Detecting the Phenomena of Sea Surface Temperature Anomaly by Vector Autoregressive

Miftahuddin¹, Eva Maulia¹, Ichsan Setiawan², Asma Gul³, Fadhli⁴, Hidayati⁵

¹Department of Statistics, Syiah Kuala University, Banda Aceh, Indonesia, 23111
²Department of Marine, Syiah Kuala University, Banda Aceh, Indonesia, 23111
³Department of Statistics, Shaheed Benazir Bhutto Women University, Peshawar, Pakistan.
⁴Department of Physics, Syiah Kuala University, Banda Aceh, Indonesia, 23111
⁵Aceh Bappeda, Banda Aceh, Indonesia, 23121

miftah@unsyiah.ac.id, evamaulia01@gmail.com, ichsansetiawan@unsyiah.ac.id, asmagul@sbbwu.edu.pk, fadhli@unsyiah.ac.id, hidayati77@ymail.com

Abstract. Climate change is one of the issues and a considerable threat to the environment in the future. These changes tend to fluctuate and vary significantly with time. Mostly, climate change issues are related to global temperature. The Earth's climate system is affected by many parameters. Sea Surface Temperature Anomaly (SSTA) is one of those parameters. The phenomena of SSTA is a necessary indicator for understanding of climate change variability. Aceh province as to the west of Indonesia has location face directly to the Indian Ocean, especially in western region, southwest, and southern. Vector Autoregressive (VAR) approach has shown that SSTA dataset has stationer and non-cointegration properties in the period 2006-2017. Based on this research, it can be concluded that the best model for SSTA with climate parameters (air temperature, rainfall, relative humidity, wind speed and short-wave radiation) is VAR with the 4th optimal lag or VAR(4). The Impulse Response Function (IRF) analysis based on VAR(4) model, which is formed to look at the phenomena of SSTA to climate parameters, shows that wind speed, rainfall and short-wave radiation have a similar pattern of detection on the equilibrium line due to shock from SSTA. It takes around 5 days for the three variables to reach the equilibrium line. Whereas the air temperature and relative humidity variables have no significant effects of shocks that occur in the sea surface temperature anomaly.

1. Introduction

Climate change is one of the big issues of the day and the future. Changes tend to fluctuate and significantly dependent on time-space. Mostly climate change issues are related to global temperatures in climate system. The Earth's climate system is affected by many parameters and sea surface temperature (SST) is one of those parameters where in fact that ocean is larger than continent.

Weather and climate on earth are determined by the amount and distribution of radiation received from the sun [1]. Climate change is the prevailing weather conditions in the region in general (in large spaces) and in the long run (long periods of time). Climate change can be distinguished by space (region), i.e. local and global climate change. Based on time, cyclical changes in climate can be observed such as daily, monthly, seasonal, and yearly. Such changes can be represented as canonical time series and canonical patterns, so there is correlation (canonical) correlation. The feature trend is essentially effected by global climate change such as by increasing atmospheric gas concentration. These climate conditions have high impact on the environment and human activities. This cause melting of polar ice and rising sea levels that leads to impacts on agriculture, economy [2, 3], increased risk of forest fires, and other life spheres such as changes in the surrounding environment,
including increasing total temperatures and changing weather conditions in the local environment [4]. Key weather and climate features include air temperature, humidity, rainfall, air pressure, wind, and sunlight duration. Factors affecting climate features that distinguish the climate in a place with climate elsewhere are called climate control. The sun is a climate control that can lead to air movement and ocean currents [5]. Sea Surface Temperature (SST) depends on the amount of heat received from the sun. The anomaly influence of the SST is seen in two forms, e.g. an increase or decrease rainfall.

When the SST anomaly is high, a lot of water vapour is released which trigger the formation of rain-producing cloud convection. SSTA conditions in the western Indian Ocean region also affect the climate in the west of Sumatra [6]. Several studies have shown that convection activity is regulated by SST [7, 8, 9]. These studies show the importance of the role of SST in the dynamics of weather and climate of a region. Indonesia has three types of climate patterns, i.e. the monsoonal climate, equatorial, and local system climate [10]. Global warming has related to El-Nino Southern Oscillation (ENSO) phenomena via SSTA investigated [11, 12]. Model prediction of the ENSO by using VAR has been investigated [13]. Whereas in this research aims to look at the phenomena of Sea Surface Temperature Anomaly (SSTA) with respect to several climate parameters, namely air temperature, rainfall, relative humidity, wind speed and short-wave radiation through VAR approach. The specific purpose of this research is to study the phenomena of Sea Surface Temperature Anomaly (SSTA) to air temperature (AIRT), precipitation/rainfall (PREC RAIN), relative humidity (RH), wind speed (WSPD) and short-wave radiation (SWRAD) in the Indian Ocean by using vector autoregressive.

