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Spatial Model of Deforestation in Jambi Province for The Periode 1990–2011

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Abstract

*In the last 2 decades, deforestation had been an international issue due to its effect to climate change. This study describes a spatial modelling for predicting deforestation in Jambi Province. The main study objective was to find out the best spatial model for predicting deforestation by considering the spatial contexts. The main data used for the analysis were multitemporal Landsat TM images acquired in 1990, 2000, and 2011, the existing land cover maps published by the Ministry of Forestry, statistical data and ground truth. Prior to any other analyses, all districts within the study area were classified into 2 typologies, i.e. low-rate and high-rate deforestation districs on the basis of social and economic factors by using clustering approaches. The spatial models of deforestation were developed by using least-square methods. The study found that the spatial model of deforestation for low-rate deforestation area is Logit (Deforestation) = -2.7046 – 0.000397*JH90*$_{(distance\ from\ forest\ edge)}$ *+ 0.000002*JJ*$_{(distance\ from\ road)}$ *– 0.000111*JKBN90*$_{(distance\ from\ estate\ crop\ edge)}$ *+ 0.000096 *JP90*$_{(distance\ from\ agricultural\ crop\ edge)}$ *+ 0.044227*PDK90*$_{(population\ density)}$ *+ 0.148187 *E*$_{(elevation)}$ *– 0.131178*S*$_{(slope);}$ *while for the high-speed deforestation area is Logit (Deforestation) = 9.1727 – 0.000788*JH90*$_{(distance\ from\ forest\ edge)}$ *– 0.000065 *JJ*$_{(distance\ from\ road)}$ *– 0.000091*JKBN90*$_{(distance\ from\ estate\ crop\ edge)}$ *+ 0.000005 *JP90*$_{(distance\ from\ agricultural\ crop\ edge)}$ *– 0.070372*PDK90*$_{(population\ density)}$ *+ 11.268539*E*$_{(elevation)}$ *– 1.495198*S*$_{(slope)}$*. The low-rate and high-rate deforestation models had relatively good ROC (Relative Operating Characteristics) values of 91.32% and 99.08%, respectively. The study concludes that the deforestation rate was significantly affected by accessibility (distance from forest edge, distance from estate crop edge, edge from agricultural land), biophysical condition (elevation and slope) as well as population density.*

Keywords: spatial model, deforestation, typologies, multitemporal landsat images, clustering

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Introduction

As the country with the fourth largest population in the world, Indonesia has a fast economic growth. In line with those economic growths, Indonesia, which has the third largest world's tropical forest is always associated with environmental issues on a worldwide level. One of the important international issue that requires the active involvement of the Indonesian nation is the issue of climate change. This concern is reasonable because Indonesia's tropical forests haves important roles in absorbing carbon dioxide from the atmosphere, so it can reduce global warming. In Indonesia whose population has reached 240 million in 2014 (BPS 2014), has a forest-population ratio per capita of only 0.3 ha ha^{-1}, nearly half of the world's forest-population ratio of 0.6 ha per capita; a change from forest to non-forest cover has always been an attractive and strategic issues for decision makers (Sumargo *et al*). Conceptually, for decision makers, the required information is not only in the form of tabular data, but also in the form of spatial context, such as location, spatial patterns, trends, the direction of change in deforestation, as well as the shape and intensity of the relationship between the location and the spatial components of the deforestation. The possibility to link between those attributal and spatial contexts had enable us to make a spatial analysis. Eventually, with regard to the case of deforestation, then the spatial modeling of deforestation has been a focus of this study. However, Indonesia's forest resources continuously decreases triggered by population growth causing the increase of demand for agriculture land, settlements and industry. The conversion from forest to non-forest areas generally occur in various areas, causing deforestation and forest degradation (Lambin *et al* 2003). Deforestation is defined as the change from forest cover to non forest permanently. According to FAO (2011) deforestation is the conversion of forests to other uses or long-term reduction of the crown canopy closure below 10%. An automated mapping of tropical deforestation and forest degradation can be found in Asner *et al*. (2009), while the deforestation monitoring can be found in Margono *et al*. (2012). The spatial models of deforestation examined in this study were predictive model, to forecat probability of occurrence as well as extent of deforestation in the next few years. Furthermore, because the forecast is the likelihood of the occurrence of deforestation, the model form analyzed was is a logistic model, in which the independent variables is in the form of binary values or criteria. Some examples of deforestation modeling with logistic model forms could be found in Mulyanto (2001) and Sulistiyono (2015).

