# Forest and land fires spatial model in Riau Province, Indonesia

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**Abstract**. Riau is one of the provinces in Indonesia that often experience forest and land fires. Forest and land fires cause enormous environmental, economic, and social losses and damages that even cause disruption of political relationship between countries. This study aims to determine the relationship between biophysical, socioeconomic, and policy factors in influencing the occurrence of forest and land fires in Riau Province; develop spatial models of forest and land fires vulnerability; and formulate policies on forest and land management and utilization to prevent forest and land fires occurrence. Based on the result of research, the form of logistic regression model is g (x) = 3.57521783 - 0.0000694DIS_PEAT + 0.0001488DIS_RIV - 0.0001306DIS_JLN - 0.0003727DIS_LCFOR - 0.0000763DIS_LCFORP - 0.0000593DIS_LCPLAN + 0.0000604DIS_LCBUIL - 0.0000431DIS_LCUPLD + 0.0000264DIS_IUPHHK + 0.000024DIS_KKEBUN - 0.000074DISSKAPL + 0.0000276DIS_SKHL - 0.0000597DIS_SKHP - 0.0000775DIS_SKHPK - 0.0000653DIS_SKHPT, where R2 is 61.7%. Based on the model, it is known that there is a correlation between forest and land fires variables in Riau Province to distance from 15 variables, i.e peatland, river, road, forest cover, plantation cover, plantation, settlement (built up area), dry land, Timber Forest Product Utilization License, plantation concession, other use areas, protected forest areas, production forests, conversion production forest and limited production forest. Logistic Regression Model that formed can predict the probability of forest and land fires incident of 90.96%.
**Key Words**: Riau, forest fire, spatial model, Spatial Logistic Regression.

**Introduction**. Forest and land fires are natural disasters that often occur in Indonesia, especially during the dry season. These fires cause enormous environmental damage, economic losses, and social problems. In fact, large forest and land fires result in a smoke devastating impact beyond state administrative boundaries (trans-national disasters). According to the Ministry of Health Republic of Indonesia (2015) forest and land fires that occurred in 2015 in some provinces, such as Riau, Jambi and South Sumatra, caused the worst catastrophe in 18 years, causing severe air pollution in some Southeast Asian countries.

Ecologically, the decline of forest area and land degradation due to fires raises the risk and uncertainty in the restoration of ecosystem conditions, the loss of future use value of timber and non-timber forest and the loss of expected value of the currently untapped biodiversity (Bahruni et al 2007).

Some research results indicate that forest and land fires are caused by various environmental factors such as climate, land cover conditions, soil types and other bio-physical environmental factors; socioeconomic factors and policy factors that can enhance human interaction with forests and land (Ruchiat 2001; Tarigan et al 2016). According to Ekadinata & Dewi (2011), the number of land use conversion activities caused by the socio-economic condition of the people and land tenure policy is the main cause of the high number of forest fires in Indonesia. It is therefore necessary to reform forestry policies and arrangements of land use based carrying capacity (Barber & Schweithelm 2000), especially in high-vulnerable ecosystems such as peatlands.

Forest and land fires can occur both inside and outside forest areas, in mineral and peat soils (Saharjo 1997; Page et al 2002; Syaufina 2008). Fires that occur in peatlands are more difficult to overcome because fire can spread through above-ground biomass and in subsurface layers of peat (Sumantri 2007). The smoldering process in this peatland is difficult to know the spread visually (Rein et al 2008). Dry peat conditions due to land clearing and canal/trench can cause peatlands to become flammable, especially in long dry seasons (Jaenicke et al 2010). Related to this matter, Riau Province becomes one of the areas that need special attention because it has peat land area of 3.867.413 ha or 43.61% of the total area (Ministry of Agriculture Republic of Indonesia 2011).

The availability of data/information on the level of vulnerability and the potential for forest and land fires in Riau Province becomes necessary. Geographical Information System (GIS) is one of the methods that can facilitate stakeholders in monitoring and understanding the occurrence of forest fires, whether the incident has occurred or the prediction of fire in the future. Spatial modeling of forest and land fires has been a topic of study by several researchers, using various approaches and considerations, including environmental (biophysical), socioeconomic, and policy factors. Jaya et al (2007) modeled fires using variations in local climate patterns (rainfall), vegetation (land cover, biomass density, and humidity), land use and some related factors such as distance from rivers, roads and settlements. Saito et al (2002) assessed the linkages between hotspots and road/river accessibility as an important factor in fire risk map mapping in Jambi, Sumatra.

The occurrence of forest and land fires is triggered by various factors, both natural and human factors. Natural factors that often trigger forest and land fires are extreme climatic conditions, such as the prolonged dry season due to the El Nino phenomenon. Based on Saharjo & Husaeni (1998) research, forest and land fires in Indonesia are allegedly caused more by the influence of human activity than natural factors. However, a quantitative analysis is needed which explains the linkages and roles of each factor that significantly affect the occurrence of forest and land fires. Different environmental characteristics in each region lead to the need for research that can be a reference in effective and efficient fire control in Riau Province.

This research is directed to study forest and land fires with quantitative analysis approach and spatial modeling of biophysical aspect, socio-economic aspect and policy aspect in Riau Province. Specifically, this study aims to: 1). knowing the linkages between biophysical factors, socioeconomic factors and policy factors in influencing the occurrence of forest and land fires in Riau Province; 2) developing spatial models of forest and land fire vulnerabilities; and 3) formulating policies on forest and land management and utilization to prevent fire occurrence forests and land. The results of this study are expected to provide an overview of the factors that significantly affect the occurrence of forest and land fires in Riau Province, so that it can provide input for Local Government and related parties in establishing policies and regulations on forest and land management and utilization.

## Material and Method

***Study site***. This research was conducted in all districts in Riau Province with the consideration that almost all areas in Riau Province affected by forest and land fires occur every year (Figure 1).

***Research approach***. This research method is to analyze the secondary data that has been collected and conduct the field observation method to get the model validation data. The research stages consist of 1) environmental biophysical, socioeconomic community and government policy data collection; 2) forest and land fires spatial analysis; 3) spatial modeling; 4) modeling results validation; and 5) forest and land fires prevention plans preparation.

***Data collection***. Data required in this research are: a) hotspot data obtained from the ASEAN Specialized Meteorogical Center (ASMC) accessed through http://asmc.asean.org

(Singapore Weather Information Portal) and the Ministry of Environment and Forestry (KLHK); b) rainfall data from BMKG (Meteorological Agency, Climatology and Geophysics); c) soil type map from the Ministry of Agriculture (Indonesian Agricultural Research and Development Center); d) land cover map from the Ministry of Environment and Forestry; e) Indonesia Earth Map with scale 1:25,000/1:50,000 (thematic roads, rivers, etc.); f) socio-economic tabulation data of all districts in Riau Province from Statistics Indonesia; g) spatial Plan Map (RTRW) of province/district; h) land use status; i) forest area map; j) concession of mining business license and Timber Forest Product Utilization License, both natural forest and plantation (formerly Forest Concession Rights and Industrial Plantation); k) regional boundary data; and l) legal and enforcement legislation.

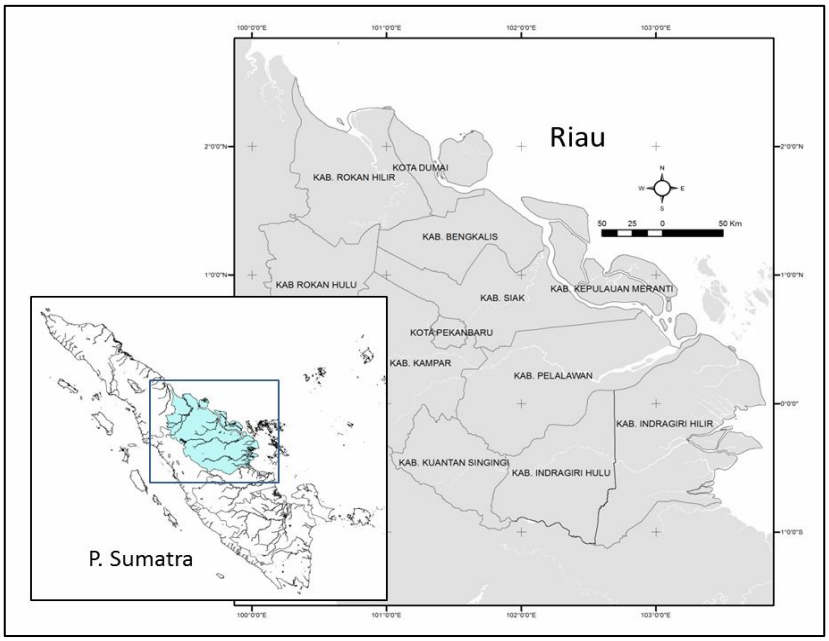



Figure 1. Study area.

***Unit analysis determination***. In this study, the bio-physical characteristics of the environment were carried out on the unit of analysis with grid size 250 m x 250 m, while the socio-economic characteristics were carried out in the village analysis unit as the observation area unit. Each variable attribute on the unit of analysis will be used as input in the process of statistical analysis.

