



## Fire Regime in a Peatland Restoration Area: Lesson from Central Kalimantan

(*Rezim Kebakaran Hutan dan Lahan di Area Restorasi Lahan Gambut: Studi dari Kalimantan Tengah*)

Bekti Larasati<sup>1,2\*</sup>, Mamoru Kanzaki<sup>1</sup>, Ris H. Purwanto<sup>2</sup>, & Ronggo Sadono<sup>2</sup>

<sup>1</sup>Department of Forest Science and Biomaterials, Kyoto University, Kyoto, 6068501

<sup>2</sup>Department of Forest Management, Universitas Gadjah Mada, 55281

\*Email : [bekti.larasati@ugm.ac.id](mailto:bekti.larasati@ugm.ac.id)

### ABSTRACT

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Peat fires have caused carbon emissions and damage to local and regional communities in Indonesia. An effective fire prevention system is required for mitigating climate change and enabling sustainable development of peatlands. This study examined the fire regime in a peatland restoration area in Central Kalimantan in order to assist the establishment of a fire prevention system. The fire regime was analysed using spatial-temporal analysis, land cover change mapping, and logistic regression analysis. Spatial-temporal analysis was done using monthly Niño 3.4 sea surface temperature anomalies, daily rainfall, and MODIS Active Fire (MCD14DL) hotspots from 2006 to 2015. Land cover change was mapped using Landsat imagery from 2014, 2015 and 2016. Logistic regression analysis was conducted to identify significant factors that increase fire risk. The temporal analysis showed that the strongest El Niño occurred in 2015, when the region experienced a 140-days drought period. The highest number of hotspots was also observed in this year, with hotspots concentrated in the latter half of drought period. Moreover, spatial analysis using Kernel Density Estimation (KDE) showed fire recur in degraded areas. The logistic regression analysis used topographic and proximity factors, land cover classes, and soil types as independent variables. It showed that fire in 2014 and 2015 was associated with several land cover classes and was related to historical fire occurrence areas based on KDE results. Several area of peatland forests burned in 2015 and occurred at the forest edge areas located near cultivated or degraded land (e.g. shrubland) and oil palm plantations. Based on the results, the fire regime in the study area is characterized by fires that occurring/recurring in relation to climatic conditions, especially drought periods, and are typically located in cultivated or degraded land cover classes. These parameters should be considered in developing a fire prevention system in the restoration area.

### INTISARI

#### KATA KUNCI

lahan gambut  
area restorasi  
rezim kebakaran  
GIS  
penginderaan jauh

Kebakaran di lahan gambut menyebabkan emisi karbon dan kerusakan sistem kehidupan masyarakat lokal dan regional. Sistem pencegahan kebakaran yang efektif diperlukan untuk mitigasi perubahan iklim serta mendorong pembangunan lahan dan hutan yang lestari di kawasan gambut. Studi ini meneliti tentang

rezim kebakaran hutan dan lahan di suatu kawasan restorasi gambut di Kalimantan Tengah. Rezim kebakaran hutan dan lahan dianalisis menggunakan analisis spasial-temporal, perubahan tutupan lahan, dan regresi logistik. Analisis spasial-temporal menggunakan parameter nilai rata-rata *sea surface temperature* (SST) bulanan, curah hujan harian, dan *hotspot* dari MODIS *Active Fire* (MCD14DL) tahun 2006-2016. Perubahan tutupan lahan dipetakan dengan analisis citra Landsat tahun 2014, 2015 dan 2016. Regresi logistik digunakan untuk menganalisis faktor yang berpengaruh pada peningkatan resiko kebakaran. Analisis temporal terhadap nilai SST tahun 2006-2016 menunjukkan bahwa El-Niño terparah terjadi di tahun 2015 yang memiliki hari tanpa hujan selama 140 hari berturut-turut dan ditemukan titik hotspot terbanyak. *Kernel Density Estimation* (KDE) digunakan dalam analisis spasial dan hasilnya menunjukkan bahwa kebakaran terjadi dan dapat berulang di area terdegradasi. Regresi logistik menggunakan parameter yang terdiri faktor topografis, kedekatan dengan sungai/kanal, tipe penutupan lahan, serta jenis tanah. Hasil analisis menunjukkan bahwa kebakaran tahun 2014 dan 2015 berhubungan dengan beberapa tipe tutupan lahan di area yang secara historis pernah terbakar berdasarkan analisis KDE, sehingga area tersebut terindikasi telah terdegradasi sebelumnya. Beberapa area hutan di lahan gambut juga mengalami kebakaran pada tahun 2015 khususnya di area tepi hutannya. Berdasarkan hasil, rezim kebakaran di area studi dapat dijelaskan bahwa kebakaran terjadi dan dapat berulang karena pengaruh iklim.

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## Introduction

Tropical peat is an organic soil usually comprised of 65% or more organic matter with a thickness of 30 cm or greater (Rieley & Page, 2016), organic carbon content (by weight) of at least 12% (Osaki et al. 2016), and composed of a partially decayed accumulation of plants (Huat et al. 2011; Keddy et al. 2009; Jaenicke et al. 2008; Joosten & Clarke 2002). Indonesian peatlands are located on the islands of Sumatera (6.44 million ha), Kalimantan (4.78 million ha), and Papua (3.69 million ha) with a total estimated area of 14.91 million ha (Ritung et al 2011; Osaki et al. 2016). Peat soil is a high carbon reservoir ecosystem (Shimamura 2016). The estimated carbon stock of Indonesian peatlands is around 27 Gt C (Shimada et al. 2016) of the 29.9-67.6 Gt C stored within Southeast Asian peat. Therefore, Indonesian peatlands play a prominent role in the context of global climate change.

Massive peatland development in the 1990s converted peatland forests into paddy fields, oil palm plantations, fast growing tree plantations, and degraded shrub and grassland landscapes (Shimamura 2016; Hooijer et al. 2010) which has been

decreasing rapidly over the last few decades owing to deforestation, drainage and fire. In this paper we estimate the carbon dioxide (CO<sub>2</sub>; Page et al. 2002). The conversion of land cover and the construction of drainage canals caused peatland degradation, carbon emissions and increased fire risk (Langner et al. 2007; Cochrane 2003). Deforested degraded peatlands are threatened by fires and have a higher risk than mountain forests which are less accessible (Langner & Siegert 2009). An estimated 25.1% of Indonesian peatlands are considered degraded land (Wahyunto & Dariah 2014). Degradation of peatlands causes a decrease in ground water levels and leads to increased oxidation and drainage of peat which can cause fires (Jaenicke et al. 2010).

Langner and Siegert (2009) said that fire-affected area in El Niño conditions was usually three times larger than in normal weather conditions. During El Niño years, which are usually defined using Sea Surface Temperature (SST) anomaly data, rainfall intensity is affected, causing a prolonged drought period during the dry season in Central Kalimantan (Putra & Hayasaka 2011). The relationship between SST and the probability of fire occurrence was also

described by Manzo-Delgado et al. (2004). Previous studies have also shown that nearly 3 million hectares of Kalimantan forests were lost during two El Niño events in 1997–1998 and 2002 (Siegert et al. 2001; Fuller et al. 2003).

In addition to climate factors, fires are highly correlated with human activities. Fires do not occur randomly but often appear close to forest edges or in forests disturbed by logging (Cochrane 2003; Siegert et al. 2001). Around 98% of all forest fires were detected in a 5 km buffer zone from the forest edge, which is the area most accessible for anthropogenic activity (Langner et al. 2007). Moreover, once a forest has been burned, the probability that it will be burned again is high (Langner et al. 2007; Cochrane 2003; Siegert et al. 2001).