Currently, deforestation has been a very sensitive issue both at national and international levels. This is due to the negative impact of deforestation on the national economy, livelihoods, and biodiversity. Without the proper policies, deforestation can threaten the existence of tropical forests in Indonesia. For example, until the year 2012 deforestation in Jambi reached 76,552.10 ha or approximately 42.89% of the forest area (BAPLAN 2008). The problems of deforestation can be viewed from two perspectives, namely the perspective of time and spatial perspective. A comphrehensive review of deforestation and climate change can be found in Moutinho and Scwartzman (2005). From the perspective of time, deforestation is influenced by time or season (period) of occurrences, while from the perspective of spatial deforestation is influenced by spatial factors such as location, area, distance, connectivity, and/or contiguities of spatial elements. In developing countries such as Indonesia, deforestation is often caused by social factors, economic, and cultural that significantly related to the spatial context (accessibility) and seasonal factors (Helmut & Lambin 2002; Bryan *et al.* 2010; Giliba *et al.* 2011; Michinaka *et al.* 2013; Banerjee & Madhurima 2013). In several cases, deforestation was also influenced by policy of the country (Sierra 2001). The drivers of deforestation are varied among countries over the world (Boucher *et al.* 2011). The research of Sasaki *et al.* (2011) found 10 variables that trigger deforestation, namely: (a) the sale of land, (b) settlement, (c) opening of the farm/garden, (d) a search of firewood, (e) natural forest fires, (f) burning for land preparation, (g) illegal logging for commercial purposes, (h) illegal logging to local needs, (i) the development of plantations, and (j) a natural disaster.

Although many studies on deforestation have been performed, the study of the spatial causes of deforestation, particularly in Jambi Province, has not been well explored, while we know that spatial modeling on deforestation is very essential to predict the location and extent of deforestation in the region. Therefore, this study objective is to develop spatial models to estimate the rate of deforestation in Jambi, by taking into account the biophysical and socioeconomic factors. Spatial factors that cause deforestation defined in this study are the factors that lead to deforestation, either directly or indirectly. The direct factors include illegal logging, farming, forest fires, forest encroachment; while the indirect causes are more commonly referred to as driving forces or triggering factors that include biophysical and socio-economic conditions as well as policies around the location of deforestation. The indirect factors include the existence of road access (expressed in a density and distance as well as road classes), slope, elevation, welfare and education levels of society, the existence of laws and policies that strengthen or weaken the chances of deforestation (Geist & Lambin 2011). Several empirical data studies can be found in Mulyanto and Jaya (2004) and Sulistiyono (2015). They showed that the magnitude of the rate and the likelihood of deforestation is strongly influenced by social and economic conditions surrounding communities (typology region). Therefore, the construction of a spatial model-based typology of regions is crucial in order to get an accurate model. Departing from the facts that the spatial factors that influence the occurrence of deforestation is very diverse, the study objective is to develop a spatial model to forecast of deforestation by taking into account the biophysical and socio-economic factors surrounding based on typology region.

Methods

Study site and date The study sites were all districts in Jambi Province. Field data collection was conducted on August 18 to 30, 2013. While the processing and data analysis were conducted at the Laboratory of Remote Sensing and GIS Department of Forest Management, Faculty of Forestry, Bogor Agricultural University from August 2013 to January 2014.

Material and equipment The main data used in this study were Landsat multitemporal data as listed in Table 1. In addition, this study also used land cover maps published by the Ministry of Forestry in 1990, 2000, 2003, 2006, 2009, and 2011. The other supporting data were administrative boundary map, road network map, contour map, slope map, and statistical data for each regency in Jambi for the period 1990–2011.

Equipment used for the field observations and measurements were a global positioning system (GPS) device, digital camera, compass, clinometer, tally sheet, measuring tape, and stationeries. Data processing unit covers laptop equipped with ERDAS software Image 9.1, ArcView 3.2 with extensions Kappa and dendrogram (Jaya's) Ver 1.6, ArcGIS 9.3, SPSS, and IDRISI.

Data analysis This study used 6 main steps to analyze the data, i.e. image analysis, land use classification, deforestation analysis, determining observation points for ground checks, developing deforestation typology, and spatial modelling on deforestation.

1 Image analysis
Image analysis consisted of a development of classification schemes, image pre-processing, image processing (mainly land cover classification) and analysis of accuracy. Image processing steps carried out to support this study included pre-processing (geometric correction, gap filling of the stripped images, minimizing the cloud cover and filtering). The geometric correction had been performed providing the RMSE (root mean squared error) less than 0.5 pixel. The gap filling and cloud removement were implemented using a "model builder" within the ERDAS Imagine software. The filtering of "noises (salt-and-peeper)" that come from

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Table 1 Landsat imageries used in this study

