Short Communication

Spatial Indicators for Human Activities May Explain the 2015 Fire Hotspot Distribution in Central Kalimantan Indonesia

Tropical Conservation Science
Volume 10: 1–9
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DOI: 10.1177/1940082917706168
journals.sagepub.com/home/trc
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Abstract
In recent years, fires regularly and extensively took place in Indonesian forest and peatland, inducing a wide range of environmental and economic impacts, particularly the very bad air quality due to smoke haze and the considerable increase of carbon emissions. The causal relationship between Indonesian fires and human intervention has been widely recognized; however, their spatial relationship is still insufficiently observed. This study examines how well the distribution of fire hotspot can be explained by variables indicating human activities, with a case study in Central Kalimantan Indonesia. This study involves five proxy variables for human activities (land uses, land status, distance to road, distance to settlement, and distance to river), in addition to elevation, slope, and one variable pertaining to the existence of peatland. This study hence provides a model for fire hotspot distribution that would be a valuable approach to identify fire risk distribution and subsequently to support fire control, which is currently the most crucial foundation for the success of peatland restoration program in Indonesia.

Keywords
forest fire, peat fire, fire risk modeling, tropical peatland, peat conservation

Introduction

Fire is one of the main drivers of Indonesian deforestation (Tsujino et al., 2016). Forest and peat fires take place almost every year in Indonesia, with several extraordinary damages in some fire occasions. For example, more than 11 million ha of Indonesian forests were destroyed by 1997/1998 fire incident, which is considered as the worst forest fire in Indonesia (Tacconi, 2003). Recently in 2015, forest and peat fires extensively spread in two main islands in Indonesia (Sumatera and Kalimantan), inducing a very bad smoke haze disaster that also affects some neighboring countries such as Singapore, Malaysia, and Thailand (BBC News, 2015; The World Bank, 2015).

The environmental impacts of forest and peat fires have been reported in a wide range of studies (Langman, 2014; Marlier et al., 2015a; Othman, Sahani, Mahmud, & Ahmad, 2014). The most serious and direct impacts include the significant increase of air pollutant (Engling, He, Betha, & Balasubramanian, 2014; Hayasaka, Noguchi, Putra, Yulianti, & Vadrevu, 2014; Kusumaningtyas & Aldrian, 2016), in particular particulate matters from the smoke haze (Fujii et al., 2016; Kusumaningtyas, Aldrian, Rahman, & Sopaheluwakan, 2016). The 2015 smoke haze, mostly coming from peat fires (The World Bank, 2015), is likely to be one of the worst smoke haze in Indonesia (BBC News, 2015). Six provinces in Sumatera and Kalimantan (South Sumatera, Jambi, Riau, West Kalimantan, Central Kalimantan, and South Kalimantan) suffered very bad air quality from the haze, with PM10 concentrations of above 500 $\mu g/m^3$ recorded in several measuring stations (Crippa et al., 2016; The Indonesian Ministry of Health, 2015). Indonesian forest and peat fires also drastically elevate carbon release

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Received 29 November 2016; Revised 23 March 2017; Accepted 24 March 2017

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into atmosphere, putting Indonesia as one of countries with the highest carbon emissions (World Resource Institute, 2016). Fire on peat forest, for example, may contribute to carbon (C) emissions up to 229 ton/ha (Konecny et al., 2016). Another crucial impact of forest fire is the destruction of wildlife habitat. Several Indonesian endemic, endangered species such as orangutan and Sumatran tiger are forest dependent, hence forest degradation due to fires directly threaten their existence and indirectly contribute to the population decrease of those species (Linkie et al., 2003; Nellemann, Milles, Kaltenborn, Virtue, & Ahlenius, 2007).

