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Prediction of El Niño La Niña & Indian Ocean Dipole Phenomena Using the ARIMA Model by Prospective Teachers in Indonesia

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Abstract: The high number of losses and casualties experienced by the Indonesian people is caused by various factors. One of the factors lies in the people who lack knowledge in dealing with climate phenomena. Student-teacher candidates must take an important role in solving climate problems. One solution is to predict climate phenomena. This study uses the ARIMA model to predict the El Niño La Niña & Indian Ocean Dipole phenomenon. The research method is the ARIMA model prediction steps using student worksheets. (1) know the model by determining ACF and PACF. (2) parameter model estimation determines ARIMA on predetermined ACF and PACF. The ARIMA parameter model is the slightest Mean Squared Error (MSE) level. (3) the diagnostic model of the smallest MSE. (4) a measure of predictive accuracy. And (5) Argumentation. Results In the IOD calculation, the correlation between the three-month prediction period is 0.92 and for six months is 0.96. This is the same as in the Niño 3.4 correlation data. The value is close to 1, which is very accurate and can be used. The predicted value of the IOD index was expected. The resulting values ranged from 0.01 to 0.17. This means that students are proficient in making climate predictions. Because students are enthusiastic and passionate about studying climate, it is a new science.

Keywords: ARIMA model, El Niño La Niña & Indian Ocean Dipole Prediction, Teacher candidates in Indonesia.

Introduction

Nur'utami & Hidayat, (2016); Anderson & Perez, (2015) states that the number of occurrences of El Niño phenomena is 37.5%. La Niña phenomena are 17.5% in the equatorial Pacific Ocean. The normal condition is 45%, while the number of occurrences of Indian Ocean Dipole is positive (+). Indian Ocean The negative Ocean Dipole (-) in the Indian Ocean at the equator is 22.5% for the Indian Ocean Dipole + and 20.0% for the Indian Ocean Dipole -. Under normal conditions, the Indian Ocean Dipole is 57.5%. From 1960-2017 data, the frequency of combined years of ENSO and Indian Ocean Dipole events is shown in Table 1.

The delay in the start of the rainy season and reduced rainfall caused by El Niño and the Indian Ocean Dipole + harmed rice cultivation, especially in Java, Sulawesi and eastern Indonesia, in addition to the impact of large-scale forest fires occurring on the island of Kalimantan, Riau and parts of Sumatra, the impact spread to neighbouring countries such as Malaysia, Thailand and Singapore (Currie et al., 2013; Lestari & Koh, 2016; Hermawan, 2018) . This is very influential in the lives of Indonesian people because people's livelihoods generally depend on rainfall for food production. A livelihood, so that has resulted in the average household being poor, so households take quick and fatal steps to be able to meet their daily needs, such as loans and asset sales and what is most striking is that Indonesians are less able to withstand the shocks of life in the future (Acaps, 2016).

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Table 1. Years of Combination of ENSO and Indian Ocean Dipole Events in Indonesia

Incident	Indian Ocean Dipole (-)	Indian Ocean Dipole Normal	Indian Ocean Dipole (+)
Very Strong El Niño	-	-	1982, 1997, and 2015
Strong El Niño	-	1965	1972
Moderate El Niño	-	1986, 1987, 2002, 2009	1963, 1991
Weak El Niño	-	1968, 1969, 1976, 1979, 2004	1994, 2006, 1977
Normal	1960, 1981, 1989, 1992, 1996, 2013, 2014	1962, 1966, 1978, 1980, 1985, 1990, 1993, 2001, 2003, 2005, 2008	1961, 2012
Weak La Niña	1964, 1974, 2016	1970, 1971, 1984, 1995, 2000, 2011	1967, 1972, 1983
Medium La Niña	1998, 2010	1999, 2007	-
Strong La Niña	1973, 1975, 1988	-	-

(Source: www.ggweather.com; www.bom.gov.au)

However, on the other hand, the high rainfall caused by La Niña and the Indian Ocean Dipole - caused various natural disasters in Indonesia (Lee, 2015; Setiawan et al., 2020). Until 2020, there were 1,549 disaster events dominated by hydrometeorological disasters. These events include floods, landslides, combinations of floods and landslides, tidal waves and abrasion. Natural disasters cause various impacts such as death, missing, injured, displacement, and suffering. In addition to damaged houses, there were heavily damaged, moderately damaged, and lightly damaged. In addition, there was damage to educational, religious, and health facilities. From a series of disasters until 2020, it is estimated that losses and damage due to disasters will reach tens of trillions of rupiah, and many people have died and gone missing (Rosmiati et al., 2020; Trenberth et al., 2018; Jailani, 2019).

Various factors cause the high number of losses and casualties experienced by the Indonesian people. One of the factors lies in people who lack knowledge in dealing with natural disasters. Most natural disasters are caused by climate change caused by the interaction of the atmosphere and oceans or marine climate that occurs every day (Rojas-Downing et al., 2017; Bose, 2017; Dai et al., 2017). As stated by (Elum et al., 2017), people need to understand and realize the impact of marine climate change. Besides that, people also have difficulty planning and preparing themselves and their families when marine climate change occurs every day, which suddenly rains during the dry season or sometimes a long dry season during the rainy season. The study's results (Rosmiati et al., 2020; Rosmiati & Satriawan, 2019; Rosmiati et al., 2020) show that student-teacher candidates have a common understanding of the impact of the marine climate and several problems were found related to the concept of marine climate.

The community needs knowledge of the marine climate because it is the primary key to understanding the marine climate change process. Thus, the community will be better prepared and more alert in dealing with the impacts of climate change due to the uncertain interaction of the atmosphere and oceans (Harker-schuch & Bugge-henriksen, 2013). According to (Acaps, 2016) the Indonesian people must create scenarios and descriptions to predict the future climate situation and review the possible impacts and consequences of climate change. This is so the community can plan, anticipate, monitor, supervise and create awareness of early preparedness for natural disasters. The public in general and the stakeholders involved in various agencies, including the most important is the Education Personnel Education Institute (LPTK).

LPTKs should have an essential role in producing human resources with the knowledge and awareness to minimize the impact of natural disasters caused by various climate change phenomena. Through expertise courses such as IPBA in physics study programs or physics education, LPTK graduates should be able to contribute to solving various problems related to disasters caused by climate change. However, until now, the contribution of LPTK graduates is still meagre. This is because the curriculum in LPTKs, especially LPTKs located on the sea coast (where locations are most likely to be affected by disasters from marine climate phenomena), do not discuss in depth the marine climate and its impacts (R. Rosmiati & Satriawan, 2019; Rosmiati Rosmiati et al., 2020).

