

Forecasting hotspots in East Kutai, Kutai Kartanegara, and West Kutai as early warning information

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Abstract. The aims of this research are to model hotspots and forecast hotspot 2017 in East Kutai, KutaiKartanegara and West Kutai. The methods which used in this research were Holt exponential smoothing, Holt's additive dump trend method, Holt-Winters' additive method, additive decomposition method, multiplicative decomposition method, Loess decomposition method and Box-Jenkins method. For smoothing techniques, additive decomposition is better than Holt's exponential smoothing. The hotspots model using Box- Jenkins method were Autoregressive Moving Average ARIMA(1,1,0), ARIMA(0,2,1), and ARIMA(0,1,0). Comparing the results from all methods which were used in this research, and based on Root of Mean Squared Error (RMSE), show that Loess decomposition method is the best times series model, because it has the least RMSE. Thus the Loess decomposition model used to forecast the number of hotspot. The forecasting result indicatethat hotspots pattern tend to increase at the end of 2017 in KutaiKartanegara and West Kutai, but stationary in East Kutai.

1. Introduction

Hotspots are one cause of forest fires. According to BNPB, Indonesian National Board for Disaster Management, East Kalimantan Province has the most hotspots in Kalimantan [1]. Forest fires caused by hotspots are a serious problem. One solution to minimize the problem of forest fires is to provide information as early as possible about the number of hotspots for the future. Temporal analysis is one of the methods that can be used to determine the level of potential vulnerability of the region.

There are several preliminary studies related to forecasting hotspots. Detection of fire, spreading of fire, and smoke in forest fires can be used a genetic algorithm [2]. Elman Recurrent Neural Network can be used to forecast air temperature as forest fire factor [3]. Correlation analysis, linear regression and nonlinear regression method can be used as seasonal forecasting of fire over Kalimantan [4]. Prediction and verification forest fire can be used smoothing method and multiple regression [5]. Elman recurrent neural network were used to predict hotspots in Riau Province [6], and Adaptive Neuro Fuzzy Inference System (ANFIS) have used for classification model for forest fire hotspot occurrences prediction [7].

The aims of this research are to model hotspots and forecast hotspot 2017 in East Kutai, KutaiKartanegara and West Kutai. The methods which used in this research were Holt's exponential smoothing, Holt's additive dump trend method, Holt-Winters' additive method, additive decomposition method, multiplicative decomposition method, Loess decomposition method and Box Jenkins method. The results of this study are expected to contribute to the government, to immediately



be able to provide early information about the number of hotspots in East Kutai, KutaiKartanegara, and West Kutai. Thus forest fires can be prevented.

2. Hotspots

Hotspots by definition can be interpreted as areas that have relatively higher surface temperatures than the surrounding area based on certain temperature thresholds observed by remote sensing satellites. The typology is a point and is calculated as the sum rather than an area. Hotspots are the result of fire/land fire detection at a certain pixel size (eg 1 km x 1 km) which is likely to burn when the satellite passes in relatively cloud-free conditions.

How remote sensing satellites monitor completely the fires of land / forest in a region is illustrated in Figure 1. It is explained that in case of land / forest fires in a location it can be detected by satellites in a hotspot (left), two fires still within a 500 m radius can be detected only one hotspot point (center), otherwise a very large fire incident can be detected as 4 or more hotspots. This illustration indicate that the hotspot point is not the same as the number of land and forest fire incidents in the field.

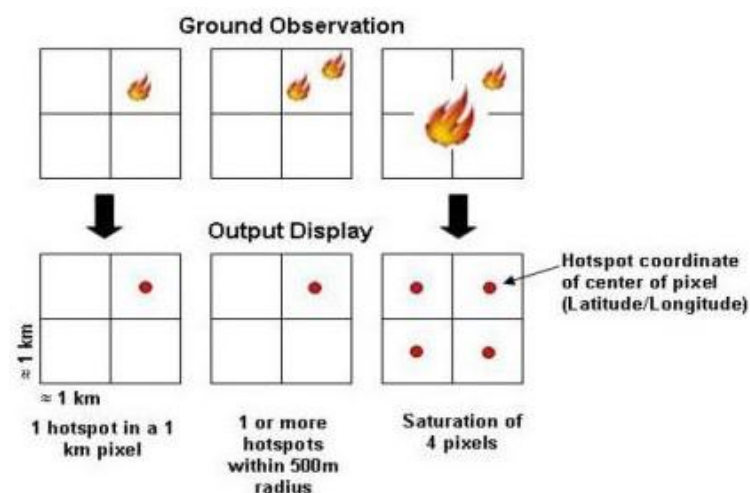


Figure 1. Illustration of land fires using remote sensing satellite data.

