Predicting the Number of Forest and Land Fire Hotspot Occurrences Using the ARIMA and SARIMA Methods

Angga Bayu Santoso [1] *, Tri Widodo [2]
Faculty of Engineering and Computer Science [1], [2]
Universitas Teknokrat Indonesia
Bandar Lampung, Lampung, Indonesia
anggabayu@teknokrat.ac.id [1], tri_widodo@teknokrat.ac.id [2]

***Abstract*— Forests are an area and part of the environmental cycle that is very important for survival because forests are areas on Earth that regulate the balance of the ecosystem. Forest fires rank second only to illegal logging in Indonesia's list of forest destruction causes. Forest fires can occur due to two factors, namely natural and human factors. Therefore, the hotspot factor that can cause forest fires is an independent variable. The population of hotspots in the West Kalimantan region in 2020 amounted to 1,416 spots. This study aims to predict the number of hotspot occurrences on land and forests that cause fires before the fires spread and are challenging to overcome or extinguish. The method to indicate the number of hotspot occurrences uses the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) methods. Modeling ARIMA (0,1,1) and SARIMA (0,1,1) (2,2,1)12 obtained Root Mean Square Error (RMSE) evaluation results for ARIMA of 6.61 while SARIMA of 7.61. The ARIMA's Mean Squared Error (MSE) evaluation value is 43.70, and the SARIMA is 58.05. Based on these results, it can be concluded that the ARIMA model provides excellent and accurate performance in describing the trend of hotspot events that will occur in the future with a smaller RMSE value compared to SARIMA.**

***Keywords*— Forestry, Land and Forest Fires, Hotspot, ARIMA, SARIMA**

I. INTRODUCTION

Forests are areas and parts of the environmental cycle that are very important for survival because forests are areas on Earth that regulate the balance of the ecosystem [1]. According to the Basic Forestry Law No.41 of 1999 concerning Forestry, a forest is an ecosystem unit in the form of an expanse of land containing biological natural resources dominated by trees in their natural environment, one and the other inseparable [2]. Indonesia is a country where almost all provinces have forest areas. Indonesia's forest and water conservation areas in 2019 were around 123.8 million hectares [3].

But today, Indonesia's deforestation rate is still relatively high, with around 115.46 thousand hectares per year in 2020 [4]. The high rate of deforestation can undoubtedly threaten the existence and sustainability of forests in Indonesia. One of the most significant contributors to the high rate of deforestation is the forest and land fires carried out illegally by local communities and large private companies to clear land [5].

Forest and land fires rank second to illegal logging in Indonesia's list of forest destruction causes [6]. Every year, millions of hectares of forest are burned. Forest and land fires in Indonesia generally occur on the islands of Sumatra and Kalimantan, where both islands are areas dominated by wetlands, especially flammable peatlands [7]. High organic matter content, porous nature, and low vertical conductivity are the causes of peatlands being highly volatile. Fires on peatlands are difficult to extinguish because they spread below the ground surface [8]. Forest fires can occur due to two factors, namely natural and human factors. Therefore, an independent variable is the hotspot factor that can cause forest fires [9].

A hotspot is a forest fire indicator that detects an area with a relatively higher temperature than the surrounding temperature [10]. The site is represented in a point with specific coordinates. Hotspots are usually used as an early indicator to detect the possibility of forest fires in an area; the greater the number of hotspots that appear, the greater the potential for forest and land fires that occur in a room [9]. Hotspots can be used as a reference for early identification of forest and land fires [11].

West Kalimantan is a tropical region with high air temperatures, with an average air temperature of 27.6°. The population of hotspots in the West Kalimantan region in 2019 was recorded at 4,005 points [12]. By this situation, the government needs effective and efficient forest and land fire prevention measures in the West Kalimantan region. One of the effective preventive measures the government can take is observing the appearance of hotspots through satellites. Hotspots that appear in forests and land can be observed through the National Aeronautics and Space Administration (NASA) satellite [8]. Observation via satellite allows quick knowledge of the appearance of hotspots that are detected directly. This observation can be carried out in the West Kalimantan region to respond to hotspots appearing in forests and land that cause fires before the fire spread and are challenging to overcome or extinguish.

Several related studies based on similar problems and solutions in preventing forest and land fires, one of which is a study aimed at forecasting the number of hotspots on Kalimantan peatlands using a zero-inflated Poisson regression model based on climatic factors, namely sun exposure, and

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rainfall. This model can map the Kalimantan region into four good areas, with the smallest RMSE value of 10.05 in area 2 [8]. Another study used multiple regression models to predict hotspots in the Southern Southeast Asia region with several significant predictors. The results of this study successfully indicated the highest area in Southern Southeast Asia with an RMSE of 11.3 [9].

Different from the previous research, another study aims to predict the occurrence of hotspots in peatlands in Riau province using long- and short-term memory. The research made predictions for the next six months, from August 2019 to January 2020. LSTM can predict time series with an RMSE value of 363.38 [13]. The research aimed at predicting the number of occurrences of hotspots was also carried out in the Rokan Hilir district using the Elman recurrent neural network, with the results of the research producing a constant actual value with the prediction results, namely the RMSE value of 437.603 [14]. Furthermore, a similar study was conducted to predict the number of hotspot events through a time series approach using the seasonal arima model using the NASA MODIS satellite data. The research produced an excellent prediction model with an RMSE value of 5.85 [15].

Another method in prediction techniques (time series) is the Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model is a model that completely ignores independent variables in forecasting [16]. ARIMA aims to determine an excellent statistical relationship between the predicted variable and the historical value of the variable so that forecasting can be done with the model [17]. Furthermore, the ARIMA model was developed into the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. SARIMA is the development of the ARIMA model, which can analyze recurring or seasonal data patterns when time is fixed, such as quarterly, semi-annually, and annually. This prediction model aims to determine a relationship between predicted variables through data on the historical value of these variables so that predictions can be made [18].

