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IMPLEMENTATION OF VECTOR AUTOREGRESSIVE (VAR) AND VECTOR ERROR CORRECTION MODEL (VECM) METHOD IN PNEUMONIA PATIENTS WITH WEATHER ELEMENTS IN PANGKALPINANG CITY

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ABSTRACT

The news about Covid-19 is no longer as scary as in previous years. As COVID-19 cases decrease, health protocols are becoming more relaxed, making it easier for the virus to spread. Besides COVID-19, ARI is one of Indonesia's leading causes of death for children under five. Around 20-40% of hospital admissions are children due to ARI, with around 1.6 million deaths due to pneumonia alone in children under five per year. Currently, ARI dominates the diseases most suffered by the people of Bangka Belitung. Based on this, using the VAR and VECM method to analyze pneumonia sufferers in toddlers regarding weather elements in the Pangkalpinang City. The VAR model has a simpler structure with a minimal number of variables where all the variables are endogenous, with the independent variable being the lag. Meanwhile, VECM can be used to model cointegrated and non-stationary time series data. The data used in this research is the number of monthly cases of toddlers suffering from pneumonia and data on climate conditions, namely rainfall, air temperature, air humidity and duration of sunlight during 2019-2021 in Pangkalpinang City. The results of the Granger Causality test show that the pneumonia variables regarding rainfall, temperature, duration of sunlight and humidity only have a one-way causality pattern. The VAR estimation results show that weather elements (rainfall, temperature and duration of sunlight) do not significantly affect pneumonia in the short term. Meanwhile, the VECM estimation results show that in the long-term pattern, humidity variables affect pneumonia. For this reason, it is recommended that the relevant agencies carry out outreach to the public, especially to pneumonia sufferers, to avoid damp weather. Because the lower the humidity value, the greater the potential for pneumonia in Pangkalpinang City, Bangka Belitung Islands Province.

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1. INTRODUCTION

The news about Covid-19 is no longer as frightening as it was in previous years. Seven districts or cities in Bangka Belitung Province, as of January 30, 2023, had no additional COVID-19 cases [1]. However, along with the decline in COVID-19 cases, health protocols have become increasingly lax. As a result, the spread of the virus is easily transmitted from one person to another. Pathogenic viruses and bacteria quickly attack the respiratory tract, which can cause severe Acute Respiratory Infections (ARI) and cause a public health emergency. For example, influenza viruses type A and B are common respiratory viruses that circulate throughout the world and can cause seasonal influenza outbreaks and epidemics. Most people recover from fever and other symptoms within a week without medical attention. However, hospitalization and death may occur, especially among high-risk groups. These annual epidemics are estimated to result in 3 to 5 million cases of severe disease and 290,000 to 650,000 respiratory deaths. In addition, new subtypes of the influenza A virus could also have pandemic potential (WHO 2022). ARI is an infection that attacks the throat, nose, and lungs and lasts no more than 14 days. Acute Respiratory Infections (ARI) is a contagious condition that tends to become an epidemic and pandemic [2][3][4] . If we look at global movements, according to data in the Covid-19 Community Mobility Report, it was found that in the Bangka Belitung Islands Province, in September – October 2022, movements or visits to drug stores or pharmacies increased by 46% compared to the expected average [5].

Currently, ARI dominates the diseases most suffered by the people of Bangka Belitung. At least 100 thousand Bangka Belitung residents are attacked by ARI annually. Based on data from the Bangka Belitung Provincial Health Service, from 2016 to 2020, of the ten diseases, ARI was always in first place. In 2016, 101,031 people were suffering from ARI; in 2017, there were 105,783 people; in 2018, there were 130,014 people; in 2019, there were 128,922 people; and in 2020 there were 129,552 people. The latest data is from 2020; the first in the dominant disease data is ARI [6]. Moreover, ARI is a contagious condition that tends to become an epidemic and pandemic. Especially in the post-COVID-19 era, with unpredictable weather changes daily, ARI can quickly attack toddlers, children, and adults [7][8].

The results of research conducted by [9] show that the trend of pneumonia cases from January 2018 to December 2019 fluctuated approximately every two months due to seasonal influences, namely the rainy and dry seasons. Mostly, during the rainy season, the number of pneumonia cases tends to experience an increasing trend. The results of statistical tests in this study show that rainfall, rainy days, humidity, and air temperature have an R Square value in modeling of 0.655, meaning that seasonal influences can explain 65.5% of the diversity of pneumonia cases.