Formulating strategy to deal with the annual forest and peat fires requires development of an early detection system of the potential fire incidents (de Groot, Field, Brady, Roswintiarti, & Mohamad, 2007). This includes the availability of proper information on spatial distribution of the predicted fires at an acceptable accuracy. The availability of this information may allow for prevention of potential fire, or at least in case of incapability to avoid fire, efforts can be prepared to minimize fire extent and its damaging impacts. However, big challenges remain exist related to the development of fire forecast. This kind of forecast seems to be more complicated, compared with weather forecast, for example, since fire incident in Indonesia is often caused by complex physical and social factors (Dennis et al., 2005). Also, fire incident is likely site specific, where its causing factors may vary site by site (Herawati & Santosa, 2011).

Regarding the challenges, development of fire forecast system requires proper understanding on the characteristics of fire distribution, and proper identification of what factors may significantly explain the distribution pattern. Different models have been developed to deal with Indonesian fires by incorporating range of factors (de Groot et al., 2007; Lestari et al., 2014; Sudiana, Kuze, Takeuchi, & Burgan, 2003). Social factors, which their link to fire accidents is widely recognized (Chisholm, Wijedasa, & Swinfield, 2016; Marlier et al., 2015b), so far are not sufficiently observed in terms of their spatial relationship with fire distribution. A deeper investigation is then urgently required to better understand the relationship. The availability of fire hotspot data, which can be used to approach the occurrence of fire, is highly supportive to build those kinds of understanding.

This study aims to analyze the spatial characteristics of fire hotspot distribution, with emphasis on spatial factors indicating human activities (such as land uses, distance from roads, distance from rivers, distance from settlements, and land status), with a case study in Central Kalimantan Indonesia. Furthermore, how fire occurrences spatially distribute in response to those factors was modeled. Central Kalimantan is selected for this study due to the high rate of deforestation and forest and peat fires in this province (Suwarno, Hein, & Sumarga, 2015; The Indonesian National Institute of Aeronautics and Space, 2015). The largest peat areas in Indonesia is also found in this province, where fire occurrences in peat areas have been widely reported to provide a more complex environmental, social, and economic impacts (Page & Hooijer, 2016; Wijedasa et al., 2017).

Methods

Study Area

Figure 1 presents the geographical information of the area for this study (Central Kalimantan). Central Kalimantan is the third largest province in Indonesia,

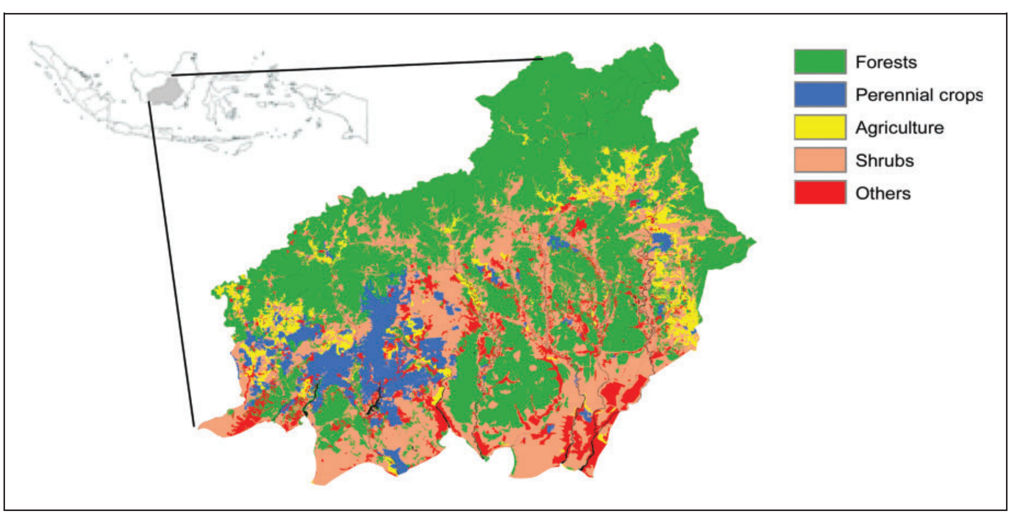

Figure 1. Geographical information and land cover map of Central Kalimantan, Indonesia. The land cover map was generated by reclassifying land cover map 2014 produced by The Indonesian Ministry of Forestry.

with the area of 15,356,400 ha. Although about 65% of this province's area is still forested, the deforestation rate in this province, on the other hand, is among the highest in Indonesia (Broich et al., 2011). During the 2015 Indonesian forest fire, Central Kalimantan suffered the worst peat fire, with burnt peat area of about 190,000 ha (The Indonesian National Institute of Aeronautics and Space, 2015).

