasting using testing data in the next 5 months are shown in Figure 8. The figure shows that the predicted SSTAn has stabilized both on the SARIMA model(2,1,1)(0,1,1)\(^{30}\) and on the GARCH(1,1) model. The red and black lines on the plot are SSTAn forecast data from August 1, 2018 to December 31, 2018. Where it is estimated that the lowest SSTAn using sarima model is 0.145°C which is on August 29, 2018, and SSTAn highest 0.190°C that is on December 5, 2018. While using GARCH model obtained the lowest SSTAn occurred on August 1, 2018 at 0.008°C and the highest SSTAn occurred on December 25, 2018 which was 0.087°C. The accuracy testing of forecasting models is calculated using MAPE, MAE, and RMSE values. The accuracy rate (MAPE) of sarima models(2,1,1)(0,1,1)\(^{30}\) in predicting SSTAn is 4.27%, MAE by 0.048, and RMSE at 0.066. While the accuracy rate of the GARCH model(1.1) was obtained MAPE value of 3.67%, MAE of 0.032, and RMSE of 0.016.

Conclusion

Based on the research that has been done, the following conclusions are obtained that the best model used for SSTAn forecasting is the SARIMA model (2,1,1)(0,1,1)\(^{30}\) - GARCH(1,1). The SSTAn forecasting for the coming period is relatively stable with no increase or decrease. The SSTAn forecasting results are fully precise in predicting SSTAn events. This is because the accuracy of forecasting obtained is less than 10%.

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