The value filling for each grid is conducted by calculating the distance (euclidean distance) to the input variable. Each grid will be filled by the distance attribute values of each variable, both dependent and independent variables used in this study.

Grid attribute filling is conducted using the ArcGIS Hawth Tools software add-on module. This module will fill the grid attribute with the distance of each variable on each grid in linear unit. Furthermore, the grid attribute filling for socioeconomic and policy variables is performed using the Zonal Attribute algorithm.

***Hotspot data collection as dependent variable***. The hotspot data analysis was conducted by plotting hotspots during the last 9 years (2007-2015) to show the hotspot position and distribution in the research location so that the fire potential of the research area can be obtained (Figure 2).

Determination of hotspot data retrieval location as dependent variable is conducted by considering the spreading of fire point on grid size 5 km x 5 km. To ensure that the hotspot location can be used as a representative dependent variable, a grid that has a hotspot number greater than 50 points will be taken to represent the hotspot data to be inputted in the statistical analysis process. Each selected grid will be represented by only one hotspot data. The sample data sample illustration of this hotspot is illustrated in Figure 2.

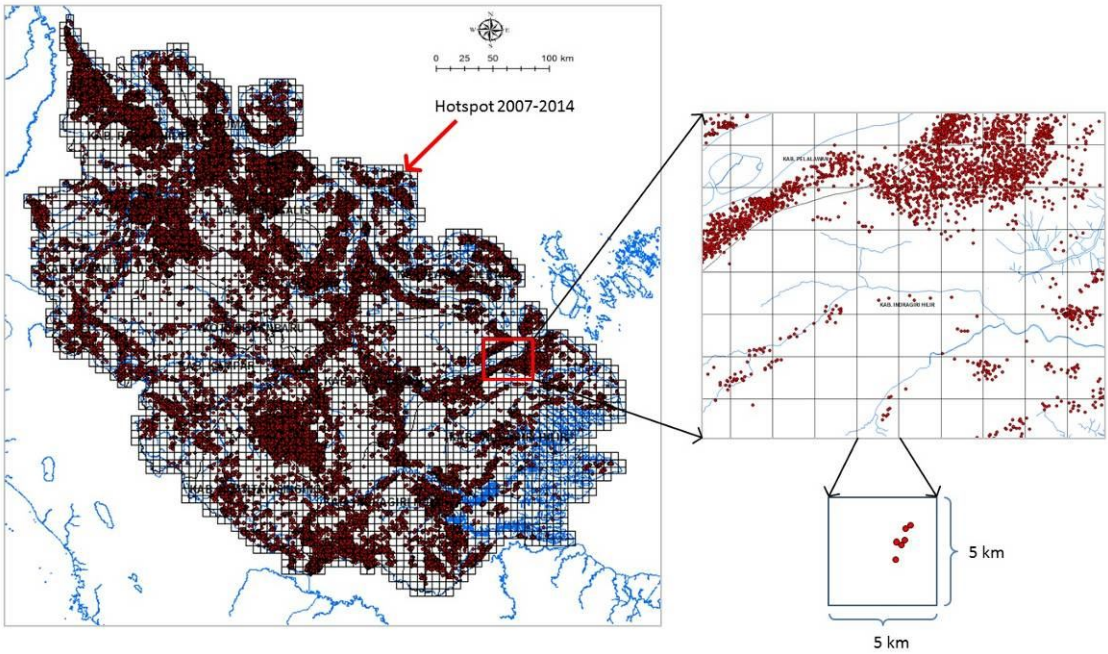



Figure 2. Determination of hotspot sample point.

***Spatial analysis and spatial modeling with Logistic Regression method***. Regression is a statistical analysis that can be used to obtain the coefficient of empirical relationship of observations made. The dependent variable of logistic regression can be either binary or categorical. The independent variable (logistic regression) can be a combination of continuous and categorical variables. The general form of logistic regression can be seen in following equation:

$$Pi = \frac{1}{1 + \exp\left[-\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ji}\right)\right]}$$

Where: Pi = probability;

β0, β1... βk = coefficient of measurement results;

X1, X2... Xk = independent variable.

The equation shows the probability of fire occurrence, which is represented by binary response variables (1 and 0). A value of 1 indicates a fire, while a value of 0 indicates no fires (Xie et al 2005).

To model fires with logistic regression, the spatial diversity of the data should be considered. Spatial statistics such as spatial dependence and spatial sampling should be considered in logistic regression with the aim of eliminating spatial auto correlation (Xie et al 2005). The results of logistic regression analysis will show the most influential variable on the occurrence of fire.

***Determination of criteria for Logistic Regression model***. The hotspot or burnt area data is the dependent variable in the logistic regression model. In this study, the hotspot or area criterion used for parameter Y is the number of hotspots per grid > 50 for criterion 1 and < 50 for criterion 0, where each grid will only be represented by one hotspot point (1 point per grid).

As described above, to link the interaction of biophysical factors, socio-economic factors and policy factors in the spatial model of forest and land fires in Riau Province used logistic regression model. This regression model has been used to determine the interaction of environmental factors and changes in land use in Java (Verburg et al 2004), spatial models for deforestation (Prasetyo et al 2009), and studies on land-use change on a regional scale (Setiawan et al 2011). Criteria determination for regression model can be viewed in Table 1.

Table 1

Criteria determination for regression model

| *Parameter* | *Assumptions and criteria* |
|---|---|
| *The occurrence of forest and land fires* | The occurrence of forest and land fires is based on the number of hot spots in 2007-2015 which calculated per grid. Limit values are taken at 50 hotspots per grid assuming this value is capable of representing the condition of the grid that has a large enough area. Therefore, the grid with the number of hotspots > 50 was used for criterion 1 and < 50 was used for criterion 0. |
| *Biophysical factors* | |
| Soil type | The input of soil variable is determined by calculating the distance of location to the peat soil. |
| Land cover | Input of land cover variable is determined by calculating the distance of the location on some following land cover types: 1. forest; 2. industrial forest; 3. plantation; 4. settlements; 5. dryland farming; 6. paddy fields. This distance to the land cover indicates how much influence of a particular land cover type may have on forest or land fire occurrence, either positively (increasing the probability of fire), or negatively correlated (reducing the probability of fire). |
| River | The input of river variable is determined by calculating the location distance to the river. River is used as one of the location access that estimated as one of the factors that influence land fires occurrence. |
| Road | The input of road variable is determined by calculating the distance of the location to the road. Similar to the river, the distance to the road is one of the data inputs associated with the location accessibility and land fire occurrence. |
| *Socio-economic factors* | |
| Livelihood in agriculture | The input of livelihood variables is taken from the number of families who have livelihoods from agriculture in the village analysis unit. The more number of families who have occupation as farmer, the more agricultural land need and forest and land fires occurrence. In order to be consistent with other input variables, these farming livelihood variables can be determined by calculating the distance of locations to settlements and agricultural land, such as dryland farming and paddyfields. |
| Land use status | Plantation and forestry concessions. The value of land use is taken under the assumption that the area under the control of the company and controlled by the community has a significant impact on the occurrence of fire. Input variable is taken by calculating the distance of location to plantation concession and Timber Forest Product Utilization License. |
| Land ownership conflict | The variable inputs of land ownership are determined by calculating the distance of the location to the boundaries of land ownership, both company and the community ownership. |
| *Policy factors* | |
| Spatial pattern | Spatial allocation for forestry and non-forestry is a policy factor taken with the assumption that the broader pattern of forestry space can reduce the pressure on the use of land/forest area. The value of this space pattern variable is based on the allocation of following forest area based on Ministry of Forestry Republic of Indonesia Decree number 878/2014, such as: 1. protected forest (HL); 2. production forest (HP); 3. limited production forest (HPT); 4. convertible production forest (HPK); 5. other use areas (APL). |
| Legislation | Legislation related to land management. The division of this category is taken with the assumption that the existence of regulations may reduce the pressure on forest and land fires occurrence. |

After the data is processed, co-efficiency value obtained from SPSS program was seen to get the relationship of biophysical environment aspect, socio-economic aspect, and policy aspect to forest and land fires occurrence.

***Test statistics and model accuracy***. After doing parameter estimation, then significance testing of these parameters was conducted. For this purpose, statistical hypothesis testing is used to determine whether the independent variables in the model are significant or significantly affect the dependent variable. Testing the significance of parameters is conducted as follows:

*Multicollinearity test.* Multicollinearity is a statistical phenomenon in which there exists a perfect or exact relationship between the predictor variables (Joshi 2012). Multicollinearity appears when two or more independent variables in the regression model are correlated. A little bit of multicollinearity sometimes will cause big problem but when it is moderate of high then it will be a problem to be solved (Daoud 2017). The prerequisite to be met in the regression model is the absence of multicollinearity. Thus, multicollinearity test is required. Multicollinearity test is used to find out whether in the regression model found the correlation between independent variables. There are several test methods that can be used such as: by looking at the Tolerance and Variance Inflation Factor (VIF) values in the regression model, by comparing the individual coefficient of determination ($r^2$) with the simultaneous determination value ($R^2$), and by looking at the value of eigenvalue and condition index. In this study, multicollinearity test used is to see the value of Tolerance and VIF. Basic decision-making based on Tolerance and VIF values is: if the Tolerance value of each independent variable > 0.1 then there is no multicolinearity and if the Tolerance value < 0.1 then the multicollinearity occurs. Furthermore, if the VIF value of each independent variable < 10 then multicollinearity does not occur and if the value > 10 then the multicollinearity occurs. If in the overall test results there are independent variables with Tolerance value < 0.1 and VIF > 10, then we must eliminate the variable. Only significant independent variables and no multicollinearity will be processed in logistic regression analysis.