In addition, several studies apply the ARIMA and SARIMA methods, such as research on predicting North Jakarta Sea wave height using machine learning by comparing ARIMA and SARIMA algorithms. The results of the study can be concluded that the ARIMA and SARIMA models made to predict the level of sea level rise have an excellent level of performance in predicting the possibility of sea level rise with a perfect prediction, namely the lower confidence level value of 92.78% [19]. Then, another study was conducted to forecast the number of domestic shipping passenger departures at Tanjung Perak port using the ARIMA and SARIMA methods. The results showed that analysis with the ARIMA method had a smaller accuracy value than analysis using the SARIMA method, which was 16.15% and was the best method for this forecasting [20]. Another study also discussed the comparison of ARIMA and SARIMA for crude oil price forecasting. The evaluation results of this study show the RMSE value of ARIMA and SARIMA is 1.905. Then, the forecasting results for the next seven days with ARIMA are 86.230003 while SARIMA is 86.260002, so ARIMA is better than SARIMA. The results of this study are expected to help policymakers make the right policies and decisions in using crude oil [21].

Based on the previous problems and some related research that has been mentioned, this research aims to build a prediction model for the number of forest and land fire hotspot occurrences in the West Kalimantan region using the ARIMA and SARIMA methods. This research has several contributions, including using hotspot data from the early detection information system for forest and land fire control (Sipongi) as a form of resource optimization. So far, the data is only stored in the database and needs to be appropriately utilized. The comparison of ARIMA and SARIMA methods in this study can also be used to identify the performance of each method in predicting the number of forest and land fire hotspot occurrences in West Kalimantan. Furthermore, analyzing the patterns and trends of hotspot occurrence can help develop more effective strategies for controlling and mitigating forest and land fires.

II. LITERATURE REVIEW

A. *Forest and Land Fires*

Forest fires are one of the environmental problems that threaten forests, causing adverse environmental impacts, creating economic problems, and ecological damage [22]. Forest fires are burning events that spread freely in unplanned areas and use natural fuels from the forest, such as litter, grass, twigs, or dead tree branches [23]. There are three efforts to prevent forest and land fires: socialization of forest and land fire prevention, forest and land fire prevention patrols, and primary forest and land fire disaster management training [24].

B. *Hotspot.*

Hotspots are indicators of forest fires that detect an area with a relatively higher temperature than the surrounding temperature [10]. Hotspots are points on the image (pixels or sub-pixels) that have very high temperatures and are associated with active Earth surface fires [21].

C. *Data Mining*

Data mining combines several computer science disciplines defined as discovering new patterns from massive data sets, including methods related to artificial intelligence [26].

D. *Prediction*

Prediction is systematically estimating something that will happen in the future based on past and present information to get forecast results close to the actual results. There are two techniques for predicting, namely qualitative prediction techniques and quantitative prediction techniques [27].

E. *Autoregressive Integrated Moving Average* (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is a forecasting model that produces forecasts based on synthesizing historical data patterns. The ARIMA method will work well if the data in the time series are dependent or statistically related [28].

F. *Seasonal Autoregressive Integrated Moving Average* (SARIMA)

Seasonal Autoregressive Integrated Moving Average (SARIMA) is developing the Autoregressive Integrated Moving Average (ARIMA) model on time series with seasonal patterns. The SARIMA model is denoted by ARIMA (p,d,q) $(P,$

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D, $Q)^s$. In the SARIMA model, two parts are designated by lowercase and capital letters, and (p,d,q) is the notation of the part of the model that is not seasonal. While (P, D, Q) is the notation of the seasonal component of the model. The power s is a notation for calculating the number of periods per season [29].

III. RESEARCH METHOD

The methodology in this study adopts the process in the ARIMA and SARIMA model framework [30]. The central core of the framework consists of five stages: data collection or acquisition, preprocessing, model identification, model parameter estimation, diagnostic checking, prediction, and result evaluation. The research stages can be seen in Figure 1.

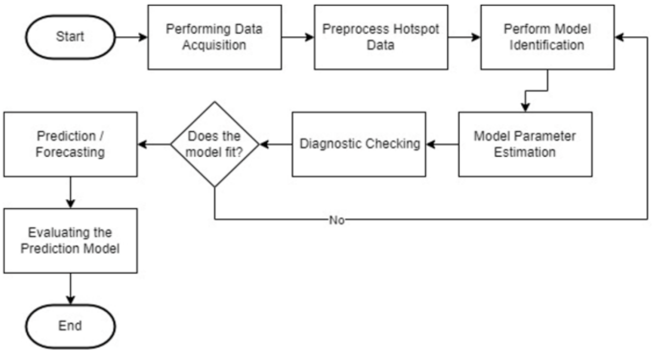

Fig 1. Research stages

A. Data Acquisition

This study uses hotspot data in the West Kalimantan region. The hotspot data is obtained from the early detection information system for forest and land fire control (Sipongi)—the dataset used from 2013 to 2022. Features or variables in the dataset include date, district, sub-district, village, time, satellite, and confidence (hotspot level). The total data obtained was 166,980 records.

B. Preprocessing

After collecting the data, the next step is to preprocess the forest and land fire hotspot data in West Kalimantan. This process aims to prepare raw data that will later be used as data for modeling input so that the resulting model will be of higher quality. Thus, data preprocessing is crucial to identifying and removing irrelevant and redundant features. In addition, the implication of these conditions will reduce the dimensionality of the data and allow the model to operate more quickly and effectively.

C. Model Identification

In this research, model identification is carried out with several steps, namely as follows:

1) They plotted the time series data to see the stationarity of the data, whether it is stationary either in mean or variance. After that, decomposing time series data into several sub-components is carried out to determine the effect of each component on the data series. Generally, two models are used, namely Additive Decomposition and Multiplicative Decomposition.
2) In addition to data plotting, the data stationary test can use the Augmented Dickey-Fuller Test to see whether the statistical test value is lower than the critical value. Also, the time series data is fixed by looking at the p-value, whether the value is smaller than 0.05. If not, then the data is non-stationary. If the time series data is not stationary to the mean or variance, it can be fixed with the Differencing process. Differencing is calculating the change or difference in observation values [31]. The difference value obtained is rechecked whether it is stationary or not. Stationarity means that there is no growth or decline in the data. So, data fluctuations are around a constant average value, independent of time and variance of these fluctuations, or remain stable at all times [32]. The differencing equation [33] is expressed in equation (1).

$$X'_t = X_t - X_{t-1} \tag{1}$$

Where:
X'_t : First differencing
X_t : X value at order t
X_{t-1} : X value at order $t-1$

3) Once the data is stationary, then use the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to identify the model. This step is done by placing seasonally patterned data by specifying the ACF plot and PACF plot to determine the order of the model used.