According to [10], one of the dominant environmental factors influencing the risk of ARI in toddlers is temperature, humidity, and lighting. Based on this, researchers intend to analyze the relationship between ARI sufferers in toddlers after the COVID-19 pandemic and elements of weather changes (air temperature, rainfall, humidity, and duration of sunlight) in Pangkalpinang City, Bangka Belitung Islands Province. This is intended to look at the climate elements that influence ARI sufferers in toddlers.

This research is intended as input to policymakers in determining good health education for the community after the COVID-19 pandemic according to the conditions of Pneumonia sufferers in Pangkalpinang City. It also strengthens community modalities in improving healthy lifestyles and increasing awareness of ARI diseases after the COVID-19 pandemic.

2. RESEARCH METHODS

In this research, quantitative data was used and sourced from secondary data. The data used in this research is the number of monthly cases of toddlers suffering from pneumonia during 2019 - 2021 in Pangkalpinang City who were registered with the Dinas Kesehatan Bangka Belitung Province. Also, climate condition data was used, namely rainfall, air temperature, air humidity and duration of sunlight during 2019 - 2021, which was sourced from the Badan Meteorologi, Klimatologi dan Geofisika (BMKG). The analysis method used is Vector Auto Regression (VAR) analysis or Vector Error Correction Model (VECM) to see the interrelationship between climate variations and the incidence of pneumonia in toddlers in Pangkalpinang City. An illustration of the research stages is in **Figure 1**.

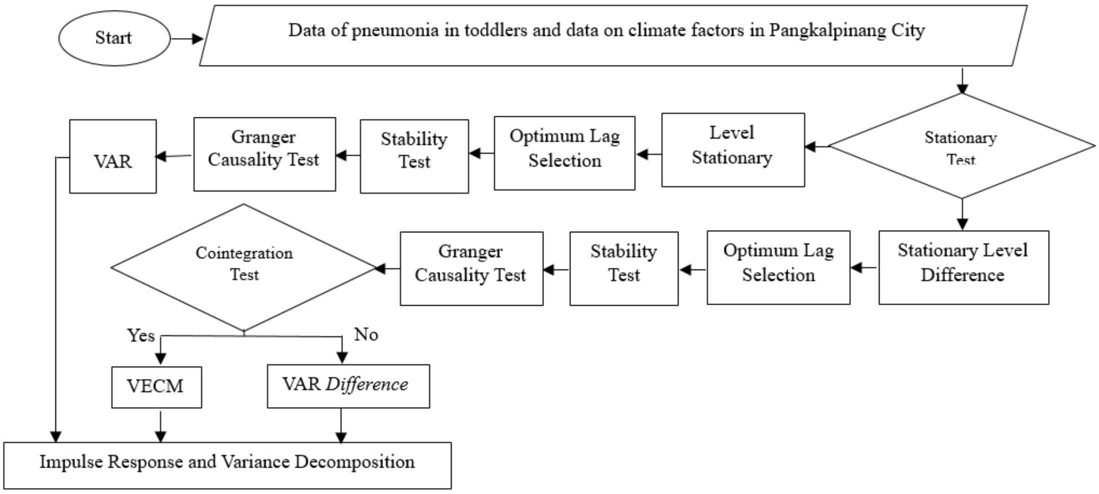


Figure 1. **An Illustration of the Research Stages**

2.1 Time Series Model

Time series analysis was introduced by George E. P. Box and Gwilym M. Jenkins in 1970 through their book Time Series Analysis: forecasting and control. Forecasting using time series has a unique feature. Time series can also be notarized very well modeled using itself [11].Time series analysis includes statistical procedures used to predict conditions that will occur in the future in decision-making [12][13]. Time series analysis is the observation, recording and arrangement of events based on a certain period [14][15][16].

2.2 Stationary Test and Determination of Optimal Lag Length

The stationarity test can be detected formally using the Augmented Dickey-Fuller test by seeing whether the unit root is in the model or not. Test statistics in the stationarity test can be calculated using ADF calculation. The optimal lag is the lag length that significantly influences or responds. Determining the optimal lag is a very important stage in the VAR model in capturing the influence of each variable on other variables [17][18].