Remote sensing and Geographic Information Systems (GIS) are useful tools to assess forest fire problems (Siljander 2009). Previous studies have utilized remote sensing and GIS to analyse deforestation and forest degradation patterns in tropical peatland forests. Usman et al. (2015) used GIS to observe hotspot distribution in peatland areas in Sumatra; Takayama et al. (2013) used hyperspectral data for assessing peatland forest conditions; and (Hayasaka et al. 2016) used peat ignition tests, surface temperature measurements, and peat fire propagation measurement to identify and map actual peat fire conditions in Kalimantan. Remote sensing and GIS are particularly advantageous for forest mapping at regional or global scales, as time-consuming and high-cost terrestrial measurements can be avoided. As peatland forests have unique characteristics that make them particularly difficult to access using terrestrial inventory, the utilization of these tools is required.

The Central Kalimantan restoration area evaluated in this study has experienced fires almost every year for the last 10 years. In addition, the El Niño phenomenon in 2015 caused a long drought period and further increased the fire risk in restoration area. Effective fire control and prevention efforts are required for climate change mitigation and sustainable development of peatland areas. To ensure efforts are effective, an understanding of the fire regime is required. The term fire regime is usually

used to describe wildfire and fire recurrence patterns. This can include the frequency, size, seasonality, intensity, and type of fires, as well as the conditions that increase fire risk such as fuel type, weather, and so on (Krebs et al. 2010). This study examined the fire regime in a restoration area and its surrounding area to assist with the establishment of a fire control and prevention system. Therefore, this study aims to analyse the relationship between rainfall, sea surface temperature anomalies, and hotspots; evaluate the impact of fires on land cover change and determine the significant factors which increase the fire risk.

## Materials and Methods

### Study area

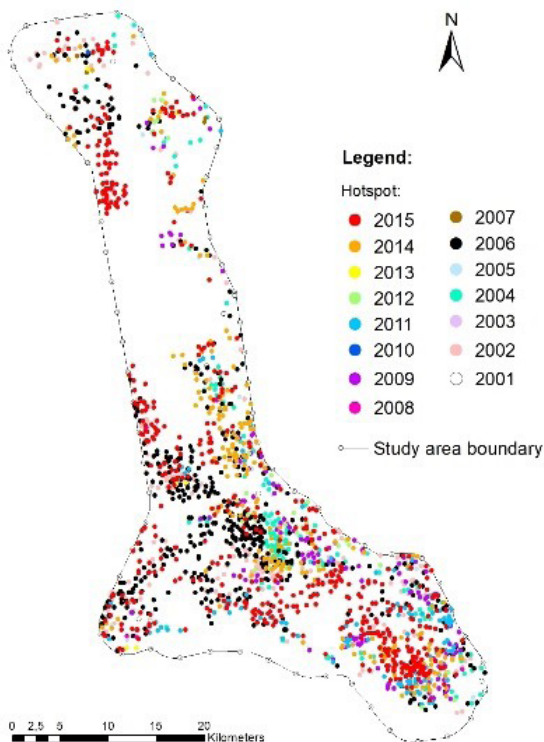
The study was conducted in a restoration area in Central Kalimantan Province, Indonesia. This restoration area aims to protect the peatland ecosystem and the habitat of several endemic species in Borneo's peatland from further encroachment such as expansion of oil palm plantation. The name of the restoration area was hidden for confidentiality. The study covered a 125,844-ha area consisting of the restoration area and 3-km buffer area. The study area was dominated by peatland falling into various land cover class including peatland forest, shrubland, wetland, grassland, burnt area, as well as non-peat landscapes including coastal forest, farmland, fishpond, mangrove, oil palm plantation, riparian forest, and water body. The study area was surrounded by nine villages and its community make their living from fishing, hunting, and farming.

### Fire data

1,539 hotspot data from 2006 to 2015 were used in this study (Figure 1). The hotspot data was observed from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite supplied by Fire Information for Resources Management System (FIRMS) from NASA. This data was commonly used in previous studies, especially to examine spatiotemporal pattern of fire such as Field et al. (2016), Thoha et al. (2014), Yulianti et al. (2012), and Tansey et al. (2008). This data was also selected here because the Indonesian Government utilizes this tool to monitor fires occurrence (see <http://www.sipongi>).

menlhk.go.id). Moreover, the MODIS satellite has high temporal resolution and the hotspot data are freely accessible from the website, earthdata.nasa.gov.

Hotspots are acquired from the Terra and Aqua satellites (MCD14DL) that detect fires from thermal anomalies (Giglio 2005). Each hotspot represents the centre of a 1 km<sup>2</sup> pixel. Terra passes over equator at approximately 10:30 am and 10:30 pm each day while Aqua passes over equator at approximately 1:30 pm and 1:30 am. Hotspot data are also equipped with confidence level information that indicates the quality of the individual hotspots (Giglio 2005). Hotspots are categorized as low confidence (<30%), nominal confidence (30-80%), and high confidence (>80%) (Giglio 2010). For monitoring tropical peatland forest fires, Tansey et al. (2008) suggested for using all available confidence levels, as the smouldering fires typical in peatland forests may cause low certainty. Therefore, this study used hotspot data from all available confidence levels.



**Figure 1.** Distribution of hotspot 2006-2015  
**Gambar 1.** Distribusi hotspot tahun 2006-2015

## Precipitation data

Daily precipitation data were obtained from the Iskandar Climatology Station. This dataset was used as historical precipitation data from the restoration area were not available at the time of the study. Daily precipitation data from 2010, 2014 and 2015 were used to compare precipitation patterns in lower fire frequency years and higher fire frequency years.

## Sea surface temperature (SST) anomalies

The El Niño phenomenon was investigated using Sea Surface Temperature (SST) anomalies for the Niño 3.4 region (1200 T - 1500 W and 50 N - 50 S), which were obtained from National Oceanic and Atmospheric Administration (NOAA) (Trenberth & Stepaniak 2001). SST anomalies can be used to detect the extent to which temperatures depart from normal conditions (Putra & Hayasaka 2011). An El Niño occurs when SST anomalies exceed +0.4°C for at least 6 months or longer and a La Nina occurs when SST anomalies fall below -0.4°C (Trenberth 1997).

## Topographic data

Several studies confirm that topographic factors have a significant influence on fire occurrences (Mukti et al. 2016; Mohammadi et al. 2014; Lozano et al. 2007). Therefore, we extracted topographic factors from the digital elevation model (DEM) Shuttle Radar Topography Mission (SRTM) which provided by USA National Geospatial Intelligence Agency (NGA). DEM SRTM Version 3.0 Global 1 Arc Second data, which has a 30 x 30m spatial resolution, was obtained from [gdex.cr.usgs.gov/gdex/](http://gdex.cr.usgs.gov/gdex/).

Topographic data used in this study includes a slope degree map, a slope aspect map, and a topographic wetness index (TWI) map (Figure 2). According to Mukti et al. (2016), fires spread more rapidly in areas with a higher slope degree. Slope degree and slope aspect maps were produced in ArcMap 10.3.1 using the Spatial Analyst tool. TWI map was produced using the Spatial Analyst tool in Arc GIS 10.3.1 based on formula by Beven and Kirk (1979).

$$TWI = \frac{\ln \alpha}{\tan \beta} \dots\dots\dots(1)$$

where  $\alpha$  is the local upslope area draining through a certain point per unit contour length (Specific Catchment Area) and  $\tan \beta$  is the local slope gradient for estimating a hydraulic gradient. TWI is a parameter that usually used for quantifying the topographic control on hydrological process (Sorensen et al. 2006) and for modelling the spatial distribution of soil moisture and surface saturation (Qin et al. 2011).