2. Material and Methods

The type of data used in this study is secondary data, obtained from the National Oceanic and Atmospheric Administration (NOAA) website in the period 2006-2017. The data is multivariate time series with six variables, namely SSTA, AIRT, PREC RAIN, RH, WSPD and SWRAD. The research method used is Vector Autoregressive (VAR) analysis. VAR model has a simple model structure with a small number of variables, where all variables are regarded as endogenous variables with the independent variable is lag [14]. The VAR model is designed for stationary variables that do not contain trend [15]. The general model of VAR is as follows.

\[
Y_t = \alpha_0 + \sum_{l=1}^{p} A_l Y_{t-l} + \varepsilon_t
\]

The outline procedure of statistical modelling as follows:
1. Input data into the R software.
2. Stationary test of the dataset for all variables: If the data on these variables are stationary, then carry the analysis process using VAR. In addition, if the data is not stationary, then the next phase of analysis is to use VECM (Vector Error Correction Model) [16].
3. Determine the length of the lag to be used on the VAR model, using the measures, AIC, SIC, FPE, and HQ values [17]. The optimal length of the lag is selected based on smallest value in these measures.
4. Formulate the VAR model.
5. IRF analysis based on the model obtained to determine the effect of each variable if given shock.

3. Results and Discussion

A picture of the SSTA dataset is displaying by using statistics descriptive analysis Figure 1 shows trend of all the variables in the period 2006-2017.

The Figure 1 it can be seen from the figure that the pattern of SSTA, AIRT, PREC RAIN, RH, and WSPD have similarities except for SWRAD pattern more fluctuating.
3.1 Stationarity test

One of the assumptions of VAR analysis is that all the variables must be stationary. There are several ways to measure the data stationary. We have implemented Augmented Dickey Fuller test (ADF) [18] for checking the data stationary. The ADF test statistics is given as:

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \beta_1 \sum_{i=1}^{P} \Delta Y_{t-i+1} + \epsilon_t$$  \hspace{1cm} (3)

The results for all the variables are reported in table 1.

| No | VARIABLE     | STAT.ADF | p-value |
|----|--------------|----------|---------|
| 1  | SSTA         | -3.843   | 0.02    |
| 2  | AIRT         | -3.739   | 0.02    |
| 3  | PREC.RAIN    | -6.850   | 0.01    |
| 4  | RH           | -5.634   | 0.01    |
| 5  | WSPD         | -4.940   | 0.01    |
| 6  | SWRAD        | -8.116   | 0.01    |

*If p-value < α (0.05) then H_0 is rejected.

Based on table 1, the results show that all the variables are stationary. Therefore, the analysis can be carried out using VAR analysis.

3.2 Determination of Optimal Lag

An optimal lag determination is important in the analysis using the VAR method. A very long or too short lag results can be make the wrong model specification. An optimal lag is selected using Final Prediction Error Correction (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQ). The values of AIC, SIC and HQ can be found using the following formula.

$$\text{AIC} = -2 \left( \frac{1}{T} \right) + 2(n + T)$$  \hspace{1cm} (4)

$$\text{SIC} = -2 \left( \frac{1}{T} \right) + n \frac{\log (T)}{T}$$  \hspace{1cm} (5)

$$\text{HQ} = -2 \left( \frac{1}{T} \right) + 2n \log \left( \frac{\log (T)}{T} \right)$$  \hspace{1cm} (6)

In VAR method, structural analysis uses Impulse Response Function (IRF). IRF analysis investigate the effect of each variable for a given shock (suddenly effect). The impact of one variable's shocks on other variables can be traced through IRF. IRF essentially traces the effect of standard deviation shocks on changes in the variable value of the present and future periods [19]. The optimal lag length using the four criteria is displayed in table 2.
Table 2. Optimal lag length determination results

| Lag | AIC          | HQ            | SC            | FPE            |
|-----|--------------|---------------|---------------|----------------|
| 1   | -13.79651    | -13.65391*    | -13.43360*    | 1.019193e-06   |
| 2   | -13.81286    | -13.54803     | -13.13889     | 1.002728e-06   |
| 3   | -13.82229    | -13.43523     | -12.83726     | 9.934814e-07   |
| 4   | -13.85552*   | -13.34623     | -12.55942     | 9.613101e-07*  |
| 5   | -13.80210    | -13.17058     | -12.19493     | 1.014570e-06   |

*Minimum value.

Table 2 shows that the optimal lag for the VAR, based on the minimum value of AIC and FPE, is the 4th lag or VAR(4) while the optimal lag for the VAR estimate based on the minimum value of HQ and SC is the 1st lag or VAR(1). As there are two optimal lag values thus these are used on the VAR model.

