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HOTSPOT PREDICTIVE MODELING USING REGRESSION DECISION TREE ALGORITHM

Dewi Asiah Shofiana[1)], Yohana Tri Utami[2)], Yunda Heningtyas[3)]

[1,2,3]Departement of Computer Science, Faculty of Mathematics and Natural Sciences, University of Lampung
[1,2,3]Jl. Prof. Dr. Sumantri Brojonegoro No.1, Gedong Meneng, Rajabasa, Bandar Lampung, Lampung, Indonesia 35141
Email: [1]dewi.asiah@fmipa.unila.ac.id, [2]yohana.utami@fmipa.unila.ac.id, [3]yunda.heningtyas@fmipa.unila.ac.id

Abstract

Forest fires had always become an international issue influencing many life sectors, including environmental, social, and economic. The forest fire in 2013 was regarded as one of the worst forest fire tragedies in history, not only in Indonesia but also in the world. Detection of hotspots on the earth's surface by the satellite can be an indication of land and forest fire occurrence. This research aims to build a predictive model of monthly hotspots in Rokan Hilir Regency using the regression tree algorithm. Several variables related to weather information are included, such as rainfall, sea surface temperature, and southern oscillation index. This research used 245 training data and 43 testing data, resulting a predictive model with a correlation of 0.875 and an error rate of 0.166. Based on the values, we can conclude that the performance of the model is considerably good.

Keyword: *forest fire, hotspot, regression tree.*

1. INTRODUCING

Forest fire is a long-term problem in Indonesia that frequently become an international spotlight since it usually causes threats to various life sector, especially the environment, society, and economy. One indication of forest fires is the emergence of hotspots, in which the data is acquired daily by the satellite. Commonly, forest fire occurs due to two factors, namely human factors (land cover and land-use change, cultivation activities, and so on) or natural factors (weather and climate) [1]. Weather and climatic conditions such as rainfall, temperature, humidity, and wind speed affect the level of dryness of the earth's surface which can cause forest fires [2]. Moreover, most of the climate in Indonesia is related to the El Nino southern oscillation (ENSO) phenomenon, which climate variables especially rainfall is closely related to. El Nino and La Nina phenomenon will affect how much it rains on land. Depending on which cycle occurs, it can either cause droughts or flooding. Typically, El Nino is associated with drought, while La Nina is linked to increased flooding [3].

Riau Province is one region in Indonesia where forest fire frequently occurs since peatlands are still covering most of the areas. The phenomenal 2013 forest fire is considered one of the worst in Riau history, where the highest record is still held by the fire event in Riau between 1990-1997 [4]. According to the data released by Pekanbaru Meteorology Climatology and Geophysics Agency (BMKG) in August 2016, Rokan Hilir is the most fire-prone region, holding the highest distribution of hotspots with 46 hotspots data. On July 23, 2017, BMKG recapitulated the hotspot data in Riau Province, showing there were five hotspots detected in Rokan Hilir Regency with a confidence level of 50%. The higher the confidence level of hotspots, the stronger it indicates real fire existence [5].

[6] conducted a study regarding the prediction of hotspots emergence in Riau Province using the autoregressive integrated moving average (ARIMA) algorithm. The study shows that the monthly hotspot data obtained were not stationary in terms of variance and had a high value of mean absolute percentage error (MAPE) which is 40,974 due to the very high actual data in June, July, and August, resulting in a high margin of error. In 2015 [7] processed the same data but with the seasonal autoregressive integrated moving average (SARIMA) algorithm. The model from this study performs the best in predicting hotspots one month in the future, but it is required to be supported by the data of hotspot occurrences at least 13 months before. Furthermore, the inability of knowing the location of hotspots predicted is one shortcoming of the SARIMA algorithm. [8] used the Elman recurrent neural network (ERNN) as a method of making temporal predictions for the emergence of hotspots in Riau province. The model from this research has a MAPE value of 67.54% and a root mean square error (RMSE) of 252.98. But this ERNN model can only predict the possibility of hotspot emergence, without involving other variables that might highly affect the observed month of the study, such as rainfall.

Based on previous studies, this research builds a predictive model of monthly hotspots in the last 15 years using

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climate data in Rokan Hilir Regency, Riau Province. Independent variables used are related to dry season rainfall, such as climate research unit (CRU) rainfall data, sea surface temperature (SST) NINO3.4, and southern oscillation index (SOI). The negative SOI value is closely related to the El Nino event which influences the prolonged dry season and drought in Indonesia. The more precise the predictor selected in the research, the better the resulting model [9]. Regression decision tree algorithm is implemented to process the data as we are expecting to predict continuous values of output (hotspots) based on independent variables. Besides, we are also working with a small amount of data which is suitable for this method.