Path/ Raw	Year							
	1990		2000		2010		2013	
	Im age	date	Image	date	image	date	Image	date
124/6 1	Landsat TM	17-05-1989	Landsat ETM+	10-05-2001	Landsat ETM+	29-10-2011	Landsat OLI/TIRS	20-06-2013
125/6 1	Landsat TM	13-09-1989	Landsat ETM+	01-09-1999	Landsat TM	29-04-2009	Landsat OLI/TIRS	27-06-2013
125/6 2	Landsat TM	13-09-1989	Landsat TM	09-07-2000	Landsat TM	29-04-2009	Landsat OLI/TIRS	27-06-2013
126/6 1	Landsat TM	03-06-1990	Landsat TM	13-05-2000	Landsat TM	20-04-2009	Landsat OLI/TIRS	18-06-2013
126/6 2	Landsat TM	02-07-1989	Landsat TM	13-05-2000	Landsat TM	22-05-2009	Landsat OLI/TIRS	17-05-2013

geometric correction process was done using a median filter. Prior to classification, 5 scenes of Landsat TM covering all Jambi Province (Table 1) that representing years 1990, 2000, 2010, and 2014 were mozaicked. To reduce significant difference of image contrast between scene-border, to get the final seamless mosaicked images, then the contrast matching was run. The land cover classes developed referred to the forest and land cover classes published by the Ministry of Forestry (BAPLAN 2008). The image classification was done using hybrid between qualitative and quantitative approaches. Quantitative process applied in the early stages of research, especially to detect and identify more general and easily recognizable classes such as a water body, bare land and very dense vegetation. For classes that are very specific, which requires a particular knowledge within the landscape and forest ecosystem in Jambi was done with a qualitative approach (interpretation method). This qualitative approach was intended to improve as well as to correct the misclassification due to the inability to distinguish the image of objects on the quantitative process.

During the image processing, classification was done in 2 steps by the hybrid method that combine the quantitative and qualitative approaches. In the first step, the mosaicked image was classified with a quantitative approach using supervised classification. This was intended to classify the easily identifiable land covers such as bodies of water, bare soil and vegetation in general. Furthermore, the second step using visual interpretation was performed.

The main class targets during implementing the qualitative classification were the classes that has not been well classified (less accurate) in the quantitative classification. In this study, we also applied the separability analysis to determine whether the classes would be reclassified or merged into only a single class. For example, we frequently found the "confusion" between the mangrove forest and swamp or peat-swamp forest due to the similarity of brightness value. However, the ecological knowledge might help to get a clear decision, where the mangrove never been exist with the freshwater ecosystem. The confusion also often found among bushes to dry land agriculture.

2 Land use classifications
Basically, the classification scheme used in this study refers to classes developed by the Ministry of Forestry, which was based on the approach of physiognomy (the appearance of the objects of the earth's surface), the presence of vegetation (ranging from non-vegetated through dense vegetation) as well as the level of interference human activity (ranging from natural objects up to the man-made). In this study, some of the classes or categories were modified and added. The forest and land cover classes used in this study were classes that has been officially issued by the ministry of forestry of Indonesia,i.e., airports, water body, swamp shrub, dryland forest, mangrove forest, swamp forest, forest plantation, mixed-dryland-agriculture, settlements, swamps, shrub, paddy field, and bare land. Several modified land cover classes are junggle rubber, rubber plantation and oil palm plantation (BAPLAN 2008).

3 Deforestation analysis
This study defined deforestation as the change in land cover from forest to non-forest vegetation permanently, either located inside or outside of the forest territory. Deforestation analysis was conducted using time series analysis through spatial overlay operation between the various layers of land cover for the period of 1990–2000, 2003–2006, 2006–2009, and 2009–2011. The outputs of spatial operations were then analyzed using the thematic change procedure. For instance, the change from year 1990 to 2000 was denoted as [Tuplah_90] ++ "_" ++ [Tuplah_00], to identify the land cover change from forest to non-forest cover as referred to as deforested area, or from high density forest to less density forest or vegetation as called to as degraded forest. For the deforestation model development, the study used the 1990–2000 data set as data for model development, while the 2000–2011 were analyzed for model validation.

4 Determining observation points for ground check
Based on changes in forest and land cover maps through the analysis of "thematic-change", especially those

categorized as deforestation, then the further operation was performed by superimposing (e.g. identity/intersection spatial overlay) the layer of deforestation with proximity from the road (road buffer), proximity from the edge of the forest (forest buffer), from plantation (estate buffer), dry land agriculture (dry land farming buffer) at intervals of 500 m, altitude, slope and population density. From the spatial operations, then we defined observation points to take a number of points that will be used to build the model as well as to conduct a ground check on the field, especially in locations that suffered deforestation. Field checking points were useful to verify the thematic maps developed by the Ministry of Forestry and to identify the location and magnitude of influence of each triggering factors (driving forces) of deforestation and forest/land degradation.

5 Developing deforestation typology
This study developed some typologies of villages based on the rate of deforestation in every district of Jambi Province. Typology development was done by using the clustering method, particularly a standardized Euclidean distance (SdED) measure. This method could be used to compare variables that have a different unit. The distance between the two districts (clusters) was calculated using Equation *[1]* (Jaya 2010):

$$SdED_{jk} = \left[\sum_{i=1}^{n} \frac{(x_{ij} - x_{ik})^2}{S_i^2} \right] \quad [1]$$

note:
S_i = variance of variable -i on cluster -k
x_{ik} = the value of variable -i and cluster -k
x_{ij} = the value of variable -i and cluster -j

The results of clustering were presented in dendrograms, which illustrate the grouping clusters to facilitate the class merging and deletion (Jaya 2007). The dendrogram was developed using the nearest neighbor method (single-linkage method), in which the distance was determined based on the distance of the nearest cluster members.