Research questions or hypotheses

What are the predictions for El Niño La Niña & Indian Ocean Dipole phenomena using the ARIMA model by prospective teachers in Indonesia? Student worksheets are made according to the ARIMA model prediction stages to answer these questions.

Theoretical underpinning

a. El Niño and La Niña

The El Niño phenomenon, which comes from Spanish, means "boy", which is the phenomenon of a warming sea surface temperature (SST). El Niño is one form of climate deviation in the Pacific Ocean, characterized by increased SST in the central and eastern Equatorial Pacific. Indicators to monitor El Niño events are measurement data (SST) at longitude 170°W - 120°W and latitude 5°S - 5°N, positive or increasing anomalies indicate that El Niño is occurring (Mann et al., 2000). While the La Niña phenomenon is a decrease in SST at longitude 170°W - 120°W and at latitude 5°S - 5°N a negative or decreasing anomaly indicates the occurrence of La Niña, often referred to as the cold phase (Dyn et al., 2015). These two phenomena in the Pacific Ocean significantly impact human life (Zhang et al., 2016). Besides ENSO, another interaction phenomenon between global climate variability is the Indian Ocean Dipole that occurs in the Indian. In addition to ENSO and the Indian Ocean Dipole, there is also a monsoon phenomenon that occurs between the continents of Asia and the continents of Australia (Iskandar et al., et al., 2014).

The cells of the zonal circulation are called the Walker circulation, while the cells of the meridional circulation are the Hadley circulation. Both of these circulations are up and down in motion in the upper troposphere. During the mature El Niño phase, wind changes occur in the western Pacific Ocean, which amplify the growth of the Sea Surface Temperature (SST) anomaly to the East to increase El Niño conditions (Farzanmanesh et al., 2014; Miralles et al., 2013; Fitria & Pratama, 2013). Walker circulation anomaly occurs contrary to customary conditions, convection in the western Pacific Ocean (Peru coast) weakens, and the eastern part (Indonesian coast) strengthens. After convection declines in the central and western Pacific, air pressure increases, causing the growth of clouds to be inhibited over the oceans in eastern Indonesia, resulting in a dry climate and a prolonged drought. Displacement of SST, a warm pool is formed due to SST, which is marked with a yellow colour above sea level. The ocean is divided into three. The topmost yellow colour is sea level, the middle is the middle of the sea, and the third layer is the deep sea layer, commonly called the thermocline layer. In this thermocline layer, underwater currents move both locally and globally. It is these currents that determine the world's climate. In the normal phase, low surface pressure develops on the Peruvian coast or the central and western Pacific, so trade winds through the Pacific Ocean move powerfully from west to east. The trade winds in the eastern part (the Peruvian coast) carry the SST to the west, bringing convective storms to Indonesia and the Australian coast. Along the Peruvian coast, cold SST is carried to the surface to replace warm water pools from the western Pacific Ocean, namely the Indonesian coast (Singh et al., 2011; Kim et al., 2011).

In addition to the El Niño phenomenon, there is the La Niña phenomenon which also comes from Spanish and means "daughter". When La Niña occurs, it also occurs along the Pacific Ocean, just like the El event, namely the trade winds from the EastEast around the Peruvian coast blowing strongly (the Walker circulation shifts to the west around the Indonesian coast) (Yamanaka, 2016). So that the pool of warm water carried by the wind from the east coast of Peru is increasing towards the Pacific west coast of Indonesia, so that in the Pacific east coast of Peru, the cold water mass from the inner layer or the thermocline layer moves up and replaces the warm water mass, the movement of warm and cold water masses is called upwelling. The SPL has decreased from its average period with the change in water mass or upwelling. In the Indonesian Maritime Continent, the La Niña phenomenon causes convective cloud activity, so rainfall increases, floods in several significant parts of Indonesia, and landslides occur. The parameters for the occurrence of El Niño and La Niña were used for SST anomalies in the 3.4 El Niño area (Cao, 2000; Wu et al., 2012; Kug et al., 2010).

b. Indian Ocean Dipole

In addition to ENSO occurring in the Pacific Ocean, there is also a phenomenon that occurs in the Indian Ocean, namely the Indian Ocean Dipole, which is a strong interaction between the atmosphere and the ocean. Namely, the increase in SST in southern India or around the waters of southern Africa 10°N-10°LS; 60°E-80°E) accompanied by a decrease in SST in Indonesian waters or the west coast of Sumatra (0°-10°S; 90°E-110° EastEast) (Du et al., 2013; Zheng et al., 2010; Annamalai et al., 2010). The same thing happened to ENSO. The term "anomaly" is used to express the magnitude of the deviation, which means that it is different or compared to the average value. The Indian Ocean Dipole is divided into two, namely (1) the heat centre in the EastEast is called "Indian Ocean Dipole negative (-)", and the heat centre in the west is called "Indian Ocean Dipole positive (+)" (Saji & Yamagata, 2003; Iskandar et al., 2014).

Indian Ocean Dipole + is a high-pressure area on the west coast of Sumatra, Indonesia. In contrast, the eastern coast of the South African continent is low pressure, so air flows from the west coast of Sumatra, Indonesia, to the east coast of South Africa, resulting in the formation of convective clouds in the southern African region (Yang et al., 2019). The hot pools marked in red in the image are on the east coast of South Africa and produce heavy rainfall, usually resulting in flooding. Moreover, in the western region of Sumatra, there is a drought. Indian Ocean Dipole + and Indian Ocean Dipole –. The characteristics of the Indian Ocean Dipole are the opposite of the Indian Ocean Dipole +. The western region of Sumatra experiences high rainfall (Annamalai et al., 2010).

In contrast, in the eastern region of Africa, there is a drought due to high pressure moving towards the east coast of South Africa. The hot pools are located on the west coast of Sumatra, to the west of Indonesia. In the picture above, it is marked with orange colour for hot pools. In contrast, the arrow is a sign of the transfer of hot pools from the west coast of Sumatra to the east coast and vice versa from the east coast of Africa to the west coast of Sumatra.

Method

The method used is prediction and argumentation. Students predict the El Niño La Niña & Indian Ocean Dipole phenomenon and then argue it into a worksheet. Steps to predict using the ARIMA model:

Stationary Mean and Variance

Stationary variants that involve data transformations. To get the stationarity of the variance, the lambda value must be close to 1. Perform a differentiation process to determine the stationary of the means. If the p-value we get is less than 0.05, then the data does not move.