2.3 Causality Test

Granger causality is a test used to see the causal or reciprocal relationship between two research variables so that it can be seen whether the two variables statistically influence each other (two-way or reciprocal relationship), have a unidirectional relationship or have no relationship at all (do not influence each other)[19]. The equation used to carry out the Granger causality test can be written as follows:

$$X_t = \sum_{i=1}^{m} \alpha_i X_{t-1} + \sum_{j=1}^{n} b_j Y_{t-j} + \mu_t \quad (1)$$

$$Y_t = \sum_{i=1}^{r} c_i X_{t-1} + \sum_{j=1}^{s} d_j Y_{t-j} + v_t \quad (2)$$

2.4 Vector AutoRegressive (VAR) and Vector Error Correction Model (VECM)

The VAR model was proposed by Christopher Sims in the 1980s, using all the current variables in the model to carry out regression for some lagged variables. It is an extension of the AR (autoregression) model, widely used for time series. The VAR model takes each variable as a function of the lag value of all endogenous variables in the system, thus extending the univariate autoregressive model to the "vector" autoregressive model composed of multiple time series variables [20].

Vector autoregression (VAR) is a simultaneous explanatory and predictive analysis method of several variables [21]. The Vector Autoregressive model is a multivariate Time Series technique that is flexible and helps describe the dynamic behaviour of specific time series data; that is, a vector of time series. This type of forecast is predominant in economics and financial analysis. In the VAR system, one equation is considered for the dependent variable with constant lags [21][22].

The VAR model has a simpler structure with a minimal number of variables where all the variables are endogenous, with the independent variable being the lag. The VAR model is designed for stationary variables that do not contain trends[23]. The VAR model equation is formulated as follows [24] :

$$x_t = A_0 + A_1 x_{t-1} + A_1 x_{t-2} + \cdots + A_p x_{t-p} + e_t \tag{3}$$

x_t : vector of size $n \times 1$ containing n variables in the VAR model
A_0 : intercept vector of size $n \times 1$
A_p : efficiency matrix of size $n \times n$
e_t : residual vector of size $n \times 1$

Meanwhile, VECM offers an easy working procedure to separate long-run and short-run components from the data formation process. Thus, VECM differs from VAR in that VECM can be used to model cointegrated and non-stationary time series data[25]. The general form of the VECM model with lag length (p-1) is as follows [26]:

$$\Delta y_t = \alpha e_{t-1} + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p+1} + \varepsilon_t \tag{4}$$

$\boldsymbol{\Delta y_t}$: vector of first derivatives of the dependent variable
$\boldsymbol{\Delta y_{t-1}}$: vector of the first derivative of the dependent variable with the 1st lag or ECT (Error Correction Term)
$\boldsymbol{\varepsilon_t}$: residual vector
$\boldsymbol{\alpha}$: cointegration coefficient matrix
$\boldsymbol{\beta_1}$: coefficient matrix of the $\boldsymbol{i}$ dependent variable, $\boldsymbol{i = 1, 2, \ldots, p}$

2.5 Impulse Response Function (IRF)

The IRF test aims to see how long a shock a variable receives [26][27]. IRF calculation is as follows:

$$IRF(h) = \Gamma^k \tag{5}$$

With:
Γ : parameter matrix of the VAR model
h : forecast period
C : Cholesky decomposition matrix of the shock variance-covariance matrix

3. RESULTS AND DISCUSSION

3.1 Data Stationarity

The data stationary test can be carried out using the graphic method and the Augmented Dickey-Fuller (ADF) test. Suppose the absolute value of the t statistic is smaller than the critical value in the MacKinnon table at various confidence levels (1%, 5%, and 10%). In that case, it indicates that the data is not stationary. Apart from that, it can also be seen from the probability value that is smaller than 0.05 that it indicates stationary data. Based on Table 1, it can be seen that the analysis of pneumonia with rainfall, temperature, and duration of sunlight will be carried out using VAR. Then, the analysis of pneumonia with humidity can use VECM.