Some previous studies confirmed that, the rate of deforestation is closely associated with triggering factors such as socioeconomic factors of society, biophysical condition and use of land in each village or district. This study, also used the hypothesis that the rate and direction of deforestation were influenced by the density of population, level of education, land requirements and sources of income. To analyze the factors that triggering deforestation, all of the 54 districts in Jambi were classified into some deforestation typologies based on variables such as listed in Table 2.

The evaluation of deforestation typology for all district-clusters were performed using the measure of *Producer' Accuracy* (PA) and *User's Accuracy* (UA) as shown in Equation *[2]* and Equation *[3]*

$$\text{Producer's Accuracy (PA)} = \frac{x_{ii}}{x_{i+}} \subset 100\% \quad [2]$$

$$\text{User's Accuracy (UA)} = \frac{x_{ii}}{x_{+i}} \subset 100\% \quad [3]$$

6 Spatial modeling of deforestation
Deforestation was defined as a permanent change from woody-forested area to non-forest area for each time interval. The forest cover classes that categorized into deforestation are from forest cover to bare land, shrub, bush (located outside forest jurisdiction, resettlement, estate crop, dryland-gariculture, dryland-mixed-agriculture. The change from forest into plantation forest was not categorized into deforestation.

The probability of deforestation (p = 1), or no deforestation (p = 0) in each district was modeled using a logistic regression model as shown in Equation *[4]* and Equation *[5]* (Hosmer & Lemeshow 2000):

$$\pi = \frac{\exp(\beta_0 + \beta_1\chi_1 + \ldots + \beta_n\chi_n)}{1 + \exp(\beta_0 + \beta_1\chi_1 + \quad + \beta_n\chi_n)} \quad [4]$$

or

$$g = \ln \frac{\pi}{1 - \pi} = (\beta_0 + \beta_1\chi_1 + \quad + \beta_n\chi_n) \quad [5]$$

note:
β_0 = intercept
β_1 = regression coefficient
x_{1-n} = variable x
π = the probability of deforestation
g = probability

$$\text{Logit(P)} = a + b_1x_1 + b_2x_2 + \quad + b_nx_n$$

note:
$x1$ = distance from the edge of the forest
$x2$ = distance from the road
$x3$ = elevation
$x4$ = slope
$x5$ = population density
$x6$ = distance from the estate crop
$x7$ = distance from the agricultural land and
e = error

The variables considered in this study were in line with the variables examined by Chowdhury (2006) for identifying the relative roles of biophysical and socioeconomic factors in driving regional deforestation roles in Mexico. Of the 22 factors used in predicting the regional deforestation in Mexico (Chowdury 2006) some of them are similar to the factors used in this study such as elevation, slope, distance from road, distance from the nearest agricultural land, density of males and females population. The study of underlying drivers of deforestation and forest degradation was also carried out by Mulyanto and Jaya (2004), Giliba *et al.* (2011) and the Goverment of Kenya (MoFW-Kenya 2013). In Kenya, agricultural expansion and wood extraction had been major direct drivers affecting the deforestation in developing country while population pressure are major indirec drivers.

Murali and Hedge (1997) and Laurance (1999) considered the population pressure as a factor that tend to promote forest coversion in developing countries, while Geist and Lambin (2002) noted that economic factors, institutions, national policies and agricultural expansion are among the most prominent factors affecting the deforestation. Allnutt *et al.* (2013) analyzed the forest disturbance patterns in relation to rivers and travel distance from permanent villages. The spatial and temporal modeling of deforestation can also be found in Vance and Geoghegan (2002), and Geoghegan *et al*. (2004).

The multicoliniearity test could be assessed by knowing the correlation coefficient between variables. One of the 2 variables having high correlation (above 0.7) would be selected, particularly that easily measurable and consistently giving less measurement error. Validation of the logistic regression models was done by using the graph of ROC (Relative Operating Characteristics) of the IDRISI software of logistigreg function criteria as presented in Table 3.

Results and Discussion

The loss of forests in Sumatra during the period of 1990–2010 was quite vary among provinces and between type and forest cover at the beginning of the period of forest usages. In general the loss of forests in Sumatra as a whole is quite high over the 1990–2000 period. During this period, nearly half of primary forest in 1990 has been deforested or degraded in 2000. Jambi Province is the province having the second largest deforestation rates after Riau Province, particularly in the period 1990–2000 with the amount of approximately 0.04 million ha (Margono 2012).