D. Model Parameter Estimation

At this stage, the parameters of Moving Average (MA), Autoregressive (AR), seasonal, and non-seasonal are estimated, and the significance of each parameter is tested. If there is a model whose parameters are not significant, it is declared not to pass the test. Each insignificant parameter will be eliminated to obtain a model with substantial parameters.

E. Diagnostic Checking

Diagnostic Checking testing in this study determines whether the model used is suitable and feasible for forecasting. The appropriate conjecture model has properties like the original data. This test is carried out by conducting a white noise diagnostic test and a standard distribution test using model diagnostics. The best model is that the residuals obtained are expected to have white noise properties, namely residuals that follow a normal distribution.

F. Prediction

In this research, the prediction stage is carried out with two models, namely ARIMA and SARIMA. The ARIMA model is a time series analysis approach using autocorrelation and time series residual variation. The ARIMA model arrangement consists of Autoregressive (AR), Moving Average (MA), and Integrated (I) models. Integrated shows the value of the differencing order of data from non-stationary to stationary. The general form of the ARIMA model [34] is expressed in equation (2).

$$\Phi_p\,(B)\nabla^d Y_t = \xi + \Theta_q\,(B)\,\varepsilon_t \tag{2}$$

Dimana:

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Φ_p : Autoregressive parameters
B : Backward sliding operator
d : Differencing Parameter
Y_t : Observation value at time t
ξ : Constant parameters
Θ_q : Moving average parameters
ε_t : Residual value (*error*)

Meanwhile, the SARIMA model uses time series data to identify patterns in past historical data and estimate future variables. The SARIMA (p,d,q) $(P,D,Q)^s$ model equation with mean where p,d,q, P, D, and Q are integers and (s) is periodicity. The general form of the ARIMA model is expressed in equation (3).

$$\Phi_p\,(B^s)\Phi_p\,(B)(1-B)^d(1-B^s)^D Y_t = \Theta_q(B)\Theta_q(B^s)\varepsilon_t \quad (3)$$

Where:
$\Phi_p\,(B)$: Non-seasonal autoregressive level
$\Phi_p\,(B^s)$: Seasonal autoregressive rate
$(1-B)^d$: Non-seasonal differencing level
$(1-B^s)^D$: Seasonal differencing level
$\Theta_q(B)$: *Non-seasonal moving average*
$\Theta_q(B^s)$: *Seasonal moving average*
Y_t : Actual data t-th
ε_t : t-period error

One of the reasons for using the ARIMA and SARIMA methods in this research is that these methods have been widely applied and researched in various fields, such as research related to the prediction of North Jakarta Sea wave height using machine learning with the comparison of ARIMA and SARIMA algorithms. The results of the study can be concluded that the ARIMA and SARIMA models made to predict the level of sea level rise have an excellent level of performance in predicting the possibility of sea level rise with a perfect prediction, namely the lower confidence level value of 92.78% [19]. Then, another study was conducted forecasting the number of domestic shipping passenger departures at Tanjung Perak port using the ARIMA and SARIMA methods. The results showed that analysis with the ARIMA method had a smaller accuracy value than analysis using the SARIMA method, which was 16.15% and was the best method for this forecasting [20]. Another study also discussed the comparison of ARIMA and SARIMA for crude oil price forecasting. The evaluation results of this study show the RMSE value of ARIMA and SARIMA is 1.905. Then, the forecasting results for the next seven days with ARIMA are 86.230003 while SARIMA is 86.260002, so ARIMA is better than SARIMA. The results of this study are expected to help policymakers make the right policies and decisions in using crude oil [21].

Then, the advantage of the ARIMA and SARIMA methods compared to other prediction methods or models is that the ARIMA model completely ignores independent variables in forecasting [16]. ARIMA aims to determine an excellent statistical relationship between the predicted variable and the historical value of the variable so that forecasting can be done with the model [17]. Furthermore, the ARIMA model was developed into a Seasonal Autoregressive Integrated Moving Average (SARIMA) model. SARIMA is developing the ARIMA model to analyze recurring or seasonal data patterns when time is fixed, such as quarterly, semi-annually, and annually. This prediction model aims to determine a relationship between predicted variables through data on the historical value of these variables so that predictions can be made [18]. Based on several previous studies and the advantages of these methods, this study uses the ARIMA and SARIMA methods to predict the number of forest and land fire hotspot occurrences in West Kalimantan.

G. *Evaluation of Results*

Evaluate the results of forecasting that has been done. The forecasting results will be a graph predicting the number of future hotspot occurrences in the West Kalimantan region. Use Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) for system testing. This test is carried out to analyze whether the system is running well or still needs updating so that the system can be by the needs. As for MSE can be calculated by equation (4).

$$MSE = \sum_{t=1}^{n} \frac{(A_t - F_t)}{n} \quad (4)$$

Meanwhile, the RMSE can be calculated with equation (5).

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(A_t - F_t)^2}{n}} \quad (5)$$

Where:
A_t : Original data value
F_t : Forecasting data value
n : Amount of data

Mean Squared Error (MSE) is the average squared error between actual and forecasting values. The Mean Squared Error method is generally used to check the estimation of how much the error value is in forecasting. Meanwhile, the Root Mean Squared Error (RMSE) obtains the error rate of the forecasting results. MSE or RMSE, if the results obtained are smaller or closer to zero, the prediction results will be more accurate. If the results obtained are equal to zero, then the prediction results are perfect.

IV. Results and Discussion

This section discusses the results of each stage described in the previous section, starting from the data collection stage, preprocessing, transformation (differencing), model identification, model parameter estimation, diagnostic checking, and prediction and evaluation of results.

This study has several limitations, namely the data variables used in predicting the number of hotspot occurrences, namely patrol dates and the number of hotspot occurrences. Meanwhile, the data source is limited to data obtained from the Early Detection Information System for Forest and Land Fire Control

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(Sipongi). The limitation of the case study area used in West Kalimantan is that this research only compares ARIMA and SARIMA methods, so it is not compared with other algorithms.

A. Data Acquisition

This study uses hotspot data in the West Kalimantan region. The hotspot data is obtained from the early detection information system for forest and land fire control (Sipongi). The dataset used is time series data from 2013 to 2022. Features or variables in the dataset include date, district, sub-district, village, time, satellite, and confidence (hotspot level). The total data obtained was 166,980 records. The details of the hotspot dataset can be seen in Fig 2.