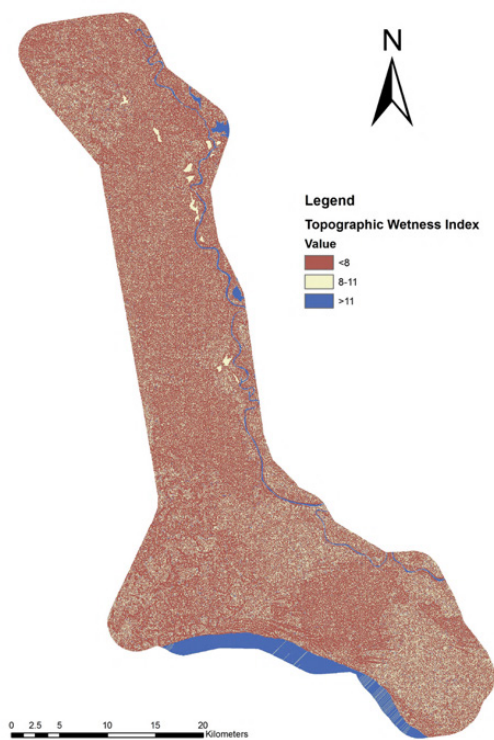


Figure 2. Topographic Wetness Index (TWI) map  
 Gambar 2. Peta Topographic Wetness Index (TWI)

**Soil type**

Soil type data came from the Soil Resource Exploration Map - Pontianak (MA49) at scale 1: 1,000,000. This dataset was produced by the Centre for Soil and Agroclimate Research in Bogor, Indonesia, and was provided by the restoration area manager. The soil types within the study area include Haplohemist Sulfihemists, Endoaquepts Sulfaquents, Endoaquepts Dystrudepts, and Quartzipsamments Durorthods (Figure 3). Grouped by soil taxonomy (Soil Survey Staff 2014), Haplohemist Sulfihemists belong to the histosols group or organic soil, i.e. peat soil; Endoaquepts belong to the inceptisols group,

which is geologically young sediment, for instance in delta areas or wetlands; and Quartzipsamments belong to the entisol group, which is a young soil type that exhibits minimal horizon development.

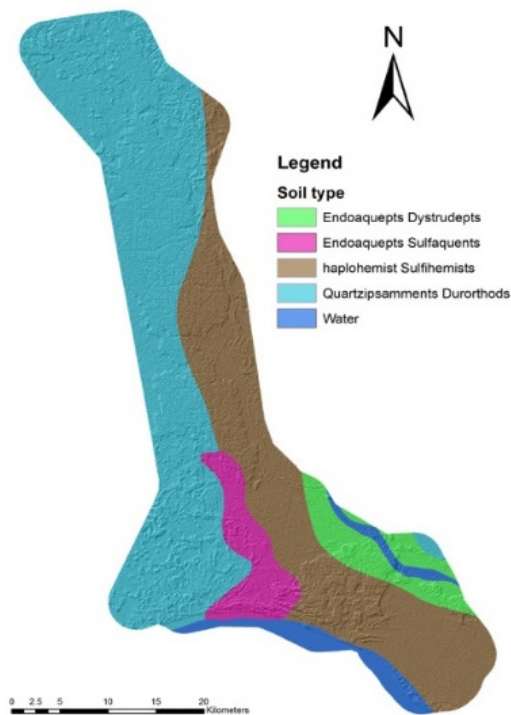
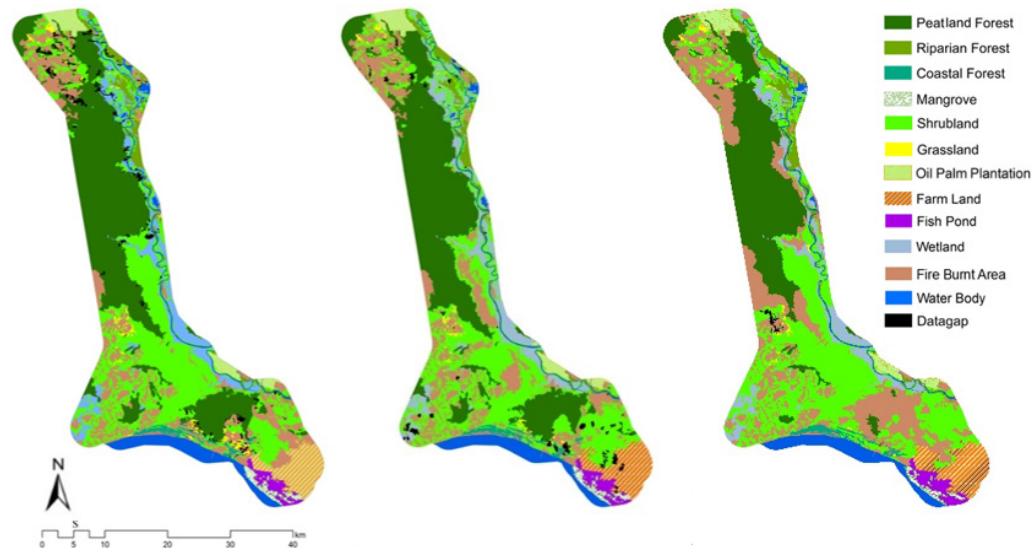


Figure 3. Soil map  
 Gambar 3. Peta jenis tanah

**Land cover class**

Land cover maps from 2014, 2015, and 2016 were used to analyse the land cover change in the study area (Figure 4). The 2014 land cover map was obtained from the restoration area and was created using Landsat imagery (30 meters of spatial resolution). The other maps were produced from Landsat 8 OLI data using a semi-automatic object-based classification method (Jensen 1996). However, to make land cover class consistency, we used the 2014 land cover map as a baseline of 2015 land cover map. This technique was done by comparing the 2014 land cover map with classification results in 2015 as well as the 2015 land cover map was used as a baseline data of 2016 land cover map.

The first stage of object-based classification was done by area segmentation using Feature Extraction tools in ENVI 5.3 with value of edge feature was 10 and merge level was 90. The second stage was grouping the areas based on land cover type homogeneity manually in ArcMAP 10.3.1. We used interpretation



**Figure 4.** Land cover map of 2014, 2015, and 2016  
**Gambar 4.** Peta tutupan lahan tahun 2014, 2015, dan 2016

parameters such as shape, size, pattern, shadow, tone, and texture (Lillesand et al. 2015). The third stage was to fulfil the attributes of landcover class, i.e. peatland forest, shrubland, farmland, etc.

A scarcity of cloud-free images over the study area hampered the analysis. For that reason, we used mosaic techniques to composite images from several acquisition dates to create a cloudless image (Table 1). The 2015 land cover map was created using a mosaic image comprised of Landsat 8 OLI scenes acquired on February 15<sup>th</sup>, April 4<sup>th</sup>, July 9<sup>th</sup>, and July 25<sup>th</sup>. All these images were acquired before fire occurrences in 2015. The 2016 land cover map was created using a mosaic image comprised of Landsat 8 OLI scenes from February 8<sup>th</sup>, April 22<sup>th</sup>, and May 24<sup>th</sup>. We applied band combination 6-5-4 to support vegetation analysis.

A land cover validation was conducted for the latest image (land cover 2016). We visited 136 sample plots during ground checks carried out from March – April 2016 (Figure 5). We placed 49 systematic sampling plots in peatland forests to coincide with the rapid assessment activity of restoration area. The other sample plots were placed randomly by considering the area proportionality of each land cover class (Soraya et al. 2016). Validation data were used to create an error matrix and to calculate the 2016 map's overall accuracy, user's accuracy, and producer's accuracy (Story & Congalton 1986) and kappa coefficient of agreement (Congalton et al. 1983).