Input Data

Two types of data were used for this study: fire hotspot distribution data and environmental data. The fire hotspot data were derived from the NOAA (National Oceanic and Atmospheric Administration), AVHRR (Advanced Very high Resolution Radiometer), and the MODIS (Moderate Resolution Imaging Spectroradiometer) Aqua/Terra satellites. The hotspot data were obtained from The Indonesian Ministry of Forestry database, in which each hotspot contains information about coordinate (latitude and longitude), time (date and hour), and administrative information (province, district, subdistrict, and village). The spatial resolution of both data is 1 km^2, with the hotspot located at the center of pixel, and the typical accuracy of about 73% (Cahyono, Fearns, & McAtee, 2012). This study used the 2015 hotspot data, more specifically, the hotspot data from mid-August to mid-November 2015, in which the extensive forest fire and smoke haze disaster in Central Kalimantan took place (The World Bank, 2015). In total, 14,113 fire hotspots that distribute in 8,872 pixels of 1 km^2 were recorded during the period. Since this study focuses on modeling the spatial pattern of fire occurrence, a binomial response variable is required, and each pixel should be classified only into either ''yes'' or ''no'' in terms of fire hotspot occurrence. This study finally used 8,872 pixels containing fire hotspots as presence points for further analysis. This study acknowledges the limitation of this approach where the density of fire hotspots, which represent the frequency and the length of fire accident in a pixel, is ignored. In terms of fire modeling, however, this approach is useful in supporting an early detection system, in which the distribution of pixels even with a small number of fire hotspot can be detected by the model.

The environmental data used for this study are physical data that provide proxies for human activities, that is, land use map, road map, river map, settlement map, and oil palm concession map. The land use and oil palm concession maps were provided by the Indonesian Ministry of Forestry, while the road, river, and settlement maps were produced by The Indonesian Agency of Geo-spatial Information. The land use map originally consists of 21 land cover classes and 7 layers of land cover from different period (1990–2014). Since this study employs logistic regression modeling that generates a very complicated regression formula when involving categorical predictors with a lot of classes, the newest map (2014) was then reclassified into five classes. Primary dry land forest, secondary (degraded) dry land forest, primary peat swamp forest, secondary peat swamp forest, primary mangrove forest, and secondary mangrove forest were reclassified as *forests*. Estates (e.g., oil palm and rubber) and plantation forest (e.g., acacia) were reclassified as *perennial crops*. Dry land shrubs and peat shrubs were reclassified as *shrubs*. Paddy rice field, dry land agriculture, and dry land agriculture with scattered shrub were reclassified as *agriculture*. The rests of classes (e.g., settlements, bare land, grass land, water body) were then reclassified as *others*. The land cover maps 1990, 2000, and 2014 were also used to detect land cover change that is used to support analysis in the Discussion section. This study also involved additional physical factors, that is, elevation map, slope map, and soil map in terms of whether the soil is categorized as peat soil or mineral soil. The elevation and slope maps were derived from the SRTM-DEM (Shuttle Radar Topography Mission–Digital Elevation Model), while the peat map was provided by Wetland International – Indonesia Program.