	Kab Kota	Kecamatan	Desa	Tanggal	Waktu	Satelit	Confidence
0	LANDAK	MEMPAWAH HULU	LINGKONONG	18-01-2022	12:24 WIB	NOAA20	High
1	KETAPANG	KENDAWANGAN	AIR HITAM BESAR	18-01-2022	09:39 WIB	TERRA/AQUA	High
2	KETAPANG	KENDAWANGAN	AIR HITAM BESAR	18-01-2022	02:45 WIB	NASA-MODIS	High
3	BENGKAYANG	Sanggau Ledo	Sango	01-02-2022	12:54 WIB	TERRA/AQUA	High
4	BENGKAYANG	Sanggau Ledo	Sango	01-02-2022	12:54 WIB	TERRA/AQUA	High
...	...	...	...	...	...	...	...
166975	KUBU RAYA	BATU AMPAR	UPT SEI KERAWANG	07-11-2013	06:00 WIB	NASA-MODIS	Medium
166976	KOTA SINGKAWANG	ROBAN	CONDONG	19-11-2013	03:25 WIB	NASA-MODIS	Medium
166977	SANGGAU	SANGGAU KAPUAS	TANJUNG KAPUAS	21-11-2013	06:10 WIB	NASA-MODIS	Medium
166978	SINTANG	KETUNGAU HILIR	SETUNGKUP	28-11-2013	03:20 WIB	NASA-MODIS	Medium
166979	MELAWI	BELIMBING	BATU NANTA	28-11-2013	06:15 WIB	NASA-MODIS	Medium

166980 rows × 7 columns

Fig 2. West Kalimantan hotspot dataset 2013-2022

B. Preprocessing

1) Missing Value Handling

After collecting the data, the next step is to preprocess the forest and land fire hotspot occurrence dataset in West Kalimantan. Preprocessing is done by checking and removing missing values. The results of checking missing values can be seen in Fig 3.

Kab Kota	0
Kecamatan	15
Desa	14
Tanggal	0
Waktu	0
Satelit	0
Confidence	0
dtype: int64	

Fig 3. Result of checking missing values dataset

The check results obtained missing values in the sub-district variable as much as 15 data and in the village variable as much as 14. Therefore, the missing values can be handled by deleting the data rows containing missing values, and the results can be seen in Fig 4.

Kab Kota	0
Kecamatan	0
Desa	0
Tanggal	0
Waktu	0
Satelit	0
Confidence	0
dtype: int64	

Fig 4. Results of handling missing values dataset

Missing values handling is done by deleting data in empty rows or columns (null) so that the amount of data decreases after handling missing values to 166,965 records. As for seeing the details of the data frame data after holding missing values, it can be seen in Fig 5.

	Kab Kota	Kecamatan	Desa	Tanggal	Waktu	Satelit	Confidence
0	LANDAK	MEMPAWAH HULU	LINGKONONG	18-01-2022	12:24 WIB	NOAA20	High
1	KETAPANG	KENDAWANGAN	AIR HITAM BESAR	18-01-2022	09:39 WIB	TERRA/AQUA	High
2	KETAPANG	KENDAWANGAN	AIR HITAM BESAR	18-01-2022	02:45 WIB	NASA-MODIS	High
3	BENGKAYANG	Sanggau Ledo	Sango	01-02-2022	12:54 WIB	TERRA/AQUA	High
4	BENGKAYANG	Sanggau Ledo	Sango	01-02-2022	12:54 WIB	TERRA/AQUA	High
...	...	...	...	...	...	...	...
166975	KUBU RAYA	BATU AMPAR	UPT SEI KERAWANG	07-11-2013	06:00 WIB	NASA-MODIS	Medium
166976	KOTA SINGKAWANG	ROBAN	CONDONG	19-11-2013	03:25 WIB	NASA-MODIS	Medium
166977	SANGGAU	SANGGAU KAPUAS	TANJUNG KAPUAS	21-11-2013	06:10 WIB	NASA-MODIS	Medium
166978	SINTANG	KETUNGAU HILIR	SETUNGKUP	28-11-2013	03:20 WIB	NASA-MODIS	Medium
166979	MELAWI	BELIMBING	BATU NANTA	28-11-2013	06:15 WIB	NASA-MODIS	Medium

166965 rows × 7 columns

Fig 5. Dataset of missing value handling results

2) Data Integration

Furthermore, data integration is carried out by checking and changing the data type, sorting data based on district variables, date, and confidence (hotspot level), grouping the number of hotspot events, and grouping hotspot data based on date, month, and year. Based on this process, 120 records were generated with two variables, namely date (index variable) and count (hotspot count variable). The results of data integration can be seen in Fig 6.

date	count
2013-01-01	16
2013-02-01	9
2013-03-01	17
2013-04-01	14
2013-05-01	9
...	...
2022-08-01	26
2022-09-01	22
2022-10-01	25
2022-11-01	18
2022-12-01	7

120 rows × 1 columns

Fig 6. Datasets resulting from the data integration stage

C. Model Identification

Several processes will be carried out in the model identification stage, such as making time series plots,

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performing the Augmented Dickey-Fuller Test stationary test, and making ACF and PACF plots. This identification aims to get the best model that matches the available data, namely West Kalimantan Forest and land fire hotspot data.

1) Create a time series plot.

Make a time series plot to see the data's stationarity in mean or variance. Then, the data is used to decompose the components in the time series data. The results of the time series plot can be seen in Fig 7.

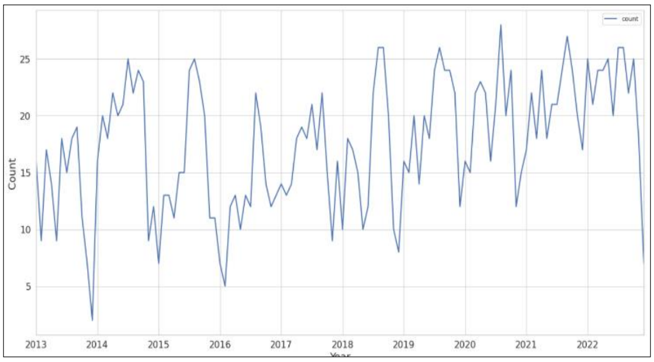

Fig 7. Time series plot of the hotspot dataset

The resulting time series plot results show that the mean and variance of hotspots are not constant throughout 2013-2022, so the hotspot data is not stationary in mean and variance.