*Model feasibility test.* The model feasibility test is useful for assessing a model's ability to predict the dependent variable. The feasibility assessment of the model relates to the search for the proximity of the predicted value of a model to the observed value. The model feasibility test uses the Hosmer-Lemeshow test. The Hosmer-Lameshow test is suitable for models consisting of several independent variables that are discrete or continuous (Hosmer et al 1997). The independent variable is considered fit with the model if the significance of the Hosmer-Lemeshow test result is above 0.05. The coefficient of determination ($R^2$) is determined by looking at the Negelkerke $R^2$ test results and the percentage correct (overall percentage). Negelkerke $R^2$ shows the importance of the independent variable in predicting the dependent variable. Nagelkerke R2 indicated that the model accounted value of the total variance (Bian 2018). The greater the value Negelkerke $R^2$ generated the better the model.

*Model validation.* Model validation is performed to determine whether the model has been made according to the actual condition. The validation point data used is primarily taken from areas that are actually changing in the real world and areas that have changed based on the map of the changes that have been made. The equation related to the percentage validity of the model was calculated using a formula in Rahmat (2012) as follows:

$$\text{Validation} = n/N \times 100\%$$

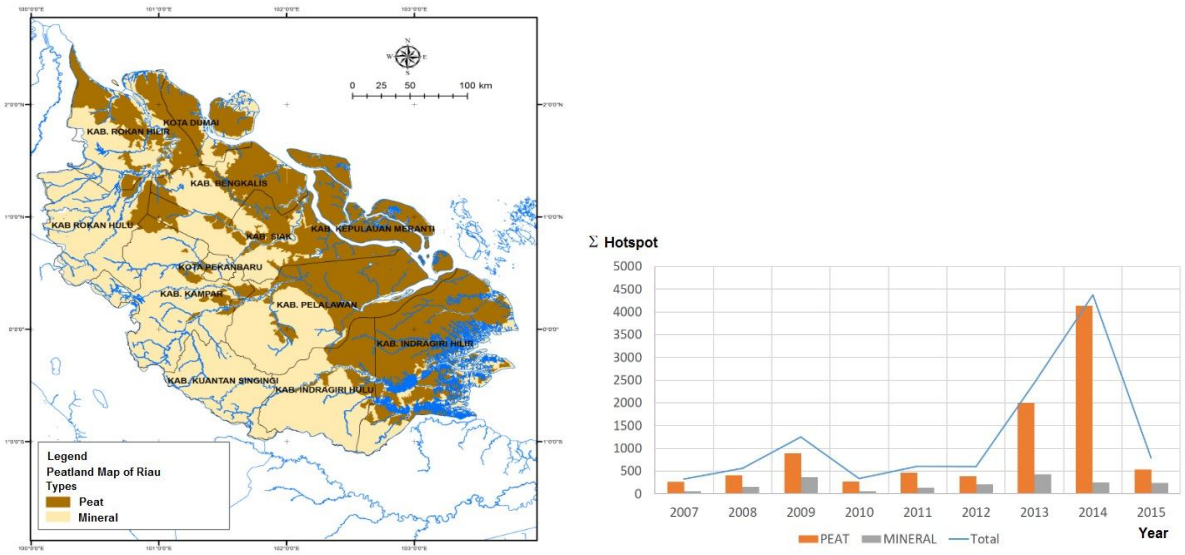
Where n = number of points of forest and land fires occurrences found on the suitability class, and N = total number of points for forest and land fires occurrences found in all conformity classes.

In the model validation stage, there are two errors: omission error and commission error. Translated from Boone & Krohn (1999) and Ottaviani et al (2004), omission error is a model predicting the location is not appropriate for the occurrence of change, but on the actual location of the change. Commission error is a model predicting

the location is appropriate for the occurrence of changes, but on the actual location there is no change.

## Results and Discussion

***Analysis of factors affecting forest and land fires***. Land characteristics and land cover are closely related to the availability of biomass which is one of the main components of land fire occurrence. Under certain conditions, such as in extreme dry season, the high availability of biomass in a field will increase the potential for land fires (Page & Hooijer 2016). Peatlands are one of the essential ecosystems that have a high level of fire vulnerability (Page 2016). Naturally, the condition of wet peatland is difficult to burn (WWF 2018). However, drainage of peatlands is often caused by land clearing activities, through the construction of canals regardless to groundwater levels and forest clearance that still occurring to this day causes peatlands to become more open, and particularly vulnerable to burning especially during the extreme dry season. In addition, the depth of peat is something that needs to be underlined, because deep peat has great potential for fire occurrence considering the amount of fuel available (Prayoto 2011). Based on the peat map issued by Ministry of Agriculture Republic of Indonesia (2011), the depth of peat in Riau Province is quite varied, from below 3 meters to above 3 meters. Map of peatland and mineral distribution and Hotspot in peatland distribution of Riau Province can be viewed in Figure 3(a,b) and 4.




a) b)

Figure 3. a) Map of peatland and mineral distribution; b) Hotspot in peatland distribution in 2007 to 2015.

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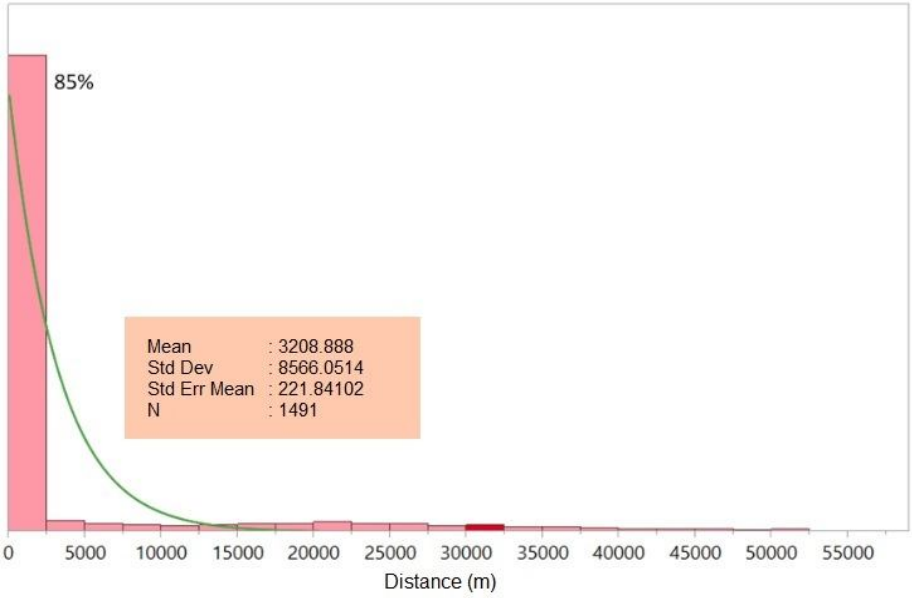



Figure 4. Hotspot distribution based on distance towards peatland.

The dynamics of changes in the area of forest cover in Riau Province is related to the increase of plantation area and industrial forest. Analysis of land cover data issued by the Ministry of Environment and Forestry (2016) shows that the decrease of forest area in 2006-2015 reached 41.22%. On the other hand, there is an increase of industrial forest of 41.4% and plantation 27.80%. The dynamics of this land cover change can be seen in Figure 5.

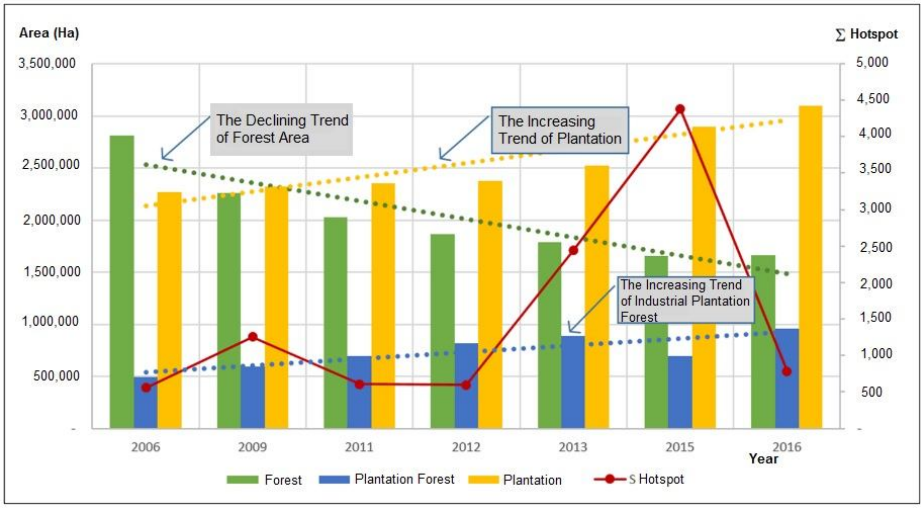



Figure 5. Fluctuation of areal extent of forest cover, forest plantation, plantation, and hotspots in 2007-2015.