3. Methodology

The variable of this study is the number of hotspots of East Kalimantan province (2014-2016) by regency/city taken from LAPAN website (<http://modis-catalog.lapan.go.id/monitoring>) [8]. The population in this study is the number of hotspots in East Kalimantan, with the sample is the number of hotspots in East Kalimantan 2014-2016. Software used were R 3.1.3 and QGIS 2.14.18. The methods used were the exponential smoothing method, the decomposition method, and the Box-Jenkins method, which is Holt's saturation, Holt's additive damped trend, Holt-Winters' additive, additive decomposition, multiplicative decomposition, Loess decomposition, and Autoregressive Integrated Moving Average (ARIMA).

4. Results and discussion

The plot of hotspots in the province of East Kalimantan from 2014 to 2016 can be seen in Figure 2. The total number of hotspots of 2014 -2016 by regency/city can be seen in Figure 3. Based on Figure 2 and 3 it was found that the areas to watch out for are East Kutai, KutaiKartanegara, and West Kutai, as they had higher number of hotspots than other regions.

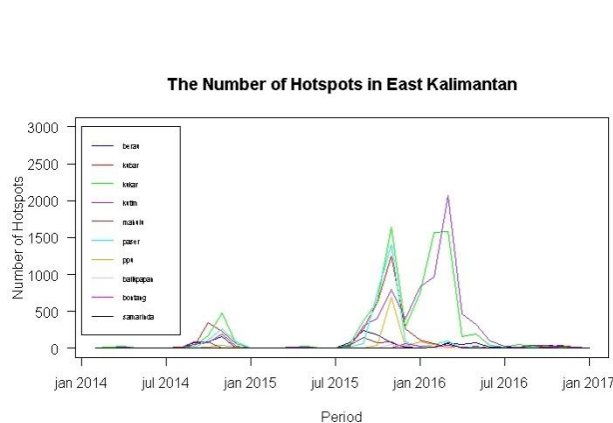


Figure 2. Hotspots distribution in East Kalimantan 2014-2016.

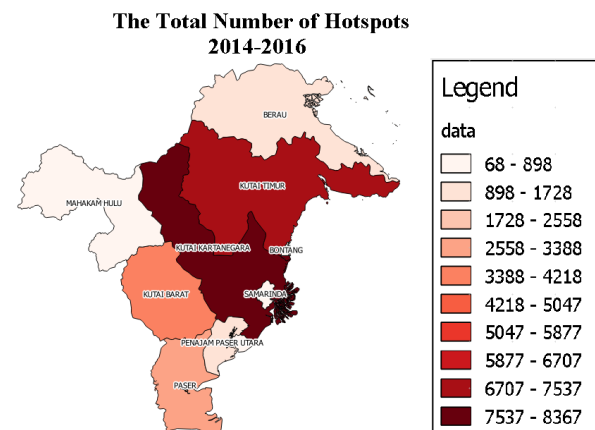


Figure 3. Spatial distribution of total hotspots 2014-2016 in East Kalimantan.

4.1. Exponential Smoothing Method

The exponential smoothing method used is Holt's linear trend method, additive damped trend, and Holt-Winters' seasonal method. The RMSE values for each model are shown in Table 1.

Table 1. Fitting Model by Exponential Smoothing

Region	Model	Parameter	RMSE
East Kutai	Holt's linear trend method	$\alpha = 0.6406, \beta = 1 \times 10^{-4}$	333.5140
	Additive damped trend	$\alpha = 0.6386, \beta = 1 \times 10^{-4}, \phi = 0.9343$	333.3407
	Holt-Winters seasonal method	$\alpha = 0.6444, \beta = 5 \times 10^{-4}, \gamma = 8 \times 10^{-4}$	288.8492
Kutai	Holt's linear trend method	$\alpha = 0.5614, \beta = 1 \times 10^{-4}$	392.1447
Kartanegara	Additive damped trend	$\alpha = 0.5561, \beta = 1 \times 10^{-4}, \phi = 0.9144$	391.6077
	Holt's-Winters seasonal method	$\alpha = 0.6317, \beta = 0.0150, \gamma = 0.0122$	323.3836
West Kutai	Holt's linear trend method	$\alpha = 0.8640, \beta = 1 \times 10^{-4}$	217.0291
	Additive damped trend	$\alpha = 0.8598, \beta = 1 \times 10^{-4}, \phi = 0.8754$	216.8285
	Holt's-Winters seasonal method	$\alpha = 0.6827, \beta = 1 \times 10^{-4}, \gamma = 1 \times 10^{-4}$	172.9971

In Table 1 it can be seen that the RMSE value for the Holt-Winters seasonal method is the smallest for the three regions, so for the best exponential smoothing model for the forecasting model is the Holt-Winters seasonal method.

