

Developing a Spatial Mathematical Model for Assessing the Rate of Natural Forest Changes

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Abstract – Establishing a spatial mathematical model that uses diverse data types such as ratio data, interval data, and ordinal and nominal data is a challenge. This paper describes how the mathematical model of the rate of natural forest cover change was developed by considering the causes and/or driving forces that come from the society's biophysical and/or socioeconomic aspects. The main objective of this research is to establish a spatial mathematical model using the environmental and socioeconomic variables that play a significant role in determining the rate of natural forest cover change. From a number of variables considered in the analysis, coupled with any other reason, the rate of natural forest cover change (y), in units of ha per year, this study found that there are 10 potential variables, namely the proximity of the road (x_4), the proximity of the river (x_5), the proximity of the settlement (x_6), proximity from the regency capital (x_8), the proximity of the capital city of the district (x_9), proximity of the edge of the forest in 2015 (x_{11}), the proximity of the plantation area in 2009 (x_{12}), the proximity of the plantation in 2015 (x_{13}), slope class (x_{16}), and elevation class (x_{17}). The standardization process successfully transformed the non-ratio data type into a ratio data type. Using the standardized data, the study obtained spatially mathematical models that are reliable in estimating the rate of forest cover change, namely $y = 0.017 + 0.00040x_9$ with SR of 17.3% and R^2 is 88.0%. The study concludes that the most significant factor affecting the natural forest cover change in the study site is the proximity from sub-district capital (x_9). Therefore, a spatial mathematical model can facilitate the government in monitoring forest cover.

Keywords: Spatial mathematical model, driving force, standardization, biophysical factor, socioeconomic factors

Introduction

In environmental management, land use forecasting is a relatively broad field where many aspects should be considered precisely (Fagariba *et al.*, 2018). However, a forecasting model would be easier to develop when the biophysical, socioeconomic, and policy variables are considered. In developing spatial-based mathematical models for forecasting the environmental condition, we commonly face a complicated problem with the availability, accessibility, and types of data to be considered (Purwanto *et al.*, 2013; Sulistiyono *et al.*, 2015). In developing a model for estimating changes or even forecasting natural forest stands in tropical regions, consideration of many variables is unavoidable. Several studies have been conducted on spatial modeling of changes in forest cover, such as the biophysical and socioeconomic (Wijaya *et al.*, 2015; Prasetyo *et al.*, 2009).

In many studies, significant population growth was commonly followed by the social-economy sector problem, then may threaten the existence of natural forest cover (Purwanto *et al.*, 2015; Sulistiyo *et al.*, 2015; Prasetyo *et al.*, 2009). High population growth may increase the need for land for livelihood, such as residences, rice fields, crop land, timber estate, etc. This should be avoided since it might threaten the whole ecosystem, particularly natural forests. Generally, the local population's prosperity and growth are the main cause of deforestation since they ignore environmental-specific factors such as biophysics, proximity, and other social-economy factors (Rudel, 2007). Other factors, such as poverty, low literacy, and significant population growth, may enhance deforestation (Fagariba *et al.*, 2018). Moreover, the actual main causes of deforestation in the tropical forest are the need for agricultural land, infrastructure development, and logging activities with the basis of the factors coming from the sector of the economy, institutional, rights, technology, socio-cultural, and population growth factors, as well as other factors including land characterization, land biophysical characteristics, and its social activities (Geist and Lambin, 2001). The natural forest cover change into a non-forest that had included plantation forest amounted to 0.45 million ha/yr of the whole forest area in 2009-2011 (KK, 2012), massively grew up to 0.73 million ha/yr in 2012-2013 (KLHK, 2014) which then somehow went down for about 0.4 million ha/yr in 2013-2014 (KLHK, 2015) and rose again up to 1.09 million ha/yr (FWI, 2014). The country lost its primary forest area from 2000 to 2012, approximately 0.84 million hectares or at least an average of 700000 hectares per year (Margono *et al.*, 2014). The rate of natural forest cover change reached an unbelievable number of 1.13 million hectares per year from 2009 to 2013 (FWI, 2014). Their existence keeps being transformed and diminishing, notably the ones in West Kalimantan wherein deforestation had occurred in the area of 41 726.00 hectares per year from 2009 to 2012 (KK, 2012), which then slightly went down to 40 477.30 hectares per year period of 2014 to 2015 (KLHK, 2017). Not to forget that from 2008 to 2013, the province lost 426 000 hectares of its natural forest cover as well, with an average detail of 106 500 hectares per year (FWI, 2014).