3.3 VAR model estimation

VAR model is designed for stationary variables, which is not contain trend [15]. The summary of VAR model for the two lags are reported in table 3.

Table 3. Summary of VAR model results

| NO | VAR Model | 1st Optimal Lag | 4th Optimal lag | p-value | RSE | Adjusted R-squared | p-value |
|----|-----------|-----------------|-----------------|---------|-----|-------------------|---------|
| 1  | SSTA      | 42.68           | 0.631           | 2.2e-16 | 41.74| 0.648             | 2.2e-16 |
| 2  | AIRT      | 0.018           | 0.591           | 2.1e-16 | 0.017| 0.623             | 2.2e-16 |
| 3  | PREC.RAIN | 0.465           | 0.065           | 1.293e-06| 0.458| 0.083             | 1.308e-05|
| 4  | RH        | 0.030           | 0.455           | 2.2e-16 | 0.029| 0.494             | 2.2e-16 |
| 5  | WSPD      | 0.451           | 0.422           | 2.2e-16 | 0.435| 0.461             | 2.2e-16 |
| 6  | SWRAD     | 0.425           | 0.135           | 3.665e-14| 0.416| 0.176             | 7.064e-14|

*RSE: Residual Standard Error

The results from table 3 reveal that the lag 4 is an optimal value for the VAR model as it gives maximum adjusted R-squared. In addition, it can also be seen that the RSE value of VAR model are smaller with the 4th lag as compared to the RSE with the 1st optimum lag. The comparative results with lag 4 and lag4 shows that the best VAR model is produced with the 4th optimum lag. Therefore, IRF analysis are carried out using the VAR model with the 4th optimal lag or VAR(4).

3.4 Impuls Respon Function (IRF)

Impulse Response Function (IRF) analysis is used in the structural analysis in VAR. IRF is implemented to investigate the effect of each variable for a given shock. IRF can trace the impact of variable shock. A graphical structural analysis of IRF in VAR(4) is depicted in the following graph.

The figure 2 shows that a shock on the SSTA variable does not result a high shock to the variables ART and RH. It is obvious as the line is close to the equilibrium line and therefore it does not take long for the variable AIRT and RH to returns stable or on the equilibrium line. For WSPD, PREC RAIN and SWRAD variables, it can be seen that in case of shocks in the SSTA variable it takes about five (5) days for the three variables to reach the equilibrium line. The figure 3 shows that there is a high shock received by the SSTA variable due to the shock of the AIRT variable. The high shock occurs on the 3rd and 5th days, then again approaches the equilibrium line on the 7th day (after one week). For WSPD variables, PREC RAIN and SWRAD have similarity patterns in equilibrium. While in the RH variable shocks are not detected.
The figure 4 displays that shocks on the PREC RAIN variable provide a high shock response received by the SSTA variable. The high shock occurs on the first day and takes more than 10 days to re-approach the equilibrium line. For WSPD variables, PREC RAIN and SWRAD almost similar patterns are detected in equilibrium. While the RH variable does not respond shock events, when the shock occurs on the PREC RAIN variable.

The figure 5 shows that there is a high shock received by the SSTA variable due to the shock of the RH variable. The high shock occurs on the first day, and then returns to the equilibrium line on the 3rd and 6th days, but again high shock occurs in the following days. For WSPD variables, PREC RAIN and SWRAD, the received shock is not so great. While the AIRT variable does not experience the impact of shock caused by RH variable. In the figure 6 shows that there is a high shock received by the SSTA variable due to the shock of the WSPD variable. The high shock occurs on the 3rd day and takes more than 10 days to re-approach the equilibrium line. For the AIRT variable, PREC RAIN and SWRAD have similarity to the detection pattern on the equilibrium, but have differences at the interval (time interval) in the day of the event. While in the RH variable the shock is undetected.
The figure 7 depicts that there is a high shock received by the SSTA variable due to the shock of the SWRAD variable. The high shock occurs on the 4th day and takes more than 10 days to re-approach the equilibrium line. For PREC RAIN and WSPD variables have similarity detection patterns on equilibrium. While no shock is detected for the variables AIRT and RH.
Overall in SSTA dataset is given different pattern shock with several variables explanatory. For example, the five days are critical point for WSPD, PREC RAIN and SWRAD variables by IRF analysis of Sea Surface Temperature Anomaly (SSTA) in VAR(4).