4.2. Decomposition Method

Decomposition method used was additive decomposition, multiplicative decomposition, and Loess decomposition. The RMSE value for each model, can be seen in Table 2. The RMSE value for Loess decomposition is the smallest for the three regions, so for the decomposition model most suitable for the hotspots forecasting model is the Loess decomposition model.

Table 2.Fitting Model by Decomposition Method

Data	Model	RMSE
East Kutai	Additive decomposition	151.3462
	Multiplicative decomposition	292.7014
	Loess decomposition	1.18×10^{-15}
KutaiKartanegara	Additive decomposition	191.177
	Multiplicative decomposition	333.8793
	Loess decomposition	9.47×10^{-15}
West Kutai	Additive decomposition	121.4384
	Multiplicative decomposition	208.8232
	Loess decomposition	3.55×10^{-15}

4.3. Autoregressive Integrated Moving Average (ARIMA)

The first step in analyzing using ARIMA model is checking stationary, model identification, and parameter estimation. This step is done by looking at the time series plot to check the stationary, then proceeded to see the Autocorrelation Functions (ACF) plot and Partial Autocorrelation Functions (PACF) plot. Both of these functions are used to determine the possibility of some ARIMA models being used. Time series plots in Figure 2 show that the number of hotspots was non-stationary. To determine the suitable ARIMA model, it is necessary differencing the real data. Figure 4 shows time series plot from hotspots data that have differencing, it can be seen that it is quite stationary. ACF plot for each region shows that ACF plot of East Kutai is cut off in lag 1 and its PACF is cut off in lag 1 as well. ACF plot and PACF plot of KutaiKartanegara is cut off in lag 2. ACF plot and PACF plot of West Kutai is dies down.

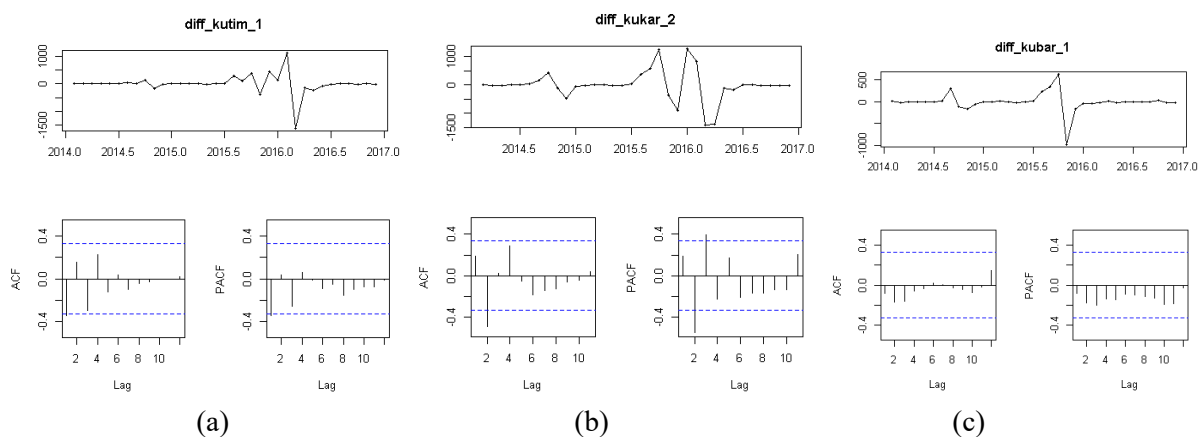


Figure 4.Time series plot, ACF plot, and PACF plot (a) East Kutai, (b) KutaiKartanegara, (c) KutaiBarat.

Table 3 shows the estimated parameter values of the significant ARIMA models for the number of hotspots in the East Kutai, Kutai Kartanegara, and West Kutai. Based on Table 3, the best models for East Kutai, Kutai Kartanegara and Kutai Barat are ARIMA (1,1,0), ARIMA (0,2,1), and ARIMA (0,1,0), respectively. These models have the smallest RMSE values in each region.