The driving forces of how the change may occur in Indonesia are technically different for each region. There are biophysical factors, the social-economy state factor, the culture factor, and even politics. The research proposed to identify this natural forest cover change case has been conducted using the spatial model method, especially in the case of deforestation in many places within the country. Some studies have been conducted as well beforehand regarding this same case, such as the ones on the area of HPH PT. Duta Maju Timber in West Sumatra, ones in Lembah Tapan in Jambi (Mulyanto and Jaya, 2004). The ones in the entire Jambi (Wijaya *et al.*, 2015) and the entire Sumatera Island (Sulistiyo *et al.*, 2015). The ones in the area of KPHP Poigar of North Sulawesi (Ahmad *et al.*, 2016) and the ones in the entire Indonesia nation (Brun *et al.*, 2017), including the spatial deforestation model conducted in Kalimantan from 2000 to 2013 (Purwanto *et al.*, 2015), with a small quantity of note that the study had included the entire Kalimantan Island. Despite all these details by Purwanto in 2015, what makes this research slightly different is that it is specifically meant solely for the West Kalimantan area, using more detailed units down to their regional unit. These previous studies show how the different units been used at certain area levels can provide with different natural forest cover change's driving forces (Sulistiyo *et al.*, 2015; Wijaya *et al.*, 2015; Rijal *et al.*, 2016).

Therefore based on the details above, the spatial rate of natural forest cover change model is automatically seen to be a private function to be applied as the primary source of spatial planning. Hence, this study aims to construct the spatial rate of natural forest cover change by identifying its driving forces. The main focus among all kinds of its change is the primary and secondary types of natural forest cover (dryland forest, mangrove, and swamp forest) that have been transformed into another kind of land cover based on each function. This includes plantation forests, so this is a novelty in this research.

Materials and Methods

Date and Site

The research was conducted in June - December 2017, located in West Kalimantan Province, Indonesia (Figure 1). The location focused on sub-districts with forests in 2009, which covered 159 sub-districts. The area is geographically located on 02° 04' 52.685" NL - 03° 02' 24.368" SL and 108° 50' 26.115" - 114° 13' 21.995" EL. Data were processed in the GISRS Laboratory, Universitas Syiah Kuala, and Remote Sensing Laboratories and GIS, Faculty of Forestry, Bogor Agricultural University.