There were 12 land cover classes that consist of peatland forest, riparian forest, coastal forest, mangrove, shrubland, grassland, oil palm plantation, farmland, fishpond, wetland, water body and fire burnt area. Fire burnt area is an area that impacted by fires and does not have vegetation cover yet. Some areas were classified as data gap (Figure 5) because of cloud cover. Land cover changes were analysed by constructing a transition matrix from two land cover maps (Gao et al. 2016).

#### Proximity data

Proximity data consists of distance to roads, distance to rivers, and distance to villages (Figure 6). These maps were created in ArcMap 10.3.1 based on administrative maps that were acquired from the restoration area manager.

#### Spatial and temporal analysis

Spatial and temporal analysis was conducted to examine the relationship between rainfall, SST anomalies and fire trends. SST anomaly data were used to determine El Niño and La Nina phenomena from 2006 to 2015. Rainfall data were used to find drought periods in the study area through 10-days period method or divide the 360-days of the year into every 10-days period, for instance early September, mid-September, and late September. This method is simpler than daily analysis (Yulianti & Hayasaka 2013) but has more detail than monthly analysis. A drought

**Table 1.** Information of remote sensing data

**Tabel 1.** Informasi tentang data penginderaan jauh

No.	Remote Sensing Imagery Data	Acquisition Date	Spatial Resolution	Sources
1	Landsat 8 OLI 2015	February 15th, April 4th, July 9th, and July 25th*	30 meters	earthexplorer.usgs.gov
2	Landsat 8 OLI 2016	February 8th, April 22th, May 24th*	30 meters	earthexplorer.usgs.gov

Note: Mosaic technique was applied to the Landsat imageries due to cloud cover issue.

Catatan: Teknik mosaik diterapkan pada citra satelit Landsat karena masalah tutupan awan

period occurs when daily precipitation is lower than the mean precipitation in a year (Putra & Hayasaka 2011). The gradual change of rainfall will be compared to hotspot number in each 10-days period.

In addition, fire density was analysed using the kernel density estimation method to identify fire-affected areas over study period (2006-2015). This method was also used to map the distribution and concentration of fires within the study area (Asgary et al. 2010). All hotspot data from 2006 to 2015 was combined into a shapefile layer and then the spatial

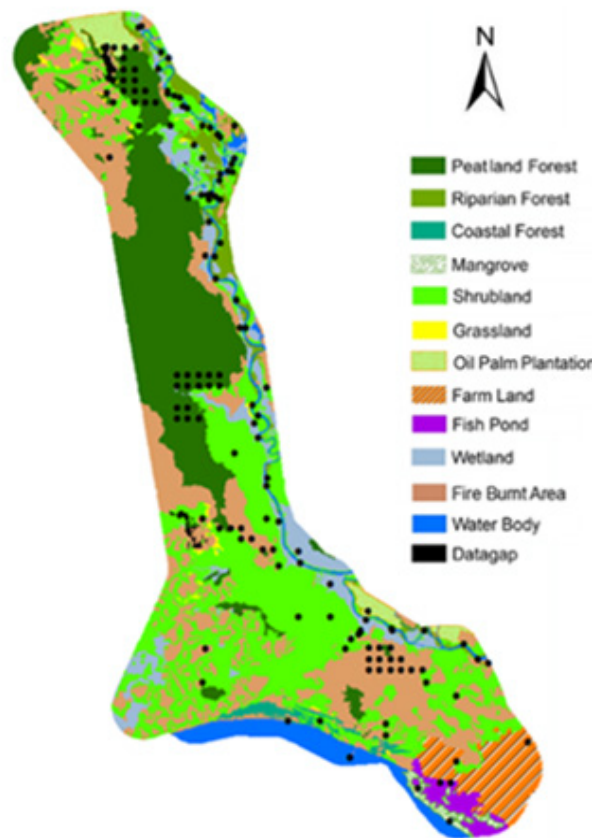
distribution of fire points was modelled using the density kernel function (Takahata et al., 2010). Kernel density is modelled as follows:

$$\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \dots \dots \dots (2)$$

where  $f_h$  is the density distribution to estimate weights,  $x$  is the observed value,  $K$  is the Kernel function, and  $h$  is the width of the Kernel function.

**Fire hazard and logistic regression analysis**

The logistic regression was used to identify factors that influence fire occurrences. We analysed hotspots from



**Figure 5.** Sample plots for ground-checking  
**Gambar 5.** Sebaran plot sampel untuk cek lapangan

2014, a year with less fire frequency, and hotspots from 2015, a high fire frequency year. In each year, hotspots data was divided into two parts, with 80% used for training data and 20% used for validation data (Figure 7).

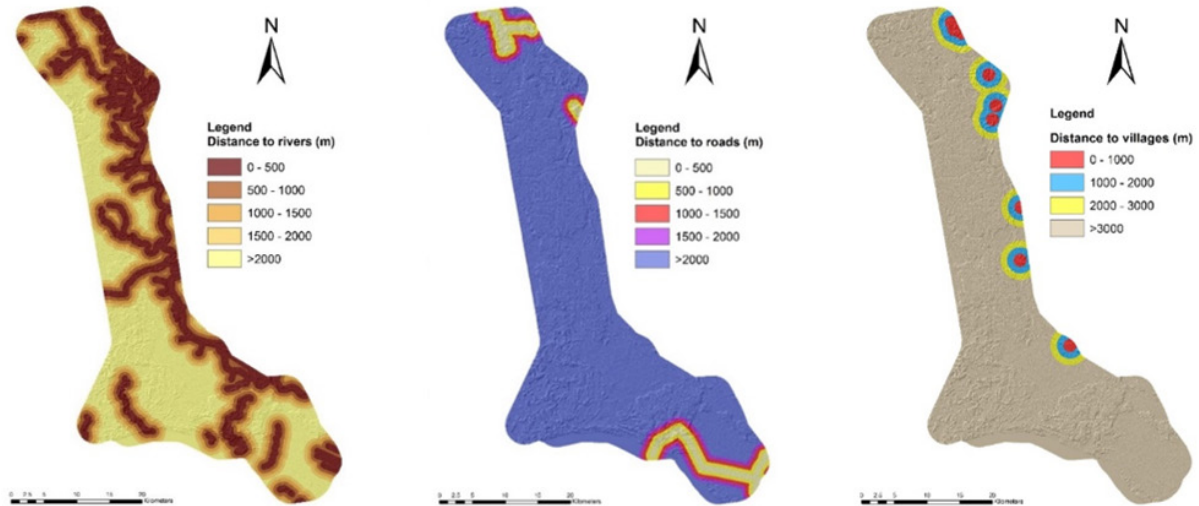


Figure 6. Map of distance to roads, distance to rivers, and distance to villages  
 Gambar 6. Peta jarak ke jalan, jarak ke sungai, dan jarak ke desa

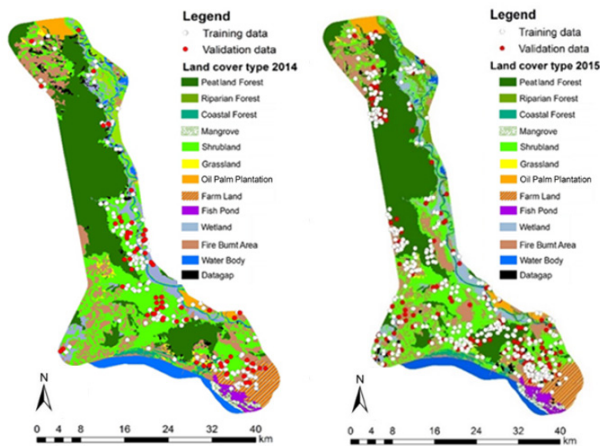


Figure 7. Training and validation sample distribution map of 2014 and 2015

Gambar 7. Peta distribusi sampel *training* dan validasi untuk tahun 2014 dan 2015