2. RESEARCH METHODS

2.1 Data

Rokan Hilir Regency is selected as the area of interest of this research based on BMKG data that shows it as the most fire-prone area in Riau. This research utilizes hotspot data and climate data from 2001 to 2015 within Rokan Hilir area, which is specifically located at coordinates 11° 4' to 24° 5' North Latitude and 100° 17' to 101° 21' East Longitude. The hotspot datasets are collected from NASA Firms website (https://firms.modaps.eosdis.nasa.gov), the rainfall data are provided by the climatic research unit (https://crudata.uea.ac.uk), the global data of SOI are acquired from the Bureau of Meteorology (http://www.bom.gov.au/climate/enso/soi/), and SST Nino 3.4 data from the climate prediction center (https://www.cpc.ncep.noaa.gov). To build the model, this study applies the 'caret' and 'rpart' package available in RStudio.

2.2 Research Steps

This research was carried out in several stages: data acquisition, data preprocessing, data splitting with K-fold cross-validation, predictive modeling using regression tree, evaluation and model analysis.

2.2.1 Data Preprocessing

This step includes four main processes: data selection, forming the frequency matrix, creating a time series dataset, and data normalization.

a. Data Selection
   Not all variables from the hotspot dataset are interesting for the research. The variables selected for further analysis are longitude, latitude, month of hotspots ocurrences, and confidence.
b. Forming the Frequency Matrix
   In determining the longitude and latitude range of Rokan Hilir area we refer to the rainfall dataset. The range is obtained from 9 grids on rainfall data that do not contain NA values (areas with no values detected by the satellite, commonly interpreted as the ocean area) [10]. Each latitude and longitude range is adjusted with hotspot data to calculate the monthly hotspot occurrence frequency. Selected Rokan Hilir areas for further analysis is the area within the research range with the highest total frequency of monthly hotspots emergences from 2001 to 2015 with a confidence level greater than 50%.
c. Create Time Series Dataset
   Based on each month information for 15 years in the selected Rokan Hilir area, the selected data is adjusted with the other three variables data: SOI data, CRU rainfall, and SST Nino 3.4 data. We create a new time series dataset for the modeling and testing process. The dataset has independent variables (SOI, CRU, and SST) as well as response variables (the number of hotspots per month).
d. Data Normalization
   Prior to the modeling process, we normalize the data specifically the data of the independent variables. This step creates the values of numeric columns in the dataset to use a common scale, without distorting differences in the ranges of values or losing information. Normalization of data is essential to avoid the dominance of values in data. Min-max normalization was carried out in this study, transforming the data values within the range of 0 to 1. According to [11], min-max normalization can be calculated using Equation 1.

$$\text{Norm}(x) = \frac{x\text{-min}(x)}{\max(x)\text{-min}(x)} \quad (1)$$

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With x is the data to be normalized, min(x) is the minimum data of the dataset, and max(x) refers to the maximum data.

2.2.2 Data Splitting

Data is split into two categories: training data and test data, using the k-fold cross-validation with k = 8. Cross-validation is a method to evaluate and compare algorithm performance by dividing the data into two parts, known as the part to train the model and the part to test the model. The k-fold cross-validation method begins by dividing the data into k data sets whose numbers are almost equal. The testing data for each iteration is the k-th dataset while the training data are the other datasets [12]. The percentage distribution with 8-fold cross-validation is 85% for training data and 15% for testing data from a total of 288 data. By this percentage, we can calculate that there are approximately 245 training data and 43 testing data utilized for modeling in each iteration. The data splitting process is conducted in R using the caret package.

2.2.3 Predictive Modeling with Regression Tree Algorithm

Predictive modeling of the monthly hotspots with regression tree algorithm is conducted in R using the rpart package. This process involves approximately 245 training data, where the resulted model is then tested using 43 testing data. The performance of the model is measured by the correlation value and error value. A higher correlation value and lower error value indicate a better model. The predicted results of the tested data are presented in a comparison graph between the number of occurrences of the actual monthly hotspots and the number of occurrences of the predicted monthly hotspots.