Based on data that has been processed from Ministry of Environment and Forestry (2016) (Figure 5), forest cover in Riau Province is dominated by swamp forest (61.30%), which consists of primary swamp forest and secondary swamp forest. This type of swamp forest has a relatively low chance of burning if it is in stable condition (protected). However, with the continuous disruption of the forest area, whether it is forest clearing, land use conversion, and illegal logging, the probability of forest fire in this area becomes large, due to the high biomass content that can become a fuel source.

Generally, it is expected that digging drainage ditches to reduce the surface water flow in a peatland (Holden et al 2004). Peatlands are drained for several reasons: to stabilize the substrate for building or road construction, to increase the soil productivity for agriculture or forestry (thereby eliminating anaerobic conditions) or for increasing the

capacity of soil to support heavy machinery for industrial activities (peat and petroleum extraction). Urban and industrial developments are often the reason for draining peatlands (Landry & Rochefort 2012). Most industrial plantation forest, oil palm plantations and other agricultural cultivation on peatlands use a canalization system to regulate water levels. Peatland canalization is not carried out thoroughly and integrated in an area. As a result, when the canalization is conducted, the flow of water will occur from the higher peat area and resulted in the loss of water discharge, causing some parts of the peatland to dry. Dry peat is a fuel that can be easily burnt if it is triggered by a source of fire that can lead to forest and land fires.

In addition to intentional and careless factors, the discourse of forest and land fires in the mass media also mentions factors beside of human controls (accidental causes) such as extreme hot temperatures or prolonged dry seasons due to El-Nino. However, this does not mean that natural factors are the main cause of forest and land fires since cumulatively forest and land fires are dominated by human factors, both categorized as intentional and accidental. According to Syaufina (2008), human factors cause almost 100% of forest and land fires, intentionally or unintentionally.

Based on the previous review of Whitmore & Burnham (1975), the fires occurring were triggered by human activities where people used the road network to improve access to cleared land. Availability of roads that can be accessible by the community can increase the chances of a fire. In other words, the more access roads, the greater chance of fire (Figure 6). One of the trigger factors of forest fire in Riau is the proximity of the distance from the road (Nasution et al 2013).

In addition to environmental biophysical factors, climatic conditions are also natural factors that can trigger forest and land fires, such as extreme dry season. One of the largest forest and land fires occurred in 1997-1998, occurred in some countries including Indonesia. In those times, some countries suffered from extreme season that believed to be a major cause of fires that devastated 25 million ha of forests worldwide. The forest and land fire disaster due to the long dry season also recurred in 2002 (Tacconi 2003).

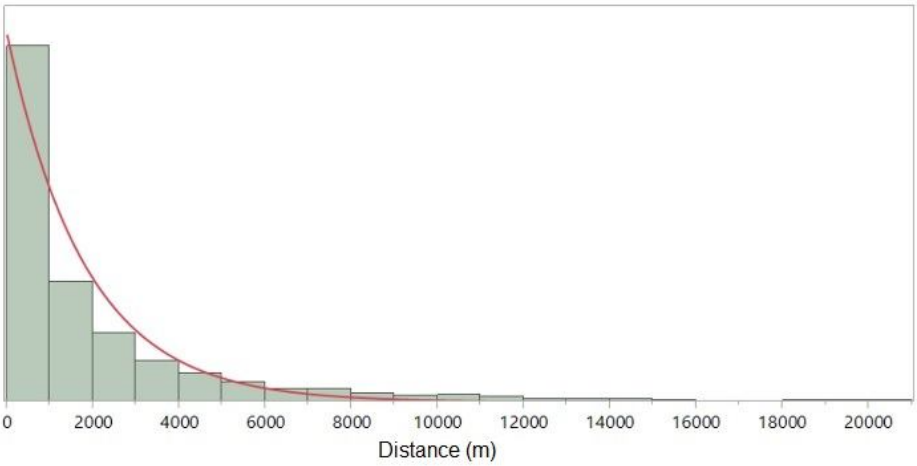
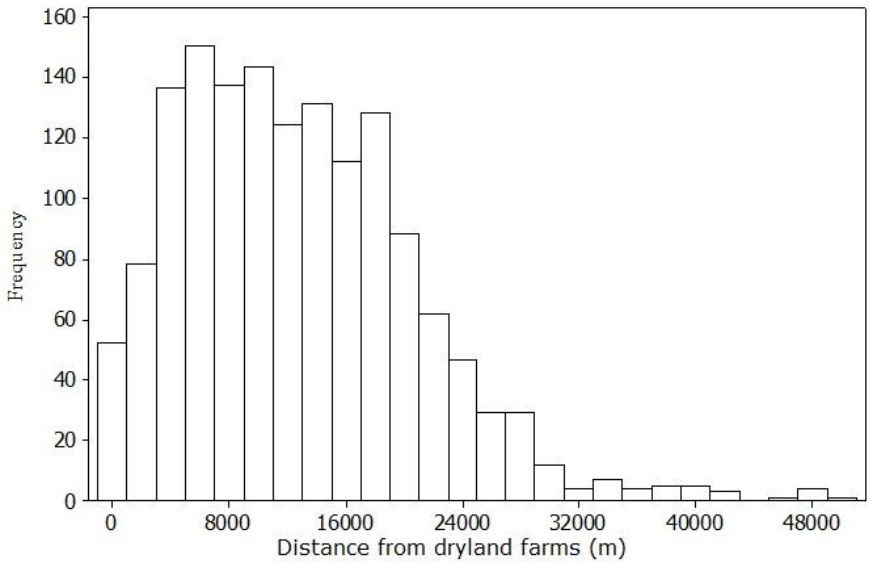


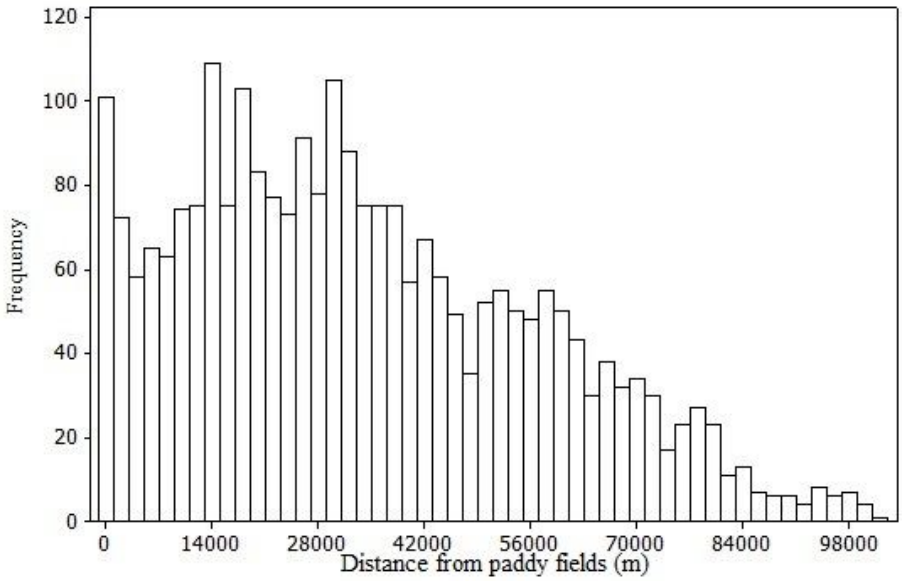

Figure 6. Distribution trend of hotspot based on distance towards road.

*Socio-economic factors.* Forest and land fires in Riau Province occur every year, particularly during dry season. It is caused by the community activities in developing agricultural land using slash and burn method. These behaviours are based from several considerations, including: workers, mobility, and capital limitation. Burning land preparation is done due to limited community capital therefore it is the easiest and cheapest way of land clearing. The relationship between the number of hotspots against their distance to the dryland and paddy fields is shown in Figure 7, which shows that the closer the distance from dryland farming and paddyfields the greater the risk of fire occurring considering that land clearing activities often use fire. Nevertheless, the effect of agricultural activity on the occurrence of land fires on dryland farming is much higher than paddyfields.

Based on hotspot distribution analysis, the highest hotspots were found up to a distance of 20 km from dryland. Approximately 1% of total hotspots were on dryland farms and 3-4% of hotspots are within a distance of less than 1 km. However, the distribution of hotspots seen was not significantly influenced by the distance to paddy fields. This is due to the land clearing by using burning method, which rarely used for paddy fields clearing.




(a)




(b)

Figure 7. Hotspot distribution based on distance towards: a) dryland farms and b) paddy fields.