Refferring to the cluster analysis using Euclidean Distance Measure with Nearest Neighbour Dendogram, the

Table 2 Variables used for developing deforestation typology

Variables	Remarks
x1	Population per district in year 1990
x2	Number of students, including elementary school SD, junior-high school (SMP), senior-high school (SMU) and university
x3	Number of school unit of SD, junior -high school (SMP), senior-high school (SMU) and university
x4	Extent of paddy field and dry land agriculture (ha)
x5	Extent of oil palm and rubber plantation (ha)
x6	Estate crop (including oil palm and rubber) (ha)
x7	Production of oil palm and rubber (ton)
x8	Production of overall agriculture land (ton)

Table 3 Criteria of ROC (*Relative Operating Characteristics*)

ROC	Description
1.00	excellent
0.75–1.00	very good
0.50–0.75	good
<0.50	worse

Table 4 The error matrix of deforestation typology

	D1	D2	Total	PA
T1	40	5	45	0.89
T2	8	1	9	0.89
Total	48	6	54	
UA	0.83	0.83		
OA	0.76			

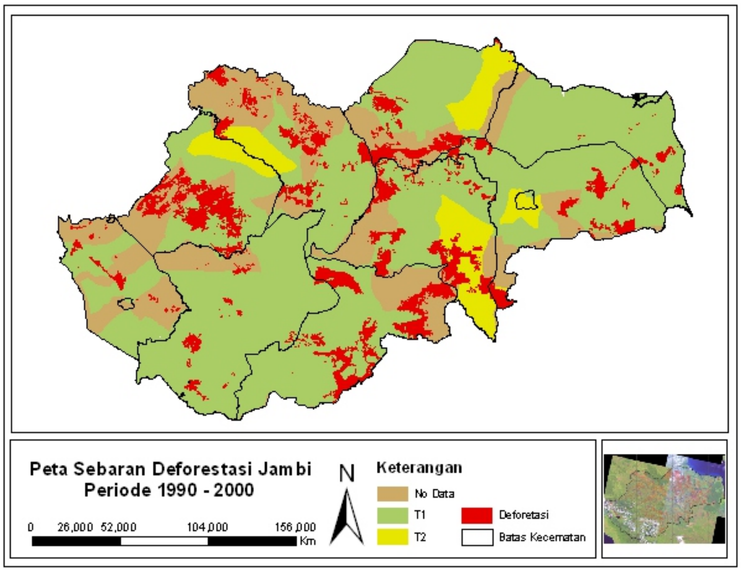

Figure 1 Map of deforestation for the period of 1990–2000 in Jambi Province by typology.

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study found 2 groups of cluster, called to as T1 and T2. Furthermore, by analyzing the mean value of the deforestation rate during 1990–2000 period for these clusters, then we recognized that T1 has the low deforestation rate of 4,238 ha year^{-1} (D1), while the T2 has high deforestation rate of 8,474 ha year^{-1} (D2). With this deforestation rate classes, we got the coincidence (overall accuracy/OA) value of the typology classification of about 76% (Table 4). Thus, all districts in Jambi Province can be grouped into 2 typologies of districts, namely: districts with low deforestation rates (T1) and districts with high deforestation rates (T2). Figure 1 presents spatial distribution of the deforestation rates for each typologies.

The spatial model of deforestation The period of forest change used to build the predictive model of deforestation was 1990–2000 period, while the data for model validation was derived from the 2000–2011 deforestation period.

The probability of deforestation for each typology can be predicted by using the following models as shown in Equation *[6]* and Equation *[7]*.

Typology 1:
Logit (Deforestation) = -2,7046 – 0.000397JH90 + 0.000002JJ – 0.000111JKBN90 + 0.000096JP90 + 0.044227PDK90 + 0.148187E – 0.131178S *[7]*

Typology 2:
Logit (Deforestation) = –9.1727 – 0.000788JH90 – 0.000065JJ – 0.000091JKBN90 + 0.000005JP90 – 0.070372PDK90 + 11.268539E – 1.495198S *[7]*

note:
JH90 = distance from the edge of forest in 1990 (m)
PDK90 = population density in 1990 (person per km^2)
E = elevation (m)
JJ = distance from the road (m)
S = slope (%)
JP = distance from the edge of agricultural land in 1990 (m)
JKBN90 = distance from the edge of estate crop in 1990 (m).

As hypothesized, the biophysical and social factors were significant factors on determining the deforestation. Although the deforestation models for T1 and T2 have the same independent variables, each model exhibited different behaviour. The model coefficients of the variables JPH90 (distance from the edge of the forest) for the typology 2 has much higher weight (coefficient regression), and even almost doubled compared to the weight of JPH90 for the T1. This means that forests located close to roads and the existing estate crops are at the greatest risk of deforestation. This also indicates that land managers in Jambi tend to choose further location for new cultivation. Both models show that the variables JPH90 contributed the highest weight than other variables. The algebraic sign of the variable JJ (distance from the road) was opposite to that of the variable and JKBN90 (distance from the edge of the plantation. In the T1, the probability of deforestation is directly proportional to JJ but inversely proportional to JKBN90. In contrast, the deforestation probability of T2 is inversely proportional to JJ but directly proportional to JKBN90. For variables E (elevation) and S (slope), although the algebraic signs of regression coefficients in each model are equals (negative for slope and positive for elevation), but the values of the regression coefficient for T2 having higher-rate of deforestation, much higher than for T1 (low-rate deforestation). The field observation confirmed that most of forest conversion occurred in areas with higher elevation and lower slope (gentle). This finding is different from Chowdhury (2006), where deforestation rate in Mexico positively correlated with the slope but negatively correlated with the elevation.