Modeling

Sea Surface Temperature Nino 3.4 data and Indian Ocean SST data from January 1982 to September 2018 must involve the ARIMA model. The ARIMA model is a model that consists of a combination of autoregressive (AR) and moving average (MA) models (Rosmiati et al., 2021). Autoregressive (AR) is similar to the linear regression model. This autoregressive model assumes a time series's current value depends on the same series's past value. (Rosmiati et al., 2020) The general formula for AR is as follows:

$$z_t = \emptyset^1 z_{t-1} + \phi_1 z_{t-2} + \cdots \phi_P z_{t-p} + a_t \quad (1)$$

$\emptyset p$ = coefficient of the occasional AR component with order p

Alternatively, it can also be written as:

$$\emptyset^{[B]} z_t = a_t \quad (2)$$

$\emptyset\ (B)$ = autoregressive operator B is the lag operator

$$Bz_t = z_{t-1} \quad (3)$$

The moving average (MA) model determines that the output variable depends linearly on the current and past values of the stochastic terms. The general formula for MA is as below (Formula 4):

$$z_t = \delta + a_t - \theta_{1a_t-1} - \theta_{2at-2} - \cdots \theta_q at - q \quad (4)$$

θq = coefficient of the occasional MA component of the order q

Generating ACF graphs in the moving average (MA) process is the same as PACF in the autoregressive (AR) process, while for ACF in the autoregressive (AR) process, it is the same as PACF in the moving average (MA) process. If the series is partly autoregressive and partly moving average, the general model is:

$$z_t = \emptyset^1 z_{t-1} + \phi_2 z_2 + \cdots + \phi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \quad (5)$$

Box and Jenkins first introduced the ARIMA model in 1976. The seasonal multiplicative ARIMA model of the Box-Jenkins form is generally as follows:

$$\phi_p(B^5)\varphi_p(B)(1-B)^d(1-B^s)^1 Y_t = \theta_q(B)\phi_Q(B^s)u_t \quad (6)$$

with

φp = coefficient of AR component with order p

Øp = p coefficient of seasonal AR component with order p

Component coefficient θq MA with order q

ØQ = coefficient of seasonal MA component of the order q

d = order of non-seasonal distinction

D = order of seasonal differentiation

B = non-seasonal fallback operator

B_S = seasonal reverse operator

Yt = time series

Ut = white noise residual

Accurate model

AIC, MAPE and MSE values are required to select the best model. Akaike criterion information (AIC) estimates the relative quality of a statistical model given a data set. Given the model set for the data, AIC estimates each model's quality relative to the other models. Thus, AIC provides a means for model selection. The absolute percentage error (MAPE), also known as the mean absolute percentage deviation (MAPD), is a measure of the predictive accuracy of a predictive method in statistics. The mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the mean of the square of the error or deviation. With the smallest values of AIC, MAPE and MSE, the model is much better to be selected as the best model (Rosmiati et al., 2021; Alsharif et al., 2019; Fattah et al., 2018).

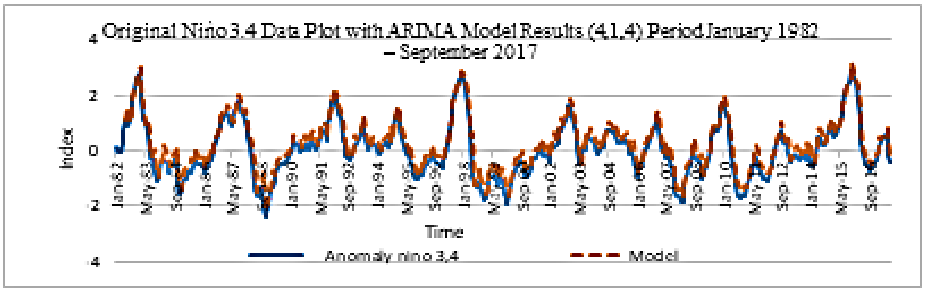
Result and Discussion

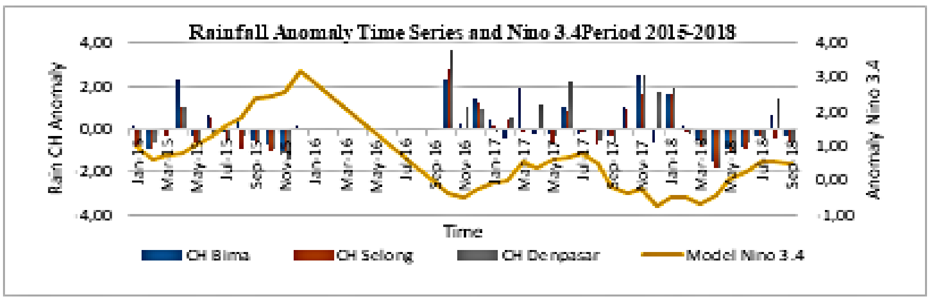
Prediction and Argument for El Nińo and La Nińa Phenomena

After students understand the phenomena and impacts of El Nińo and La Nińa, students work on task sheet one about predictions of El Niño and La Niña events in several Indonesian cities. Prediction of El Niño and La Niña events using the ARIMA model. Autoregressive Integrated Moving Average (ARIMA) is a model that completely ignores independent variables in making predictions. Initially, students were given a problem in the form of 2 graphs. The first graph plots the original Niño 3.4 data with the ARIMA model results (4, 1, 4). This graph contains a plot of Niño 3.4 data taken from the NOAA Website from January 1982 to September 2017. Initially, this was until September 2018 but stored for validation data for 12 months or one year. The second graph is the time series of rainfall anomalies and Niño 3.4. Rainfall data (CH) is taken on the CHIRPS Web according to the latitude and longitude of the city from which the CH data is taken. Rainfall data was taken from 2015 to 2018. The purpose of giving the initial problem in this graph is to stimulate students' initial thinking responses to make climate predictions using the ARIMA method and then argue for the prediction results that have been tested. The data of the two graphs in the initial assignment of problem sheet one is presented in Figure 1.

A. Giving problem

Look at the following chart!!!





The plot of the original sea surface temperature anomaly in the Niño 3.4 area with the ARIMA model (4.1.4) for the period January 1982 – September 2017 shows the following trend. Can this model predict the occurrence of El Niño and La Niña? ....

What are the claims, warrants and backing of the time series graphs of rainfall anomalies and Nino 3.4 in the 2015 – 2018 period? before answering this question, do this LKM in accordance with the Work Steps.