All the environmental data were selected due to their availability and their potential relationship with the spatial distribution of fires hence they can potentially be used in developing models for fire forecast. Land use and land status (oil palm concession) inform different types of human activities, which in the context of Indonesia can be linked to the potential use of fire such as in slash and burn practices for traditional shifting cultivation (Medrilzam, Dargusch, Herbohn, & Smith, 2013), land claiming (Purnomo et al., 2017) and in land clearing for agricultural and plantation forestry purposes (Simorangkir, 2007). Settlements, roads, and rivers represent the access of human intervention that may influence the occurrence of fires through two possible ways: by intentionally triggering fires or conversely by preventing potential fires. Rivers may also impact the occurrence of fires through their effect on water table and subsequently on ground or peat moisture (Ainuddin Nuruddin, Leng, & Basaruddin, 2006). Elevation and slope also represent the easiness of human access, where the place with high elevation and steep slope typically has low level of human intervention. Peat distribution is a key factor for fire occurrence in Central Kalimantan due to the high accumulation of flammable biomass during dry season, especially in degraded (drained) peat (Turetsky et al., 2015).

Spatial Characteristics of Hotspot Distribution

To analyze the spatial characteristics of fire hotspot distribution, values of each environmental variables were extracted at all pixels containing fire hotspot. For the categorical variables (land uses, soil types, land status), the characteristics were analyzed based on the proportion of the number of pixels with the existence of fire hotspot in each category of the variables. For the continuous variables, a descriptive statistics was used to analyze the characteristics by calculating some parameters such as mean, range, and standard deviation.

Spatial Patterns of fire Hotspot Distribution

Given that fire hotspot occurrence is a binomial variable, the spatial pattern of hotspot distribution was analyzed using a logistic regression. Logistic regression is a kind of Generalized Linear Model that is usually used to model the relationship between a binomial response variable and some predictor variables (either categorical or continuous variables; Hosmer & Lemeshow, 2000). The general formula for logistic regression is as follows:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_i x_i)}}$$

where
p = occurrence probability
$\beta_0, \beta_1, \ldots \beta_i$ = coefficients
$x_1, x_2, \ldots x_i$ = explanatory variables

This study used the presence and the absence of fire hotspot as response variable. The same number of presence and absence points (i.e., 8,872 points) was involved in this analysis. The absence points were randomly selected from locations presumably having no fire incidents during mid-August to mid-November 2015, that is, at locations with distance more than 5 km from fire hotspots. The values of all explanatory variables at all presence and absence points were extracted. Before incorporating the explanatory variables in logistic regression analysis, correlation among them was evaluated by calculating their variance inflation factor (VIF). Variables with a VIF less than 10 (indicating that there is no multicollinearity problem) were then combined in logistic regression analysis using a statistical software of "R." The accuracy of the regression model was analyzed by measuring its sensitivity, specificity, and area under the ROC curve (AUC). The ROC is a graph of *sensitivity* versus (1- *specificity*) at different thresholds. The *sensitivity* represents the model's accuracy in predicting the occurrence of fire at specific threshold, while the *specificity* does for the absence of the fire. The maximum value of the AUC is 1 which represents a perfect accuracy. The accuracy assessment was analyzed using an "R" script of Rossiter and Loza (2010).

Results

Spatial Characteristics of Fire Hotspot Distribution

Table 1 summarizes the spatial characteristics of the 2015 fire hotspot distribution in Central Kalimantan in relation to the environmental variables used in this study. The pixels with fire hotspots mostly distribute in shrubs areas, that is, about 80%, which is comparable to the proportion of those land cover types in Central Kalimantan (about 79%). Another interesting figure is that about 22% of pixels with fire hotspots spread in the oil palm concession areas, which ideally should have near zero evidence of fires (Lim, Lim, Paris, & Suharto, 2012). The percentage is proportionate with the proportion of oil palm concession areas, that is, about 21% of the area of Central Kalimantan.