Low levels of community life and income force them to use cheap and inexpensive land clearing techniques that have become the traditions of their ancestors. Economic factors and land tenure encourage them to burn the forests, particularly to obtain agricultural land (dry land). Thus, the occurrence of forest and land fires can not be separated from the agrarian problem, where the economic development related to the fulfillment of community needs is partly done by clearing land for agricultural business. Therefore, to input socioeconomic variable inputs in spatial modeling, socioeconomic data is used in the form of data on the number of families who have livelihoods in agriculture within the administrative unit of the village. The assumption is that more and more number of families who work as farmers will increase the need for agricultural land, which will increase the occurrence of forest and land fires.

Facts obtained from the field, the number of media and research results (Rasyid 2014) indicate human factors as the main cause of smog disaster through the land burning that is done both sporadically and systematically. Figure 8 shows the distance of the settlement in influencing the occurrence of forest and land fires. The result of the analysis shows that the spreading of hotspots is quite high at a distance of 4-10 km from the settlement (built up area).

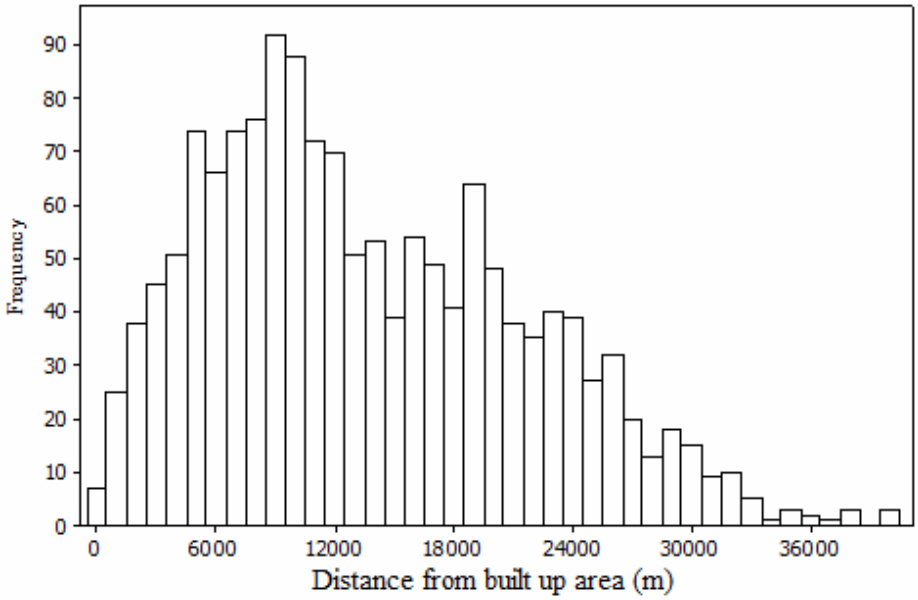
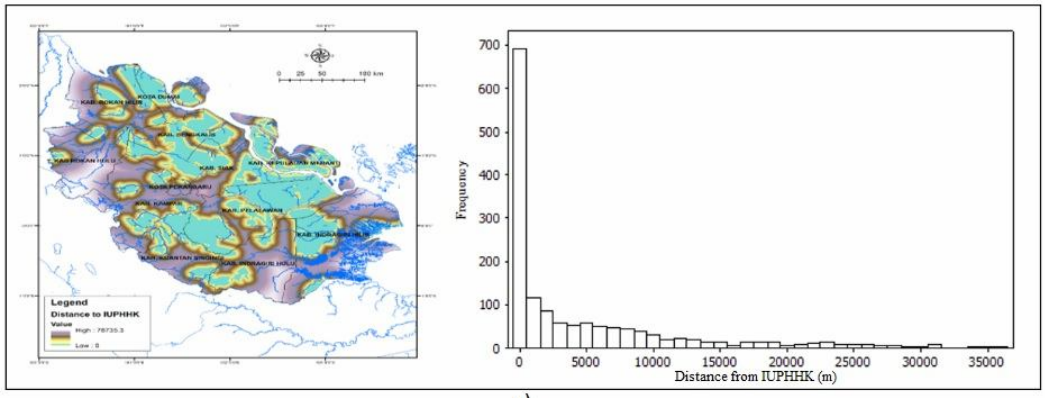



Figure 8. Hotspot distribution based on distance towards settlement (built-up area).

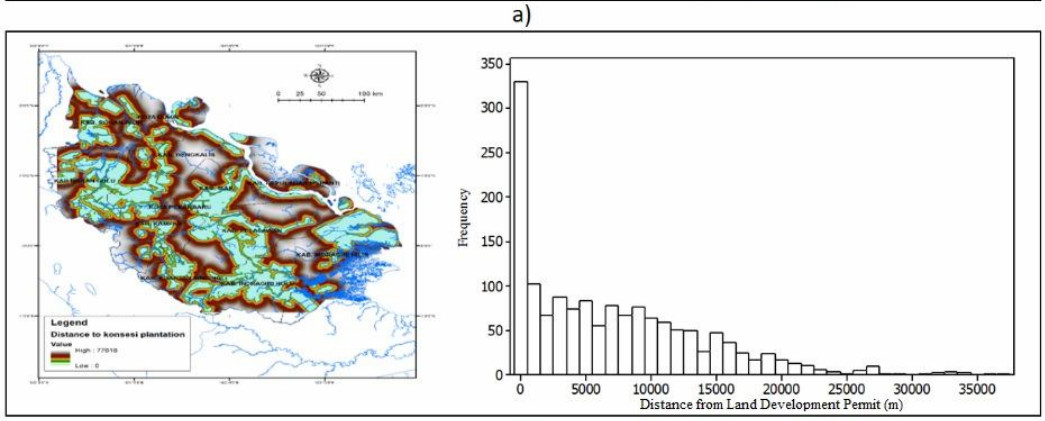
Several cases of fire incidents in Riau Province occurred in area owned by some company or groups of people who claimed to be the community who have Land Development Permit/Hak Guna Lahan (HGU), moreover, certain conservation areas controlled or managed by the company, therefore necessary analysis of land use status and land tenure conflict.

To identify the influenced of company's area ownership to the hotspot, land use permit location data, both IUPHHKK and HGU were used. Figure 9 shows that most hotspots are within the concession area of a) IUPHHKK and b) HGU. As 642 hotspots suspected were located less than 1000 m from IUPHHK area. As for the plantation concession (HGU), 297 hotspots (19.92%) were right in the plantation concession area, 384 hotspots (25.75%) were located at less than 1000 m from the plantation area.

Another factor which is not less important to trigger the forest fires is the migration within the forest areas (Rasyid 2014). Increasing of migration from outside Riau to develop and open new land/plantations, might causing more conflicts to occur. These migrant communities can change mind of local people in terms of land clearing. Most people open land not only to meet the economic needs, but have been thinking the economy widely by opening up to thousands of hectares.




a)




b)

Figure 9. Hotspot distribution based on distance towards permit location of a) IUPHHK, b) Land Development Permit/Hak Guna Lahan (HGU).

*Policy and spatial factors.* Purnomo et al (2015) and Purnomo et al (2016) stated that several policy factors which influence the high level of forest and land fires in Riau Province are as follows:

a. Riau Province does not yet have a definite Spatial Plan;

b. Government does not strict in handling the area of: 1. the ex-HPH areas that does not have clear status at this time; 2. river border area; 3. IUPHHK-HT/HA which permit has been issued but not yet cultivated.

Figure 10 shows that the closer the distance to forest area location, both production forest (HP), limited production forest (HPT), and conversion production forest (HPK), were have more risk to the fire. Forest cover has a relatively low chance to burn under normal conditions, but the proliferation of both legal and illegal logging in natural forests the chances of wildfire are increasing.

Based on the analysis of hotspots distribution, as many as 594 spots that were suspected as hotspots (39.91%) were right in the production forest, 718 hotspots (48.16%) were at less than 1000 m from production forest. While in production forest area, 179 hotspots (12.01%) were found in conversion forest production area, 316 hotspots (21.19%) were located at less than 1000 m from forest. Approximately 20% of the hotspots were in limited production forest areas, and as many as 374 hotspots (25.08%) were at less than 1000 m from limited production forests.