A. Problem Formulation

1. How accurate is the teleconnection model at the Niño 3.4 index?

2. What is the prediction of the teleconnection index at Niño 3.4 for the next few months?

3. What is the effect of rainfall based on El Niño and La Nina in several cities in Indonesia?

Figure 1. Initial Assignment of Problems on the Task Sheet

Figure 1 bellow is a graph presented at the beginning of the assignment sheet, stimulating students' initial thinking before starting the experiment, namely predicting climate. From the graph presented, it turned out that most students responded by asking various questions such as: how the graph was made, with what data, why to use ARIMA (4, 1, 4), and why the rainfall graph was inversely proportional to the Niño 3.4 graph. These questions become an opportunity to conduct a good climate prediction experiment. After students have successfully responded to their initial thoughts, the next step is under the ARIMA method working steps starting from (1) identifying the model by determining ACF and PACF. (2) estimation of model parameters, namely determining ARIMA on the specified ACF and PACF. The ARIMA model parameter is the slightest Mean Squared Error (MSE) level. (3) model diagnosis of the smallest MSE. And (4) a measure of predictive accuracy.

The prediction accuracy parameter is measured if the correlation value of the original Nińo 3.4 data with the ARIMA model that has been calculated the correlation is close to 1. The closer the correlation is to 1, the more valid or correct prediction. Most of the students succeeded in conducting climate prediction experiments by reading the instructions in the ARIMA and SARIMA model modules. The ARIMA Nińo 3.4 model is the position of the blue line ACF = 5 and PACF = 5. Before modelling, the Nińo 3.4 data must be stationary first. In experiments conducted by students, all students produced differences = 1.

Then the parameter estimation stage of the model, students can do it well, looking for the smallest MSE by one from the ARIMA model. The ACF and PACF plots show that the ACF and PACF Nińo 3.4 are significant at the fifth lag. Thus the provisional model of the Nińo 3.4 data plot is a mixture of autoregressive, the first distinction, and the moving average or ARIMA model (p, 1, q). With values of p and q were chosen 1, 2, 3, 4, and 5. Based on experiments conducted by students, it is known that the model with the smallest MSE and SSE values compared to other models is the ARIMA model (4,1,4), which describes the order of AR as four. The order of MA is four, and the differencing value is 1. By looking at MSE and SSE as the best predictive model measures, the ARIMA (4,1,4) model deserves to be chosen as the best prediction model. The following is an example of student performance at the model identification stage and model parameter estimation presented in 2.

A. Work Steps (more details in the ARIMA and SARIMA modules)

1. Download the Nińo 3.4 Anomaly Data on the page http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices and Rainfall Data on the page https://iridl.ldeo.columbia.edu/SOURCES/.UCSB/.CHIRPS
2. Model identification
3. Estimation of model parameters
4. Model diagnostics
5. A measure of forecasting accuracy
6. Extreme Weather App

B. Arguments on the MFI Sheet

1. Include and analyze data from SST Nino 3.4 to support ENSO claims!

a. Model identification

Number of Positional	Differences Blue Lines	
	ACF	PACF
1	5	5

b. Estimation of model parameters

Arima Model (*p, d, q*)	Score (Sum of Squared Errors) SSE	Score (*Mean Squared Error*) MSE
1, 1, 0		0,0681
2, 1, 0		0,0676
3, 1, 0		0,0678
4, 1, 0		0,0678
0, 1, 0		0, 0721
1, 1, 1		0,0677
2, 1, 1		0,0678
0, 1, 2		0,0688
1, 1, 2		0,0677
3, 1, 2		0,0651
4, 1, 2		0,0652
0, 1, 3		0,0680
0,1, 4		0,0671
1, 1, 3		0,0671
2, 1, 3		0,0671
3, 1, 3		0,0674
0, 1, 4		0,0679
4, 1, 4		0,0639
Note : does not include an error value		

Figure 2. Student performance at the model identification stage and model parameter estimation

Figure 2. Shows point C of tools and materials. On average, students have written the tools and materials used in climate prediction experiments well. Then point D is the work steps. On the task sheet, only briefly the work steps are written. More clearly, the climate prediction work steps are found in the ARIMA and SARIMA model modules, ARIMA and SARIMA models using MINITAB and MS Excel software. At Dan, the core stage is argumentation. The prediction stage is in the argumentation stage because Toulmin's argumentation

pattern consists of claims, data, warrants and backings. Predictions are data needed to determine claims, warrants and backings. At point E, part a, there is model identification. All students answered that the identification of the El Niño La Niña material model is difference = 1, PACF at lag five and ACF at lag 5. Point B determines the estimation of model parameters, namely analyzing which model is the smallest value of the mean squared error (MSE) to be used as the chosen model. Climate prediction experiments are the data in the argument. After determining the data, it will be followed by an explanation of claims, warrants and backing. Prediction data follows the stages of the Box – Jenkins prediction method. The estimation data of the advanced model parameters are written on the back of the paper. Almost all students correctly determined the ARIMA model that will be used to predict climate by looking at which model has the smallest MSE.

The next step is a model diagnosis. After obtaining the best predictive model, the next step is to test the suitability of the model. Because the prediction model obtained by the residual value already meets the white noise requirements and is typically distributed, the initial prediction model is appropriate. The ARIMA (4,1,4) model means that the forecast for Niño 3.4 data for the future depends on Niño 3.4 data 4 months earlier and the error four months earlier. The estimated value is obtained using the ARIMA (4,1,4) model. Comparison of original data, forecast values, and error values. These results indicate that the ARIMA method can recognize patterns in Niño3.4 data well and make predictions with relatively small error values.