Table 3. The Significant ARIMA Models for The Number of Hotspots

Region	Model	RMSE	Parameter	Coefficient	t
East Kutai	ARIMA(1,1,1)	328.8194	ϕ_1	-0.7753	-3.326
			θ_1	0.5361	1.6795
	ARIMA(1,1,0)	332.7136	ϕ_1	-0.3375	-2.1662
	ARIMA(0,1,1)	333.4766	θ_1	-0.3485	-2.116
	ARIMA(0,1,0)	354.7523			
KutaiKartanegara	ARIMA(3,2,2)	364.6174	ϕ_1	-0.9547	-3.3891
			ϕ_2	-0.5233	-2.5062
			ϕ_3	-0.3868	-2.5995
			θ_1	-0.3227	-1.0225
			θ_2	-0.6773	-2.2728
	ARIMA(3,2,1)	375.2607	ϕ_1	-0.3175	-1.8721
			ϕ_2	-0.3452	-2.1191
			ϕ_3	-0.1505	-0.9205
			θ_1	-1	-6.5963
	ARIMA(3,2,0)	415.4831	ϕ_1	-0.9361	-6.7008
			ϕ_2	-0.816	-5.3368
			ϕ_3	-0.523	-3.9383
	ARIMA(2,2,2)	379.0022	ϕ_1	-0.0897	-0.2595
			ϕ_2	-0.2728	-1.5447
			θ_1	-1.1984	-3.2681
			θ_2	0.1984	0.5751
	ARIMA(2,2,1)	381.898	ϕ_1	-0.2614	-1.6156
			ϕ_2	-0.2975	-1.8841
			θ_1	-1	-9.0662
	ARIMA(2,2,0)	503.5177	ϕ_1	-0.6798	-4.532
			ϕ_2	-0.4394	-3.0075
	ARIMA(1,2,2)	387.2013	ϕ_1	0.2974	0.6897
			θ_1	-1.6228	-3.9745
			θ_2	0.6228	1.5803
	ARIMA(1,2,1)	404.9793	ϕ_1	-0.1882	-1.129
			θ_1	-1	-11.5473
	ARIMA(1,2,0)	568.4219	ϕ_1	-0.464	-3.1458
	ARIMA(0,2,2)	392.6058	θ_1	-1.3696	-6.2855

		θ_2	0.3697	1.9175
	ARIMA(0,2,1)	414.6641	θ_1	-1
	ARIMA(0,2,0)	646.8521		-12.4069
West kutai	ARIMA(0,1,0)	217.853		

4.4. Selection of The Best Model

The comparison for the best model chosen for each method can be seen in Table 4. The model with Loess decomposition has the smallest RMSE value, making it the best model for predicting the number of hotspots in East Kutai, KutaiKartanegara, and West Kutai.

Table 4. The Comparison of RMSE Values for Each Model

Data	Model	RMSE
East Kutai	Holt	333.51
	Loess	1.18E-15
	ARIMA(1,1,0)	332.71
KutaiKartanegara	Holt	392.14
	Loess	9.47E-15
	ARIMA(0,2,1)	414.66
West Kutai	Holt	217.03
	Loess	3.55E-15
	ARIMA(0,1,0)	217.85

Figure 5 indicates that there is an increase in the number of hotspots in the second half of 2017 for KutaiKartanegara and West Kutai. The forecasting result for East Kutai is stationary (not high at the end of 2017).

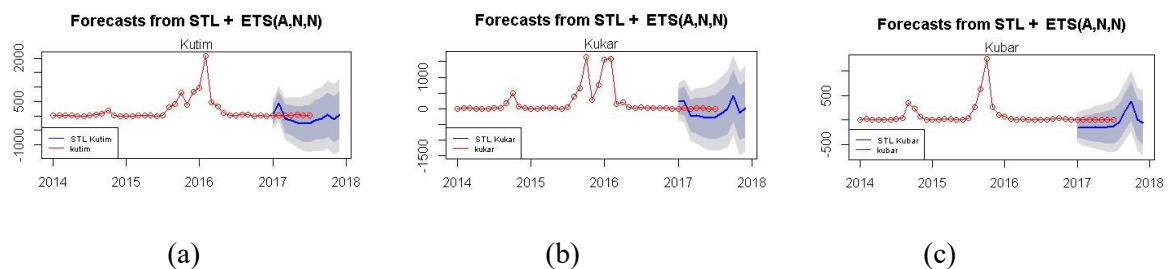


Figure 5. Forecasting hotspots using Loess decomposition (a) East Kutai, (b) KutaiKartanegara, (c) West Kutai.

5. Conclusions

The best model to forecast the number of hotspots is to use Loess decomposition method. The results of forecasting the number of hotspots in 2017 indicate that there is an increase in the number of hotspots in the second half of 2017 for KutaiKartanegara and West Kutai. The forecasting result for East Kutai is stationary (not high at the end of 2017). These results can be used as input for the forest fire information system.

Acknowledgement

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