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Spatial Modeling of Forest Cover Change in Kubu Raya Regency, West Kalimantan

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Abstract

Forest cover change is one of the environmental issues that continually gotten international attention. This study describes how to develop a spatial model of this change in each village-based typology by considering various biophysical and social-economic factors. The village typologies were investigated by applying the clustering analysis approach. The objective of this study was to develop the spatial model and to identify the driving forces of forest cover change by the village in Kubu Raya Regency of West Kalimantan. Based on the proportion of forest in 2015, the study found that there are two village typologies within the study area with 81% overall accuracy (OA). The Typology 1 (T1) which has low change rate of 5,001.8 ha year^{-1} consisted of 56 villages, while the Typology 2 (T2) which has high change rate about 8,050.6 ha year^{-1} covered 34 villages. The study also recognized that the most significant driving forces of change in T1 were the distance from rivers (X_2) and settlements (X_3), whereas in T2 were the distance from roads (X_1) and the edge of the forest in 2015 (X_9). The best spatial model of the change are $Y = -0.01+0.0001X_2+0.0004X_3$ with OA of 83% and mean deviation (SR) 10.5% for T1 and $Y = 0.02+0.0001X_1-0.0002X_9$ with OA 53% and SR 13.3% for T2. The study concludes that the proximity from the center of the human activities holds a significant influence on the behavior of forest cover changes.

Keywords: clustering, driving force, lowland forest, village typologies

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Introduction

The issue of deforestation and forest degradation in Indonesia has been a long story and still a debatable issue. However, it is increasingly threatened by the demands of new land for other uses, which are the implications of economic and population growth. Even with the alarming rates, certain forest areas were still decreasing within the last three decades (FWI 2014; KLHK 2017). The primary forest cover changes in Indonesia have reached a rate of 0.84 million ha or 700,000 ha per year (Margono *et al*. 2014). Up to now, forest cover change has been a very sensitive issue becauseit will lead to climate change, while on the other hand there is a high necessity of opening less productive areas for development purposes (Siswoko 2008; IPCC 2013). Based on several studies that have been conducted in regions such as Sumatra (Sulistiyono *et al*. 2015; Wijaya *et al*. 2015; Albar *et al*. 2016), behaviors and characteristics on certain areas are varied significantly according to their biophysical, economic, social, and even political conditions.

Forest cover change might occur due to many factors from biophysical characteristics, socioeconomic, and cultural conditions, even due to the political situation within the community (Geist *et al.* 2002; Sloan *et al*. 2015). In Indonesia, the changes that occurred within each region are varied in terms of their rates and the driving forces causing the dynamic change. Therefore, an estimation method using spatial approaches was expected to describe a more reliable relationship among various forces as mentioned to the forest cover change that was happening in theIndonesian region. Estimation of the change using spatial approaches could be found in Sulistiyono *et al*. (2015), Albar *et al*. (2016), and Wijaya *et al*. (2015). In this studytypology was done to obtain the more reliable model, all villages were grouped into a more homogenous class, which then is referred to as village typology. Typology can be defined asthe grouping of study units into a subpopulation that is homogenous. The use of typology has been conducted in several studies and was considered necessarily effective in increasing the accuracy of the model and identifying the causing or supporting forces of forest cover changes within an area. Several studies showed that the change rates were in line with the typology of the area (Valbuena *et al*. 2008; Lastini 2012; Pincus *et al*. 2015). Typology would also make it easier to consider the triggering factors and spatial patterns of the forest cover changes (Valbuena *et al*. 2008; Sulistyono *et al*. 2015).

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In this study, the smallest unit of administrative boundary used asobservationwas the village. It was expected that within this level, the forest cover change would relate with their socioeconomic, cultural, and even institutional conditions of each village area. Hence, it would be very important to conduct a typology study of these changes within the village administrative area. This would expect to increase the accuracy of the spatial model of forest cover change that wasdeveloped for each region.

Research in forest cover change in Indonesia would be important because it would also consider the regional planning act at the regency level that has been enactedsince the Autonomy Law Regions No. 22 in 1999, as well as the Autonomy Law Regions in year 2000. Also, the studies done in Indonesia regarding these changes are very few, mostly only for province or island region levels (Sulistiyono *et al*. 2015; Wijaya *et al*. 2015; Albar *et al*. 2016). One of the islands in Indonesia that often became national and global attention was the Island of Borneo because of the very high rates of changes that were happening within the island. West Kalimantan Province was also one of the areas in Borneo Island that had a very high rate of changes that was happening within that area. This study emphasizes the change in Kubu Raya Regency which was one of the regencies in West KalimantanProvince of Borneo Island that had high rates of the change. Kubu Raya Regency area was regency dominated by wetlands, swamp of forest ecosystems, and mangrove forest that was a forest cover within lowland forest areas.