At the stage of measuring the accuracy of predictions, the correlation between the original data is Niño 3.4, and the ARIMA model (4, 1, 4) is 0.98. This value is possible to make predictions because it is almost close to 1. After being predicted using three months and six months, the correlation value is also close to 1, which is both 0.99. An example of an assignment sheet done by students in the model diagnosis stage, a measure of the accuracy of predictions and the application of rainfall, is presented in Figure 3.

a. Models diagnostics

No	AR value	MA value	Constant
1	0,5136	0,1838	-0,0000724
2	0,5206	0,5255	
3	0,0104	0,2650	
4	0,1985	0,0346	

b. A measure of forecasting accuracy

Niño 3.4 Original Data Correlation and Arima Model = 0.99

Prediction	Correlation	Time Niño Index Prediction 3.4	Niño 3.4 Index Prediction
3 Months	0,996	Oct-18	0,39
		Nov-18	0,395
		Dec-18	0,426
6 Months	0,992	Oct-18	0,34
		Nov-18	0,39
		Dec-18	0,426
		Jan-19	0,508
		Feb-19	0,549
		Mar-19	0,59

c. Extreme Weather App

The Influence of Bima, Selong and Denpasar Rainfall on ENSO events for the period 2016 - 2018

City	Year/Month Rainfall	Anomaly	Index Niño 3.4	Extreme Weather
Bima	October 2016	2,4	-0,8	Wet
	September 2018	2,06	0,06	Dry
Selong	October 2016	2,5	-0,0	Wet
	August 2017	-2,0	-0,0	Dry
Denpasar	October 2016	2,8	-0,0	Wet
	August 2017	0,4	-0,0	Dry

Figure 3. The assignment sheet is done by students in the stages of model diagnosis, measurement of the accuracy of prediction and application of rainfall

Experiments carried out by all students to obtain data plots from the ARIMA model (4,1,4) for Niño 3.4 can follow the original data with a correlation of 0.98 or 98%. Prediction results with the ARIMA model (4,1,4) are pretty good because they produce a small error value. The following is an image of the original Niño 3.4 data plot with the ARIMA model results (4,1,4) in the

Indian Ocean Dipole e January 1982–September 2017, presented in Figure 4.

In Figure 4. it can be seen that the original Nińo 3.4 data closely follows the ARIMA model data (4,1,4). The graph tells that in 1982-1983, 1992-1993, 1997-1998 and 2015-2016, there were prolonged droughts in Indonesia. Indonesia because of the El Nińo phenomenon.

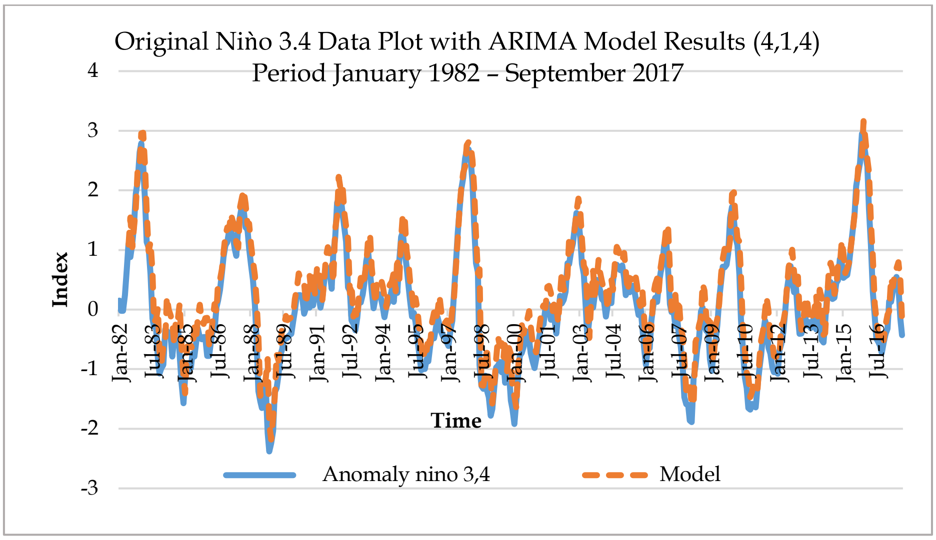


Figure 4. A plot of the original Nińo 3.4 data with ARIMA model results (4,1,4)

The next stage is the application of extreme weather conditions carried out by analyzing the short term in the last year of arid and extremely wet conditions, namely in 2015 and 2018. This extreme weather was taken in 3 cities in eastern Indonesia, namely Bima, Selong and Denpasar. From the application of extreme weather, it can be seen that the ARIMA (4,1,4) model can be applied to predict rain and drought in Indonesia. The extreme weather application data on the TASK SHEET is obtained from the second graph beginning of the TASK SHEET. Students read the graph. The extreme weather graph is presented in Figure 5.

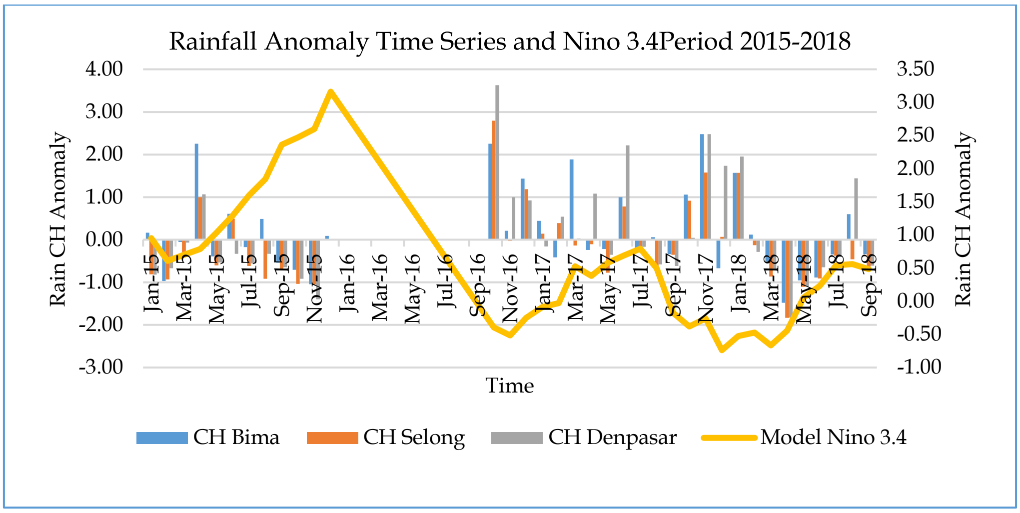


Figure 5. Graph of extreme weather in 3 cities in Indonesia

From Figure 5. there was extreme wet weather in the Bima area in April 2015 and November 2017 and extremely dry weather in May 2018. Then in the Selong area, extreme wet weather occurred in October 2016 and dry in May 2018. Furthermore, the last is in the Selong area. Denpasar's exceptionally wet weather occurred in September 2016, while dry weather in May 2018. The outline is that if Nino 3.4 increases or is positive, rainfall decreases, or there is a long dry spell in the study area or almost all parts of Indonesia and vice versa. If Nino 3.4 decreases or is negative, rainfall increases or floods occur in almost all parts of Indonesia. All students can read these extreme weather charts and can predict extreme weather in the future based on the El Nino and La Nina predictions that have been made.