Table 1. Stationary Pneumonia Test for Rainfall, Air Humidity, Temperature, and Duration of Sunlight

Variable	*Unit Root*	Probability
Rainfall	Level	0.0004
Air Humidity	1st difference	0.0001

Variable	*Unit Root*	Probability
Temperature	Level	0.0001
Duration of Sunlight	Level	0.0475

3.2 Optimal Lag Test

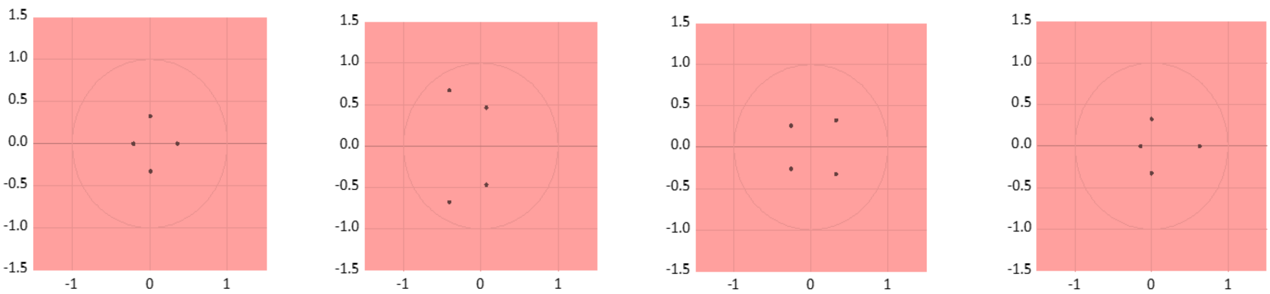
The VAR approach is very sensitive to the amount of data lag used. Therefore, it is necessary to determine the optimal lag length. The lag length determines the period of influence on an endogenous variable in the past or other endogenous variables. In this research, determining the optimal lag length will be seen from the smallest Akaike Information Criterion (AIC) value, indicating optimal lag. In **Table 2** shows that the analysis of pneumonia on rainfall does not have a past influence on these two variables. Meanwhile, pneumonia analysis of air humidity, temperature, and duration of sunlight influences the past for each variable with pneumonia.

Table 2. Optimal Lag Test for Rainfall, Air Humidity, Temperature, and Duration of Sunlight

	Rainfall	Air Humidity	Temperature	Duration of sunlight
AIC	23.7248	16.7335	12.8380	19.4760
Optimal Lag	0	2	1	1

3.3 VAR Stability Test Results

A VAR condition stability check is carried out to test whether the VAR estimates that have been determined are stable, namely in the form of roots of characteristic polynomials. Based on **Figure 2**, all points of the inverse roots of the AR polynomial are inside the circle, so the pneumonia data and climate variations are stable.



(a) (b) (c) (d)

Figure 2. Plot of Inverse Roots of AR Characteristic Polynomial (a) Pneumonia against rainfall (b) Pneumonia against air humidity (c) Pneumonia against temperature (d) Pneumonia against duration of sunlight

3.4 Granger Causality Test

This research shows that the variable number of pneumonia and variations in climate elements do not have a two-way or reciprocal relationship. It can be seen in the probability value, which is greater than 0.05. Based on this test, all weather elements have no causal relationship with pneumonia data.

Table 3. Granger Causality Test

Null Hypothesis:	Obs	Probability
Pneumonia does not Granger Cause Rainfall	34	0.7503
Rainfall does not Granger Cause pneumonia		0.9619
Pneumonia does not Granger Cause Air Humidity	34	0.7191
Air Humidity does not Granger Cause Pneumonia		0.7375
Pneumonia does not Granger Cause Temperature	34	0.4331
Temperature does not Granger Cause Pneumonia		0.3603
Pneumonia does not Granger Cause Duration of Sunlight	34	0.9838
Duration of Sunlight does not Granger Cause Pneumonia		0.8889

3.5 Cointegration Test

The cointegration test determines whether there will be long-term balance, namely whether there is a similarity in movement and stability of the relationship between the variables in this study. The cointegration test was carried out using Johansen's Cointegration Test method. If the probability value < 0.05 means there is a cointegration equation, it has a long-term balance. In this study, the cointegration test will only be carried out to analyze pneumonia and air humidity because these two variables are stationary at the first difference.

Based on **Table 4**, it is known that the probability value is less than 5%, which indicates that there is a cointegration relationship between pneumonia and humidity. So, the following analysis for pneumonia and air humidity variables uses the VECM model. Then, it is explained that at the 5% significance test level, two variable ranks have a cointegration relationship. It can be seen from the trace statistical values, namely 29.087 and 10.0327, which are greater than the Critical Value of 5%, namely 15.49471 and 3.841465. This value means that the pneumonia and humidity variables are indicated to have a long-term relationship (cointegration) with each other.