Considering the information mentioned above, the main objective of this study was to develop a spatial model of the forest cover change, specifically in identifying the village typologies and the driving forces causing the changes in Kubu Raya Regency, West Kalimantan. This spatial modeling was expected to explain the spatial coverage of forest cover change and driving factors causing the change within each typology within this area.

Methods

The study was carried out from September 2017-April 2018. This study was in Kubu Raya Regency, West Kalimantan Province, Indonesia which was geographically located in 108°35'−109°58'BT and 00°44'LU−10°01'LS. Kubu Raya Regency has nine districts and 118 villages. This study was also carried out in the Remote Sensing Laboratory of Faculty of Forestry, IPB Bogor, Indonesia.

In this study, Global Positioning System (GPS), camera, tally sheet, and stationery were used for fields observation and conducting inspections. For the processing, the hardware used was a set of computers with software *ArcGIS 10.1*, *Erdas imagine 9.1*, and *Minitab 17*. The main data that were used for this research were Landsat TM Multitemporal Images acquired in March 5 year 2011 and February 12 year 2015, land cover data of 2000 and 2015 issued by the Ministry of Environment and Forestry (KLHK), district-level statistical data of Kubu Raya Regency in 2009 and 2016, administrative data published by the Geospatial Information Agency (BIG), and field observation data.

Selection of typologyvariables

Forest cover change can be defined as the change in forest cover conditions from forest to non-forest areas. The analysis of the change rates was done by overlay each land cover each period. The development of the typology of the change area in Kubu Raya Regency was conducted using a quantitative approach with the clustering method. Cluster analysis was a technique designed to find similarity in a data set. Cluster analysis aims to find the category structure that is in accordance with the observation (finding the natural group).Clustering method was used to find the grouping patterns of a village. In this analysis, the selection of variables was conducted through correlation analysis to define if there were closeness and direct relationship between two variables that were used as variables for the construction of typology (Lastini 2012; Sulistiyono *et al*. 2015; Albar *et al*. 2016 2012). This study excludes the forest cover changes in industrial plantation forests (hutan tanaman industri, HTI) from this calculation. This research uses variables that were based on biophysical and socio-economic conditions of the community within the village in the year 2000−2015.

The independent variable that was used for developing typology were proportion of forest in 2000 (X_1), proportion of forest in 2015 (X_2), population year 2000−2015 (X_3), population rate of 2000−2015 (X_4), the pace of the number of schools in 2000−2015 (X_5), number of school year 2000-2015 (X_7), the pace of the number of students in 2000−2015 (X_8), number of student year 2000−2015 (X_8), the rate of teachers in 2000−2015 (X_9), number of teachers from 2000−2015 (X_{10}), the rate of doctors in 2000−2015 (X_{11}), number of doctors in 2000−2015 (X_{12}), the rate of number of community health center in 2000−2015 (X_{13}), and the number of community health center in 2000−2015 (X_{14}). As for the dependent variable was the forest cover change rate. All the X variables went through correlation analysis which resulted in 14 variables produced from the analysis. The independent variables are then analyzed again using correlation test with the dependent variable. The correlation test matrix variable is presented in Table 1.

Development offorest cover change typology

Development of village typology was done using a clustering approach with standardized Euclidean distance (Valbuena *et al*. 2008; Lastini 2012). Euclidean distance was the type of distance measurement in cluster analysis that is most commonly used to measure the distance from a data object to the cluster center. Euclidean distance was a geometric distance between two data objects so that the closer the distance the more it looks like a data object. The clustering process was then analyzed graphically using dendrogram with the average linkage method. To evaluate the indication of multicollinearity between the causing factors and the driving factors, as well as between the ratio of forests to the driving factors and causes, therefore a correlationtest was conducted (Table 1).

The analysis shows that there were two driving factors that were highly correlated with the proportion of forest, namely the proportion of forest in 2000 (X_1) and the proportion of forest in 2015 (X_2). However, since between X_1

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Table 1 Coefficient of correlation the driving factors and the rate of forest cover change