After the application of extreme weather, the next step is argumentation. The arguments on the assignment sheet start from determining claims, warrants and backings. At the end of the argument, students are asked to write down the purpose of the experiment that has been carried out. The following is an example of a student's argumentation, the first assignment sheet for El Nino La Nina material. Explanation below.

- Claim according to the ENSO problem
"At Nino 3.4, the Nino index (-) shows that rainfall in Indonesia is replaced by the warming of seawater temperatures in the central to eastern Pacific Ocean (El-Nino that occurs in several areas in Indonesia is dry conditions from reduced rainfall".
- Explain the relationship between SST data and ENSO claims
"El - Nino and La Nina are atmospheric and water dynamics that have weather around the Pacific Ocean when. El Nino occurs when the dry season becomes very dry and the rainy season surface is late".
- Foundational reform to support ENSO!
"Characteristics of Indonesia is an archipelagic country flanked by two continents, namely Asia and Australia and two oceans, namely the Pacific and India. Indonesia also consists of 70% water and 30% land. There are three types of rainfall, monsoon, equatorial and local".
- Write down the purpose of the practicum that you have done!
"To find out the rainfall in Indonesia and to know the drought in Indonesia.
It has been predicted that El Niño La Niǹa events will continue to increase with a positive Anomaly (1.30) until March 2019, with a correlation of the Original data and the Predicted Model of 0.98. However, some students answered that only if Nino 3.4 increases or is positive, then rainfall decreases, or there is a long dry spell in the study area or almost all parts of Indonesia and vice versa if Nino 3.4 decreases or is negative. Rainfall increases or floods occur in almost all parts of Indonesia. This happens because students' thoughts are different. Some students still have not reflected on their thoughts on the material that has been delivered".

In the warrant section, most of the students explained very well. They explained that the Nusa Tenggara and Bali areas have apparent differences between the Indian Ocean Dipole e rainy and dry seasons. Sea Surface Temperature (SST) Niǹo 3.4 influences rainfall patterns in the region. The. As seen in the table of extreme weather applications carried out by analyzing the short term on the Indian Ocean Dipole e 2015-2018, the rainfall data and the Niǹo 3.4 model data have different phases. When the Niǹo 3.4 area is in a positive phase, rainfall in the study area has decreased, namely the movement of the hot pool from the western equatorial Pacific (Indonesia) to the EastEast (Peru). Above the centre of the anomaly (in Peru), the temperature is hot, so strong convection causes solid air to move upward. Due to upward air currents, the trade winds in the EastEast strengthen, while when Niǹo 3.4 is in a negative phase, rainfall in the study area increases or there is movement. Hot pools from the eastern equatorial Pacific (Peru) to the west (Indonesia). However, some students only explain the definition of the El Nino and La Nina phenomena.

From the worksheets that were done, all students were precise in explaining the backing. The explanation of the backing on task sheet 1 & task sheet 2 is the same because it explains the characteristics of the Indonesian Maritime Continent (BMI) region. Namely, the main characteristic of the Indonesian territory is a mixture of land and sea surfaces, covering 70% of water and 30% of the land, located between the Pacific Ocean and the Indian Ocean as well as the Asian continent and the Australian continent, thus forming the Indonesian Maritime Continent (BMI), which is in the equatorial area where tropospheric convection and cumulonimbus (Cb) cloud formation are most active, thus becoming the primary heat source of the Earth's atmosphere that controls the world's climate.

Most of the students explained the claim correctly. They explained that the negative anomaly in the Niǹo 3.4 area would occur as a La Nińa phenomenon. Namely, rainfall will increase in Indonesia, especially the West Nusa Tenggara and Bali areas, due to widespread flooding and landslides, while positive anomalies will occur. El Niǹo is reduced rainfall, resulting in prolonged droughts, water shortages and forest fires.

Predictions and Arguments for the Indian Ocean Dipole Phenomenon

This Indian Ocean dipole prediction experiment was carried out on task sheet 2, using the ARIMA model and the task sheet. So that students immediately conduct experiments on task sheet two because they are already proficient in doing it on task sheet one about El Niǹo La Niǹa. The difference lies only in collecting data on the Indian Ocean SST anomaly. Indian Ocean SST anomaly data was taken from the Japan Agency for Marine-Earth Science and Technology (JAMSTEC) website.

It is the same with task sheet 1; on task sheet two, all students did it well. Because face-to-face time with lecturers is two times a week, consisting of 1 credit of theory and two credits of practicum or climate prediction experiments. So students experiment with lecturer supervision. After the lecturer finished delivering the material and discussing it with the students, the students were invited to work on task sheet 2, which was to predict the phenomena and events of the Indian Ocean Dipole. The results obtained from this task sheet 2 are at the model identification stage, differences = 1, ACF = 4 and PACF = 4. Examples of what students do on the assignment sheet are presented in Figure 6.

1. Include and analyze Indian Ocean SST data to support IOD claims

a. Model identification

Number of Differences	Blue Line Position	
	ACF	PACF
1	4	4

Figure 6. Assignment sheet of student experiment results in the model identification stage

From Figure 6, the determination of differences, ACF and PACF from these values, students conduct experiments to the next stage, namely the estimation of model parameters. As in the stage of task sheet 1, the model that is taken is the model with the lowest MSE value. The result of determining the students is the ARIMA model (0, 1, 3) because the MSE value is the smallest. Furthermore, the determination of the diagnosis model from ARIMA (0, 1, 3). An example of a model diagnosis stage done by students is presented in Figure 7.

c. Models diagnostics

No	AR value	MA value	Constant
1	0	0,0819	-0,0000724
2	0	0,1122	
3	0	0,1798	

Figure 7. Stages of diagnosis of ARIMA model (0, 1, 3) on Indian Ocean Dipole predictions

After the model diagnosis, the AR, MA and constant values are entered into the ARIMA formula. From the ARIMA formula, the model values appear to be used as a reference for predicting the Indian Ocean Dipole and other climates using the ARIMA method. From the results of student calculations, it has been found that the correlation between the original data of the Indian Ocean SST and the ARIMA model (0, 1, 3) is 0.78 or the accuracy is 78%. In the partial correlation, the value of 0.78 is still in the strong category. The correlation graph of the original Indian Ocean SST data with the ARIMA model (0, 1, 3) is presented in Figure 8.