2.2.4 Evaluation and Model Analysis

The quality of model is measured by the value of the correlation coefficient (R) and the normalized root mean square error (NRMSE). Correlation coefficient shows the proximity of the relationship between actual and predicted response variables. The correlation value generally ranges from 1 to -1. Value closer to 1 or -1 indicate a stronger relationship between two variables. Conversely, value close to 0 shows that the relationship between the two variables is weak. Correlation can be calculated using Equation 2 [13].

$$R=\frac{n\sum_{i=1}^{n}x_iy_i-\sum_{i=1}^{n}x_i\sum_{i=1}^{n}y_i}{\sqrt{\left[n\sum_{i=1}^{n}x_i^2-\left[\sum_{i=1}^{n}x_i\right]^2\right]\left[n\sum_{i=1}^{n}y_i^2-\left[\sum_{i=1}^{n}y_i\right]^2\right]}} \quad (2)$$

With x_i shows actual monthly hotspots, shows y_i predicted monthly hotspots, and n shows the number of data row.
The error value is also calculated to measure the error rate in the predictive model built. Normalized root mean square error (NRMSE) is an alternative method to evaluate the accuracy of a predictive modeling process. NRMSE is the average value of the number of squares of errors, it can also state the size of the error generated by a predictive model. A low NRMSE value indicates that the variation in the value produced by a predictive model is close to the variation in the observed value. According to [14] NRMSE can be calculated using Equation 3.

$$NRMSE=\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_i-y_i)^2}}{\sigma_y} \quad (3)$$

With x_i shows actual monthly hotspots, shows y_i predicted monthly hotspots, n shows the number of data row, and σ_y shows the standard deviation of the number of predicted hotspot occurrences. [15] stated that if the R value is close to 1 and the NRMSE value is close to 0, the model can be concluded as a good model.

3. RESULT AND DISCUSSIONS

3.1 Data Preprocessing

3.1.1. Forming the Frequency Matrix

The number of hotspots in Rokan Hilir before filtering it based on the confidence level are 48915 data. After filtering the data with confidence level greater and equal to 50%, the remaining number of hotspots reduced to 37295. Hotspot frequency matrix comes from the calculation of hotspots occurrences per month in an area. The area of interest is selected based on the number of hotspots. As a result, areas within the coordinates of 1.00 to

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2.50 North Latitude and 100.00 to 101.50 East Longitude shows the highest frequency of hotspots occurrences in the 2000-2015 period, with a total of 25510 hotspots.

3.1.2. Create Time Series Dataset and Data Normalization

Dataset generated from this step has 34 variables: CRU1 to CRU27, SOI1 to SOI3, SST1 to SST3, and hotspots. There are 288 rows of data, in which each referring to hotspots data per month from January 2001 to December 2015. The variables SOI1 to SOI3 indicate SOI values taken from the Bureau of Meteorology site three months earlier. For example, the SOI1-SOI3 value in the January 2001 dataset is the SOI value from October to December 2000. This rule also applies to the CRU and SST data. Variables CRU1 to CRU27 indicate rainfall in the previous three months on the 9 grid areas selected in the CRU rainfall data. Variables SST1 to SST3 indicate SST values from the CPC site three months earlier. The hotspot variable is the response variable which implies the number of hotspots appearing per month. Variables SOI1 to SST3 are independent variables or predictor variables. The independent variables in the resulting dataset are then normalized. Calculation of data normalization uses min-max normalization as given in Equation 1.

3.2 Data Splitting

Data splitting in this study applies the 8-fold cross-validation, resulting training data and testing data with a ratio of 85:15 from 288 data. The training data consists of approximately 245 rows of data and approximately 43 testing data for each fold. The data splitting process implements the caret package available in R. The proportion of distribution of training data and testing data with 8-fold cross-validation is presented in Table 1.

Table 1. Distribution Proportion of Training Data and Testing Data for Each Fold

Fold	Numbers of data (rows)	
	Training data	Testing data
1	245	43
2	247	41
3	246	42
4	245	43
5	244	44
6	246	42
7	247	41
8	245	43

3.3. Predictive Modeling with Regression Tree Algorithm

After normalizing the data on the independent variables, we build predictive models using the regression tree algorithm. Training data for each fold in Table 1 is used in developing the model, and normalization was also carried out on the actual response variable (Y) and the prediction results of the model. The model obtained was tested using testing data for each data fold as provided in Table 1. Figure 1 and Figure 2 show the best and worst graphs based on the testing results on all data folds.