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_{19}	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
Y	1.0														
X_1	-0.3	1.0													
X_2	-0.8	0.7	1.0												
X_3	-0.1	0.1	0.2	1.0											
X_4	0.0	-0.2	-0.1	-0.3	1.0										
X_5	0.0	0.0	0.0	-0.1	0.5	1.0									
X_6	-0.1	-0.1	0.0	-0.2	0.7	0.4	1.0								
X_7	0.1	0.0	0.0	-0.2	0.8	0.7	0.7	1.0							
X_8	0.0	-0.2	-0.1	-0.2	0.9	0.6	0.8	0.9	1.0						
X_9	-0.1	-0.1	0.0	-0.2	0.7	0.4	0.8	0.6	0.7	1.0					
X_{10}	0.0	-0.2	-0.1	-0.2	0.9	0.5	0.9	0.8	0.9	0.7	1.0				
X_{11}	0.0	0.0	0.0	-0.2	0.3	0.3	0.2	0.4	0.4	0.2	0.3	1.0			
X_{12}	0.0	-0.1	0.0	-0.2	0.4	0.2	0.4	0.2	0.4	0.2	0.4	0.5	1.0		
X_{13}	-0.2	0.0	0.1	0.1	-0.1	-0.1	-0.2	-0.1	-0.1	-0.1	-0.2	0.0	-0.6	1.0	
X_{14}	0.0	-0.1	0.0	-0.1	0.2	0.2	0.4	0.1	0.2	0.1	0.3	0.2	0.8	-0.7	1.0

and $X_2$are of considerable correlations, i.e., 0.7, the development of typology uses one of these variables. Accuracy tests were conducted where the chosen typology class are based on the highest overall accuracy (OA) score.

Development of a typology of forest cover changes The development of village typology was done using a clustering approach with standardized Euclidean distance (Standardized Euclidean Distance), and calculated with the following Equation *[1]*.

$$SdED_{jk} = \sum \frac{(X_{ij} - X_{ik})^2}{S_i{}^2} \quad [1]$$

note: $sdED_{jk}$: standardized Euclidean distance; S_i^2:the variance of the variable *I*; X_{ij} : the value of the variable *i* of the cluster j; Xik : the value of the variable *i* of the cluster *k*.

As for the technique in grouping the villages, the average linkage from the dendrogram method was used. To make it easier to conduct a classification analysis based on the level of similarity of each cluster size used, a technique is needed to compile a cluster clustering sequence, from a large number to a small number.This determined the closest distance between the members of each typology that were calculated based on the average values of the members within the group. Theclustering method has been successfully examined in previous studies (, Valbuena *et al*. 2008, Jaya 2010; Lastini 2012; Pang *et al*. 2013; Wijaya *et al*. 2015). Typology was based on selected variables from the correlation analysis which are X_2 (proportion of forest area to the total area in each sample plot in 2015). To test the reliability of each class of village typology, then a spatial accuracy test was conducted based on the rate of classes of forest cover change.

Identification of driving forces Identification of the driving forces of forest cover change was processed using GIS spatial operation functions such as buffering, intersection, union, and clip. The buffering was done with 500-meter intervals to determine the distance attributes of the existing driving factors (Ahmad *et al*. 2015; *Bennet* 2015; Setiawan 2015; Sulistyono *et al*. 2015; Wijaya *et al*. 2015). Data for analyzing the driving forces were selected using the systematic sampling method with random start with the sampling intensity of 15%, where each sample represents the area of 1 km × 5 km.

The number of selected samples were 285 samples. These data samples were then used for the standardization process of data, and model development at each using 95 samples. The rate of forest cover change was denoted as dependent variables (Y). Driving factors were expressed as independent variables (X). The independent variables used in developing this model were distance of forest cover from the road (X_1), distance of forest cover from the river (X_2), distance of forest cover change from settlement (X_3), distance of forest cover changes from plantation in 2000 (X_4), distance of forest cover change from plantation in 2015 (X_5), distance of forest cover change from agriculture in 2000 (X_6), distance of forest cover change from agriculture in 2015 (X_7), distance of forest cover change from the edge of the forest in 2000 (X_8), distance of forest cover change from the edge of the forest in 2015 (X_9), and distance of forest cover change from sub-district capital (X_{10}).

Data standardization Prior develop the model, the model must have the ability to describe the weight for each driving factors, where all the driving factors had to be standardized, so the data used had the same scale and units. In this study, data standardization was conducted by converting the actual data values into scores. The transformation equation from the actual data values into scores was done using regression equation between each driving factors and the rate of each forest cover change. This conversion process could be done if the regression relationship of X and Y variables have R^2> 50%. The scores generated based on that equation was made in a range of values between 10 until 100. To calculate the weight values of the model to always have a positive value, then the conversion equation from the actual data values to

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score was done using the equation as follows:

Equation *[2]* of score conversion with positive correlation coefficient is :

$$Skor = \left(\frac{x-min}{max-min}\right) \times 90 + 10 \qquad [2]$$

The score conversion Equation *[3]* with negative correlation coefficient is:

$$Skor = \left(\frac{max-x}{max-min}\right) \times 90 + 10 \qquad [3]$$

note: x:The value of the relationship equation between driving forces and the rate of forest cover change; min and max: the lowest and highest value of the value of the driving factor

Development of forest cover change model Within each village typology, a spatial model by considering the forest cover change rates and their corresponding variables were analyzed through multiple regression analysis where driving factors were considered as the independent variables, and forest cover change rate was considered as the dependent variables. The selected model would have had to not only fulfilled the statistical requirements (p-*value*<0.05 and R^2>50%), but also had to have the least value of validation error.