Table 4. Johansen Cointegration Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Probability
None*	0.4487	29.0868	15.4947	0.0003
At most 1*	0.2691	10.0327	3.8415	0.0015

3.6 VAR Stability Test Results

In this case, the validity test is carried out by comparing the t-table and t-statistic values, where the t-table used in this study has a significance level of 5% of 2.013. Based on **Table 5**, it is found that the t-statistic value for rainfall is less than 2.013. This value indicates that rainfall does not affect the incidence of pneumonia. However, other variables influence the incidence of pneumonia, which is indicated by the t-statistic value of the C coefficient, which is greater than the t-table value.

Table 5. Vector Auto Regression Stability Test for Pneumonia with Rainfall

	Rainfall	Pneumonia
Rainfall(-1)	0.1885	0.0239
	(0.1580)	(0.0879)
t-statistic	[1.1931]	**[0.2716]**
Rainfall(-2)	0.0598	-0.0086
	(0.1746)	(0.0972)
t-statistic	[0.3310]	**[-0.0912]**
Pneumonia(-1)	-0.0437	0.0307
	(0.3311)	(0.1842)
t-statistic	**[-0.1320]**	[-0.1664]
Pneumonia(-2)	-0.22468	0.0307
	(0.3311)	(0.1842)
t-statistic	**[-0.1320]**	[-0.5372]
C	153.3073	49.1175
	(52.0326)	(28.9540)
t-statistic	**[2.9464]**	[1.6964]

Table 6. Vector Auto Regression Stability Test for Pneumonia with temperature

	Temperature	Pneumonia
Pneumonia(-1)	-0.0360	0.0016
	(0.1751)	(0.0021)
t-statistic	**[-0.2053]**	[0.7938]
Temperature(-1)	-13.43925	0.3176
	(14.4799)	(0.1691)

	Temperature	Pneumonia
t-statistic	**[-0.9281]**	[1.8783]
C	412.6281	18.3771
	(392.576)	(4.5837)
t-statistic	**[1.0511]**	[4.0093]

Table 7. Vector Auto Regression Stability Test for Pneumonia with Duration of Sunlight

	Duration of sunlight	Pneumonia
Pneumonia(-1)	0.5710	-0.1041
	(0.1471)	(0.7396)
t-statistic	**[3.8808]**	[-0.1408]
Duration of sunlight(-1)	-0.0007	-0.0243
	(14.4799)	(0.1776)
t-statistic	[-0.9281]	**[-0.1368]**
C	22.8440	53.9514
	(8.2080)	(41.2595)
t-statistic	**[2.7832]**	[1.3076]

Then, in **Table 6**, the incidence of pneumonia is also not influenced by temperature, which is indicated by the t-statistic value being smaller than the t-table value. In contrast to the results of the duration of sunlight, a t-statistic of 3.8808 was obtained in period one, so it can be said that the length of sunlight in the previous period also influenced the incidence of pneumonia. Apart from the duration of sunlight, other factors influence the incidence of pneumonia in Pangkalpinang City (see **Table 7**).

3.7 Vector Error Correction Model (VECM)

In the long-term relationship between humidity and pneumonia (see **Table 8**), it is found that the t-statistic value (-4.5998) is greater than the t-table and is negative. Based on this, air humidity has a long-term influence on the incidence of pneumonia in Pangkalpinang City. The lower the humidity, the more cases of pneumonia will occur in children in Pangkalpinang City. Furthermore, based on short-term effects (see **Table 9**), it was found that humidity did not significantly affect the incidence of pneumonia.

Table 8. Vector Error Correction Estimates from Air Humidity with Pneumonia (Long-Term)

	Cointegrating Eq:	CointEq1
Long-term	D(air humidity(-1))	1.0000
	D(Pneumonia(-1))	-227.8059
		(49.5249)
	t-statistic	**[-4.5998]**
	C	-384.6350

Table 9. Vector Error Correction Estimates from Air Humidity with Pneumonia (Short-Term)

Error Correction	D(Air Humidity)	D(Pneumonia)
CointEq1	-4.58E-05	0.010357
	(0.00013)	(0.0023)
t-statistic	[-0.36104]	**[4.5943]**
D(Air Humidity(-1),2)	-0.6022	3.9243
	(0.1778)	(3.1553)
t-statistic	[-3.3889]	**[1.2437]**
D(Air Humidity(-2),2)	-0.3597	-2.3802
	(0.1820)	(3.2317)
t-statistic	[-1.9761]	**[-0.7365]**