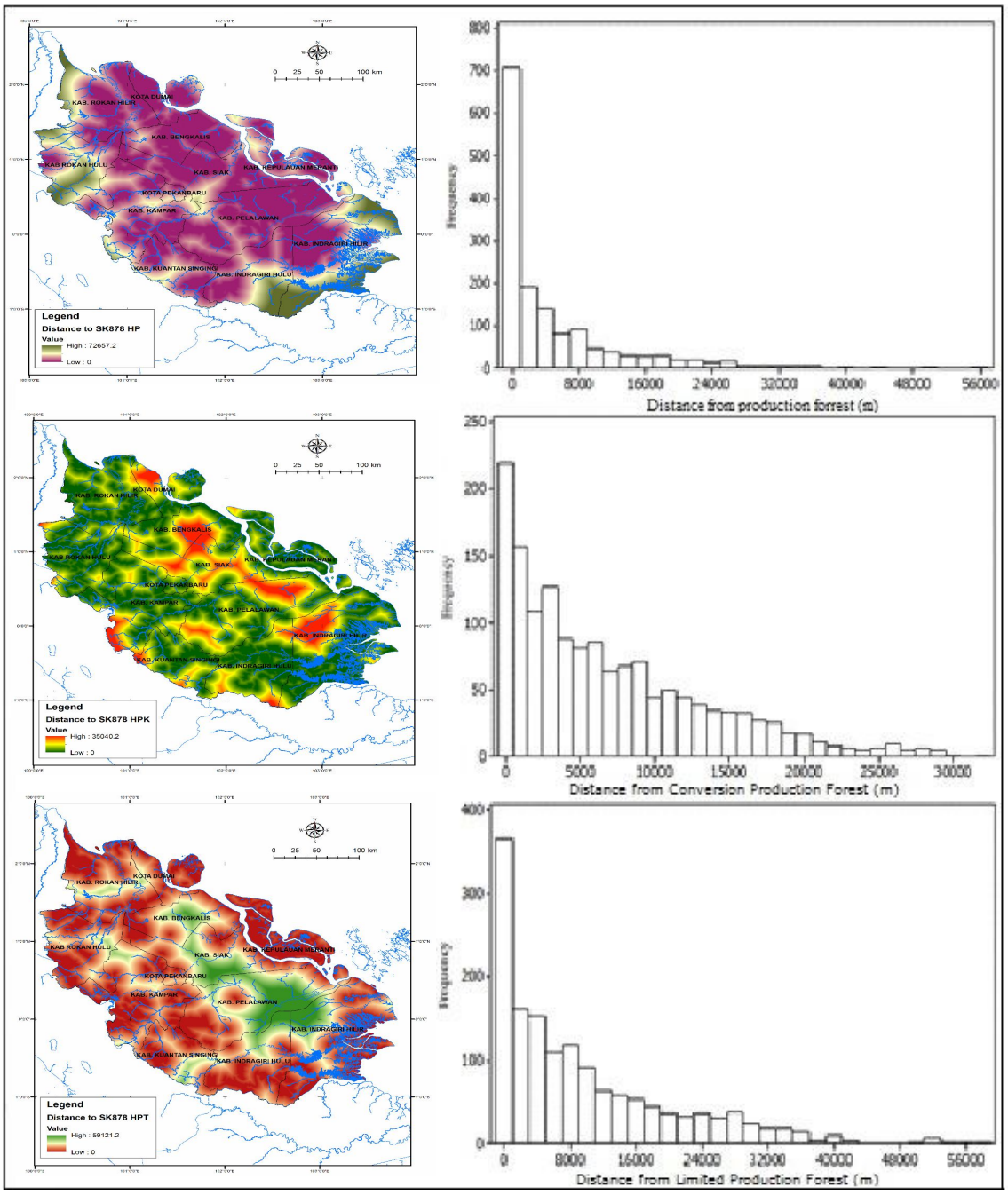



Figure 10. Hotspot distribution based on distance towards forest location correspond to Ministry of Forestry Republic of Indonesia Decree number 878/2014 a) Production forest, b) Conversion Production Forest and c) Limited Production Forest.

Protected areas such as the protected forest, natural reserve area (KSA) or natural conservation area (KPA) are rare for forest and land fires. This can be seen from Figure 11 which shows that only about 1% of hotspot is in the protected forest area. In the conservation area, there were 93 hotspots suspected of fire incidence (6.24%) located at the conservation area, 119 hotspots (7.98%) located less than 1000 m from the conservation area.

Figure 11 shows that the closer the distance to protected forest and the KSA/KPA conservation areas location, the smaller the risk to wildfire and vice versa. This type of land cover has a relatively low chance of burning because the protected forest area has a clear boundary arrangement. In addition, law enforcement of protected areas has been made strictly against those entering or penetrating protected areas.

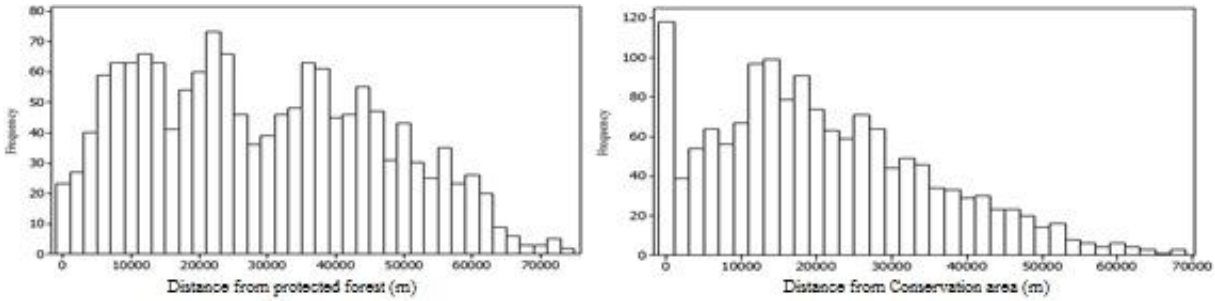



Figure 11. Hotspot distribution based on distance towards forest location correspond to Ministry of Forestry Republic of Indonesia Decree number 878/2014: a) protected Forest, b) conservation area.

Other use areas (APLs) are areas that can be utilized by the community. APL area is an area that is quite vulnerable to wildfire. Based on the analysis of hotspot there are 50% of hotspots located at APL locations or locations less than 1 km away from this APL. Figure 12 shows that the closer the APL area is, the greater the risk of fire, this is because most people use fire in land clearing activities.

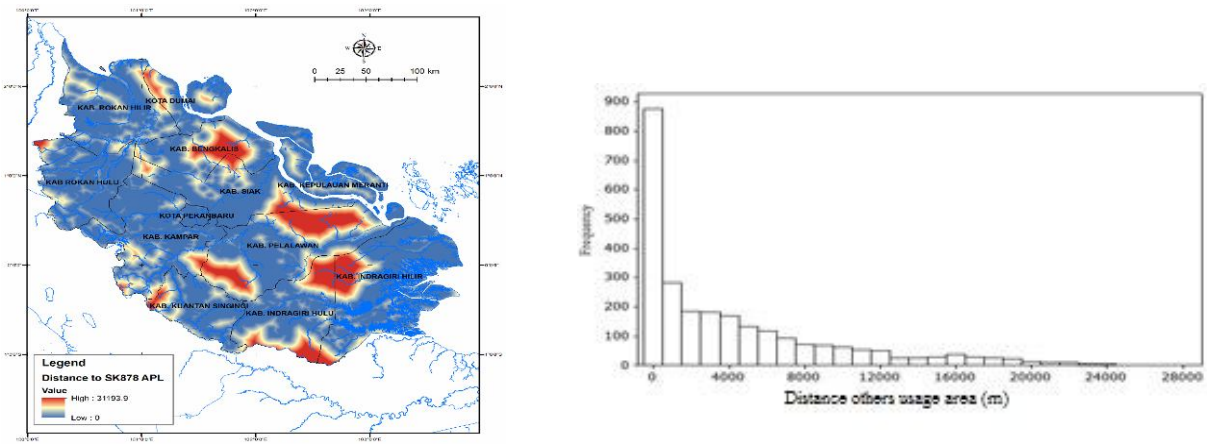



Figure 12. Hotspot distribution based on distance towards others usage area correspond to Ministry of Forestry Republic of Indonesia Decree number 878/2014.

Based on environmental biophysical, socioeconomic and spatial factors analysis on hotspots distribution, it can be briefly described that the distance of several parameters or input variables has significant relation to wildfire occurence (hotspot), such as peatland, Land Development Permit/Hak Guna Lahan (HGU) and IUPHHKK, production forest areas, forest cover and other areas of use. Briefly the ratio of the number of hotspots and their location to several parameters is shown in Table 2 and Figure 13.

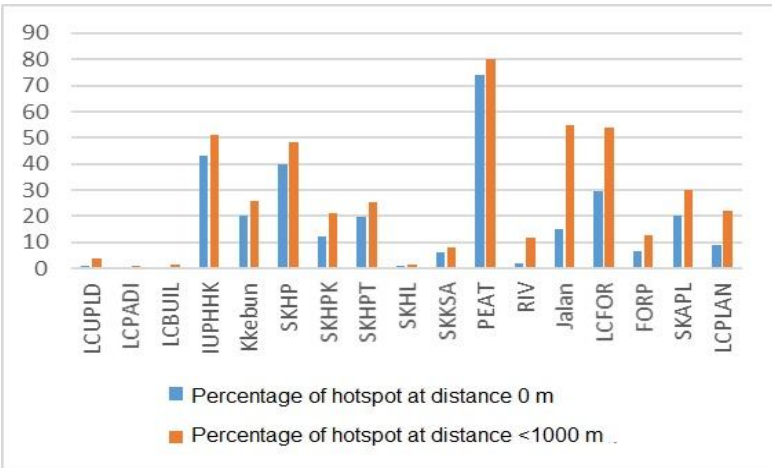



Figure 13. Comparison of hotspot within variables at distance of 0 m (exact location) and distance of < 1000 m.