Model validation The model validation was intended to obtain the most optimum model through the model accuracy test (Jaya *et al*. 1995; Jaya 2010; Kumar *et al*. 2014; Muis *et al*. 2016). The best model accuracy test was conducted using data plot of 95 plots that were classified into three classes that follow the intervals of classes of the rate of forest cover change. To show the spatial distribution of the forest cover change, the rates of the change was classified into low, medium, and high. The accuracy assessments used were the overall accuracy (OA) that is naturally obtained from the confusion matrix and mean deviation (SR). The most optimum model selected would have the highest OA and SR.

Results and Discusion

Village typology

As depicted in Figure 1, the dendrogram distinctly classified the villages into two groups, then referred to as T1 and T2. The accuracy test result showed that the two typologies were closely related with the forest cover change rates. From the error matrix analysis, the study found that the villages could be divided into two typology classes having overall accuracy of 81% (Table 2).Village distribution map that includes T1 and T2 is presented in Figure 2.

Based on the proportion of forest, T1 had a proportion of forest 36.8%, as for T2 had 75.4%. From the forest cover change of view, T1 has a rate of 5,001.8 ha year-1 which was smaller than T2 that has 8,050.6 ha year-1. This shows that the decline in forest area in each typology continues to occur and cannot be avoided. Forest stock in an area can affect the changes. Areas that have small forest stocks (T1) have a smaller rate of change than regions with large forest stocks (T2). The largest forest change for T1 is the conversions of forest to plantations and for T2 is to swamp scrub. In T1, changes in forest cover have become a lot of other covers, so the change rate is low. In T2, larger forest stocks makeforest cover changes higher due to forest conversion. The largest forest change for T2 is the conversion of forests into swamp shrub. Conversions into swamp scrub are thought to be largely unauthorized forest conversion. Graeub *et al*. (2016) and Austin *et al*. (2017) state that uncontrolled forest

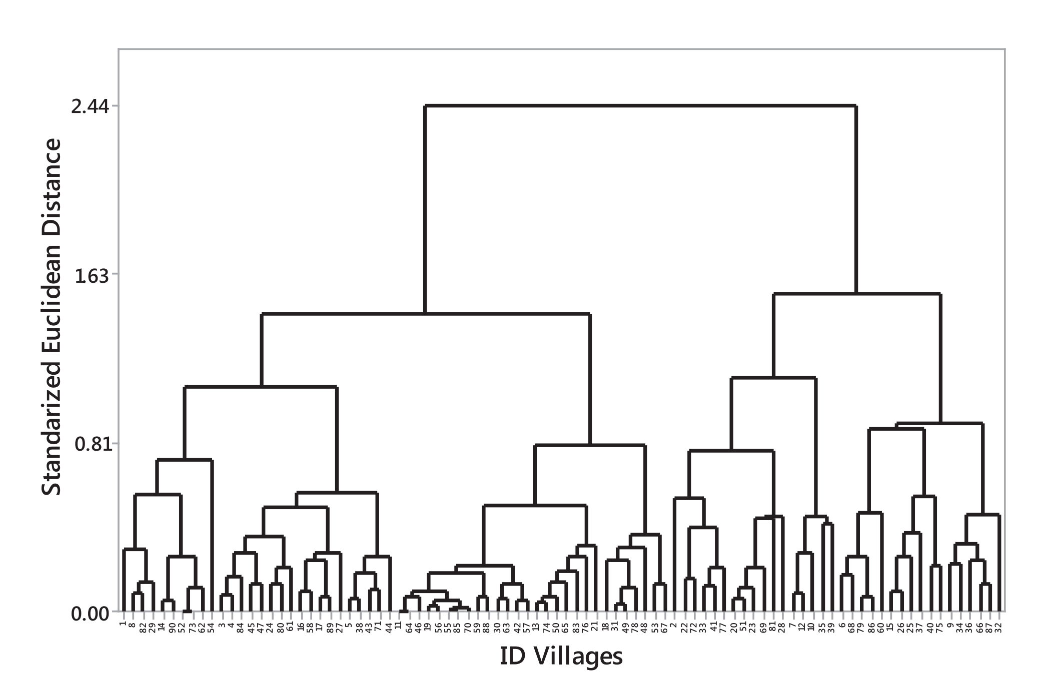

Figure 1 Dendrogram with proportion of forest in 2015 with average linkage method

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Table 2 Assessment results for accuracy of village typology grouping