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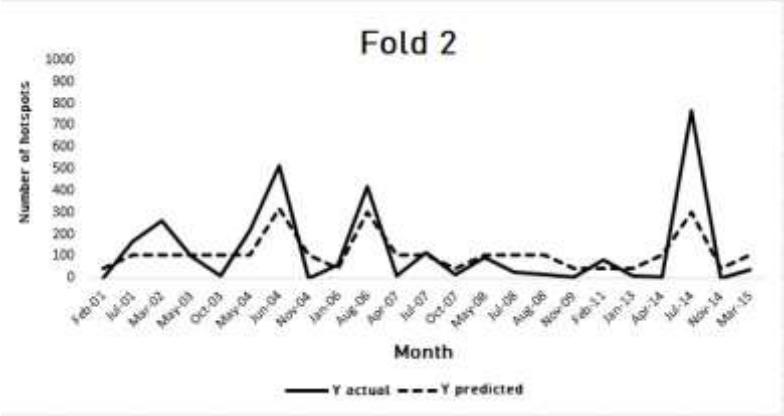

Figure 1. Best graph based on the testing results.

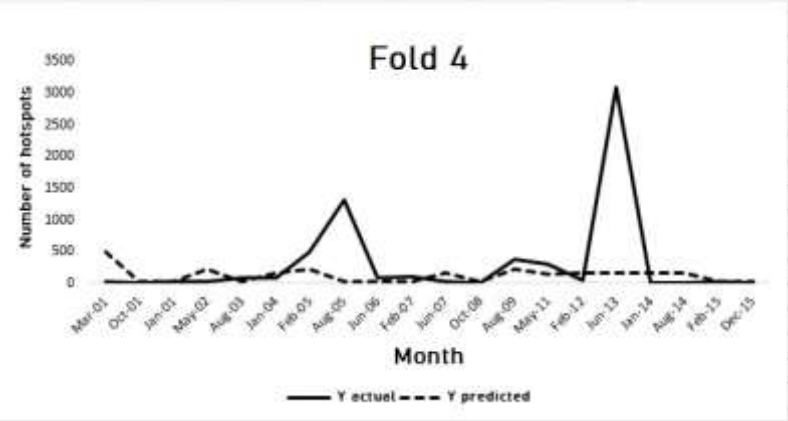

Figure 2. Worst graph based on the testing results.

The graph in Figure 1 is categorized as good since the two lines that represent the value of each actual variable and the predicted variable formed is not so different or aligned, while Figure 2 shows a contrary graph. In Figure 2 (4th fold) exist a very high value in the actual data while the predicted value is low, resulting the graphs of actual and predicted variables very different. As in Figure 1, the actual high value is the number of monthly hotspots detected high, which occurred in July 2014 with a total of 765 hotspots. The predicted value in the same month is 301 hotspots, making the comparison of the actual and predicted value quite far, but still considered as good since it does not prevail the alignment of the resulted graph. Figure 2 shows a comparison between the prediction and actual value in the 4th fold. A very high value in the actual variable occurred in July 2013 where 3097 hotspots are detected, while the predicted value at only 162 hotspots, causing extreme difference between both variables. Another extreme condition occurred in August 2005 with the actual value reaching 1313, but the predicted value was only 35. These events made the comparison graph out of alignment and considered as the worst graph compared to all folds. The incapability or error of the model in predicting can cause quite significant difference between the actual and the predicted. Prediction errors can occur due to several things, one of which is the possibility of including wet months (months with high rainfall) in the independent variables as predictors. A higher rainfall value can prevail the predicted value of the number of monthly hotspots do not match the actual value. The inability of the model in learning the pattern can also be a factor of prediction errors [16].

3.4. Evaluation and Model Analysis

Tested models are evaluated by calculating the correlation value and error value. We calculate the correlation is to see how strong the relationship between the response variable (Y) actual and predicted. Predictions of the number of monthly hotspots using a regression tree produces various correlation coefficients and NRMSE error values. Correlation and error values for each fold are presented in Table 2.