In terms of distances to some places with potential human access (roads, settlements, rivers), all distance distributions skew to the right, with skewness higher than 1. This indicates an asymmetric distribution of the distances with the mass of the distribution concentrated in the left (a longer right tail). The variable soil type also provides an interesting figure where about 58% of pixels with fire hotspots distribute in peatland. The proportion is considered too high since peatland only covers about 20% of Central Kalimantan. In terms of elevation and slope, pixels with fire hotspots mostly distribute at lowland with relatively flat slope. The highest place in Central Kalimantan is about 1,280 m above sea level, and the

Table 1. Spatial Characteristics of the 2015 Hotspot Distribution in Central Kalimantan.

Environmental variables	Key characteristics
Land uses[a]	Forests: 2,325 pixels; Perennial crops: 434 pixels; Agriculture: 355 pixels; Shrubs: 4,772 pixels; Others: 986 pixels
Distance to roads	*M*: 14,289 m; *SD*: 16,899 m; range: 73,600 m; skewness: 1.54
Distance to settlements	*M*: 21,970 m; *SD*: 14,297 m; range: 76,120 m; skewness: 1.23
Distance to rivers	*M*: 4,701 m; *SD*: 4,304 m; range: 34,796 m; skewness: 2.1
Land status[a]	Oil palm concessions: 1,928 pixels; non-oil palm concessions: 6,944 pixels
Soil type[a]	Mineral soils: 3,762 pixels; peat soils: 5,110 pixels
Elevation	*M*: 26.6 m; *SD*: 34.7 m; range: 542 m; skewness: 4.3
Slope	*M*: 0.4°; *SD*: 0.9°; range: 22.4°; skewness: 8.8

[a]Data indicate the number of pixels with the occurrence of fire hotspot.

highest elevation where fire hotspot takes place is only about 540 m above sea level.

Spatial Pattern of Fire Distribution

Different from the previous analysis, this section analyses both the distribution of pixels with fire hotspots and the distribution of some randomly sampled pixels with no fire incidents. This section investigates which environmental variables significantly explain the probability of the presence (and the absence) of fire hotspot and additionally provides a model estimating the spatial pattern of fire distribution. Multicollinearity analysis identified that there is no multicollinearity problem among the selected environmental variables (with the highest VIF of only 2.5), hence all variables were then involved in logistic regression modeling. Table 2 summarizes the coefficients of the environmental variables and their significances resulting from logistic regression analysis.

Table 2 shows that all explanatory variables are significant in explaining the probability of the occurrence of fire hotspot, with p values considered as 0 (confident level considered as 100%). With the full model (all variables are included), the coefficients indicate that the higher probability of fire hotspot occurrence is potentially found in shrubs areas (compared with the other land uses), peat areas, oil palm concession areas, low elevation areas, steep slope areas, areas close to settlements, and areas far from roads and rivers. The success of the regression model is described in Figure 2. At a probability threshold of 0.5, the model performs better in predicting the occurrence of fire hotspot compared with predicting the absence of fire hotspot. The sensitivity of the model is 0.8 (7,124 out of 8,872 hotspot occurrences are correctly predicted), while its specificity is 0.74 (6,589 out of 8,872 absence points are correctly predicted). Overall, the model provides a high accuracy with an AUC of 0.86.

By applying the general formula of logistic regression, using the independent variable maps and the coefficients listed in Table 2, a map of predicted probability of fire hotspot occurrence in Central Kalimantan can then be generated as presented in Figure 3. This map estimates that about 36% areas of Central Kalimantan (5.5 million ha) are under risk of fires (with probability of fire occurrence more than 0.5), particularly during the periods with extreme drought as it took place in this province in 2015. The average fire probability is 0.36 with a *SD* of 0.31.

Table 2. Coefficients and p Values of Explanatory Variables.