Number of typology classes	*Overall Accuracy* (%)
4 Classes	48.9
3 Classes	62.2
2 Classes	81.1

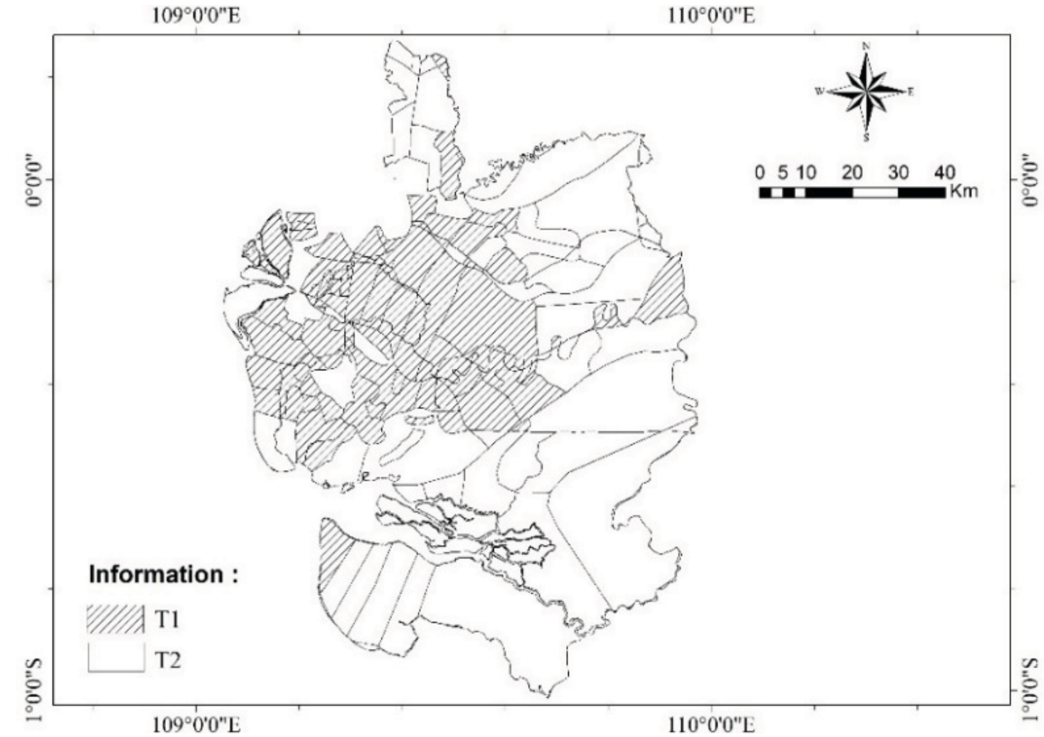

Figure 2 Distribution of villages in T1 and T2.

clearance can increase theforest cover change rates. The number of villages that included in T1 and T2 were 56 and 34 villages respectively.

Driving force of forest cover changes The selected variables of the driving forces ofchange for T1 and T2 were the variables that had a high value in determinant coefficients (R^2>0.5). The relationship between the change and each variable in T1 and T2 can be observed in Table 3. The driving forces of change fromeach typology that were selected from Table 3 were then standardized by converting into scores. The selected driving forces were X_1, X_2, X_3, X_5, X_6, X_8, and X_9. The result of the standardized variables from each typology is shown in Figure 3.

The variable of distance from the road in typology with high change rates (T2) showed that the closer the distance from forest edge to the roads, the larger the forest cover change rate since there is an illegal land encroached and land conversion (Figure 3a). The close distance between the forest areas and roads would easily facilitate the access (. 2014, Mulyanto *et al*. 2004; Mahapatr*et al*. 2005; Perez-Verdin *et al*. 2009; Wyman *et al*. 2010; Arekhi 2011; Kumar et al. 2014; Ahmad et al. 2015). Based on the conditions seen in the field, it was found that there were several accesses within the forest areas in the form of small paths that were often used and passed by the community. For the variable of distance from rivers, it only highly influenced by typology with low-cover change rates (T1) (Figure 3b). This might due to the fact, the closer area from the river are mostly privately owned land, in contrast, the further the distance from the rivers are mostly state-owned forest. The forest areas with closer distance to the river banks were still protected for conservation purposes (Deng *et al*. 2011;, Lira *et al*. 2012).