After seeing the trend of the data from the time series plot, decompose the data, which aims to decompose the time series data into several components or identify seasonality and trends from a series of data. The results of the hotspot dataset decomposition can be seen in Figs. 8 and 9.

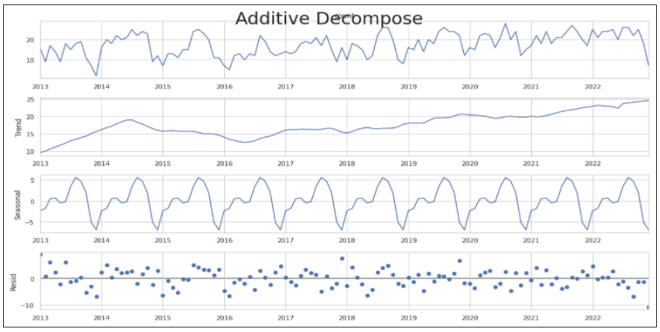

Fig 8. Additive decomposition plot of data hotspots

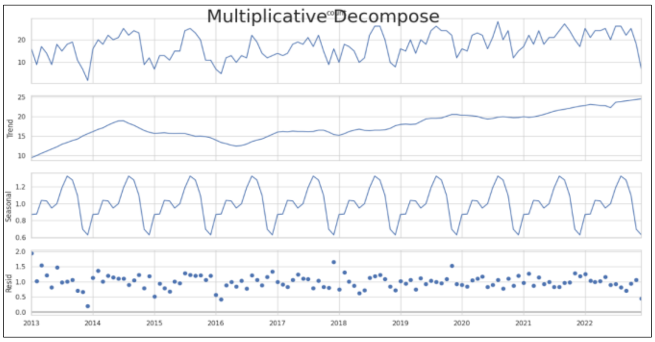

Fig 9. Multiplicative decompose plot of hotspot data

The results of additive decomposition and multiplicative decomposition explain the trend component related to the fluctuation of the data; the seasonal part shows the recurring pattern of variation that occurs in the hotspot data, and the residual component shows the remaining noise from the hotspot data. The three members explain the fluctuations of non-stationary time series data.

2) *Augmented Dickey-Fuller Test*

They are using the Augmented Dickey-Fuller Test to see the value of the test statistic, whether it is lower than the critical value or not. Also, by looking at the p-value, whether the value is smaller than 0.05 so that the time series data can be said to be stationary; otherwise, the data is non-stationary. Based on the time series plot and decomposed data, it is concluded that the data is non-stationary. This is evidenced by the ADF test value, namely the p-value, with a value of 0.4567. The results' data plot and ADF value before differencing can be seen in Figs. 10 and 11.

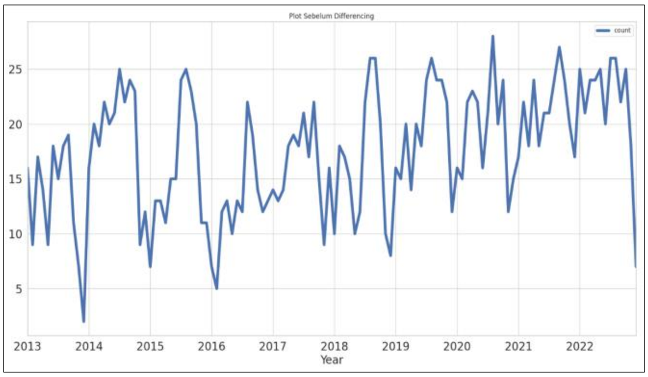

Fig 10. Plot of data before differencing

```
ADF Statistic: -1.6504677023303629
p-value: 0.4567965155120682
Critical Values:
        1%: -3.494
        5%: -2.889
        10%: -2.582
```

Fig 11. ADF test results before differencing

The next stage of differencing is calculating the change or difference in observation values. In this study, differencing was done twice to make the data stationary. The plot of differencing results can be seen in Fig 12 and Fig 13.

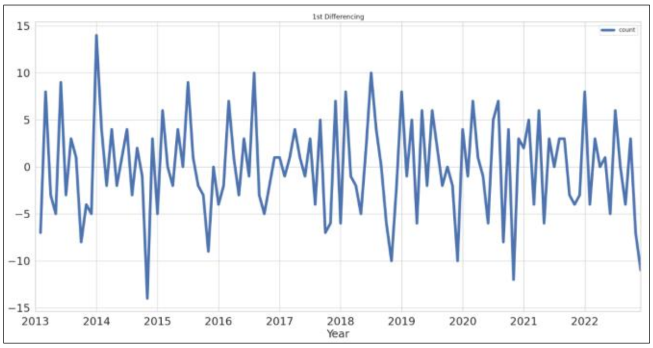

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Fig 12. Data plot after first differencing

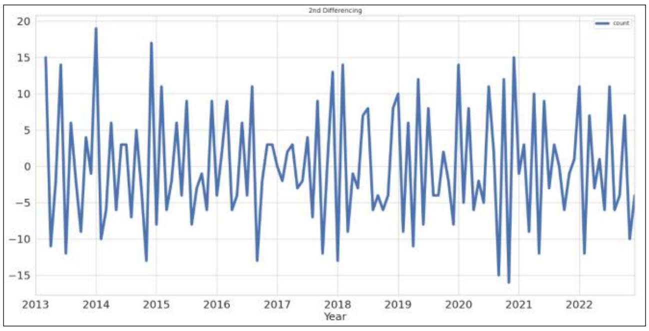

Fig 13. Data plot after second differencing

The ADF test value after differencing is the p-value with a value of 0.046. Based on these results, it can be concluded that the hotspot data shows stationary data.

```
ADF Statistic: -2.8874711818630154
p-value: 0.04682444713606669
Critical Values:
        1%: -3.501
        5%: -2.892
        10%: -2.583
```

Fig 14. ADF test results after differencing

3) *Autocorrelation Function* (ACF) *and Partial Autocorrelation Function* (PACF)

ACF and PACF plots after the data is stationary, and the next step is to identify seasonally patterned data by specifying the ACF plot and PACF plot to determine the order of the model used.

a) *Autocorrelation Function* (ACF)

The ACF plot is used to identify the order of the Moving Average (MA) model. This study aims to see the stationarity of the data in the mean. In Fig 15, it can be seen that lags 1, 2, 3, 11, 12, and 13 pass through the confidence interval. These results explain that there is still autocorrelation, and the data is not stationary in the mean. In Fig 16, it can be seen that the lags are already relatively in the confidence interval, so the data is more stationary compared to the previous ACF plot.