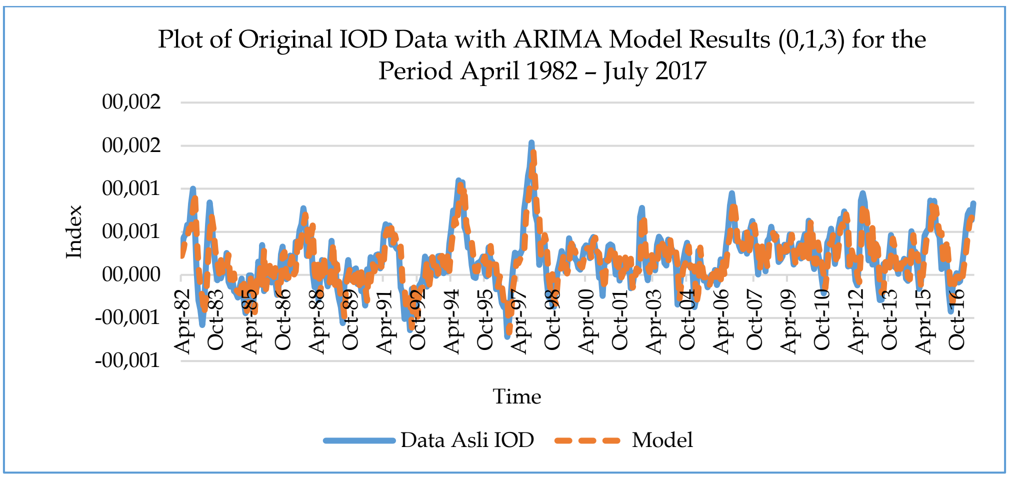
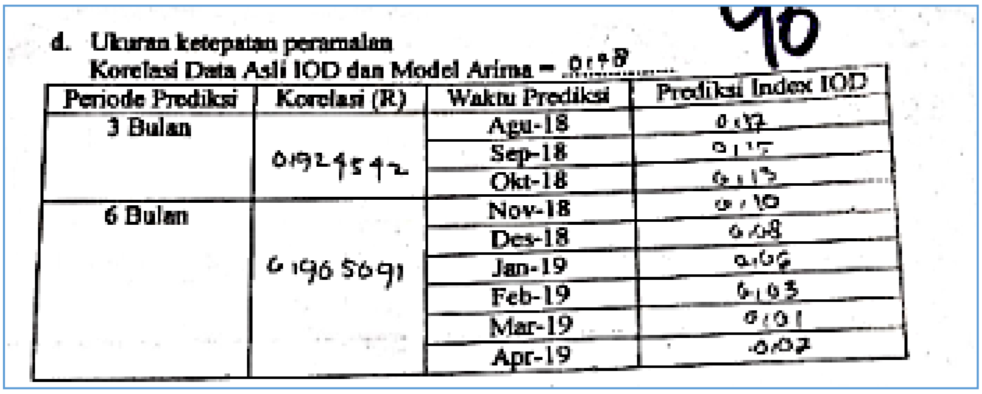


Figure 8. Correlation of the original Indian Ocean SST data with ARIMA model (0, 1, 3)

From Figure 8, it can be concluded that the positive Indian Ocean Dipole phenomenon that caused the prolonged drought in Indonesia occurred in 1997-1998. Although the correlation value of the Indian Ocean SST anomaly and the ARIMA model (0, 1, 3) is equal to 0.78, the prediction correlation values for the next three months and six months of Indian Ocean Dipole events of 0.92 and 0.96 are in the category extreme. Figure 9 is an example of an assignment sheet that students do at the stage of measuring the accuracy of predictions.


d. Ukuran ketepatan peramalan
Korelasi Data Asli IOD dan Model Arima = 0,98

90

Periode Prediksi	Korelasi (R)	Waktu Prediksi	Prediksi Index IOD
3 Bulan	0,9249542	Agu-18	0,17
		Sep-18	0,15
		Okt-18	0,13
6 Bulan	0,965091	Nov-18	0,10
		Des-18	0,08
		Jan-19	0,06
		Feb-19	0,03
		Mar-19	0,01
		Apr-19	-0,02

Figure 9. Students do the assignment sheet at the Indian Ocean Dipole prediction stage

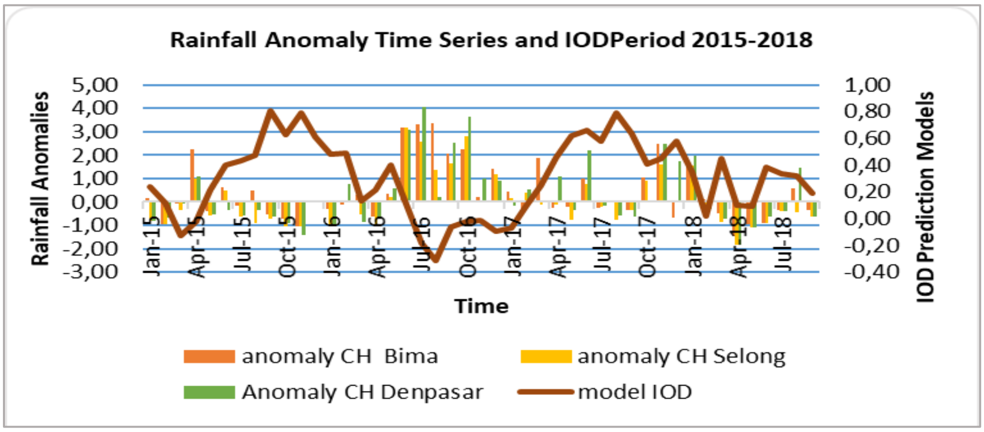


Figure 10. Graph of rainfall anomalies and Indian Ocean Dipole

From the graphic data in Figure 10. Students analyze and then write into tables. It can be seen from the graph that it can be concluded that when the Indian Ocean SST anomaly is positive, the rainfall anomaly value in the Bima, Selong and Denpasar areas will be negative. The positive Indian Ocean Dipole caused prolonged droughts in 2015 and 2017. Then the negative Indian Ocean SST anomaly value caused floods in mid-2016. These extreme weather application charts and tables serve as a reference for students to explain claims. Examples of student performance results in analyzing rainfall anomaly graphs and the Indian Ocean Dipole are presented in Figure 11.

d. Extreme Weather App

The Influence of Bima, Selong and Denpasar Rainfall on IOD events for the period 2016 - 2018

City	Year/Month Rainfall	Anomaly	Index IOD	Extreme Weather
Bima	October 2016	3.40	0,30	Wet
	September 2018	-1,50	0,20	Dry
Selong	October 2016	3,00	0,20	Wet
	August 2017	-1.80	0,20	Dry
Denpasar	October 2016	4,00	-0,20	Wet
	August 2017	-1,80	0,20	Dry

Figure 11. Student performance results analyzing rainfall anomaly graphs and Indian Ocean Dipole

The results of the student arguments for the Indian Ocean Dipole are presented in the following explanation: From the explanation of the claims section, most of the students had good explanations. Namely, the negative anomaly of the Indian Ocean Dipole index caused high rainfall in the Nusa Tenggara and Bali regions, causing flooding. In contrast, the positive anomaly caused reduced rainfall, causing drought and water shortages. Indian Ocean Dipole predictions for the next six months Indian Ocean Dipole August 2018 –

April 2019 shows an average anomaly reaching 0.90 with a correlation of the original Indian Ocean Dipole data with prediction data of 0.78. Students can explain claims according to the Indian Ocean Dipole problem.

