Developing models to establish seasonal forest fire early warning system

D E Nuryanto1,2*, R P Pradana1, I D G A Putra1, E Heriyanto1, U A Linarka1, R Satyaningsih1, N Hidayanto1, A Sopaheluwakan2 and D S Permana1

1Center for Research and Development, Indonesian Agency for Meteorology Climatology and Geophysics (BMKG), Jakarta, 10610, Indonesia
2Center for Applied Climate Services, Indonesian Agency for Meteorology Climatology and Geophysics (BMKG), Jakarta, 10610, Indonesia

*E-mail: danang.eko@bmkg.go.id

Abstract. During a typically dry season in Sumatra or Kalimantan, the forest fire starts. In 2015, an El Nino year, forest fires in Sumatra and Kalimantan ranked among the worst episodes on record. Understanding the connection between accumulated monthly rainfall and the risk of hotspot occurrence is key to improving forest fire management decision-making. This study addresses model development to predict the number of 6-month fire hotspots, by combining the prediction of rainfall with hotspot patterns. Hotspot data were obtained from the Fire Information for Resources Management System (FIRMS) for the period of 2001–2018. For rainfall prediction, we use the output model of the European Centre for Medium-Range Weather Forecasts (ECMWF). The threshold of more than 10 hotspot events has been used to establish hotspot climatology. To get a threshold for rainfall that can cause forest fires, we used the Pulang Pisau rain station. We applied two rainfall thresholds to determine three categorical forecasts (low, moderate, high) as environment quality indicator. The two thresholds are 100 mm/month for the lower threshold and 130 mm/month for the upper threshold. The verification of the observational data showed an accuracy of > 0.83, which is relatively consistent and persistent with forest fire events. The weakness of this system is that it cannot determine the exact location of the forest fire because the spatial resolution used is 0.25 degrees. The predictions of the monthly climate index values were reasonably good suggesting the potential to be used as an operational tool to predict the number of fire hotspots expected. The seasonal forest fire early warning system is expected to be an effort to anticipate forest fires for the next six months. The modeling strategy presented in this study could be replicated for any fire index in any region, based on predictive rainfall information and patterns of the hotspot.

1. Introduction

Hundred million hectares of forest and other plants in Sumatra and Borneo are burned every year [1]. Forest fires are more common in Central Kalimantan Province, which has a wide area of peatland. Peatland fires are more severe than other forest fires because they reach the bottom layer of the soil to create a funnel hole, and then spread horizontally under the surface, with climate variations often playing a role in affecting peatland fires [1]. Forest fires occur in Sumatra and Kalimantan during the dry season. Forest fires in Sumatra and Kalimantan were the worst event on record in 2015, an El Nino year.

Forest fires are caused by interactions among environmental factors, such as fuel availability, weather, topography, and ignition source [2]. When conditions such as low humidity, strong wind,
topography, and wind direction are favorable, a fire will spread quickly if the amount and availability of fuel are adequate [3]. According to them, one of the most important methods for avoiding major forest fires is fire detection. Correctly determining the spatial position of a fire tower is critical for detecting and monitoring forest fires.

The definition of forest fire risk encompasses the likelihood of an occurrence and the implications of that event. The prediction of forest fire risk entails determining fire risk levels, which are heavily influenced by weather conditions and other factors such as vegetation condition and topography [2]. The hotter, drier, and more extended the weather is, for example. The greater the likelihood of forest fires, the hotter, drier, and more prolonged the weather conditions are. Vegetation characteristics also influence forest fire risk. Forests with dry peatlands are more vulnerable to fire [4–8].

In the Sumatra and Kalimantan regions, there are forest areas with peatlands in them. Of course, the peatland in the dry season has a higher burning potential. This condition requires an early warning system capable of detecting the potential for forest fires to occur in the area. Extended early warning (i.e., 3-6 months) can be obtained using predicted conditions from the high resolution of numerical weather models [9,10]. This extra time enables better resource-sharing and mobilization coordination both within and between countries.

The present study is to prepare a forest fire risk map by integrating hotspot distribution and certain thresholds of monthly rainfall in Indonesia. This study aims to develop a seasonal forest fire early warning system for predicting hotspot occurrence in Indonesia. The result will be based on three categories: low, moderate, and high.