The variable distance from settlements shows a different pattern for each typology (Figure 3c). In typology with lowforest cover change rates (T1) displayed that the farther the distance of forest areas to settlements, the smaller the effect of the change. There were smaller changes within forest areas that are further from settlements because the natural forest resources are a bit closer to the settlements. The

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Table 3 The equation for transforming the original value of each driving forces into score

Typology	Mathematical formula	R^2
T1	$Y = 0.00000000251X_1^2 - 0.000017024144X_1 + 0.027222470352$	0.95
T2	$Y = -0.00000000009X_1^2 - 0.000000118474X_1 + 0.012429803765$	0.53
T1	$Y = -0.00000000318X_2^2 + 0.000019499388X_2 - 0.001985026757$	0.94
T2	$Y = -0.00000003382X_2^2 + 0.000199066163X_2 + 0.053848857241$	0.27
T1	$Y = 0.00011763751X_3^{0.615618289104}$	0.64
T2	$Y = -0.00000000015X_3^2 + 0.000001178696X_3 + 0.015096839342$	0.66
T1	$Y = -0.00000000001X_4^2 - 0.000000308959X_4 + 0.022459076293$	0.33
T2	$Y = 0.00000000036X_4^2 - 0.000002029254X_4 + 0.153799602246$	0.35
T1	$Y = -0.007135972\ln(X_5) + 0.064012545043$	0.73
T2	$Y = -0.044273306\ln(X_5) + 0.535760111409$	0.12
T1	$Y = -0.003220283\ln(X_6) + 0.048778828928$	0.72
T2	$Y = -0.00000000168X_6^2 + 0.000027153510X_6 + 0.168090078343$	0.08
T1	$Y = 175.78262e^{-0.00068X_7}$	0.33
T2	$Y = 0.00000000278X_7^2 - 0.000024632469X_7 + 0.265907741119$	0.48
T1	$Y = 0.00000000119X_8^2 - 0.000009458233X_8 + 0.016342389534$	0.51
T2	$Y = 0.00000003094X_8^2 - 0.000188764886X_8 + 0.255296771422$	0.62
T1	$Y = 0.00000001526X_9^2 - 0.000068081686X_9 + 0.291898116417$	0.83
T2	$Y = 0.00000002504X_9^2 - 0.000034535004X_9 + 0.343130459328$	0.76
T1	$Y = -0.00000000023X_{10}^2 + 0.000010999422X_{10} + 0.098412942415$	0.06
T2	$Y = 0.00000000035X_{10}^2 - 0.000021645620X_{10} + 0.526875531666$	0.06

distance fromnearbysettlements affects the timber quality (Lira *et al*. 2012). As for the villages in typology with highchange rates (T2) displayed that the closer the distance of forest areas to settlements, the larger the effect of change. T2 were villages with large forest areas.Villages with large forest areas tended to easily facilitate forest encroaching activities by the community (Perez-Verdin *et al*. 2009).

The distance from the plantation and the distance from agriculture only affects the rate ofchange rates in typology with lowchange rates or T1 (Figure 3d , Figure 3e). The closer the distance from the plantation, the higher the forest cover change rates. This can mean that plantation areasare getting closer to forest areas, and there have been conversions of forests to plantations, making it easier to enter the forests. This variable is in line with Wijaya *et al*. (2015) that the distance from the garden is a factor that influences the change of forest to non-forest in Jambi. On the other hand, the variable distance from agriculture shows that the farther the distance from agriculture, the higher the change rates. Based on observations in the field, in general, the location of agriculture is close to the edge of the main road, and this is inversely proportional to the existence of the forest, so that areas further from agriculture become closer to the forest and be converted as non-forest.

In typologies with lowchange rates (T1) and high (T2), the distance from the forest edge in 2000 (Figure 3f) shows similar trends. The closerto the forest edge the higher the change rateboth at T1 and T2. Variations in distance from the initial forest edge still have high forest stocks in each typology, changes in forest cover tend to spend the outer part of the forest first.

Similar trends were also found in the 2015 distance from the edge of forest in T1 (Figure 3g). The variable distance from the forest edge in 2015 shows that the farther from the edge of the forest, the higher the forest cover change rate. This shows that forests are increasingly being transformed into non-forests, so the changes that occur are farther away from the edge of the forest. However, in typologies with high rates of change (T2), the closer the distance from the forest edge in 2015, then the change rateis higher. This is because, in the high forest stock, the change patterns change at the closest distance to the forest first. Setiawan (2015) found that the distance fromforest edge is the most influential variable on deforestation. Wijaya *et al*. (2015) found that high deforestation tends to occur at close distances from the edge of the forest.

Spatial models of forest cover changes in T1 and T2 The spatial model was built based on the scores from selected variables through multiple regression analysis. Based on the result of the diversity analysis from the model, it was obtained several combinations of selected driving forces (independent variables) along with the accuracy test results presented in Table 4.