The relationship between deforestation probability and its driving factors, the authors made a table expressing the probability of deforestation, as presented in Tables 5 and Table 6. Table 5 describes the deforestation probability for the typology 1 and Table 6 for tipology 2, using a regression equation which had been developed earlier. In Table 5, it is generally shown that a extreem increase in the probability of deforestation greatly influenced by the variables of JH90 (distance from the edge of the forest). The second largerst variable is PDK90 (population density), then followed by variables of E (elevation), S (slope), JKBN90 (Distance from plantations) and JJ (distance from the road). In the Table 5 (T1), low probability is expressed in green color, mostly found in a farther distance, more than or equal to 1,5000 m. The moderate probability having yellow and light green, mainly occurred at distances between 5,000 m and less than 15 km. High deforestation probability that represented by the red color occurs at a distance of less than or equal to 5,000 m. Distance from estate crop and the distance from the agricutural land also provide a relatively large influence on the probability of the deforestation.

At the T1, the increase of deforestation probability is directly proportional to the distance from agricultural land, but inversely proportional to the distance from the estate crop. Probability of deforestation will be higher in area away from the agricultural lands, but close to the locations of the estate crop. Deforestation due to the opening of a new agricultural land tend to occur in locations far away from the existing agricultural land. In general, the occurrence of deforestation in the T1, has a higher probability in the areas densely populated and at a relatively steeper slope. In this regions, more population density translate into higher deforestation probabilities. This concides with study of Chowdhury (2006). The increasing population density would lead to a drastic increase in deforestation probability. This is a specific characteristic of the typology having low-rate deforestation level, which is generally caused by local communities performing small scale bussiness, where high deforestation probability mainly occurred in densely populated areas, flat slope, high elevation, away from the road, close to the forest, and near with estate crop but far away from the road. High deforestation likelihoods commonly occur in areas with high elevation, but at a relatively flat land configuration (a positive algebraic sign for elevation and negative sign for slope variable). However, since these areas belong to the typology with low rates of deforestation, the increase in the rate of deforestation caused by population density will not be too high. The deforestation

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Table 5 Probability of deforestation on T1

PDK90 (Population density), E (Elevation), S (Slope), JP (Distance from agricultural land)				Jh90 (Distance from forest edge), JKBN90 (Distance from estate crop), JJ (Distance from roads)							
			JH90	5,000	5,000	5,000	5,000	25,000	25,000	25,000	25,000
			JKBN90	5,000	5,000	25,000	25,000	5,000	5,000	25,000	25,000
			JJ	5,000	50,000	5,000	50,000	5,000	50,000	5,000	50,000
Pddk90	S	E	JP	Probability of deforestation							
10	1	1	5,000	0.0136	0.0149	0.0015	0.0016	0.0000	0.0000	0.0000	0.0000
10	1	1	25,000	0.0930	0.1017	0.0101	0.0111	0.0000	0.0000	0.0000	0.0000
10	1	5	5,000	0.0247	0.0270	0.0027	0.0029	0.0000	0.0000	0.0000	0.0000
10	1	5	25,000	0.1682	0.1840	0.0183	0.0200	0.0001	0.0001	0.0000	0.0000
10	5	1	5,000	0.0081	0.0088	0.0009	0.0010	0.0000	0.0000	0.0000	0.0000
10	5	1	25,000	0.0550	0.0602	0.0060	0.0065	0.0000	0.0000	0.0000	0.0000
10	5	5	5,000	0.0146	0.0160	0.0016	0.0017	0.0000	0.0000	0.0000	0.0000
10	5	5	2,500	0.0995	0.1089	0.0108	0.0118	0.0000	0.0000	0.0000	0.0000
30	1	1	5,000	0.0330	0.0361	0.0036	0.0039	0.0000	0.0000	0.0000	0.0000
30	1	1	25,000	0.2252	0.2464	0.0245	0.0268	0.0001	0.0001	0.0000	0.0000
30	1	5	5,000	0.0597	0.0653	0.0065	0.0071	0.0000	0.0000	0.0000	0.0000
30	1	5	25,000	0.4074	0.4457	0.0442	0.0484	0.0001	0.0002	0.0000	0.0000
30	5	1	5,000	0.0195	0.0214	0.0021	0.0023	0.0000	0.0000	0.0000	0.0000
30	5	1	25,000	0.1333	0.1458	0.0145	0.0158	0.0000	0.0001	0.0000	0.0000
30	5	5	5,000	0.0353	0.0387	0.0038	0.0042	0.0000	0.0000	0.0000	0.0000
30	5	5	25,000	0.2411	0.2638	0.0262	0.0286	0.0001	0.0001	0.0000	0.0000

occurred in this typology mainly small-scale deforestation caused by many traditional factors such as shifting cultivation, opening a new small-scale agricultural land by local people or establishing a new mixed-garden by local people.