2. Method

The fundamental data used in this research are hotspot (grid) that obtained from the Fire Information for Resources Management System (FIRMS) for the period of 2001–2019 [11,12], precipitation from the Tropical Rainfall Measuring Mission (TRMM) period of 1998-2013 [13–15] and precipitation prediction from the new European Centre for Medium-Range Weather Forecasts (ECMWF) seasonal forecast system [10]. All data were interpolated into a spatial resolution of 0.25 x 0.25 degrees.

To account for the assessment of the fire susceptibility of forest fire for the region of Indonesia, we have developed the Climate Index for Suitability of Hotspots Occurrence (CISHO). This index is based on rainfall prediction by a high-resolution model with hotspot statistics towards its occurrences approximating fire danger. For diagnostics, calculations are performed at a Pulang Pisau site scale using TRMM data while for forecasting purposes, the ECMWF model data are used. CISHO is generally based on the following physical definitions:

- Fire danger rating is approximated by rainfall thresholds
- Rainfall threshold results from the stepwise regression between hotspot and TRMM precipitation
- Scaling of CISHO to designate the susceptibility to fire indicator by 3-level quantitative index.

Classes or fire danger are defined

The research domain to obtain the threshold for rainfall includes Pulang Pisau Regency, South Kalimantan (Fig. 1). First of all, hotspot climatology was developed using a threshold of more than ten hotspot events. To get a threshold for rainfall that can cause forest fires, we used the relationship between rainfall and hotspot numbers (Fig. 2).

The peatland forest region of South Kalimantan is particularly vulnerable to forest fires due to its location in the tropics, with high temperatures and little to no precipitation during the dry season. The peatland is particularly susceptible to burning. This study investigated whether the forest fire occurrence is influenced by hotspot history and rainfall factors using deterministic approach. A stepwise regression [16] used in a multiple-regression model. The assumption is that the more possible predictors there are, the more useful stepwise regression becomes.
Figure 1. Area study is used to identify rainfall thresholds that potentially to forest fires.

Figure 2. Scatter plot of monthly TRMM precipitation vs Hotspot. Line is step wise regression between hotspot and TRMM precipitation.
We applied two rainfall thresholds to determine three categorical forecasts (low, moderate, high) as environment quality indicator (Fig. 3). Warning design describe as follows: Low risk, % of Precipitation > Threshold 1, Moderate Risk, % of Precipitation < Threshold 1 (Risk of burning equivalent to “normal” dry period), High Risk, % of precipitation < Threshold 2 (Risk of burning equivalent to or higher than El Nino moderate). The example of two threshold is 100 mm/month for the lower threshold (Threshold 1) and 130 mm/month for the upper threshold (Threshold 2).

![Figure 3: The fundamental concept of seasonal forest fire early warning system.](image)

In this flowchart, the main process is how to categorized the location with rainfall threshold that we have calculated before. There are two selections in determining the CISHO value category based on the rainfall prediction model. The first selection uses threshold \(T_{r1} = 130\) mm/month and \(T_{r2} = 100\) mm/month as a representation of rainfall in Kalimantan. Furthermore, for the representation of rainfall in Riau, selection is used with threshold \(T_{r1} = 180\) mm/month and \(T_{r2} = 130\) mm/month.

The category \((\text{cat})\) count of three conditions developed as follow:

\[
c_i = \begin{cases} 
  & \text{if } R_{loc} > T_{r1} \text{ then count}(i = 1) \\
  & \text{if } T_{r1} \geq R_{loc} \geq T_{r2} \text{ then count}(i = 2) \\
  & \text{if } R_{loc} < T_{r2} \text{ then count}(i = 3) 
\end{cases}
\]

(1)

where \(R_{loc}\) is rainfall in certain location, for example South Kalimantan or South Sumatra etc.

The total value of the category is then made a percentage based on the number of ensemble members. The equation to get the rate is as follows:

\[
rate_i = \frac{c_i}{n} \times 100\%
\]

(2)

where \(n\) is total ensemble of ECMWF models.
Figure 4. Structure of the concept of CISHO calculation for forest fires early warning system.
The next step is to determine which is greater between $c_1$ and $c_3$. If $c_1 > c_3$, then it is included in the Low category. If $c_3 > 80\%$ is in the High category, the rest is in the Moderate category. Then monthly hotspot data is used for final filtering. If the number of hotspots is $< 10$, then it is in a Low category.