Based on the accuracy test, a combination that has an influence on forest cover change rates in T1 or typology with a low change rates is the distance from the river and the distance from the settlement, while in T2 typology withhigh change rates, were the distance from the road and distance from forest edge in 2015. The distance from roads, rivers, settlements, and the distance from the forest edge in 2015

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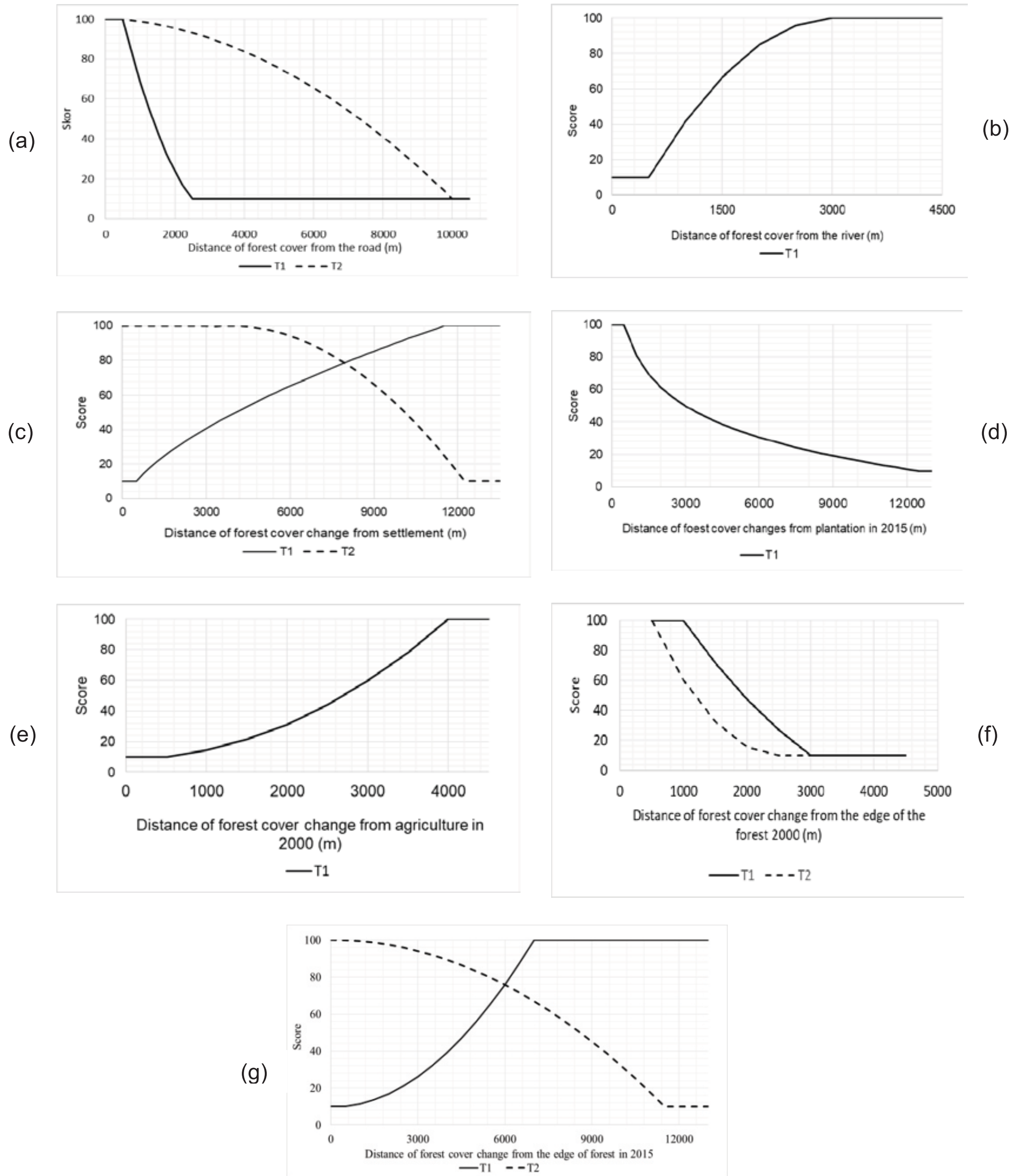

Figure 3 Relationship between score and model variables on T1 and T2. Distance of forest cover change from road (a); distance of forest cover change from river (b); distance of forest cover change from settlement (c); distance of forest cover change from plantation 2015(d); distance of forest cover change from agriculture in 2000(e); distance of forest cover change from the edge of the forest in 2000(f); distance of forest cover change fromthe edge of forest in 2015 (g).

Table 4 Models of the driving forces and the rate of forest cover change

Typology	Equation Model	OA (%)	SR(%)
T1	$Y = -0.01 + 0.0001X_2 + 0.0004X_3$	83	10.5
T2	$Y = 0.02 + 0.0001X_1 - 0.0002X_9$	53	13.3

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were the most influencing factor for the changesbecause it relates to accessibility into forest areas and the availability of forest resources (Wyman *et al*. 2010; Arekhi 2011; Wijaya *et al*. 2015).