Logistic regression employs independent variables to create a mathematical formula to predict the probability that fire occurs on any given parcel of land (Kleinbaum & Klein 2010). The dependent variable is dichotomous (1 and 0), while independent variables can be a nominal, ordinal, interval or ratio scale. The relationship between dependent and independent variables is nonlinear (Kleinbaum & Klein 2010). A stepwise method was utilised to build a model by inputting all independent variables through the subsequent steps. These steps were used to determine which variables are significant and should be added

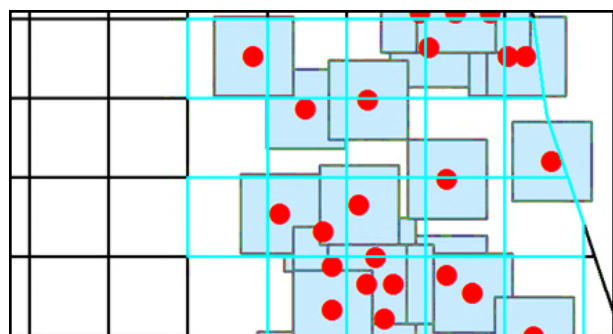
to the model. This analysis was conducted using SPSS Statistic 20.

The logistic regression model was built using dependent and independent variables as described in Table 1. We define the dependent variable by constructing a fishnet polygon which has cells of 1 km<sup>2</sup> area throughout the whole study area. In addition, we converted each hotspot point feature to a square that has 1 km<sup>2</sup> in size with the point feature as the centroid according to MODIS active fire pixel (1 km<sup>2</sup>). Then we overlapped the fishnet polygon with the square hotspot polygons. Every fishnet square that overlapped with the square hotspot polygon was defined as a fire square (1) and all other fishnet squares were defined as non-fire (0) (Figure 8). We then created a fires hazard map using formula as follows:

$$\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \dots \dots \dots (3)$$

where p is the probability of fire occurrence which varies from 0 to 1 on an s-shaped curve, x<sub>j</sub> is independent variable, i is pixel, β<sub>0</sub> and β<sub>j</sub> are estimated coefficients, and k is the number of independent variables.





**Figure 8.** Dependent variable (blue ey line areas = fire, black line areas = non-fire)

**Gambar 8.** Variabel terikat (area dalam garis abu-abu = kebakaran, area dalam garis hitam = tidak terjadi kebakaran)

Fire hazard map were constructed using the logistic regression results and only significant variables were used to build the map. Hereinafter, the significant variables were summed using the raster calculator tool in Arc GIS 10.3.1 software package.

We used a prediction-rate curve and success-rate curve to validate model quality. By comparing the fire hazard map and validation data, we obtained a prediction-rate curve. A success-rate curve was obtained by comparing the fire hazard map with the training data used in the modelling process. Prediction-rate curve provides the validation of prediction while the success-rate curve measures a goodness of fit assuming that model is “correct” (Chung & Fabbri 2003).

The validation method was done using a Receiver Operating Characteristic (ROC) curve in SPSS software. The ROC curve is a graphic representation of the reciprocal relationship between sensitivity and specificity, calculated for all possible threshold

values (Erkel et al. 1998). The indicator from the ROC curve to measure model quality is the area under the ROC curve (AUC). The value range of AUC is from 0 to 1. The closer the AUC is to 1, the better the overall diagnostic performance of model., If a test has a value of 1, the model is perfectly accurate (Erkel et al. 1998; Park et al. 2004; Vanagas 2004).

## Results and Discussion

### Spatial-temporal characteristics

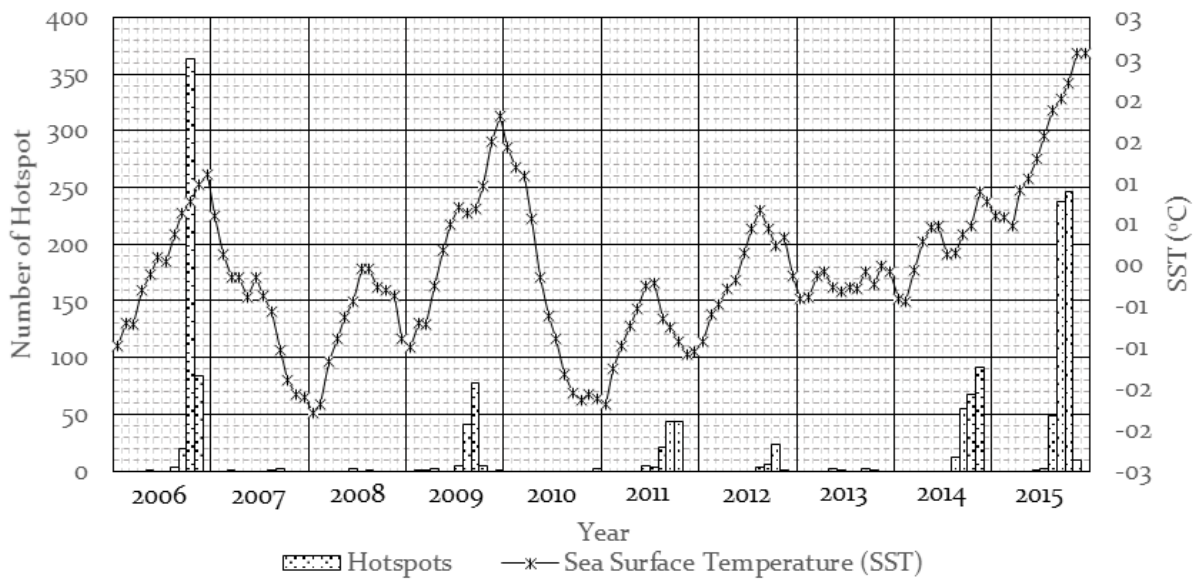
SST anomalies data analysis showed that 2006-2007, 2009-2010, and 2015 were El Niño years and 2007-2008, 2008-2009, and 2010-2011 were La Nina years (Figure 9) based on the Trenberth’s (1997) statement that an El Niño occurs when SST anomalies exceed +0.4°C for 6 months or longer and, conversely, La Nina occurs when SST anomalies are bellow -0.4°C for 6 months or longer. There were fire occurrences in those El Niño years and the biggest number of total hotspots was in 2015. This coincided with SST anomalies that were highest in 2015.

Furthermore, we compared rainfall and hotspot data between 2010, a La Nina year with a lower frequency of fire (2 hotspots); 2014, a normal SST year with a higher frequency of fire (226 hotspots); and 2015, as an El Niño year (546 hotspots) (Figure 10). From 10-days period analysis, we could find that there was no significant drought period in 2010. This means that the precipitation was higher than the other years. Only 2 hotspots were detected in the middle of December when the rainfall was

**Table 2.** Dependent and independent variables for logistic regression model.

**Tabel 2.** Variabel terikat dan variabel bebas untuk model regresi logistik.

Variables	
Dependent (Binary)	Fire (1) and non-fire (0)
Independent	Topographic factor
	1 Slope (<5°, 5°-15°, >15°)
	2 Slope aspect (flat, north, south, etc)
	3 Topographic wetness index (<8°, 8-11°, >11°)
	Proximity factor
	1 Distance from village (<1km, 1-2km, 2-3km, >3km)
2 Distance from river/canal (<0.5km, 0.5-1km, 1-1.5km, 1.5-2km, >2km)	
Soil type (categorical)	
Land Cover type (categorical)	



**Figure 9.** The comparison between number of hotspots and sea surface temperature  
**Gambar 9.** Perbandingan antara jumlah hotspot dan suhu permukaan laut

relatively low. Compared to 2010, 2014 had drought period from late August to late October (a 70-days continuous rainless period). The hotspots were detected starting in early August and stopped in the middle of November, and the total number of hotspots was 226. In 2015, SST anomalies influenced the precipitation intensity and caused the worst drought condition with a 140-day continuous rainless period and the highest occurrence of hotspots (546 spots). Based on other studies, ground water tables decrease and cause peat drainage during drought periods, meaning vulnerable peat can be affected to ignite fire (Putra & Hayasaka 2011; Hirano et al. 2012).