Error Correction	D(Air Humidity)	D(Pneumonia)
D(Pneumonia(-1),2)	-0.0022	0.6742
	(0.0202)	(0.3592)
t-statistic	**[-0.1105]**	[1.8767]
D(Pneumonia(-1),2)	0.0035	0.0108
	(0.0108)	(0.1914)
t-statistic	**[0.3197]**	[0.0563]
C	0.0877	-1.5770
	(0.6822)	(12.1122)
t-statistic	**[0.1286]**	[-0.1302]

3.8 Impulse Response Function and Variance Decomposition

Estimation of the impulse response function was carried out to examine the surprise response of the innovation variable to other variables. The estimation assumes that each innovation variable is not correlated with each other, so tracing the influence of a surprise can be direct. **Figure 3 (a)** shows that the shock movement only reaches the fifth to seventh period; the rest of the movement gets closer to the balance point. This condition means that the higher the period, the lower the response.

The shock movement is also shown by **Figures 3(b)** and **Figure 3(c)** that the longer the period, the lower the response to temperature and duration of solar radiation. This condition is different from the response given by humidity (see **Figure 4**), which is fluctuating. The longer the period, the higher the humidity response to the incidence of pneumonia fluctuates.

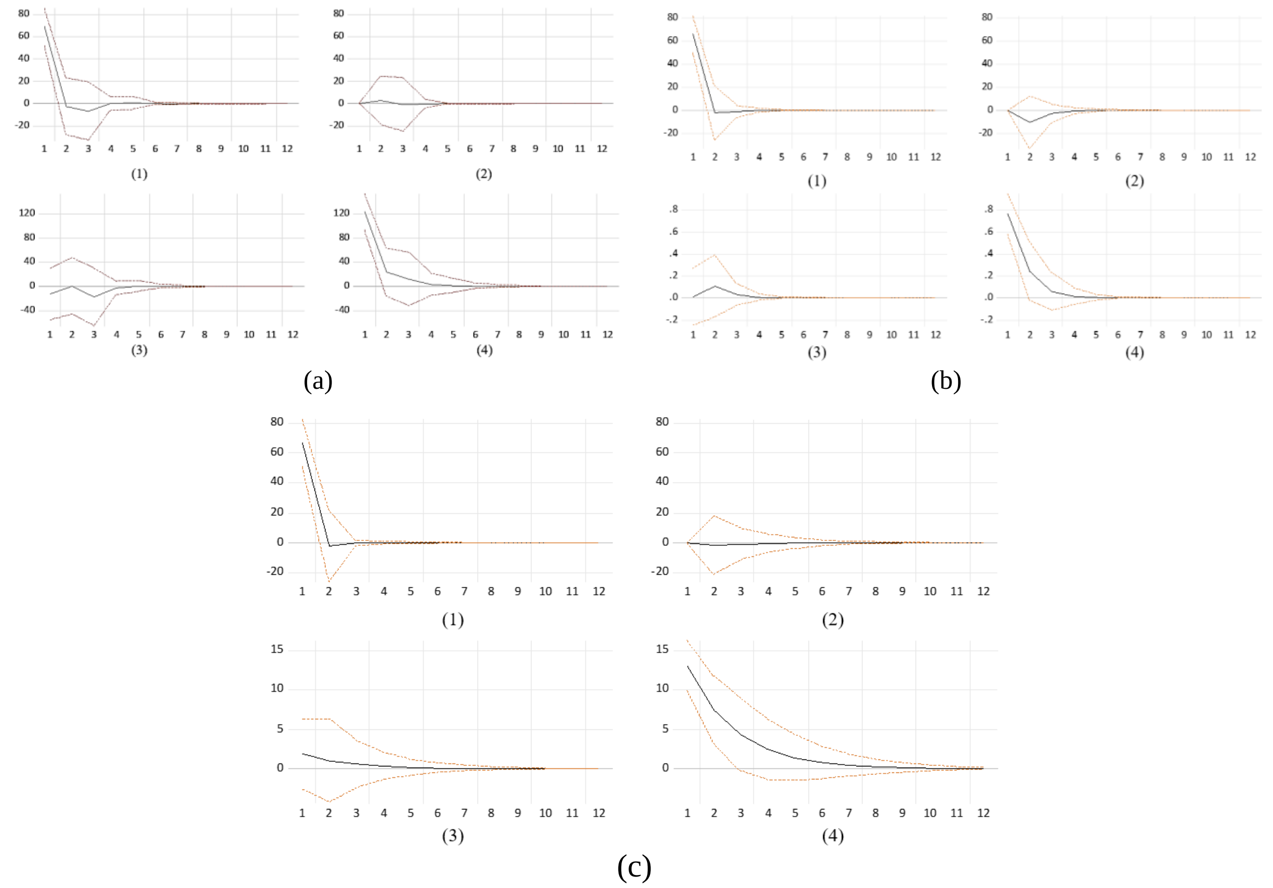


Figure 3. Impulse Response Function of Pneumonia with (a) Pneumonia to Pneumonia, Pneumonia to Rainfall, Rainfall to Pneumonia, and Rainfall to Rainfall; (b) Pneumonia to Pneumonia, Pneumonia to Temperature, Temperature to Pneumonia, and Temperature to Temperature; and (c) Pneumonia to Pneumonia, Pneumonia to Temperature, Temperature to Pneumonia, and Temperature to Temperature.

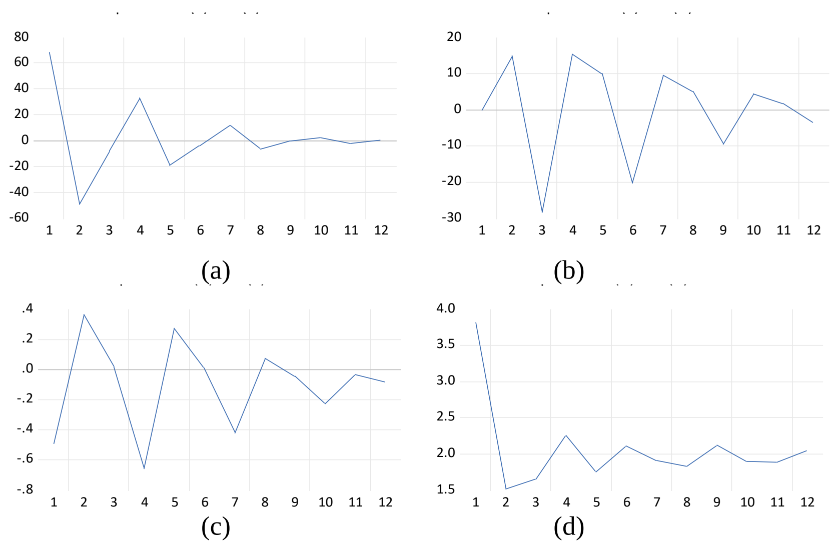


Figure 4. Impulse Response Function of (a) Pneumonia to Pneumonia; (b) Pneumonia to Air Humidity; (c) Air Humidity to Pneumonia and (d) Air Humidity to Air Humidity