Predictors	Coefficients	p
Intercept	−6.178e-01	<2e-16***
Land uses (perennial crops)	5.956e-01	1.76e-10***
Land uses (forests)	4.595e-01	3.19e-09***
Land uses (shrubs)	1.774e+00	<2e-16***
Land uses (others)	1.416e+00	<2e-16***
Distance to roads	3.519e-05	<2e-16***
Distance to settlements	−2.221e-05	<2e-16***
Distance to rivers	3.019e-05	2.54e-07***
Land status (oil palm concessions)	3.555e-01	8.86e-14***
Soil types (peat)	1.076e+00	<2e-16***
Elevation	−1.962e-02	<2e-16***
Slope	1.528e-01	<2e-16***

***$p = 0$.

Discussion

Significant Factors Explaining Fire Hotspot Distribution

This study identifies five proxy variables for human activities that are capable of explaining the probability of fire

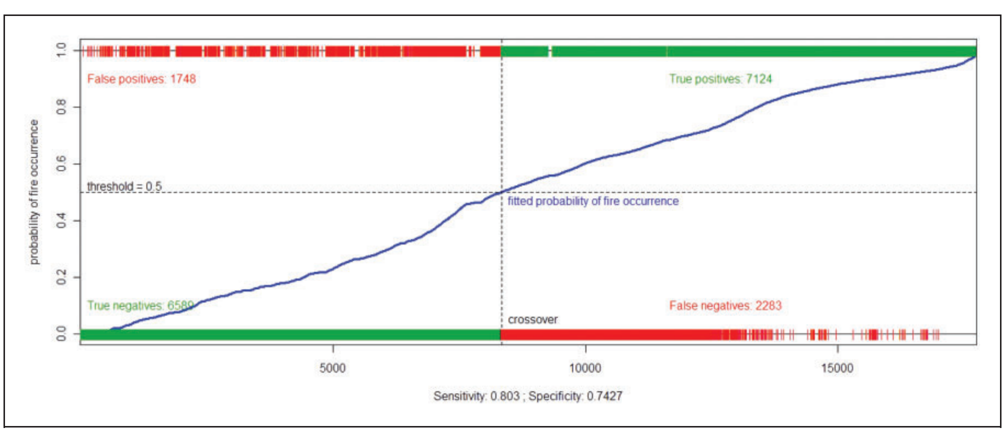

Figure 2. The success of fire hotspot occurrence model.

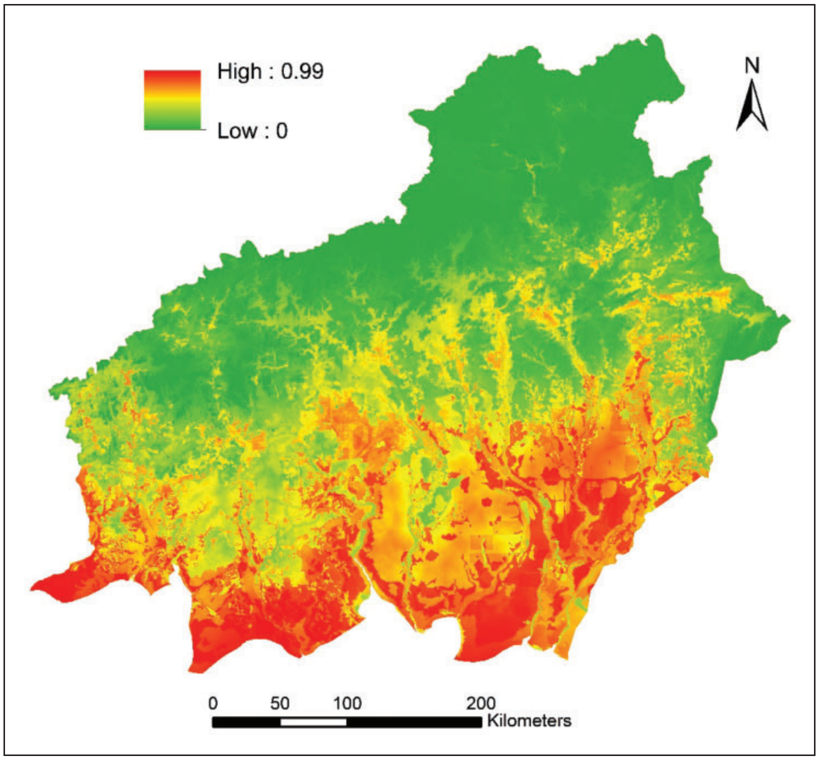

Figure 3. Map of predicted probability of fire hotspot distribution in Central Kalimantan, Indonesia, generated from logistic regression model.