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Table 2. Correlation and NRMSE value of each fold

Fold	Correlation	NRMSE
1	0.101	0.462
2	0.875	0.166
3	0.527	0.302
4	0.036	0.348
5	0.681	0.290
6	0.776	0.217
7	0.247	0.317
8	0.319	0.299
Average	0.445	0.301

A favored predictive model comes from the fold with a high value of correlation and a small value of NRMSE error. Table 1 shows that the 2nd fold has the best correlation and NRMSE results compared to others. The 2nd fold has a correlation value of 0.875 which is the highest correlation value of all, while the 4th fold has the smallest correlation value at only 0.036. The correlation value of the 2nd fold has a good predictive result of the number of monthly hotspots, as shown in Figure 1. On the other hand, the unreliable predictive model of the 4th fold can be seen in Figure 2. The extreme difference of actual and predicted values affecting the correlation coefficients to be low. In addition, the low correlation might also come from a bias toward data with small values.
The lowest NRMSE error value is 0.166 from the 2nd fold. The prediction error in the 2nd fold is very low, making the 2nd fold the best model based from both the correlation and NRMSE value. In addition, the 1st fold has the highest NRMSE compared to the others, reaching 0.462. Prediction error of monthly hotspots can affect the correlation, as seen in fold-1 with a correlation value at 0.101. The evaluation values of predictive models are influenced by the independent variables involved in the study. Table 3 shows the minimum, maximum, and average values of the independent variables of testing data involved in this study for each fold.

Table 3. Minimum, maximum, and mean values of the independent variables for each fold

Fold	SOI			CRU			SST		
	Min	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*
1	-14.70	21.40	0.76	71.10	432.70	214.89	25.01	28.93	27.19
2	-15.90	22.30	-0.67	60.50	567.80	236.04	25.32	28.16	27.02
3	-16.00	25.10	1.67	56.60	520.20	225.86	25.00	28.85	26.71
4	-18.60	13.90	-2.04	63.60	548.40	238.34	26.05	29.26	27.07
5	-12.00	21.30	1.91	66.90	430.90	216.63	25.00	28.03	27.06
6	-11.20	17.10	-0.64	108.40	462.77	242.90	25.65	28.15	27.17
7	-19.80	24.90	2.03	58.10	298.10	231.37	25.03	28.93	27.20
8	-12.00	18.30	1.92	55.30	491.60	223.72	24.86	28.90	27.01

As we can see in Table 3, the 2nd fold testing data has a minimum SOI of -15.90, a maximum SOI of 22.30 and an average SOI of -0.67. Judging from the minimum negative value, it shows the El Nino phenomenon occurs, where this phenomenon is related to the long dry season and drought in the southern area, including Indonesia. In the second fold, there is a minimum CRU of 60.50, a maximum CRU of 567.80, and an average CRU of 236.04. This fold also has a minimum SST of 25.32, a maximum SST of 28.13, and an average SST of 27.02. Viewing the values of the climatic variables, the sea surface temperature from the 2nd fold predictive model is not too high as indicated by the maximum SST value, but it has the highest maximum rainfall value compared to the other folds. This situation appears since the 2nd fold testing data has various months, including the months both from earlier and later of the year, making the data vary since rainy and dry season all exist in this fold.

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The 4th fold model is considered the worst, with the lowest correlation and a high error value. In this fold, the minimum SOI value is very low at -18.60, the maximum SOI is 13.90, and the average is -2.04. The maximum and average SOI value in this fold sis considered the lowest among the others, but the CRU rainfall value and sea surface temperature are high. Low SOI values indicate El Nino phenomenon exist, but it is contrary to the CRU value that shows high rainfall intensity and sea surface temperatures. The data shows there is a discrepancy between the climatic data variables, which all affect the predicted value of the number of monthly hotspots. Therefore, the predictive model in the 4th fold cannot recognize the pattern of the test data properly.

4. CONCLUSION

This research successfully builds a predictive model using a regression tree algorithm. The model evaluation shows an average correlation score of 0.445 and the NRMSE error with an average of 0.301. Generally, the models developed in this study have a correlation value in the moderate range, while the error value is considerably small. The 2nd fold performs the best with a correlation value of 0.875 and an NRMSE value of 0.166. Based on the correlation and error values, the 2nd fold model can be considered a good predictive model in forecasting monthly hotspots in Rokan Hilir Regency, Riau Province. In this study, there are folds that have low correlations. The model resulted from this study can only predict the number of monthly hotspots without knowing the location of their occurrence. Therefore, spatial variables can be added in further research in order to predict the location of hotspots. It is also necessary to pay attention to other aspects related to the occurrence of hotspots and forest fires, such as temperature or humidity, so that the prediction accuracy is better and more evenly distributed for each fold. In addition, future research can also use hotspots with a confidence level of 70% since a higher confidence level indicates a higher possibility a fire indeed exists.

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