Then, the Variance Decomposition table (see attachment) shows that for the variable rainfall, temperature and duration of sunlight, the more extended period, the variance decomposition shows a stable value. This condition shows that these three weather elements do not influence the incidence of pneumonia. In contrast to the Variance Decomposition of humidity against pneumonia, the value fluctuates. Therefore, from the four existing weather elements, it was found that there was an influence of the humidity variable on pneumonia.

Then, based on the Variance Decomposition table (see appendix), it shows that for the variables rainfall, temperature and duration of sunlight, the longer the period, the more the Variance Decomposition value shows a stable value. This condition shows that these three weather elements do not influence the incidence of pneumonia. In contrast to the Variance Decomposition of humidity against pneumonia, the value fluctuates. Therefore, from the four existing weather elements, it was found that there was an influence of the humidity variable on pneumonia.

4. CONCLUSIONS

The Granger Causality test's research results show that the pneumonia variable concerning rainfall, temperature, duration of sunlight and humidity only has a one-way causality pattern. Where each climate element only affects Pneumonia, while Pneumonia does not affect climate elements (unidirectional causality). The VAR estimation results show that the three weather elements (rainfall, temperature and duration of sunlight) do not significantly affect the short term. Meanwhile, the VECM estimation results show that in the long term, the humidity variable affects pneumonia. However, the impact is negative; the lower the humidity value, the greater the potential for pneumonia in Pangkalpinang City, Bangka Belitung Islands Province. Based on the results of this study, it was found that humidity affects pneumonia in the long term. For this reason, there is a need for guidance or outreach to the community in Pangkalpinang City, especially pneumonia sufferers in toddlers, to be careful about humid weather conditions.

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