hotspot occurrence in Central Kalimantan, that is, land uses, land status, distance to roads, distance to settlements, and distance to rivers. The hotspot distribution can also be significantly explained by the additional physical factors involved in this study, that is, elevation, slope, and soil type. This section discusses three significant factors (land uses, land status, and soil types), which are considered to have relevance with current environmental issues and further to policy implications.

Compared with other land cover types, shrubs have the highest probability for fire occurrences. This is also confirmed by the fact that the highest number of fire hotspot is found in shrub areas. Indonesian shrub is one of the typical transition types of land use conversion from natural forests into man-made land uses such as agriculture and perennial crops (Medrilzam et al., 2013), including oil palm plantations. Analysis of land cover change in Central Kalimantan 1990 to 2014 shows that about 1,344,000 ha out of 11,014,000 of forests in 1990 have been deforested into shrubs in 2000, and 178,000 ha of them were then converted into man-made land uses in 2014. These areas account for about 21% of man-made land use areas in 2014 which were forested in 1990. Both natural and assisted secondary succession processes may actually allow for reforestation from shrubs, but unfortunately, land cover change data show the very low success of this kind of reforestation. In the context of Central Kalimantan, only about 0.3% of shrubs areas in 2000 are eventually forested in 2014. Related to the finding of this study, in terms of reforestation, the high probability of fire in shrubs seems to worsen the reforestation processes. Moreover, local communities usually still apply slash-and-burn practices to clear shrub land for agricultural purposes, which potentially lead to uncontrolled fires (Medrilzam et al., 2013).

In terms of land status, areas with oil palm concessions are estimated to have higher probability of fire hotspot occurrences. This is interesting given the fact that only about 22% of the hotspots distribute in oil palm concession areas. The distribution of absence points may contribute to this pattern, where most of the randomly selected absence points (about 83%) are found in areas with no oil palm concession. This finding warns about another potential environmental effect of oil palm expansion. In the context of Central Kalimantan, there has been an exponential growth of oil palm areas from 257,000 ha in 2000 to 394,000 ha in 2005 and 1,200,000 ha in 2010 (Sumarga & Hein, 2016). Depending on the regulations to be applied, the oil palm areas will continue to increase with estimated expansion from about 600,000 ha to 1,200,000 ha during 2015 to 2025 (Sumarga & Hein, 2016). The environmental effects are known to be higher from oil palm expansion on peat, particularly due to carbon emissions and irreversible peat subsidence, with subsequent effect on regular and permanent flooding (Sumarga, Hein, Hooijer, & Vernimmen, 2016). The illegal use of fire in land preparation practices will enhance amount of released carbon and more importantly lead to smoke haze disaster with its complex health and economic impacts (Koplitz et al., 2016). Best practices for oil palm cultivation, both on peat and mineral soils, requires a zero use of fire (Lim et al., 2012). The findings of this study hence reveal that at least at current time, independent of naturally or intentionally ignited, fires are still commonly and potentially linked to oil palm cultivation. This is in line with findings from several studies, for example, Marlier et al. (2015a) and Cattau et al. (2016). Please note that not all oil palm, both developed by companies and smallholders, is currently cultivated inside oil palm concession areas. Depending on the status of land ownership, this may indicate the illegal development of oil palm.