4. Conclusion
To investigate Sea Surface Temperature Anomaly phenomena using VAR method it can be concluded that the best model for the SSTA and climate parameters (Air Temperature, Precipitation/Rainfall, Relative Humidity, Wind Speed and Short-wave Radiation) is VAR with the 4th optimal lag or VAR(4). The Impuls Respon Fuction (IRF) analysis based on VAR(4) model shows that Wind Speed (WSPD), Precipitation/Rainfall (PREC RAIN) and Short-wave Radiation (SWRAD) have a similar pattern of detection on the equilibrium line due to shock from SST Anomaly (SSTA). Our study reveals that it takes around 5 days (short-time) for the three variables to reach the equilibrium line. However, the variables Air Temperature (AIRT) and Relative Humidity (RH) have no significant
effect of shocks that occur in the SSTA. We recommend that the VAR approach is useful to give information related SSTA phenomena in time duration regarding the shock events with several climate parameters given.

5. References
[1] Trenberth, K.E., Fasullo, J.T & Kiehl, J. 2009. Earth’s global energy budget. Bull. Am. Meteorol. Soc. 90(3): 311–323.
[2] Chen, C.C., McCarl, B.A & Adams R.M. 2000. Economic Implication of Potential ENSO Frequency and Strength Shifts. National Assessment of Climate Change, USA: Agriculture Focus Group.
[3] Chen, M., Parton, W. J., Del Grosso, S. J., Hartman, M. D., Day, K. A., Tucker, C. J., & Gao, W. 2017. The signature of sea surface temperature anomalies on the dynamics of semiarid grassland productivity. Ecosphere, 8(12).
[4] He, Z., Wu, R., Wang, W., Wen, Z., & Wang, D. 2017. Contributions of Surface Heat Fluxes and Oceanic Processes to Tropical SST Changes: Seasonal and Regional Dependence. Journal of Climate, 30(11), 4185-4205.
[5] Tjasyono, H.K & Bayong. 1999. Klimatologi Umum. Bandung: ITB. (Indonesia)
[6] Pramudia, A., Estiningtyas, W., Susanti, E., dan Suciantini. 2013. Fenomena dan Perubahan Iklim Indonesia serta Pemanfaatan Informasi Iklim untuk Kalender Tanam. Litbang Pertanian (Indonesia).
[7] McBride J.L, Haylock M.R, Nichols N. 2003. Relationships between the maritime continent heat source and the El Niño–Southern oscillation phenomenon. J Clim; 16(2): 905-2,914.
[8] Neale, R.B, and Slingo J.M. 2003. The Maritime Continent and its role in the global climate: A GCM study. J Clim; 16: 834-848.
[9] Miftahuddin. 2016. Fundamental fitting of the SST data using linear regression models. Journal of IEEE: 128-133.
[10] Aldrian, 2011. Aldrian, E., Karmini, M., and Budiman. 2011. Adaptasi dan Mitigasi Perubahan Iklim di Indonesia. BMKG, Jakarta. (Indonesia)
[11] Pan, Y. H., & Oort, A. H. 1983. Global climate variations connected with sea surface temperature anomalies in the eastern equatorial Pacific Ocean for the 1958–1973 period. Monthly Weather Review, 111(6), 1244-1258.
[12] Huang, P., Chen, D., & Ying, J. 2017. Weakening of the Tropical Atmospheric Circulation Response to Local Sea Surface Temperature Anomalies under Global Warming. Journal of Climate, 30(20), 8149-8158.
[13] Chapman D., Cane M. A, Henderson N., Lee D. E., and Chen C. 2015. A Vector Autoregressive ENSO Prediction Model. American Meteorological Society.
[14] Maddala, G. S. 2004. Introduction to Econometrics 3rd ed. Prentice-Hall, Inc. UK
[15] Gujarati, D. 2006. Basic Econometrics 4th ed, Mc. Graw Hill, New York.
[16] Sofyan, H., Maulia, E., & Miftahuddin. 2017. Structure analysis of tax revenue and inflation rate in Banda Aceh using vector error correction model with multiple alpha. In AIP Conference Proceedings (Vol. 1905, No. 1, p. 050029). AIP Publishing.
[17] Maulia, E., & Sofyan, H. 2018. Tax revenue and inflation rate predictions in Banda Aceh using Vector Error Correction Model (VECM). In IOP Conference Series: Materials Science and Engineering (Vol. 352, No. 1, p. 012056). IOP Publishing.
[18] Lutkepohl, H. 2006. New Introduction to Multiple Time Series Analysis, Springer-Verlag, Berlin.
[19] Ariefanto, M. D. 2012. Econometrics of Essence and Application by Using Eviews.

Acknowledges
The authors would like to thank the Department of statistics, Faculty of Mathematics and Sciences, LPPM Syiah Kuala University and Directorate of Research and Community Service (or DPRM) Ristekdikti Jakarta. We also would like to thank the TDMRC and anonymous reviewers for their valuable suggestions.