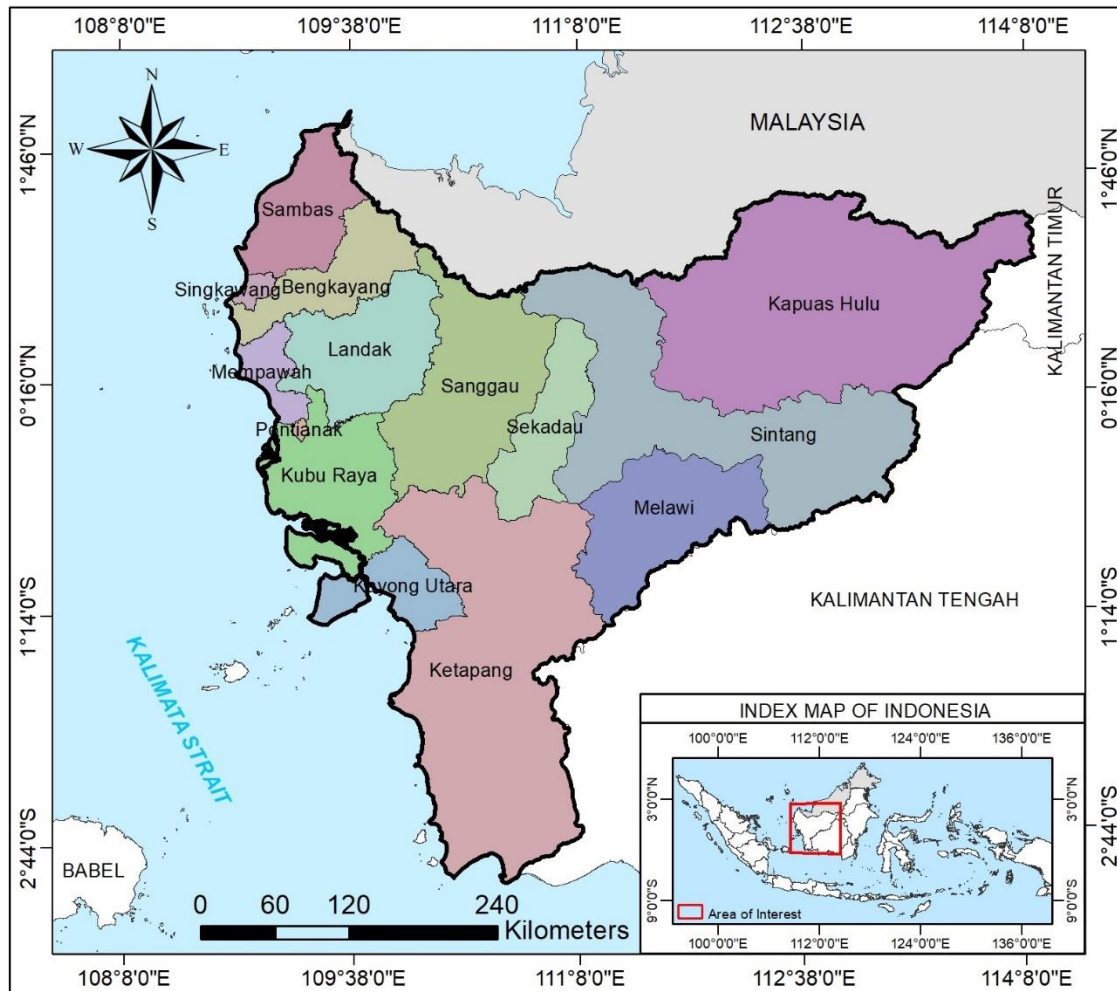


Figure 1. Study area in West Kalimantan

Data, Equipment, Software, and Hardware

The data used in this research were the land cover data from the Ministry of Environment and Forestry (KLHK RI), land border data of all sub-districts in West Kalimantan Province from Geospatial Information Agency (BIG), social-economy data in the form of a 2010 and 2016 issue named Kabupaten Dalam Angka published by the Statistics Centre Agency (BPS), and 2009/2010 and 2015/2016 Landsat satellite image data of the entire West Kalimantan (USGS, 2017). The devices used in this research were Global Positioning System (GPS), camera, and questionnaire. Then data processing itself was processed using the following software: ArcGIS 10.3, Erdas Imagine, IBM SPSS Statistics, and Microsoft Excel.

Research Procedure

Land Cover Data Validation

After the collection, land cover data were all acquired from The Ministry of Environment and Forestry. Then the validations were done using Landsat satellite image data or other images and ground checking. Landsat image data was initially pre-processed with band fusion (layer stacking), geometric correction, and image enhancement. Validation was conducted solely to compare any illogical interpretation of KLHK RI land cover data without modifying the polygon. Considering the data scale, the validated polygon was bare ≥ 6.25 ha in size.

Change of Natural Forest Cover

The change of natural forest cover into other land covers, including changes in plantation forest cover in the period of 2009-2015, was analyzed under a method called thematic change. The data of natural forest cover change as the result of the thematic change was later on utilized in order to calculate the rate of natural forest cover change with the following formula (Mulyanto and Jaya, 2004):

$$r = \frac{A}{t_2 - t_1} \quad (1)$$

Note:

- r = the rate of natural forest cover change
- A = the area of natural forest cover change within a certain period
- t₂ = the year in which the period ended
- t₁ = the year in which the period started

Sample Size Determination

Sample size determination was then created as the corresponding result of spatial operation with overlay method between the driving force of the rate of natural forest cover change (y) towards the other change-inducing driving forces (x). A few studies have identified this change driving force of forest cover case through a spatial operation with some biophysical and social-economy factors (Wijaya *et al.*, 2015; Chowdhury, 2006; Liu *et al.*, 2010; Xindong *et al.*, 2014; Bennet, 2015). At this moment, sample plots were constructed within 2 km x 10 km in all research locations. The sample plot selections purposed to examine the driving forces, model construction, and model validation were conducted through a systematic sampling with random start with samples that amounts to 5% of the entire plot. The sample plot used to identify the driving forces and model construction were the same sample plot which amounts to 281 plots. In contrast, sample plots with different locations were used for model validation, which amounts to 281 plots too.