Another significant factor is soil type, where the probability of fire hotspot occurrence in peat areas is higher than the one in non-peat areas. The hotspot data also show that about 58% of the pixels with hotspots occurrence distribute in peat areas. This finding confirms a wide range of analysis and studies indicating the vulnerability of peatland to fires (Herawati & Santosa, 2011; Page & Baird, 2016; Turetsky et al., 2015). Drainage practices in various peatland uses (such as for agricultural crops, oil palm plantations, rubber plantation, plantation forest, and selective logging in natural forests) highly contribute to escalate the flammability of the areas. In dry season, drained peat tends to be more sensitive to fire due to the high availability of dry, flammable materials (Turetsky et al., 2015). Peat drainage, with water tables commonly more than 60 cm from the peat surface, easily discharges surface and sub-surface water into rivers and subsequently decrease the wetness and the moist of peat layers (Lim et al., 2012). Besides escalating the fire risks, this condition also creates additional difficulties in fire fighting, since fires potentially burn both surface and sub-surface layers of peat (Rein, 2013).

Implications for Conservation

Conservation of tropical peat ecosystem is one of the major environmental issues in Indonesia. Tropical peat ecosystems, particularly natural peat forests, provide a wide range of benefits for society, prominent among them are carbon storage, water regulation, biodiversity habitat, and timber and non-timber forest products. However, in the last two decades, Indonesian peat forests have been extensively converted and degraded (Miettinen, Shi, & Liew, 2011). Comparison of land cover map 2000 and 2014 shows that nearly 3 million ha of natural peat forests have been converted into different types of land uses, including for oil palm and acacia plantations.

This study notifies that in terms of fire risk, at least for the case of Central Kalimantan, peatland is highly under threat. Supported by several factors indicating human activities (land uses, land status, and distances to road and settlements), this study further may identify the distribution of peat areas with high probability of fire incidents. Considering the complex environmental, economic, and social impacts of peat fires, and the fact that fires commonly lead to peat degradation and further to peat conversion, it is urgently required to assign fire control as the top priority of the Indonesian peatland conservation programs.

In response to the 2015 haze disaster, which is mostly due to peat fires, Indonesian government established a new national agency responsible to peat restoration (i.e., Peat Restoration Agency) in early 2016. The main task of this agency is to restore about 2 million ha of degraded peatland in 5 years (2016–2020), with degraded peatland in Central Kalimantan as one of the priority regions. In the context of peat restoration in Central Kalimantan, the main contribution of this study is particularly in the identification of peat areas with high probability of fires, which would be the valuable input for determining the focus areas for fire prevention actions, for example, through the rewetting program and the artesian well construction. The success of peat fire control will be a critical point for the Peat Restoration Agency, at least for two reasons. First, compared with the success of the other restoration programs, the success of peat fire control can be the most immediate indicator for the agency's performances, given peat fires potentially take place annually. This is also the easiest way for most people to understand whether a better peat management have been implemented. Second, the success of peat fire control will be a key requirement for the other restoration programs. With fires still regularly and extensively take place in Indonesian peat, the success of peat restoration programs such as reforestation and paludiculture development, will be impossibly achieved.

Conclusion

This study investigated the spatial relationship between fire hotspot distribution and physical factors indicating human activities in Central Kalimantan Indonesia. Five proxy variables for human activities, in addition to elevation, slope, and variable indicating peat existence, were examined. This study found that all selected variables can significantly explain the spatial pattern of fire distribution. More specifically, this study identified that a higher probability of fire occurrence is potentially found in shrub areas on peatland with specific distances to road and settlements, including in oil palm concession areas. This pattern, particularly the high probability of fire on peatland, indicates that environmental hazards such as smoke haze, and its complex health and economic impacts will remain unavoidable in case there is no proper fire control. In the context of fire control, this study hence contributes in identifying sites where fire prevention should be focused in in order to effectively mitigate the damage impacts of fires. In a broader context, this study also confirms the state of emergency of Indonesian tropical peatland and suggests an integrative approach with fire control as a key step in peatland restoration program.

Acknowledgments

This study was benefited from the availability of fire hotspot and other spatial data provided by The Indonesian Ministry of Forestry. I thank two anonymous reviewers for their comments and suggestions.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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