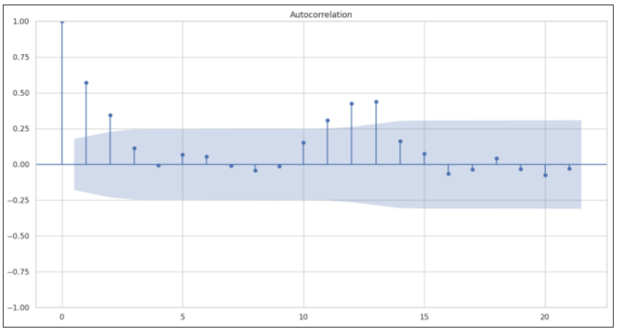

Fig 15. ACF plot results before differencing

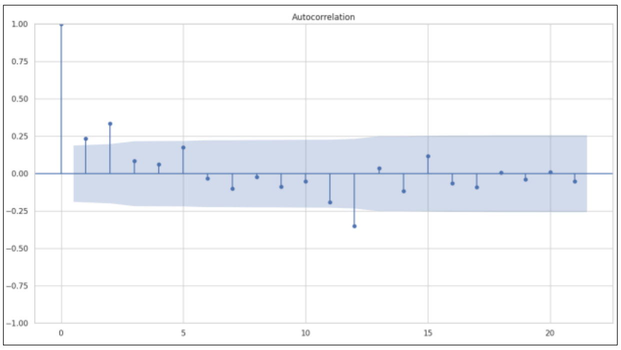

Fig 16. ACF plot results after differencing

b) *Partial Autocorrelation Function* (PACF)

The PACF plot is used to identify the Autoregressive (AR) model. In Fig 17, it can be seen that lags 1, 2, and 14 cross the confidence interval. These results explain that there is still autocorrelation, and the data is not stationary in the mean. In Fig. 18, it can be seen that the lags are already relatively in the confidence interval, so the data is more stationary compared to the previous PACF plot.

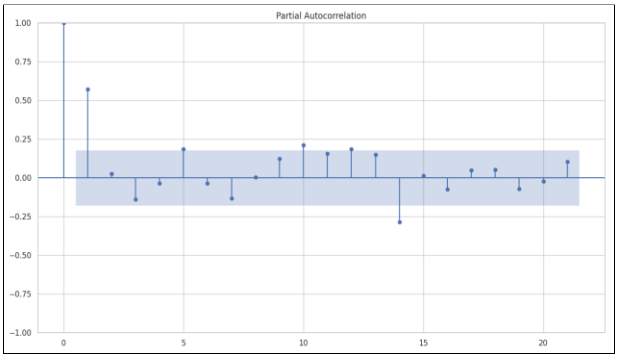

Fig 17. PACF plot results before differencing

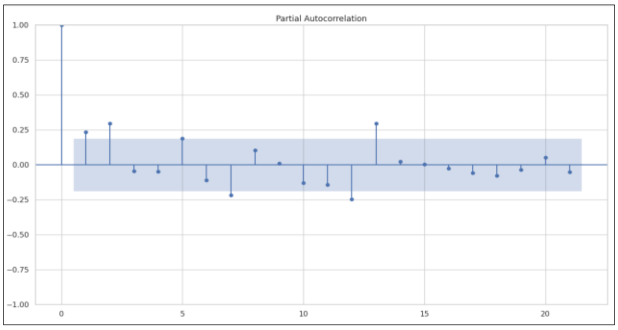

Fig 18. PACF plot results after differencing

D. *Estimasi Parameter Model*

At this stage, MA, AR, seasonal, and non-seasonal parameters are estimated, and the significance of each parameter is tested. If there is a model whose parameters are not significant, it is declared not to pass the test. For determining model parameters for either ARIMA or SARIMA, the information criteria commonly used in selecting ARIMA models are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Parameter estimates for ARIMA and SARIMA are as follows.

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The ARIMA model significance test results can be seen in Fig. 19 shows that there is only one significant ARIMA model, namely the ARIMA (0, 1, 1) model.

```
                              ARIMA Model Results
==============================================================================
Dep. Variable:                D.count   No. Observations:                  107
Model:                 ARIMA(0, 1, 1)   Log Likelihood                -331.657
Method:                       css-mle   S.D. of innovations              5.351
Date:                Wed, 14 Dec 2022   AIC                            669.314
Time:                        20:43:47   BIC                            677.333
Sample:                    02-01-2014   HQIC                           672.565
                         - 12-01-2022
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const            -0.0757      0.147     -0.514      0.607      -0.364       0.213
ma.L1.D.count    -0.7230      0.087     -8.271      0.000      -0.894      -0.552
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
MA.1            1.3831           +0.0000j            1.3831            0.0000
-----------------------------------------------------------------------------
```

Fig 19. Parameter Estimation of ARIMA Model

The significance test results in Figure 20 show only one significant SARIMA model, namely the SARIMA (0, 1, 1) (2, 2, 1, 12) model. Based on these results, it can be concluded that the best possible model of the ARIMA method is the ARIMA (0, 1, 1) model, while the best model of the SARIMA method is the SARIMA (0, 1, 1) model (2, 2, 1, 12).

