Utilization of ECMWF Seasonal Rainfall Forecast System (SEAS5) for forest fire prediction over Sumatera Island, Indonesia

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Abstract. As part of the lungs of the world, the forest which covers Sumatra Island has a significant impact on the world oxygen production and the absorption of carbon dioxide. Drought over Sumatra Island often causes forest fires that can damage the function of forests as the world's lungs. Prediction of the seasonality of forest fires is needed to prevent and overcome forest fires that will occur next month. This study utilized seasonal rainfall predictions to predict the incidence of forest fires based on the drought index obtained. The result showed that ECMWF SEAS5 had good performance to predict rainfall over Sumatera Island for the first until the fourth months (lead time of 0 - 3). The Negative Standardized Precipitation Index (SPI) coincided with the increasing number of the hotspots. Furthermore, a linear equation has been applied to the calculated number of hotspots based on SPI from ECMWF.

1. Introduction
Sumatera Island is part of Indonesian Maritime Continent which has annual hottest area in the world and strong seasonal rainfall variability [1]. The wet season has an impact on large flooding [2,3], while dry season has an impact on drought event [4 – 6]. Sumatera Island has unique rainfall pattern because the shape of Sumatera Island extends along the latitude from North to South Hemisphere and has high mountain along the western coastal area. This condition induced different types in coastal and central of Sumatera Island [7]. Beside high mountain, coastline shape also affects the dry and wet season pattern [8,9].

The most part of Sumatra is peatland area, so it is very possible that the forest fires induce when drought happens. Fire over peat areas generally starts from the surface then spreads to underground to burn the organic material or the remaining of plants, leaves, twigs, and roots. During strong El-Nino incidence in 2015, widespread forest and peatland were burned in Southeast Asia maritime, especially in Sumatera and Kalimantan. Most of burned area was located in Southeast of Sumatra Island [10]. There were 1.34 million km² area reported burnt during this incidence [11].

Although some of the forest fires are triggered by human activities, natural factors also contribute to greater forest fires. Most of the massive forest fires generated climate conditions such as El-Nino that causes long drought. Forest fire over Sumatera is related to dry-wet seasons [5]. Relay et al. (2013) have evaluated the relationship between forest fire and drought index for fire prediction under current and future climates over western United States during 1984–2008. Their study showed that short-term drought has stronger relationships with large fire occurrence than long-term drought index [12]. Although some studies showed that drought is a contributing factor to forest fire incidence, the relationships between drought and forest fire are very complex. There are some feedbacks from forest fire to drought [13].
In this study, we predicted drought conditions over Sumatera using rainfall predictions from the European Centre for Medium Range Weather (ECMWF) seasonal forecast employing the ECMWF S4 Forecast system model. Drought condition was described by the standardized precipitation index (SPI). After we got SPI, we examined the correlation between SPI and forest fire to create forest fire prediction equations based on linear regressions.

2. Data and Method

2.1. The ECMWF Seasonal Forecast System (SEAS5)
We used the ECMWF SEAS5 for calculating the drought index. SEAS5 is an ensemble model and has 51 members for the forecast system and 25 members for the hindcasts. The spatial resolution was about 35 km² and the forecast ran out to 7 months. It was operated and released in 2017 [14]. In this study, we focused on forecasts with a six until seven-month lead time, referring to forecasts on a dry season (July – August) that was issued in February.

2.2. Rain Gauge Observation
The rain gauge observations were used as the basic truth for verifying SEAS5 and consisted of more than 111 meteorological station observations. Those rain gauge observations were obtained from the Indonesian Agency for Meteorology Climatology and Geophysics. In addition, it covers the whole Sumatera Island (Figure 1).

![Figure 1. Distributions of Rain gauge observations over Sumatera Island (red dots)](image)

2.3. Hotspot Density
Hotspot is a location with relatively higher temperature than the surrounding area and usually identified as fire location [15]. It was generated from Moderate Resolution Imaging Spectroradiometer (MODIS) on TERRA-AQUA satellite. The resolution of hotspot density on this paper was 25 km x 25 km. The number of hotspots is associated with more forest fires.

2.4. The Standardized Precipitation Index (SPI)
One of the methods used in meteorological drought analysis is SPI Index. This method was developed by McKee et al. (1993) [16]. SPI was generated by rainfall deficits at various periods based on normal conditions. It can be created for difference periods from 1 to 36 months. If the SPI is negative, it means that the location has rainfall deficits and potentially induces the drought.

2.5. Validation
The validation periods used the ECMWF SEAS5 rainfall and forest fires data from 2001 to 2018. In the validation process, the author determined the coefficient of linear regression equations with an independent variable of SPI which was calculated from the seasonal rainfall predictions from SEAS5 ECMWF, while the dependent variable was the number of forest fires represented by hotspot density.

The evaluation of the ability of the ECMWF SEAS5 model during the validation process was divided into 7 lead times, those are lead time 0, 1, 2, 3, 4, 5, and 6. Lead time 0 refers to the rainfall forecast of the first month (31 days) issued in early date of the first month (date 1st). Meanwhile, lead time forecast 1 refers to the rainfall forecast on the second month issued in the early date of second month, and etc.

3. Result and Discussion
The monthly rainfall prediction capability of the ECMWF SEAS5 model in Sumatra was evaluated using rain gauge data that had data availability exceeding 95% during 2001 - 2018. The results showed that ECMWF SEAS5 was able to simulate rainfall only at lead time forecasts of 0, 1, 2, 3 marked by a positive correlation coefficient, even though it has a fairly low value. At the lead time forecast 4, 5, and 6, the value of the correlation coefficient was negative and the predicted ECMWF SEAS5 rainfall was the opposite of the rain gauge data. This condition indicated that ECMWF SEAS5 was not able to simulate rainfall properly (see figure 2a).