Kernel density estimation (KDE) map shows the areas that experienced fire from 2006 to 2013 (Figure 11). Fire affected areas are marked with dotted lines. Those areas were indicated as degraded land caused by fires. Hotspots in 2014 and 2015 occurred in indicated degraded land area if compared to the historical hotspot area in 2006 to 2013. Therefore, the results were consistent with previous studies showing that degraded land is more susceptible to burning than non-degraded land (Langner & Siegert 2009; Jaenicke et al. 2010).

### Land cover change

The land cover maps used in this study included land cover from 2014, 2015, and 2016. The 2016 land

cover map was validated through ground checks, which were used to calculate an error matrix table (Table 3). A kappa coefficient of 0.91 means the accuracy of the classification was high.

Remark: PF (peatland forest), FBA (fire burnt area), SR (shrubland), RF (riparian forest), OPP (oil palm plantation), WT (water), WL (wetland), FP (fish pond), G (grass), CF (coastal forest), and M (mangrove).

Keterangan: PF (hutan lahan gambut), FBA (area yang terbakar), SR (semak), RF (hutan riparian), OPP (tanaman sawit), WT (air), WL (lahan basah), FP (tambak), G (rumput), CF (hutan pantai), and M (*mangrove*).

Figure 12 shows the relationship between hotspot distribution and land cover changes. For instance, the blue circles in the 2014 and 2015 maps show the changes from shrubland to fire burnt area. Figure 13 shows that hotspot density in shrubland in 2014 was high compared to other land cover classes. In addition, the yellow circle in Figure 12 in 2015 and 2016 showed the changes from peatland forest to fire burnt area. Figure 13 shows that hotspot density in peatland forest increased significantly from 2014 to 2015.

### Significant factors which increase fire risk

The result of our logistic regression analysis is shown in Table 4. The significant variables in 2014

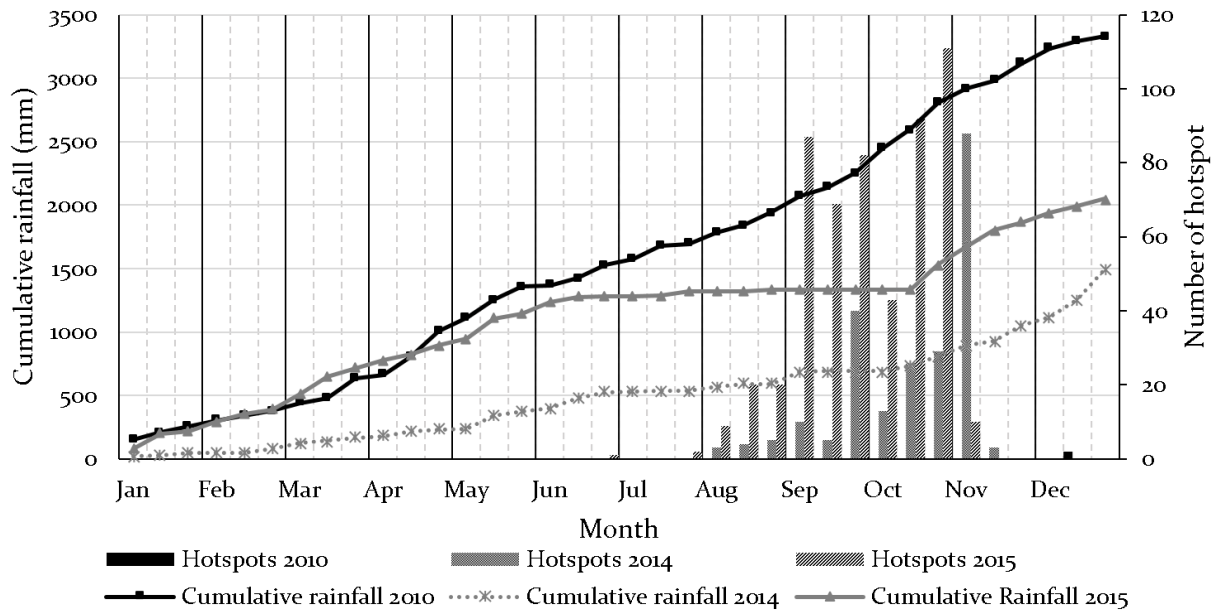


Figure 10. The comparison between cumulative rainfall and number of hotspots in 2010, 2014, and 2015  
 Gambar 10. Perbandingan antara curah hujan kumulatif dan jumlah hotspot pada tahun 2010, 2014, dan 2015

were distance to village, land cover class, with oil palm plantations having the highest likelihood of fire, and soil type, i.e Haplohemist Sulfihemists and Endoaquepts Dystrudepts. The significant variables in 2015 were distance to river, land cover class, and soil type (Endoaquepts Dystrudepts, Haplohemist Sulfihemists, Quartzipsammments Durorthods, and Endoaquepts Sulfaquents). There were several differences in significant variables in 2014 and 2015, for instance distance to village had a positive coefficient ( $\beta$ ) in 2014 yet it did not appear in 2015. Conversely,

the distance to rivers/canals and the peatland forest land cover class both had a positive coefficient in 2015 yet it did not occur in 2014. These differences could be due to the different climatic situations in each year. The SST dynamic in 2014 was relatively more normal and fewer hotspots occurred than in 2015, while 2015 was an El Nino year and had more scattered hotspots, especially in degraded and fragmented forest areas (Figure 12). This result was in line with previous studies about fires in El Nino years, which found that severe fires in 2015 was the worst since 1997 (Albar et

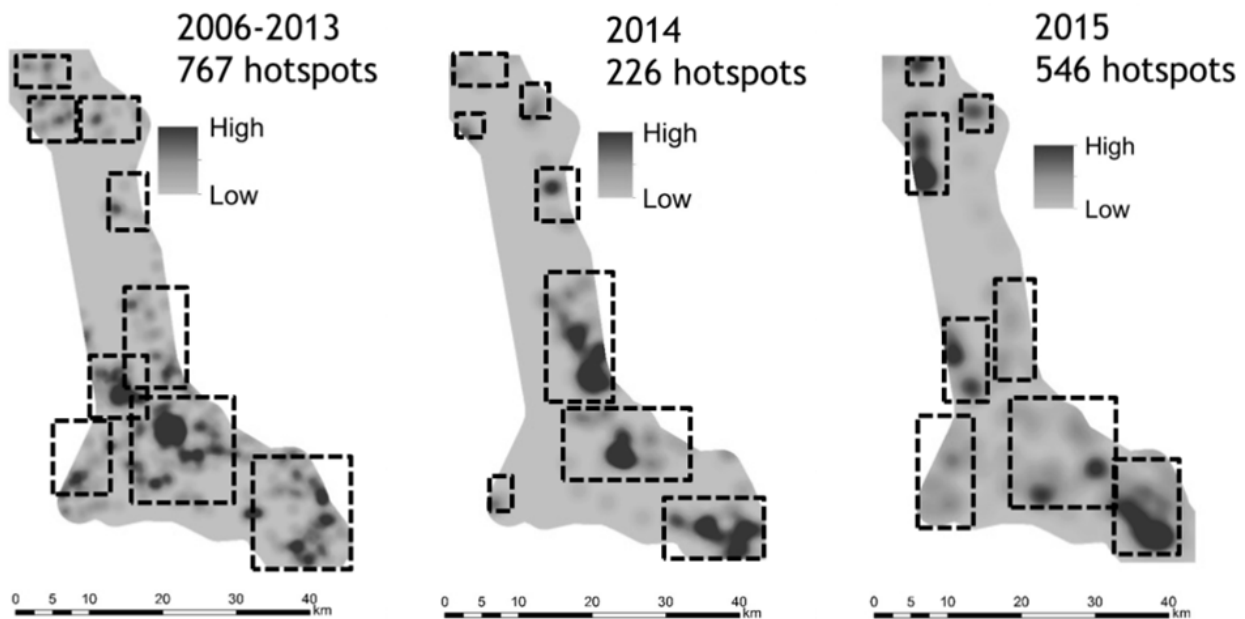


Figure 11. Fire density using kernel density analysis  
 Gambar 11. Kerapatan area kebakaran menggunakan analisis kernel density