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                              count   No. Observations:                  108
Model:             SARIMAX(0, 1, 1)x(2, 2, 1, 12)   Log Likelihood                -298.772
Date:                            Wed, 14 Dec 2022   AIC                            607.545
Time:                                    20:44:38   BIC                            619.639
Sample:                                01-01-2014   HQIC                           612.403
                                     - 12-01-2022
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.7196      0.084     -8.531      0.000      -0.885      -0.554
ar.S.L12      -0.8288      0.129     -6.441      0.000      -1.081      -0.577
ar.S.L24      -0.5223      0.126     -4.130      0.000      -0.770      -0.274
ma.S.L12      -0.9996    230.208     -0.004      0.997    -452.199     450.200
sigma2        40.2835   9268.999      0.004      0.997   -1.81e+04    1.82e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.46   Jarque-Bera (JB):                 0.33
Prob(Q):                              0.50   Prob(JB):                         0.85
Heteroskedasticity (H):               0.84   Skew:                             0.06
Prob(H) (two-sided):                  0.64   Kurtosis:                         2.71
===================================================================================
```

Fig 20. Parameter Estimation of SARIMA Model

E. *Diagnostic Checking*

After the ARIMA and SARIMA models have their parameters estimated, the next stage is diagnostic checking to determine whether the model is suitable and feasible for forecasting.

Fig 21 is the result of diagnostic checking on the ARIMA model by looking at the residuals and density plots. A good ARIMA model is when there is no accumulation of residual plots. A good ARIMA model is also when the density graph is bell-shaped around the value of 0 on the X-axis.

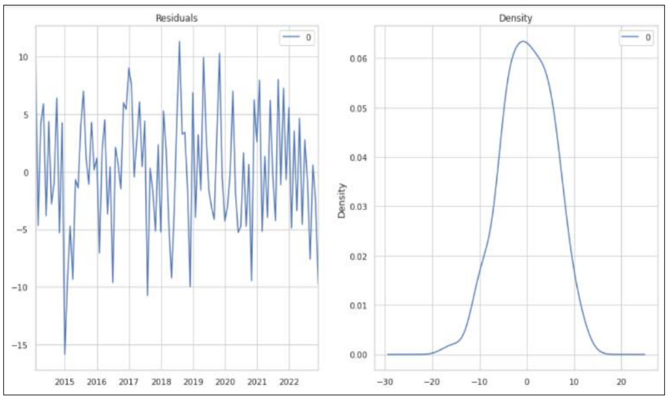

Fig 21. Diagnostic check results of the ARIMA model

Diagnostic checking is also carried out on the SARIMA model. In Fig 22, the SARIMA model is checked by looking at four graphs. The standardized residual plot in this study explains the fluctuation of hotspot data around the average value of 0 (zero). The second plot is the histogram density, which shows the normal distribution of the hotspot data. Then, the correlation plot shows a normal linear distribution that follows a linear line. The last plot is the ACF plot, which shows that no lag passes through the confidence interval, so the data is stationary in the mean.

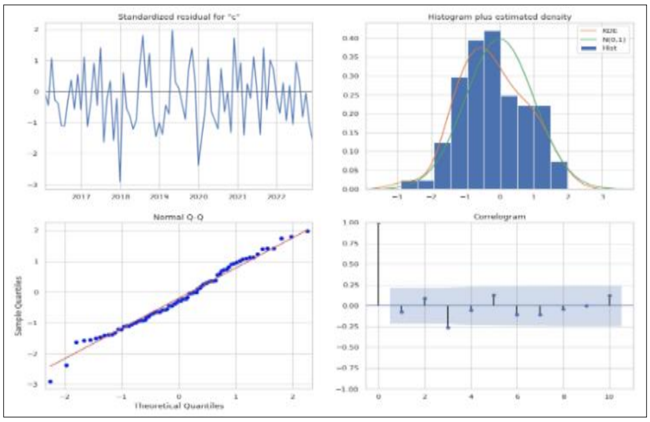

Fig 22. SARIMA model diagnostic checking results

F. *Prediction*

After diagnostic checking, the next step is to perform forecasting on each model obtained by comparing the predicted value with the real (actual) value of the time series data, which can help the accuracy of the forecast.

Predictions are made using test data on the ARIMA model and SARIMA model. Predictions are made to determine the alignment between actual data and predicted data. Figures 23 (ARIMA model prediction) and 24 (SARIMA model prediction) show that the expected data fluctuations are similar to the actual data fluctuations. Although there are several various hotspot occurrences, they are not too significant. So, the ARIMA (0, 1, 1) and SARIMA (0, 1, 1) (2, 2, 1, 12) models can be maximally used for predicting hotspot occurrence.

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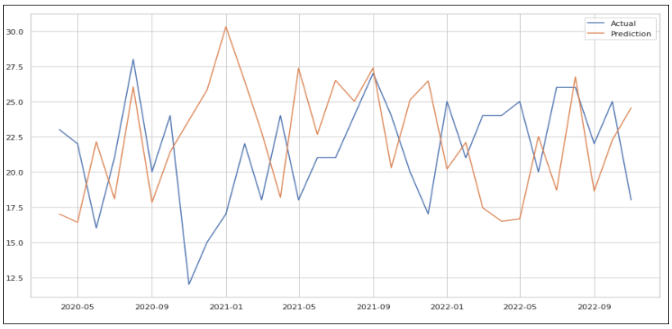

Fig 23. Prediction results of ARIMA model test data

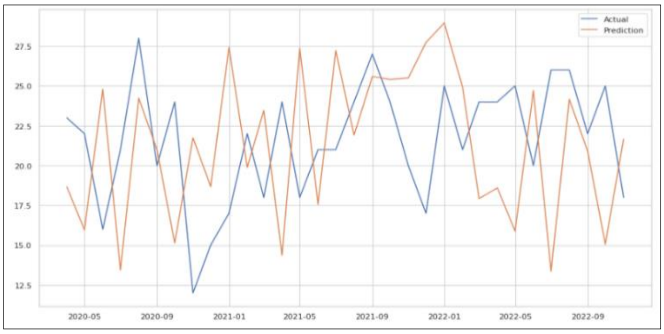

Fig 24. SARIMA model test data prediction results

Furthermore, forecasting is carried out using training data on the ARIMA and SARIMA models. Forecasting in this study was carried out to see the trend of forecasting data results for the next year, namely from 2022 to 2023, based on training data. Fig 25 (ARIMA model forecasting) and Fig 26 (SARIMA model prediction) show a downward trend at the beginning, then a decrease in the middle, and a decrease again at the end of 2023. Based on these results, it is concluded that the highest occurrence of hotspots is in the middle of 2023, so forest and land fires can be prevented.

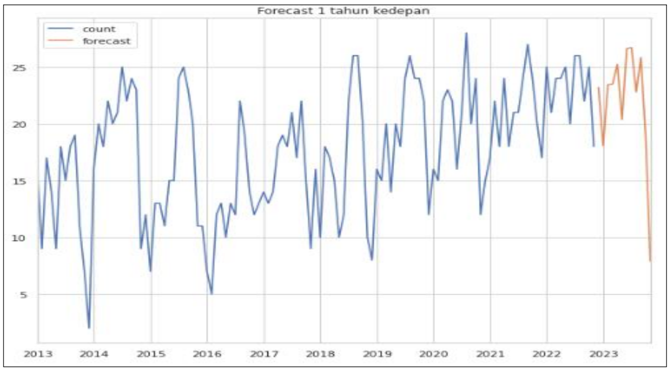

Fig 25. ARIMA model training data forecasting results

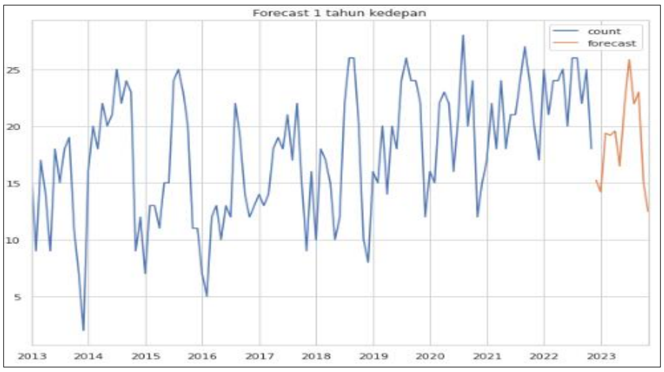

Fig 26. SARIMA model training data forecasting results