3. Results and Discussion

Figure 5 shows an example of CISHO plotting results spatially. The land was deliberately taken to indicate the potential for forest fires only on land. There is a distribution of fire hazard level categories, namely: low (green), medium (yellow) and high (red). CISHO in densely populated areas usually indicates a high level of controlled fire activity. As demonstrated in Table 1, these findings can be used to guide policymakers in taking specific actions.

Figure 5. Example of forest fires Early Warning System products for Indonesia. In this example, CISHO have been interpreted as three categorical levels, i.e., low (green), moderate (yellow) and high (red).

Table 1 is an example of fire management recommendations used in conjunction with forest fire danger information to aid decision-making. Preventive activity and fire severity, for example, can be utilized to develop prevention and action strategies ahead of extreme fire conditions.

| Categorical levels | Prevention activity | Fire severity |
|--------------------|---------------------|--------------|
| Low                | None                | Nil – Low    |
| Moderate           | Local warning sign  | Moderate     |
|                     | Local media warning |              |
|                     | Open burning restrictions |   |
| High               | TV and radio warnings | High         |
|                     | Open burning ban    |              |
|                     | Local community actions | |

Table 1. Example of fire prevention action plans for decision maker

Sections should be numbered with a dot following the number and then separated by a single space: Figure 6 shows the results of CISHO verification in August 2019 with three different initials, namely:
(a) June 2019, (b) July 2019 and (c) August 2019. From the three separate data initials, there is a consistent CISHO pattern. The presence of high categories throughout Sumatra, Kalimantan, and even some parts of Java is a constant pattern. Compared to the establishment of hotspots in the region, the high category pattern has a reasonably good connection. Although the distribution of hotspots is not the same as the distribution of the high category, some locations show an increased number of hotspots (> 21) in the high class.

![Initial time June 2019](image1)

![Initial time July 2019](image2)

![Initial time August 2019](image3)

**Figure 6.** The verification of CISHO model with satellite observation of hotspot events. The initial for models are (a) June 2019, (b) July 2019 and (c) August 2019.

Furthermore, Figure 7 shows the skill scores between the CISHO model and the hotspot observed by FIRMS, with three differentials of data initial. It is seen that the CISHO model with initial data for June 2019, July 2019 and August 2019 all three showed the same high fit-score (0.84). While the miss-score offers a deficient value (<0.1).

![Score AUG 2019](image4)

**Figure 7.** The score skills of CISHO model. The initial for models are representing by color blue (initial June 2019), red (initial July 2019) and green (initial August 2019).
Based on the analysis above, we used a rainfall threshold that associated with hotspot, and it can be used for specific region with certain rainfall type. Our rainfall threshold could be different at different region with different rainfall types.

Predicting forest fires for several months was a challenge for previous researchers [17,18]. This long-term prediction is due to the efforts of policymakers to take better steps ahead of time. Several researchers have applied calculations similar to daily scale predictions with some modifications to obtain seasonal scale predictions [19]. This study shows that the output of the high-resolution model can predict forest fires with the best skills.

4. Future system development and implementation plans
The forest fire early warning system is being improved with satellite data and modeling. Developing a forest fire early warning system for a regional scale (ASEAN, for example) will be an added value that will be useful for anticipating potential forest fires in the ASEAN region. For this reason, it is planned to develop an application that can cover the ASEAN region, as shown in Figure 8.

![Climate Index for Suitability of Hotspots Occurence](image)

**Figure 8.** Example of Regional Early Warning System products for ASEAN domain. In this example, CISHO have been also interpreted as three categorical levels, i.e., low (green), moderate (yellow) and high (red).
5. Conclusion

Unlike the previous forest fires early warning systems, this study discusses the relationship between climatology and hotspot through deterministic approach. Rainfall exert influence on the hotspot in the environment condition that provide sufficient situation for getting forest fires. This suggests a strong connection between monthly hotspot and rainfall data.

Rainfall is closely associated with water supply on peatland area, and the low rainfall in Sumatra and Kalimantan often perceive the climate as indicator for occurrence of hotspot. The influence of climatology of hotspot on this early warning system must be considered, and hotspot is also heavily influenced by peatland area.