In the T2, high deforestation probabilities are affected by the same variables that exist in the T1, but with relativeley different weight values. In the T2 regions, a quite different behaviour of deforestation can be observed. Based on the algebraic sign of each coefficient, the probability of deforestation is a function of the distance from the edge of forest. The closer the distance will lead to changes in the high deforestation. In this typology region, high probability of the deforestation occurred at a closer distance from the road. Probabilities will increase sharply if the location is close to the forest edge, having sparse population density, relatively high elevation and gentle slope (Table 6). It is also noted that the T2 which belong to the area with high deforestation rate, the population density coefficient even inversely related to deforestation probability. This is different from the study of Chowdhury (2006). In other words, a high deforestation probability will occur in areas of low population density. It is very common that large-scale and massive forest conversion for extensive estate crop or transmigration were mainly located at a low population density but has a good accessibility. Forest damages due to natural disasters caused by large and long forest fires frequently occurred in relatively low population density. A very high deforestation probability existed in the locations having a population density of about 30 people per km2 or more, with a distance of approximately 5000 m of forest and at an elevation 250 m asl (dark red color) but on a relatively flat slope.

In the typology region with low deforestation rates (T1), by taking into account the distance factor (proximity), it is qualitatively known that the distance from the edge of forests provide a very large influence, which is then followed by the distance from the estate crop and the distance of community agricultural lands. This is similar to the result of Giliba *et al.* (2011) where the level of deforestation is a function of distance to forest edge. Locations with high probabilities are found in areas close to the edge of the forest, from estate crop, from agriculture but away from the existing roads. High probability is found on a relatively flat slope with higher elevation, but the lower population density. The uniqueness of this typology is that, deforestation probability will be higher if it is located far away from the agricultural lands of the community. For T1, our study is in line with Laurance (1999) and Murali & Hedge (1997) that conversion pressure is increasing throughout the developing world due to the population increase. In T1, the deforestation probability is highly correlated with the population density.

In the areas of T2, based on the algebraic sign of each coefficient point of view, spatially, change the distance from the edge of the forest will lead to a high probability of deforestation. In this typology, locations closer of the road, the edge of the forests and plantations will have a higher deforestation probability. It is also shown, the coefficient of population density is inversely proportional to the probability of deforestation. In other words, high deforestation occurs in areas of low population density, although located at a higher altitude. Changes in deforestation probabilities will not be too high despite there

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is a significant change in a distance from agricultural lands. It is also very common in areas with high deforestation rates, where there is large-scale forest conversion and developed massively, for example, the conversion of forests into estate crop, from forest to forest transmigration area or loss of forest due to natural disasters such as forest fires. In the area of T2, high deforestation generally occur in areas with a relatively high elevation, but on a relatively flat slope. The results from T2 is similar to the results of forest disturbance analysis performed by Allnutt *et al.* (2013)and Michinaka *et al.* (2013), where the population density have a negative impact to the deforestation. Descriptively, the probabilities of high and low deforestation rate are presented in Table 7.

Based on the regression analysis performed before, it is known that the independent variables that affect deforestation in typology 1 and typology 2 are distance from the edge of the forests, road distance, the distance from edge of estate crops, the distance from the edge of agricultural lands, elevation, slope, and population. Figures 2a and 2b show that the higher the probability of occurrence of deforestation is shown in reddish to red colors while the lowest probability is described by the purple.

The spatial deforestation models for the T1 and T2 have the ROC values of 91.32% and 99.08%. respectively. The high ROC values expressed that the deforestation models can be used to predict a probability of deforestation precisely.

Based on the model developed (2000–2011 period), then we performed the verification tests on the prediction model by using the deforestation and non-deforestation data of Jambi Province occurred between 2000 and 2011. By comparing the results between the predicted deforestation and the actual deforestation of the year 2000, then we