The graphs in Fig 25 and Fig 26 are visualizations of forecasting for the next year, namely 2023. In this research, forecasting is carried out monthly because the data is daily but must be combined into months.

Furthermore, Fig 27 shows the value of the ARIMA model forecasting results. The value of the ARIMA model forecasting results is seen from 2020 to 2021. The lowest occurrence of hotspots was seen in the five months of 2020, then experienced the highest increase in month 1 of 2021 and dropped again in month 11 of 2021. Meanwhile, Fig 28 is the value of the SARIMA model forecasting results. The value of the ARIMA model forecasting results is seen from 2020 to 2021. The lowest occurrence of hotspots was seen in month 1 of 2020, then experienced the highest increase in month 1 of 2021 and dropped again in month 10 of 2021. Based on the value of the forecasting results, it can be used as a reference in preventing forest and land fires in that period.

	count	forecast
2020-04-01	23	17.000757
2020-05-01	22	16.412864
2020-06-01	16	22.134622
2020-07-01	21	18.079548
2020-08-01	28	26.045396
2020-09-01	20	17.823599
2020-10-01	24	21.412890
2020-11-01	12	23.667441
2020-12-01	15	25.823651
2021-01-01	17	30.311805
2021-02-01	22	26.445696
2021-03-01	18	22.811792
2021-04-01	24	18.179287
2021-05-01	18	27.356418
2021-06-01	21	22.656980
2021-07-01	21	26.500770
2021-08-01	24	25.012616
2021-09-01	27	27.378738
2021-10-01	24	20.278973

Fig 27. ARIMA model forecasting result value

	count	forecast
2020-04-01	23	11.224278
2020-05-01	22	12.649075
2020-06-01	16	24.123492
2020-07-01	21	21.132012
2020-08-01	28	22.099795
2020-09-01	20	21.243398
2020-10-01	24	17.681049
2020-11-01	12	22.919632
2020-12-01	15	24.952515
2021-01-01	17	28.964407
2021-02-01	22	23.445756
2021-03-01	18	25.296625
2021-04-01	24	13.304674
2021-05-01	18	28.544873
2021-06-01	21	21.860115
2021-07-01	21	28.614593
2021-08-01	24	27.050798
2021-09-01	27	23.804722
2021-10-01	24	17.583791
2021-11-01	20	23.087273

Fig 28. SARIMA model forecasting result value

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G. Prediction Model Evaluation

The last stage after prediction is to evaluate the results of forecasting that has been done. Model testing is carried out using the calculation of Root Mean Square Error (RMSE) and Mean Squared Error (MSE). Root Mean Square Error (RMSE) is a method used to measure the error of the results of a prediction. A small RMSE value indicates a prediction result close to the actual value (the smaller the RMSE value, the higher the prediction accuracy) [35]. Meanwhile, Mean Square Error (MSE) is a parameter in forecasting that tests the accuracy of the forecasting results that have been carried out. The smaller the MSE value, the more accurate the forecasting results are [36]. In this study, the ARIMA model obtained an MSE value of 43.70 and an RMSE of 6.61.

Meanwhile, the SARIMA model obtained an MSE value of 58.05 and an RMSE of 7.61. Based on the results of this comparison, it can be concluded that the ARIMA (0, 1, 1) model is best for predicting the occurrence of hotspots of forest and land fires in the West Kalimantan region. The details of the model evaluation results can be seen in Table 1.

Table 1. Evaluation of ARIMA and SARIMA prediction models

Metode	ARIMA	SARIMA
MAP	43,70	58,05
RMSE	6,61	7,61

V. CONCLUSIONS

Based on the modeling that has been done to predict the number of forest and land fire hotspot occurrences in the West Kalimantan region, the best models are ARIMA (0,1,1) and SARIMA (0,1,1) (2,2,1)12 models. The ARIMA's Root Mean Square Error (RMSE) evaluation result is 6.61, while SARIMA is 7.61. Meanwhile, ARIMA's Mean Squared Error (MSE) evaluation value is 43.70, and SARIMA is 58.05. Therefore, the ARIMA model performs well in predicting the occurrence of hotspots with a smaller RMSE value than SARIMA. Then, the highest average event of hotspots in the West Kalimantan region occurs in the mid-year period so that it can be used as a reference in preventing forest fires that are more effective and efficient in that period.

The suggestions for further research development are expected to add weather and temperature factors in predicting the number of hotspot occurrences in the future. In addition, further research can also be compared with other time series algorithms to increase the accuracy of the model. Then, in the future, the prediction model for the number of hotspot occurrences can be applied to the Early Detection Information System for Forest and Land Fire Control (Sipongi) so that it will help control forest and land fires effectively.

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