Table 2

Comparison of hotspots number between variables at a distance of 0 and < 1000 m

| *Variable* | *Total hotspot at 0 m* | *Hotspot percentage at 0 m (%)* | *Total hotspot at < 1000 m* | *Hotspot percentage at < 1000 m* |
|---|---|---|---|---|
| LCUPLD | 14 | 0.94 | 55 | 3.69 |
| LCPADI | 8 | 0.54 | 11 | 0.74 |
| LCBUIL | 3 | 0.2 | 19 | 1.27 |
| IUPHHK | 642 | 43.06 | 760 | 50.97 |
| Kkebun | 297 | 19.92 | 384 | 25.75 |
| SKHP | 595 | 39.91 | 718 | 48.16 |
| SKHPK | 179 | 12.01 | 316 | 21.19 |
| SKHPT | 291 | 19.52 | 374 | 25.08 |
| SKHL | 15 | 1.01 | 23 | 1.54 |
| SKKSA | 93 | 6.24 | 119 | 7.98 |
| PEAT | 1102 | 73.91 | 1192 | 79.95 |
| RIV | 26 | 1.74 | 177 | 11.87 |
| JALAN | 222 | 14.89 | 820 | 55 |
| LCFOR | 443 | 29.71 | 801 | 53.72 |
| FORP | 99 | 6.64 | 188 | 12.61 |
| SKAPL | 299 | 20.05 | 446 | 29.91 |
| LCPLAN | 135 | 9.05 | 328 | 22 |

Note: LCUPLD - dryland farms; LCPADI – paddyfield ; LCBUIL – settlement; IUPHHK - IUPHHK location; Kkebun - plantation concession; SKHP - production forest; SKHPK conversion production forest area; SKHPT - limited production forest area; SKHL - protected forest; SKKSA conservation area; PEAT - peatland; RIV - river; JALAN - roads; LCFOR - forest; FORP - forest plantation; SKAPL - other usage area; LCPLAN - plantation cover.

***Vulnerability prediction model of forest and land fires***. The multicollinearity test used is by indicating the tolerance and variance inflation factor values. Variables undergoing multicollinearity will be excluded/eliminated. Only independent variables that do not experience multicolinearity will be processed in logistic regression analysis.

The variables observed in the probability model of forest and land fires are 17 variables, such as: DIS_LCUPLD - distance towards dryland farms; DIS_LCPADI - distance towards paddyfield; DIS_LCBUIL - distance towards settlement; DIS_IUPHHK - distance towards IUPHHK location; DIS_KKEBUN - distance towards plantation concession; DIS_SKHP - distance towards production forest; DIS_SKHPK - distance towards conversion production forest area; DIS_SKHPT - distance towards limited production forest area; DIS_SKHL - distance towards protected forest; DIS_SKKSA - distance towards conservation area; DIS_PEAT - distance towards peatland; DIS_RIV - distance towards river; DIS_JLN - distance towards roads; DIS_LCFOR - distance towards forest; DIS_LCFORP - distance towards forest plantation; DIS_SKAPL - distance towards other usage area; DIS_LCPLAN - distance towards plantation cover. Based on multicolinearity test results using Tolerance and VIF values, each has a tolerance value ranging from 0.284 to 0.720 and VIF values ranging from 1.267 to 3.631. These results indicate that the Tolerance value is greater than 0.1 and the VIF value is less than 10. This means that all tested variables are eligible for further analysis because they are free from multicolinearity. Generally, variable which experiencing multicollinearity must be completed before doing further analysis. The process of further statistical analysis involves only variables that do not experience multicollinearity. The multicollinearity test can be seen in Table 3.

The variables that did not experience multicolinearity were analyzed further using Binary Logistic Regression with center method. Table 3 shows output p-value (0.000) < alpha (0.05) which means reject H0. Therefore at least 1 explanatory variables that significantly affect the health status at 5% of significance level. The result of logistic regression analysis shows that from 17 variables, not all variables have significant influence on the occurrence of change. The regression logistic results showed, p-value> DIS_LCPADI and DIS_SKKSA in alpha (0.05), nevertheless DIS_LCPADI and DIS_SKKSA variables were eliminated from the equation.

Table 3

Multicollinearity test of variables to be used in the prediction model of fire vulnerability

| *Model* | *Collinearity statistics* | |
|---|---|---|
| | *Tolerance* | *VIF* |
| DIS_PEAT | 0.628 | 1.593 |
| DIS_RIV | 0.789 | 1.267 |
| DIS_JLN | 0.560 | 1.785 |
| DIS_LCFOR | 0.545 | 1.836 |
| DIS_LCFORP | 0.391 | 2.558 |
| DIS_LCPLAN | 0.410 | 2.439 |
| DIS_LCBUIL | 0.397 | 2.518 |
| DIS_LCUPLD | 0.675 | 1.482 |
| DIS_LCPADI | 0.720 | 1.389 |
| DIS_IUPHHK | 0.275 | 3.631 |
| DIS_KKEBUN | 0.481 | 2.080 |
| DIS_SKAPL | 0.289 | 3.455 |
| DIS_SKHL | 0.569 | 1.757 |
| DIS_SKHP | 0.284 | 3.523 |
| DIS_SKHPK | 0.419 | 2.389 |
| DIS_SKHPT | 0.606 | 1.651 |
| DIS_SKKSA | 0.434 | 2.307 |

Then the probability equation of forest and land fires below were obtained based on logistic regression method (Table 4):

$$Pi = \frac{1}{1 + \exp[-(Z)]}$$

Where: Z = 3.57521783 - 0.0000694DIS_PEAT + 0.0001488DIS_RIV - 0.0001306DIS_JLN - 0.0003727DIS_LCFOR - 0.0000763DIS_LCFORP - 0.0000593DIS_LCPLAN + 0.0000604DIS_LCBUIL - 0.0000431DIS_LCUPLD + 0.0000264DIS_IUPHHK + 0.000024DIS_KKEBUN - 0.000074DISSKAPL + 0.0000276DIS_SKHL - 0.0000597DIS_SKHP - 0.0000775DIS_SKHPK - 0.0000653DIS_SKHPT.

Table 4

Logistic regression probability model, predictor, coefficient and its significance value

| *Predictor* | *Coef* | *SE Coef* | *p – value (Sig.)* | *Hosmer & Lemeshow* | *Nagelkerke $R^2$* |
|---|---|---|---|---|---|
| Constant | 3.57522 | 0.258729 | 0.000 | 0.249 | 61.8% |
| DIS_PEAT | -0.0000694 | 0.0000075 | 0.000 | | |
| DIS_RIV | 0.0001488 | 0.0000157 | 0.000 | | |
| DIS_JLN | -0.0001306 | 0.0000213 | 0.000 | | |
| DIS_LCFOR | -0.0003727 | 0.0000245 | 0.000 | | |
| DIS_LCFORP | -0.0000763 | 0.0000073 | 0.000 | | |
| DIS_LCPLAN | -0.0000593 | 0.0000128 | 0.000 | | |
| DIS_LCBUIL | 0.0000604 | 0.0000098 | 0.000 | | |
| DIS_LCUPLD | -0.0000431 | 0.0000083 | 0.000 | | |
| DIS_LCPADI | 0.0000024 | 0.0000032 | 0.457 | | |
| DIS_IUPHHK | 0.0000264 | 0.0000125 | 0.035 | | |
| DIS_KKEBUN | 0.000024 | 0.0000105 | 0.023 | | |
| DIS_SKAPL | -0.000074 | 0.0000208 | 0.000 | | |
| DIS_SKHL | 0.0000276 | 0.0000048 | 0.000 | | |
| DIS_SKHP | -0.0000597 | 0.0000103 | 0.000 | | |
| DIS_SKHPK | -0.0000775 | 0.0000124 | 0.000 | | |
| DIS_SKHPT | -0.0000653 | 0.0000068 | 0.000 | | |
| DIS_SKKSA | -0.0000007 | 0.0000041 | 0.873 | | |

The feasibility test of the model using Hosmer-Lemeshow test showed that the model has sufficiently explained the data (fit) because it has statistical significance of 0.329 (> 0.05). Nagelkerke R2 value was 0.617%. It showed that 61.7% probability of forest and land fires can be explained by the variables in the model, while the remaining 38.3% is explained by other variables or factors outside the model. Classification table value (overall percentage) obtained from the analysis is 58.2% of the presence and absence parameters. This value illustrates that 58.2% of the built model can correctly predict the condition. The binary logistic regression formulation that has been obtained will result in a probability model of forest and land fires (Figure 14). While the relationship between each variable with the probability of forest and land fires can be seen in Figure 15.

Forest and land fires in Riau Province were affected by 17 variables, namely 1) peatlands; 2) rivers; 3) roads; 4) forest cover; 5) plantation cover; 6) plantations; 7) settlements (built land); 8) dryland; 9) paddies area; 10) IUPHHK; 11) plantation concession (HGU); 12) other use areas (APL); 13) protected forest areas; 14) production forest; 15) conversion production forest; 16) limited production forest; 17) Natural Reserve Area (KSA).