1. Claim according to the Indian Ocean Dipole problem!

"When the Indian Ocean Dipole occurs (+), Indonesia will experience a drought because the convection zone will be shifted to the southwest towards the waters in the middle of the Indian Ocean and the east coast waters. As a result, the rain zone will shift to the west".

2. Explain the relationship between the Indian Ocean SST data and the Indian Ocean Dipole claim.

"The Indian Ocean Dipole is a symptom of weather deviation produced by the interaction between the ocean surface and the atmosphere in the Indian Ocean region around the equator and south of Java".

3. Justify the claims of the Indian Ocean Dipole.

"*Indonesia is an archipelago with ± 13508 islands. Indonesia's position is located between the ocean and 2 continents. Indonesia is between 100 – 110 LS and 950 BT – 191 0. Indonesia has two seasons, namely rainy and dry. The world's mountains traverse the territory of Indonesia*".

After explaining the claim, the next student explained the warrant. In this stage, students explain the relationship between Indian Ocean SST data and Indian Ocean Dipole claims. At this stage, students can explain well, but some students still need to reflect on their thoughts. Some theories have been submitted. It can be seen from the students' answers who explained that the Indian Ocean Dipole is a symptom of weather irregularities produced by the interaction between the ocean surface and the atmosphere in the Indian Ocean region around the equator and south of Java. The student's explanation still needs to be appropriate for warrants.

In addition to students whose answers were not perfect, some students had perfect answers to the explanation of the Indian Ocean Dipole warrant, which explained that the West Nusa Tenggara and Bali regions have a clear difference between the Indian Ocean Dipole e rainy season and dry season, Sea Surface Temperature in the Indian Ocean is very influential on the rainfall pattern in the study area. As can be seen in the table for extreme weather applications carried out by analyzing the short term in the 2015-2018 Indian Ocean Dipole, the rainfall data and the Indian Ocean Dipole model data have different phases. When the Indian Ocean Dipole is in a positive phase, rainfall in the study area decreases. Hot pools are located on the coast near Africa when the west coast of Sumatra is under high pressure, while the east coast of the African continent is under low pressure so that air flows from the west of Sumatra to the east. Africa which results in the formation of convective clouds in the African region and produces above-normal rainfall.

On the other hand, there is a drought in the western region of Sumatra after the mass of water vapour failed to reduce it as rain. On the other hand, when the Indian Ocean Dipole is in a negative phase, rainfall in the study area experiences an increase in rainfall. This answer indicates that the student has succeeded in reflecting on his thoughts.

Conclusion

The students' prediction results on the average predictive ability are perfect. Students are enthusiastic about working on the worksheet by reading step by step to predict ENSO, IOD and monsoon events in Indonesia. From the worksheet used by students, they stimulated the initial thought response by providing a graph of the original data plot of the ARIMA prediction model for a specific year period and a time series graph of rainfall anomalies. From the graph, students feel curious about how the graph is processed. Because this worksheet begins with problem-based learning with the objectives: problem-based learning involves students in an active, collaborative, student-centred learning process, which develops problem-solving skills and independent learning skills needed to face challenges in life and careers in an environment that is increasingly complex (Häkkinen et al., 2017; Shultz & Li, 2016).

Students carry out the ARIMA method stages carefully according to the Box-Jenskis scheme. In contrast, the steps carried out in the outline are (1) Identification of tentative (temporary) models, (2) Parameter estimation, (3) Diagnostic checks, (4) Forecasting (Alsharif et al., 2019; Fattah et al., 2018). From the prediction results obtained, the incidence of ENSO and IOD in the next year will increase, with the correlation level of the original data and the ARIMA model for ENSO being 0.98, which is a number close to 1, which means the number is valid, and the correlation results from the original IOD and IOD data. ARIMA model data obtained the number 0.87, which is a value above 7.5. Because according to (As-syakur et al., 2014; Pillai & Mohankumar, 2010), the prediction results can be used and are said to be valid if the correlation value between the original anomaly data and the ARIMA modified data is above 0.75.

The correlation between the prediction period for Nińo 3.4 is very high for three months and six months, namely 0.99. The value is almost close to 1. The predicted value for the Nińo 3.4 index is increasing day by day, indicating that rainfall is decreasing. Positive anomalies indicate the occurrence of El Nińo (Mann et al., 2000; Rosmiati et al., 2021). While the La Nińa phenomenon is characterized by a decrease in sea surface temperature at longitudes of 170°W - 120°W and at latitudes of 5°S - 5°N where the anomaly is negative, so it is often referred to as the cold phase (Wu et al., 2012). Students argue ENSO by determining claims, warrants and backings. The average student scores a range of 90 – 10, a score of 10 is an answer under ENSO's claim. In comparison, the score of 90 students answered only to the positive and negative phase events in ENSO because some students still had not reflected their thoughts on the material that had been delivered. Recently some regions and regions in Indonesia have experienced droughts that are faster than usual.

In the IOD calculation, the three-month correlation prediction period is 0.92, and for six months is 0.96. This is the same as in the Nińo 3.4 data correlation. The correlation value is close to 1. The value is very accurate and can be used. The predicted value of the IOD index was average. The resulting values ranged from 0.01 to 0.17. This indicates that students are already proficient in making climate predictions. Because students are very enthusiastic and enthusiastic in studying climate prediction, and it is a new science (Rosmiati & Satriawan, 2019; Rosmiati et al., 2020; Rosmiati et al., 2020).

Author Contributions

Rosmiati conceptualization, which includes research ideas, design with methodology, data analysis, and coordination of respondents. Muhammad Satriawan conceptualization has been carried out by reviewing investigation research and literature review. Rarasaning Satianingsih conceptualization provided feedback on the manuscript.

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Conflicts of Interest

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