Map of forest cover change The map was created based on the selected model from the result of multiple regression analysis of typology with low rates of changes (T1) and typology with high rates of changes (T2). The model for typology (T1) was$Y = -0.01+0.0001X_2+0.0004X_3$ and typology (T2) was$Y = 0.02+ 0.0001X_1 - 0.0002X_9$. For(T1), the land cover change were lowly influenced by the distance from rivers and distance from settlements, as for (T2) were by distance from roads and distance from the edge of forest in 2015. Within the study site, the forest cover change were significantly influenced by the distance from roads (X_1), rivers (X_2), settlements (X_3), and the edge of forest in 2015 (X_3). These variables were suspected to have highly influenced the cover changes. This finding is in line with the previous study that have also stated that distance from roads, rivers, settlements, and the edge of forest in 2015 influencedforest cover changes and were one of the variables that have highly influenced the occurrence of the change (Wyman *et al*. 2010; ......*et al*. 2012; Ahmad *et al*. 2015; Wijaya *et al*. 2015).

The result of the spatial operations showed several potential locations based on the suitability between the resulting model score and thechange rates as presented in Table 5. The results showed that forest cover change consisted of three classes, i.e. low, medium, and high. The locations of the percent classes of the change are displayed in Figure 4.

Conclusions

From the foregoing analysis and discussion, it was found that forest cover change rates differ between each village typology. Typology of changes at the village level in Kubu Raya Regency could be grouped into two typology classes with accuracy 81%, i.e., typology 1 (T1) that had low change rate of 5001.8 Ha per year and typology 2 (T2) with high change rate with the average of 8050.6 Ha per year. Within the typology (T1) the model for forest cover change is Y = -

Table 5 The class division of the rate of change of forest cover

Forest cover change classes	Interval of forest cover change (Ha per year)	Forest cover changes (Ha per year)
Low	0.4-1.6	68462.6
Middle	1.6-2.8	602411.1
High	2.8-3.9	142926.6
Total		813800.3

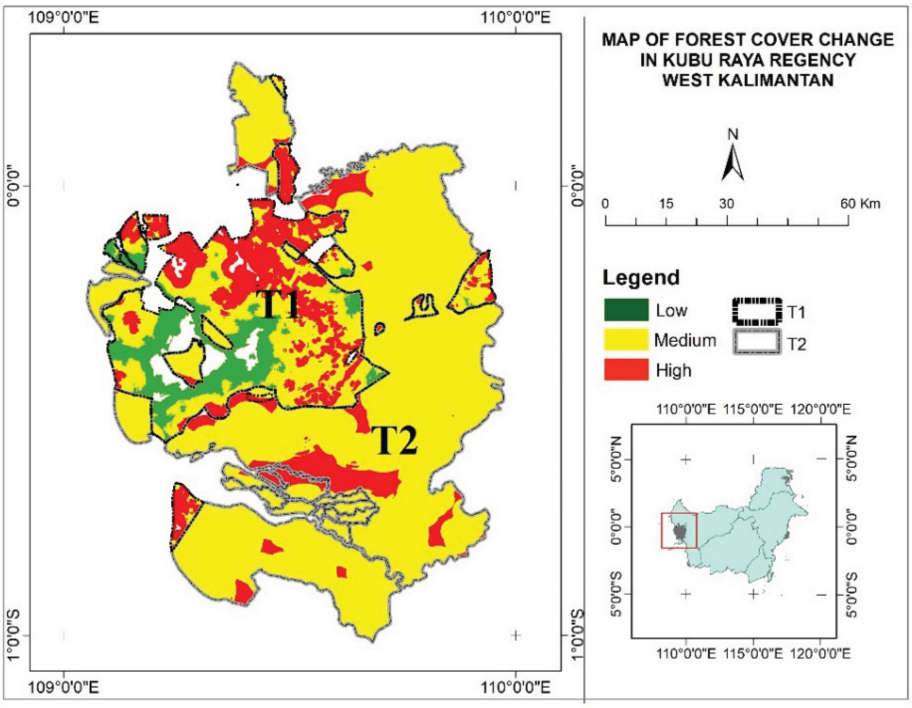

Figure 4 Map of forest cover change .

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0.01 + 0.0001X_2(distance of forest cover from the river) + 0.0004X_3(distance of forest cover change from settlement) with OA 83%and SR 10.5%; while within the typology (T2) the spatial model is Y = 0.02 + 0.0001X_1 (distance of forest cover change from the road) -0.0002X_9(distance of forest cover change from the edge of forest in 2015) with OA 85%.

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