Table 6 Probability of deforestation on T2

PDK90 (Population density), E (Elevation), S (Slope), JP (Distance from agricultural land)				JH90 (Distance from forest edge), JKBN90 (Distance from estate crop), JJ (Distance from roads)							
			JH90	5000	5000	5000	5000	25000	25000	25000	25000
			JKBN90	5000	5000	25000	25000	5000	5000	25000	25000
			JJ	5000	50000	5000	50000	5000	50000	5000	50000
Pddk90	S	E	JP	Probability of deforestation							
10	1	1	5000	0.0082	0.0004	0.0013	0.0001	0.0000	0.0000	0.0000	0.0000
10	1	1	25000	0.0091	0.0005	0.0015	0.0001	0.0000	0.0000	0.0000	0.0000
10	1	2	5000	1.0000	1.0000	1.0000	1.0000	0.0001	0.0000	0.0000	0.0000
10	1	2	25000	1.0000	1.0000	1.0000	1.0000	0.0001	0.0000	0.0000	0.0000
10	5	1	5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	5	1	25000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	5	2	5000	1.0000	0.0876	0.2644	0.0142	0.0000	0.0000	0.0000	0.0000
10	5	2	25000	1.0000	0.0968	0.2922	0.0157	0.0000	0.0000	0.0000	0.0000
30	1	1	5000	0.0020	0.0001	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000
30	1	1	25000	0.0022	0.0001	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
30	1	2	5000	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000
30	1	2	25000	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000
30	5	1	5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	5	1	25000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	5	2	5000	0.3994	0.0214	0.0647	0.0035	0.0000	0.0000	0.0000	0.0000
30	5	2	25000	0.4414	0.0237	0.0715	0.0038	0.0000	0.0000	0.0000	0.0000

Table 7 Description of the role of deforestation variables affecting the probability of deforestation at each typology

Independent variables	Deforestation probability			
	Typology 1*		Typology 2*	
	Low	High	Low	High
JH90 (Distance from forest edge)	Far	Near	Far	Near
JKBN90 (Distance from estate crop)	Far	Near	Far	Near
JJ (Distance from roads)	Near	Far	Far	Near
JP (Distance from agricultural land)	Near	Far	Far	Near
PDK90 (Population density)	Low	High	High	Low
E (Elevation)	Ligh	High	Low	High
S (Slope)	Steep	Gentle	Steep	Gentle

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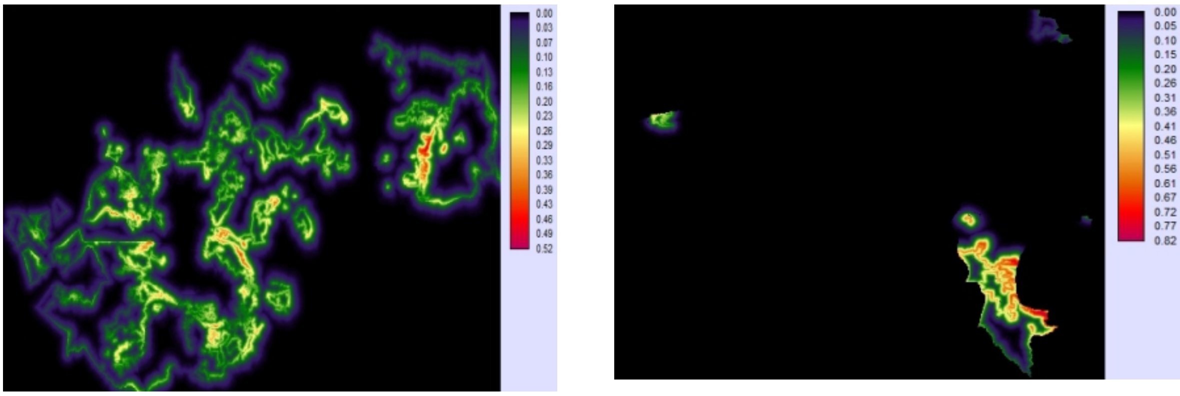

(a) (b)

Figure 2 Spatial distribution of the deforestation probability in the year 2000 for T1 (a) and T2 (b).

Table 8 Validation model of T1

	Actual		
Prediction	Deforestation (ha)	Non deforestation (ha)	Total (ha)
Deforestation	8153139	116744	8269883
Non -deforestation	158853	27897	186750
Total			8456633
Overall Accuracy (%)			96.74

Table 9 Validation model of T2

	Actual		
Prediction	Deforestation (ha)	Non deforestation (ha)	Total (ha)
Deforestation	3875609	35621	3911230
Non-deforestation	9420	1070	10490
Total			3921720
Overall Accuracy (%)			98,85

obtained overall accuracy of approximately 96.14% for the T1 and 98.99% for the T2 (Tables 8, Table 9). These express that the reliability of the spatial model of deforestation is very good in predicting the occurrence or non-occurrence of deforestation in Jambi Province in 2000.

Conclusion

Factors affecting the probability of deforestation are distance from the edge of the forest, the distance from edge of estate crops, the distance from edge of agricultural lands, the distance from road, elevation, slope and population density. This study successfully classified the area of Jambi Province into 2 groups of deforestation typology, i.e. region with low deforestation-rate (T1) and regions with high deforestation-rate (T2) having an accuracy of about 96.14% for typology 1 and 98.99% for typology 2. The spatial deforestation model developed in this study exemplifies the spatial driving forces related to the behaviour of forest change in a study area concerned. The deforestation model for T1 and T2 are as shown in Equatiion *[6]* and Equation *[7]*. The spatial deforestation models have a very high ROC value, i.e. 91.32% for T1 and 99.08% for T2. The models also provide good assessment, i.e. 96.7% for T1 and 98.8% for T2.

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