Figure 2b shows that the mean absolute percentage error (MAPE) for ECMWF SEAS5 increased continuously with the addition of lead time forecast. Best performance for ECMWF SEAS5 occurred at lead time forecast 0 with the value of MAPE lower than 70% for all event of ECMWF SEAS5 forecast. Lead time forecasts 1, 2, and 3 have MAPE lower than 100%.

Based on the consideration variable of coefficient correlation (positive value) and MAPE (lower than 100%) in figure 2, we can use ECMWF SEAS5 forecast just for next four months. Furthermore, bias correction can be applied to change the ECMWF SEAS5 prediction for a better result and good forecast for the next 7 months [17].

Figure 2. Correlation coefficient (a) and MAPE (b) for simulation ECMWF SEAS5 over Sumatera Island during 2000 - 2018
Figure 3. Annual number of hotspot density over Sumatera Island (a) SPI based on ECMWF SEAS5 prediction for lead time forecast 0 (b), lead time forecast 1 (c), lead time forecast 2 (d), lead time forecast 3 (e), lead time forecast 4 (f), lead time forecast 5 (g), lead time forecast 6 (h).

In the span of 18 years i.e., 2001-2018 during El Niño incident coinciding with dry-season, the amount of monthly rainfall can be less than half of normal and severe El Niño incidents have long been associated with forest fire (e.g., El Niño event on 2002, 2004, 2006, 2009, 2014, 2015, 2016) (See Figure 3a). The highest frequency of the number of hotspots ensued in 2015 coincided with the strongest El Nino condition which has Oceanic Niño Index (ONI) value of 2.5. Besides the increase number of hotspots, El Nino affects the duration of the highest hotspot period due to drought events.

The simulation of drought event on lead time forecast 0 is shown in Figure 3b. These results showed that in case there is a quite long drought event, the number of fire incidence also increases. This is quite clear in the events occurred in 2015 where the SPI showed a strong negative value coincides with the increase of the number of hotspots. Although some studies showed that forest fires occur due to human activity, the relationship between drought and forest fires is quite clear in this picture.

In case we compared the drought event on 2015 for lead time forecast 0, lead time forecast 1 (see figure 3c), lead time forecast 2 (see figure 3d), lead time forecast 3 (see figure 3e), lead time forecast 4 (see figure 3f), lead time forecast 5 (see figure 3g) and lead time forecast 6 (see figure 3h), the drought event on lead time forecast 0 tends to be stronger than others. This can be seen from the lowest SPI value compared to the other lead time forecast. The effect of wet monsoons on increasing rainfall is also proven during the drought event even though the EL Nino condition was strong. The peak minimum value of SPI was divided into two parts in the case of the negative of SPI that exceeds the 6-month. The value of SPI tends to be close to zero between two minimum peaks during wet-seasons.

In some research projects, 3-monthly SPI, 6-monthly SPI, and 9 monthly SPI have different capability in describing the drought conditions. The 3-monthly SPI has good performance for describing drought in monsoonal area [18]. In this research, we used 3-monthly SPI in which the effect of monsoonal variation over Sumatera strongly looks in variations of SPI.
All lead time forecasts were able to simulate drought conditions in 2015, although with varying intensities. In the case of the year 2002, the ONI value was only around 1.2, not all the lead time forecasts were able to simulate the occurrence of drought. Only lead time forecast 0 was able to simulate the occurrence of drought. At the end of 2004, where the ONI value reached 0.7, only lead time 0 was able to simulate the drought weakly. The ability to simulate drought in the ECMWF SEAS5 model depends on the ONI value. The stronger the ONI value, the stronger the drought effect produced in the ECMWF SEAS5 simulation.

Relationship between SPI and number of hotspots over Sumatera Island was evaluated on Figure 3. Increased hotspot due to drought event can elucidate clearly in lead time forecast 0, lead time forecast 1, lead time forecast 2, and lead time forecast 3. This graph shows that the smaller the SPI value (drier conditions), the greater the forest fires (increase number of hotspot). Meanwhile, lead time forecast 4, lead time forecast 5 and lead time forecast 6 could not describe the increase of fire due to drought events. It shows that higher SPI (wetter conditions) induced higher hotspot. It is not realistic conditions.

Based on its consideration, we can apply maximum forecast time just for three next month using ECMWF SEAS5 prediction. We developed regression linear equations to forecast number of hotspots for each lead time forecast. The equations are as follow:

\[ Y = 1255.9022X + 659.8759 \]  \hspace{1cm} (1)
\[ Y = 996.4545X + 1203.4965 \]  \hspace{1cm} (2)
\[ Y = 751.2082X + 1252.7196 \]  \hspace{1cm} (3)
\[ Y = 742.1939X + 1000.4507 \]  \hspace{1cm} (4)

Where \( Y \) is the number of hotspots and \( X \) is SPI based on ECMWF SEAS5. Equation (1) is the formulation to predict number of hotspots in lead time forecast 0, Equation (2) for lead time forecast 1, Equation (3) for lead time forecast 2, and Equation (4) for lead time forecast 3.
4. Conclusion
The utilization of rainfall prediction from ECMWF SEAS5 to predict seasonal hotspot over Sumatera Island has a great opportunity to be continuously developed. The linear relationship between SPI depicting drought is proportional to the increase of the number of hotspots. When the SPI value is more negative, there are an increasing of hotspots. This increased significantly in 2015 when there was a drought due to El Nino, which resulted in massive forest fires (highest hotspot). Application for hotspot prediction just good for next first, second, third and four months, while in fifth, sixth and seventh month, it has inversely relationship.

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