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, Kutai Kartanegara 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 indicated that hotspots pattern tend to increase at the end of 2017 in Kutai Kartanegara 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, Kutai Kartanegara 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, Kutai Kartanegara, 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.](image)

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, Kutai Kartanegara, and West Kutai, as they had higher number of hotspots than other regions.
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.

![The Number of Hotspots in East Kalimantan](image1)

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

![The Total Number of Hotspots 2014-2016](image2)

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

### 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         | 292.7014   |
|                 | Loess decomposition    | 1.18 × 10^{-15} |
| Kutai Kartanegara | Additive decomposition | 191.177    |
|                 | Multiplicative         | 333.8793   |
|                 | Loess decomposition    | 9.47 × 10^{-15} |
| West Kutai      | Additive decomposition | 121.4384   |
|                 | Multiplicative         | 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 Kutai Kartanegara is cut off in lag 2. ACF plot and PACF plot of West Kutai is dies down.

![Figure 4](image)

(a) diff_kutim_1  (b) diff_kutar_2  (c) diff_kutar_1

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   |
|-----------------|-------------|-------|-----------|-------------|-----|
|                 | ARIMA(1,1,1)| 328.8194 | $\phi_1$ | -0.7753     | -3.326 |
|                 |             |       | $\theta_1$ | 0.5361      | 1.6795 |
|                 | ARIMA(1,1,0)| 332.7136 | $\phi_1$ | -0.3375     | -2.1662 |
|                 | ARIMA(0,1,1)| 333.4766 | $\theta_1$ | -0.3485     | -2.116 |
|                 | ARIMA(0,1,0)| 354.7523 |           |             |      |
| East Kutai      | ARIMA(3,2,2)| 364.6174 | $\phi_1$ | -0.9547     | -3.891 |
|                 |             |       | $\phi_2$ | -0.5233     | -2.5062 |
|                 |             |       | $\phi_3$ | -0.3868     | -2.5995 |
|                 |             |       | $\theta_1$ | -0.3227     | -1.0225 |
|                 |             |       | $\theta_2$ | -0.6773     | -2.2728 |
| Kutai Kartanegara | ARIMA(3,2,1)| 375.2607 | $\phi_1$ | -0.3175     | -1.8721 |
|                 |             |       | $\phi_2$ | -0.3452     | -2.1191 |
|                 |             |       | $\phi_3$ | -0.1505     | -0.9205 |
|                 |             |       | $\theta_1$ | -1          | -6.5963 |
|                 | ARIMA(3,2,0)| 415.4831 | $\phi_1$ | -0.9361     | -6.7008 |
|                 |             |       | $\phi_2$ | -0.816      | -5.3368 |
|                 |             |       | $\phi_3$ | -0.523      | -3.9383 |
|                 | ARIMA(2,2,2)| 379.0022 | $\phi_1$ | -0.0897     | -0.2595 |
|                 |             |       | $\phi_2$ | -0.2728     | -1.5447 |
|                 |             |       | $\theta_1$ | -1.1984     | -3.2681 |
|                 |             |       | $\theta_2$ | 0.1984      | 0.5751 |
|                 | ARIMA(2,2,1)| 381.898  | $\phi_1$ | -0.2614     | -1.6156 |
|                 |             |       | $\phi_2$ | -0.2975     | -1.8841 |
|                 |             |       | $\theta_1$ | -1          | -9.0662 |
|                 | ARIMA(2,2,0)| 503.5177 | $\phi_1$ | -0.6798     | -4.532 |
|                 |             |       | $\phi_2$ | -0.4394     | -3.0075 |
|                 | ARIMA(1,2,2)| 387.2013 | $\phi_1$ | 0.2974      | 0.6897 |
|                 |             |       | $\theta_1$ | -1.6228     | -3.9745 |
|                 |             |       | $\theta_2$ | 0.6228      | 1.5803 |
|                 | ARIMA(1,2,1)| 404.9793 | $\phi_1$ | -0.1882     | -1.129 |
|                 |             |       | $\theta_1$ | -1          | -11.5473 |
|                 | ARIMA(1,2,0)| 568.4219 | $\phi_1$ | -0.464      | -3.1458 |
|                 | ARIMA(0,2,2)| 392.6058 | $\theta_1$ | -1.3696     | -6.2855 |
\[
\begin{array}{ccc}
\theta_2 & 0.3697 & 1.9175 \\
\theta_1 & -1 & -12.4069 \\
\hline
\text{ARIMA}(0,2,1) & 414.6641 & \text{ARIMA}(0,2,0) & 646.8521 \\
\text{ARIMA}(0,1,0) & 217.853 & \\
\hline
\text{West kutai} & \\
\end{array}
\]

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.

| 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).

![Forecasting hotspots using Loess decomposition](image)

(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.

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