Table 3. Error matrix for land cover map 2016

Tabel 3. Matriks kesalahan untuk peta penutupan lahan tahun 2016

		Class types determined from reference source											Totals (Ni)	User's accuracy
		PF	FBA	SR	RF	OPP	WT	WL	FP	G	CF	M		
Class types determined from classified map	PF	49											49	100,0
	FBA		3										3	100,0
	SR	5		27					1				33	81,8
	RF				14								14	100,0
	OPP					8							8	100,0
	WT												13	100,0
	WL			1									7	71,4
	FP									2			2	100,0
	G				1	1						1	3	33,3
	CF										2		2	100,0
	M											2	2	100,0
	Totals (Mi)		54	3	29	15	8	14	6	2	1	2	2	136
Producer's accuracy		90,74	100,00	93,10	93,33	100,00	92,86	83,33	100,00	100,00	100,00	100,00		92,6

al. 2018, Huijnen et al. 2016). Fires occurrence is also related to land use/land cover class (Page & Hooijer 2016). This research also showed that the oil palm plantation and farmland land use/land cover classes contributed to fire risk in restoration area.

The logistic regression models for 2014 and 2015 were tested to determine their feasibility according to several rules, i.e. an Omnibus Tests of Model < 0.05, a Hosmer-Lemeshow test Chi Square result > 0.05, and an area under the curve (AUC) close to 1 (Table

5). The AUC value for 2014 and 2015 was 77 and 0.71, respectively, meaning that 77% and 71% of fires can be predicted by the model (Kleinbaum & Klein 2010).

Table 5. Feasibility test of the regression logistic model

Tabel 5. Tes kelayakan model regresi logistik

Parameter	2014	2015
Omnibus Test of Model Coefficients	p<0.001	p<0.001
Hosmer-Lemeshow test Chi Square	0.78	0.14
AUC and SE	0.77 and 0.02	0.71 and 0.00

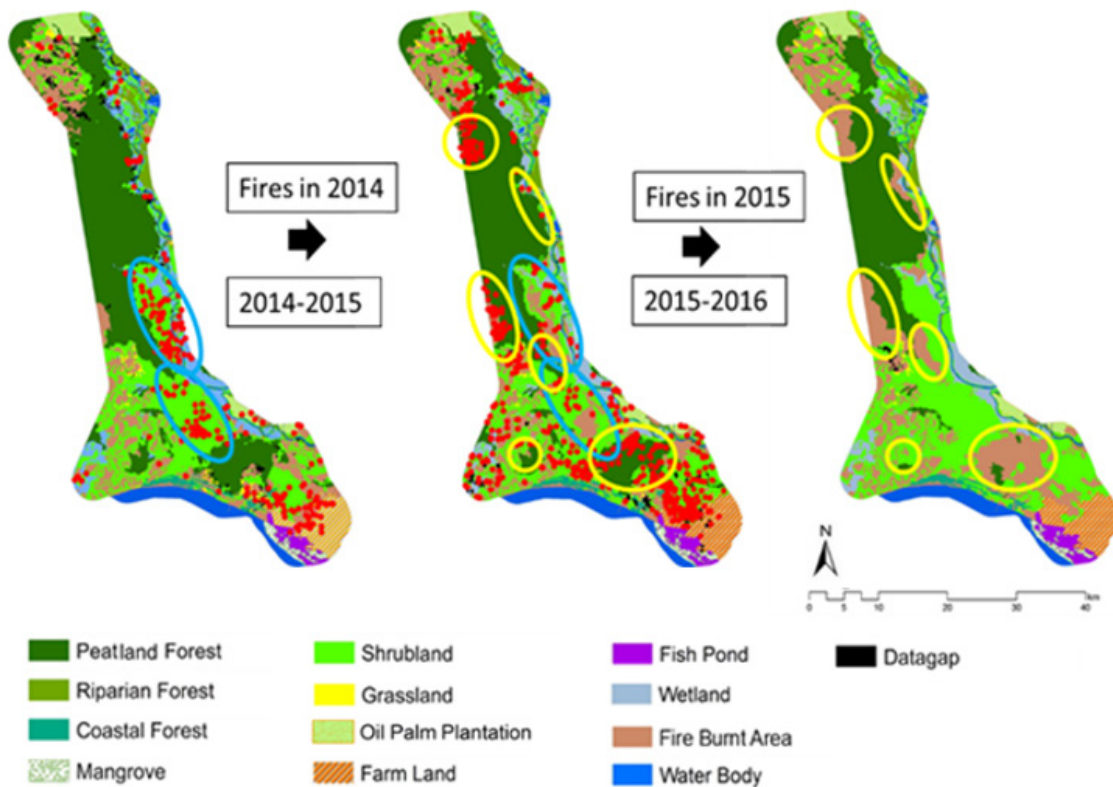


Figure 12. Land cover changes from 2014 to 2015 and 2015 to 2016  
Gambar 12. Perubahan tutupan lahan dari 2014 ke 2015 dan 2015 ke 2016

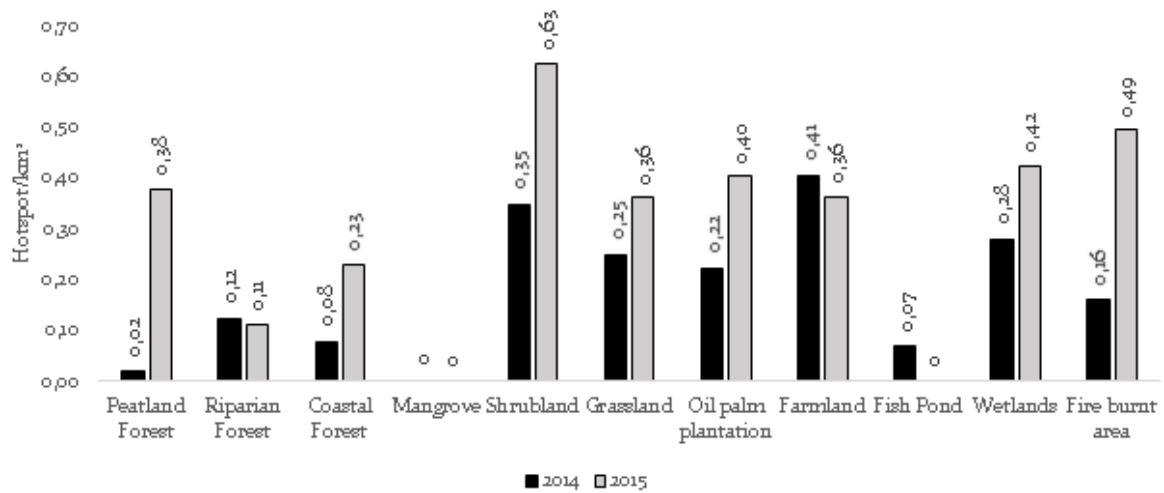


Figure 13. Hostspot density per km² in study area.  
 Gambar 13. Kerapatan hostpot per km² di area studi

A fire hazard map was constructed based on the significant variables identified in the 2015 model (Figure 14). The variables were summed using the raster calculator tool in ArcGIS software packages and an equation based on the logistic regression model as follows:

$$Z = -3.464 + (0.270 \times \text{distance to river}) + \text{land cover class} + \text{soil type} \dots\dots\dots (4)$$

A fire hazard map will be beneficial for developing a fire prevention system because it can identify which areas are prone to fire and should be prioritized. The hazard map shows that the southern area of the restoration area will be more susceptible to future fires. Based on the 2015 land cover map, this area was dominated by degraded land cover such as shrubland, fire burnt area, and degraded peat swamp forest.