The lower threshold is set at 100 mm/month, while the upper threshold is set at 130 mm/month. The observational data was verified with an accuracy of > 0.83, which is relatively consistent and persistent with forest fire incidents. The spatial resolution used in this method is 0.25 degrees, which means it can't pinpoint the exact position of the forest fire.

The monthly climate index values predicted the number of fire hotspots expected reasonably well, indicating that it could be used as an operational method to forecast the number of fire hotspots expected. Forest fires are likely to be predicted for the next six months using the seasonal forest fire early warning system. We could repeat the modeling strategy described in this study for any fire index in any area based on predicted rainfall information and hotspot trends.

Acknowledgments

Authors wishing to acknowledge assistance or encouragement from colleagues, special work by technical staff and financial support from R&D BMKG. DEN is the main contributor; RPP, IDGAP, EH, UAL, RS, NH, AS and DSP are the member contributor. All the authors joined the discussion on the results, and read and approved the manuscript.

References

[1] Wijayanto A K, Sani O, Kartika N D and Herdiyeni Y 2017 IOP Conf. Series: Earth and Environmental Science vol 54
[2] Hoang T Van, Chou T Y, Fang Y M, Nguyen N T, Nguyen Q H, Canh P X, Toan D N B, Nguyen X L and Meadows M E 2020 Appl. Sci. 10 1–19
[3] Sivrikaya F, Sağlam B, Akay A E and Bozali N 2014 Polish J. Environ. Stud. 23 187–94
[4] Page S E and Hooijer A 2016 Philos. Trans. R. Soc. B Biol. Sci. 371
[5] Page S, Hoscilo A, Langner A, Tansey K, Siegfert F, Limin S and Rieley J 2009 Tropical Fire Ecology (Springer, Berlin, Heidelberg: Springer Praxis Books)
[6] Bourgeau-Chavez L L, Grelik S L, Billmire M, Jenkins L K, Kasischke E S and Turetsky M R 2020 Front. For. Glob. Chang. 3 1–13
[7] Thoha A S, Saharjo B H, Boer R and Ardiansyah M 2019 C Biodiversitas 20 110–7
[8] Cole L E S, Bhagwat S A and Willis K J 2019 Front. For. Glob. Chang. 2 1–15
[9] Sutanto S J, Van Lanen H A J, Wetterhall F and Llort X 2020 Bull. Am. Meteorol. Soc. 101 E368–93
[10] Johnson S J, Stockdale T N, Ferranti L, Balmaseda M A, Molteni F, Magnusson L, Tietsche S, Decremer D, Weisheimer A, Balsamo G, Keeley S P E, Mogensen K, Zuo H and Monge-Sanz B M 2019 Geosci. Model Dev. 12 1087–1117
[11] Putra I D G A, Heriyyanto E, Sopaheluwakan A, Pradana R P and Nuryanto D E 2020 IEEE Asia-Pacific Conference on Geoscience, Electronics and Remote Sensing Technology (AGERS) (Jakarta, Indonesia: IEEE) pp 63–8
[12] Putra I D G A, Heriyyanto E, Sopaheluwakan A, Pradana R P and Haryoko U 2019 Semin. Nas. Geomatika 3 1123
[13] Huffman G J, Adler R F, Bolvin D T, Gu G, Nelkin E J, Bowman K P, Hong Y, Stocker E F and Wolff D B 2007 J. Hydrometeorol. 8 38–55
[14] Huffman G J, Adler R F, Bolvin D T, Nelkin E J and Code N G 2008 *Satell. Rainfall Appl. Surf. Hydrol.* 1–19
[15] Huffman G J, Stocker E F, Bolvin D T and Nelkin E J 2014 *Tropical Rainfall Measuring Mission (TRMM) 3B42 v 6 Data Sets* (Greenbelt, MD, USA)
[16] Smith G 2018 *J. Big Data* 5
[17] Resco de Dios V and Nolan R H 2021 *Forests* 12 1–5
[18] Ferreira L N, Vega-Oliveros D A, Zhao L, Cardoso M F and Macau E E N 2020 *Comput. Geosci.* 134
[19] Bedia J, Golding N, Casanueva A, Iturbide M, Buontempo C and Gutiérrez J M 2018 *Clim. Serv.* 9 101–10