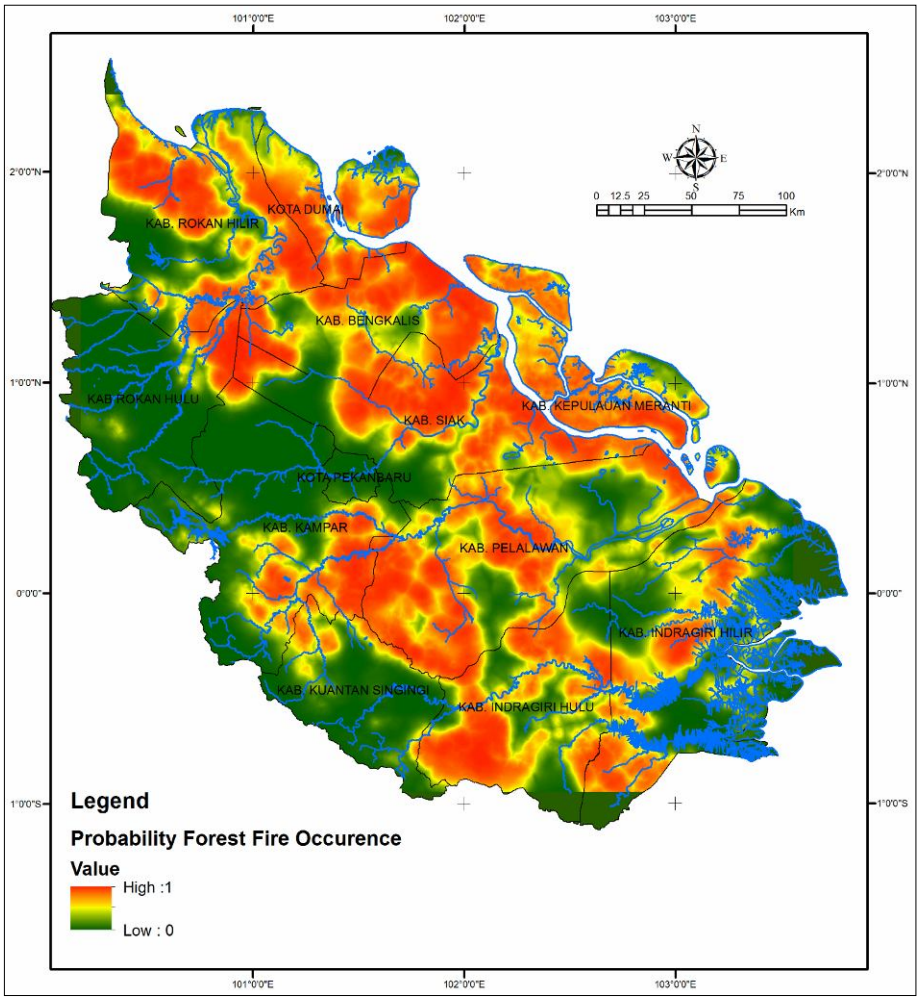



Figure 14. Map of forest and land fire's probability.

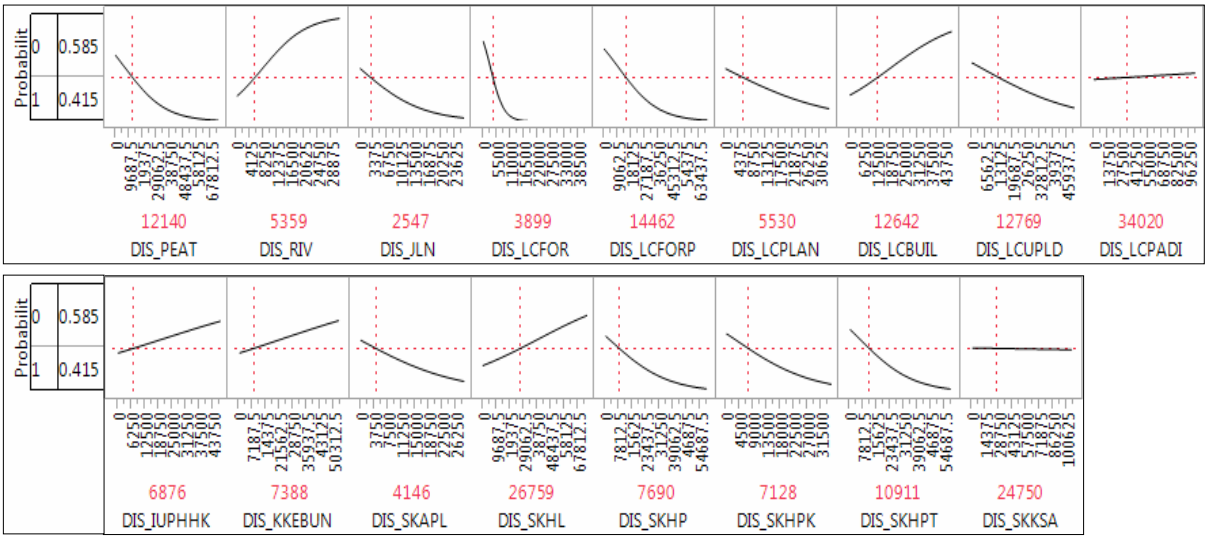



Figure 15. The relationship between each variable with the probability of forest and land fires.

***Accuracy of logistic regression model for prediction of fire resistance***. The measurement of model accuracy was done by using hotspot data of 2016. The measurement of the accuracy of this model is done to know the level of trust to the model built. The accuracy test results using hotspot recorded by MODIS sensor 2016 shows that the model is able to predict the probability of forest and land fires in high-very high category as much as 83.83% (Table 5). The distribution of presence-validation hotspot, i.e. 83.83% in the probability category of more than 60% (high-very high category) can be seen in Figure 16. While the remaining 16.17% are in moderate to very low probability categories. Validation results that have been done show the model that has been made in accordance with the actual conditions in the field.

Table 5

Measurement accuracy based on hotspot data of 2016
(confidence level 100% Terra-Aqua data: MODIS)

| *Probability (%)* | *Category* | *Total hotspot* | *Percentage (%)* |
|---|---|---|---|
| 0-20 | Very low | 33 | 5.74 |
| 20-40 | Low | 19 | 3.30 |
| 40-60 | Moderate | 41 | 7.13 |
| 60-80 | High | 101 | 17.57 |
| 80-100 | Very high | 381 | 66.26 |

Validation points overlapped with the model showed that from 575 validation points, 90.96% change point corresponding to the change in the model. Approximately 9.04% of hotspot were located in areas that do not match the changes in the model (omission error). The inappropriate hotspots were in areas with low to very low probability category of forest and land fires in Riau Province. Those hotspots were mainly located near to the settlement, rivers, IUPHHK locations and protected forest areas. While the suitable hotspot was mostly categorized as medium, high and very high probability and located near to forest areas, peat, roads, plantations, plantations, drylands, other use areas (APL), production forest areas, conversion production forest areas and limited production forest areas.

The relation of these variables and probabilities can be seen in Figure 15. Generally, the validation value of 90.96% is sufficient to show that the forest and land fires model is feasible.

***Interpretation of fire vulnerability prediction result***. The probability model of forest and land fires shows that there are five levels of probability, i.e very high, high, medium, low and very low (Table 6). Areas with high probability indicate high fire probability. Areas with low probability indicate low fire probability. More than half the total area of Riau Province (51.46%) includes areas with moderate to very high probability of fire occurrence. While the remaining 48.54% are in areas with low to very low probability of fire occurrence.

Table 6

Categories of forest and land fires probability

| *Probability* | *Category* | *Areal extent (ha)* | *Percentage (%)* |
|---|---|---|---|
| 0-20 | Very low | 3,351,900.20 | 37.21 |
| 20-40 | Low | 1,020,100.01 | 11.33 |
| 40-60 | Moderate | 991,500.74 | 11.01 |
| 60-80 | High | 1,354,600.65 | 15.04 |
| 80-100 | Very high | 2,288,900.91 | 25.41 |

The trend of high to very high probability area was spreading in the middle towards the southern part of Riau Province as well as coastal area and area adjacent to coastal area of Riau Province. Center point to the southern part of Riau Province is largely an area adjacent to forests, plantations, other agricultural dryland used area, production forests, conversion production forests and limited production forests. While the coastal areas and areas adjacent to these coastal areas are mostly located in peatlands, adjacent to forests, plantations, roads, other usage area, production forest areas and limited production forests. In moderate to very high probability area is mostly located far away from built-up area. While low probabilities area is located close to built-up area, IUPHHK locations, rivers, plantation concessions and protected areas.

**Conclusions**. Based on environmental biophysical, socioeconomic and spatial factors analysis, it can be described that the distance of several parameters or input variables has significant relation to wildfire occurence (hotspot), such as peatland, Land Development Permit (HGU) and IUPHHKK, production forest areas, forest cover and other areas of use.

Based on the logistic regression model, it is known that there is a correlation between forest and land fires variables in Riau Province to distance from 15 variables, i.e peatland, river, road, forest cover, plantation cover, plantation, settlement (built up area), dry land, Timber Forest Product Utilization License, plantation concession, other use areas, protected forest areas, production forests, conversion production forest and limited production forest. More than half the total area of Riau Province (51.46%) includes areas with moderate to very high probability of fire occurrence. While the remaining 48.54% are in areas with low to very low probability of fire occurrence.

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