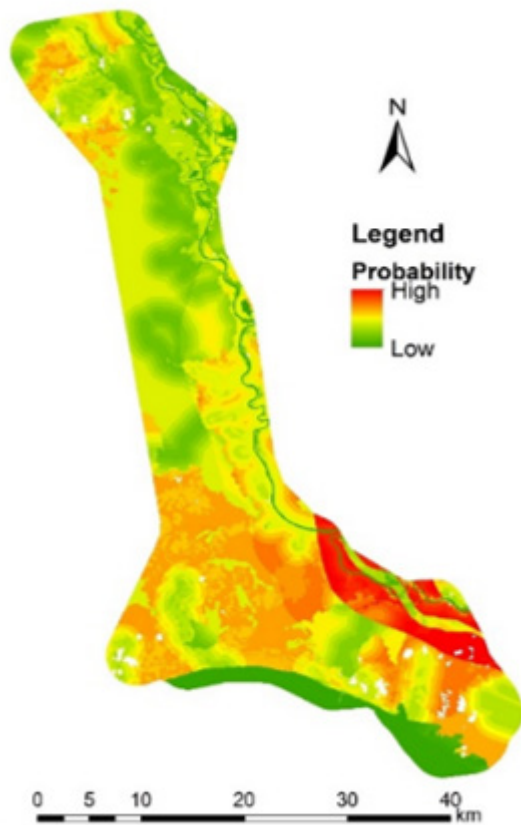
Table 4. The results of logistic regression analysis in 5% of confidence level  
 Tabel 4. Hasil analisis regresi logistik pada level kepercayaan 5%

Variable	2014		2015	
	β	Sig.	β	Sig.
Distance to village	0.475	0.001		
Distance to river/canal	-0.136	0.01	0.27	0
Fire burnt area	1.525	0.003	2.083	0
Coastal forest	1.944	0.006	2.127	0.003
Farm land	1.179	0.04	1.951	0.001
Fish pond	-1.241	0.278	-0.455	0.689
Grass land	0.823	0.402	2.118	0.028
Mangrove	-19.271	0.999	-18.816	0.999
Oil palm plantation	1.949	0.002	2.443	0
Peatland forest	-0.181	0.734	1.5	0.003
Riparian forest	1.35	0.032	1.308	0.037
Shrub land	1.645	0.001	2.325	0
Wetland	1.472	0.007	2.368	0
Endoaquepts Dystrudepts	0.041	0.934	2.323	0
Endoaquepts Sulfaquents	-0.159	0.754	0.256	0.595
Haplohemist Sulfihemists	1.035	0.019	0.569	0.191
Quartzipsamments Durorthods	-0.719	0.107	0.258	0.55

accessed by human (Langner et al. 2007).

Land cover change analysis is necessary in fire regime research because it can determine the relationship between fires and land cover. Based on our results, it can be determined that fires influence land cover changes in study area. In 2014, fires occurred intensively in shrubland, which is one of degraded land cover classes in the study site. These areas were then changed to fire burnt area in 2015. Miettinen and Liew (2010) said that degraded land cover classes were more easily burned than forest cover. This study, however, found a huge area of forest cover that was disturbed by fires and subsequently reclassified as fire burnt area (Figure 12). Based on the comparison between hotspot density in 2014 and 2015 (Figure 14), it was shown that hotspot density in peatland forest increased from 0,02 (2014) to 0,38 (2015). It could be predicted that these forests may have already been degraded (Cochrane 2003; Siegert et al. 2001) because they were fragmented and close to cultivated land e.g. farmland or near the degraded area e.g. shrubland. The KDE analysis results (Figure 11) also confirmed that fires in 2015 occurred in degraded land areas. The degraded conditions and long drought period increased the risk of fire in peatland forest area especially along the forest edge, therefore it is essential to improve fire prevention management and intensively preserve such areas.

Information about significant variables that influence fire risk is important for developing a fire prevention system. The logistic regression results in Table 3, both for 2014 and 2015, confirmed that land cover classes such as oil palm plantations, farmlands, shrublands, fire burnt areas, wetlands, coastal forests, and riparian forests were associated with fire risk. All these land cover classes were in degraded land (caused by fires) when compared to the KDE analysis results (Figure 11). In addition, fragmented and degraded peatland forests were also susceptible to fires during the 2015 El Nino event. The areas that have been burned in 2015 are at risk to future fire as identified in the hazard map. The restoration area shall be more vigilant in areas affected by fire, especially in drought periods.



**Figure 14.** Fires hazard map based on logistic regression model 2015

**Gambar 14.** Peta kerawanan kebakaran berdasarkan model regresi logistik tahun 2015

### General discussion

The fire regime in the peatland restoration area was examined using three kinds of analyses namely spatial-temporal, land cover change, and logistic regression analysis. We used spatial-temporal analysis to characterize the dynamic and pattern of fires based on SST anomalies, daily rainfall and hotspots during 2006-2015. The comparison between SST anomalies, daily rainfall, and hotspot numbers confirmed that climate conditions affected the spatial and temporal pattern of fires. SST anomalies data shows that an El Nino caused a continuous drought period, which drove more severe fire occurrences than under normal climate condition. This confirms the findings of previous studies such as Putra and Hayasaka (2011) and Prasetyo (2016). In addition, the result from KDE analysis shows that degraded land caused by previous fires was more susceptible to burning than non-degraded area. All degraded lands were found on the edges of forests, which are easily

## Conclusion

Three different methods, namely spatial-temporal analysis, land cover change analysis, and logistic regression model, were utilized to characterize the fire regime in our study area. The comparison between the number of hotspots and SST anomalies over a decade from 2006 to 2015 confirmed that fire occurrence increased intensively in El Nino years. The comparison of cumulative rainfall and hotspots between a La Nina year (2010), normal SST anomaly year (2014), and an El Nino year (2015) show that continuous drought periods impact hotspot appearances. The longer the drought period, the higher the number of hotspots occurred, as we found in our comparison of hotspots in 2014 and 2015. In addition to climate behaviour, several degraded land cover classes (e.g. shrubland, oil palm plantation, fire burnt area, degraded peatland forest) were significant factors increasing the likelihood of fire occurrences in the restoration area. We also found that the degraded peatland forests in the study area were more prone to fires during El Nino years than other years, which was also confirmed with our hotspot density analysis (hotspot/ha) that shows a significant difference in hotspot density inside peatland forest between 2014 and 2015. Moreover, this hotspot density clearly affected the land cover changes in peatland forest areas based on the comparison between the land cover maps. Regarding these results, this fire regime information can assist in the improvement of future fires prevention systems within the restoration area.

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