Data Standardization

This research constructed a spatial rate model of the natural forest cover change under some biophysical and social-economy variables. Before the spatial model was constructed, all independent variables were standardized using an empirical approach between the connection of independent variables (biophysical and social-economy factors) and dependent variables (The rate of natural forest cover change). Data standardization was done to uniform the variations (standard deviation) and variable data units, wherein got transformed into a score value. The formula used to score the change has a positive trend and a negative trend, as follows (Sulistiyono *et al.*, 2015):

$$Score (+) = \left(\frac{y - \min}{\max - \min} \right) \times 90 + 10 \text{ and } Score (-) = \left(\frac{\max - y}{\max - \min} \right) \times 90 + 10 \quad (2)$$

Note:

- Score (+) = rank determining value based on the positive trend
- Score (-) = rank determining value based on the negative trend
- y = resulting value of connection equation between y_n and x_n variables
- min = maximum value of y value
- max = maximum value of x value

Driving Force Identification

The driving forces of natural forest cover change in this research were identified through exploratory analysis based on initial presumption, literature study, and data availability that served as the bases for selecting a few variables from the abundance of variables that might be used. According to the initial presumption, the selections were then tested using statistical methods to determine the variable that might act as the driving force toward the natural forest cover change rate. Factors or variables that were equipped in this research to identify the driving forces of natural forest cover change are listed in Table 1 down below.

Table 1. Natural forest cover change driving force variables

No	Code	Variable	Unit	Source
1	x ₁	The male resident density of 2015	lives/km ²	BPS-BIG
2	x ₂	Student rate of 2009-2015 period	students/year	BPS
3	x ₃	Ratio percentage of coffee plant area in 2009 and the area of the sub-district	%	BPS-BIG
4	x ₄	Distance from road	km	BIG
5	x ₅	Distance from river	km	BIG
6	x ₆	Distance from settlement	km	BIG
7	x ₇	Distance from the province's capital	km	BIG
8	x ₈	Distance from regency/city capital	km	BIG
9	x ₉	Distance from sub-district capital	km	BIG
10	x ₁₀	Distance from the center of the village/urban community	km	BIG
11	x ₁₁	Distance from forest edge in 2015	km	KLHK RI
12	x ₁₂	Distance from plantation land in 2009	km	KLHK RI
13	x ₁₃	Distance from plantation land in 2015	km	KLHK RI
14	x ₁₄	Distance from farmland in 2009	km	KLHK RI
15	x ₁₅	Distance from farmland in 2015	km	KLHK RI
16	x ₁₆	Slope class	%	USGS
17	x ₁₇	Elevation	masl	USGS

Multicollinearity Test

The multicollinearity test shows the connection between variables on driving force (x) as an independent variable. It is not permitted to be a connection between x variables (multicollinearity) when you construct a multiple linear regression model. The multicollinearity between the independent variable (x) can be eradicated through the approach of the level of correlation between the connection of the independent variable (x) using the Pearson correlation coefficient. Suppose the correlation between variable (x) correlates r for more than 0.7. In that case, the one with a high correlation under the rate of natural forest cover change (y) will be selected.

Spatial Model Construction

A spatial model of the rate of natural forest cover change applied in this research is a model named multiple linear regression. The construction of this specific model was graded statistically, which involved the evaluation of the determination coefficient (R²) and P-value. The chosen model had its R² being < 0.50 and its P-value being < 0.05, making the natural forest cover change driving force f independent variable (x) able to explain the variability of the natural forest cover change dependent variable (y).

Model Validation Test

Model validation tests were carried out to get the best model by testing the accuracy of the model [25-27]. Model validation was carried out using sample plots outside the model plot, using a measure of aggregate deviation (SA), mean deviation (SR), root means squared error (RMSE), and Chi-squared test (x²) with the following formula (Jaya, 2015):

$$SA = \left(\frac{\sum E - \sum O}{\sum E} \right); SR = \left(\frac{\sum \frac{E-O}{E}}{n} \right) \times 100; RMSE = \sqrt{\frac{\sum \frac{(O-E)^2}{E}}{n}} \times 100\%; x^2 = \sum \frac{(O-E)^2}{E} \quad (3)$$

Validation was carried out using a separate sample plot, in addition to the sample plot to identify the driving force and model development by 5% from 281 of the entire sample plots.

Results

Driving Force Identification

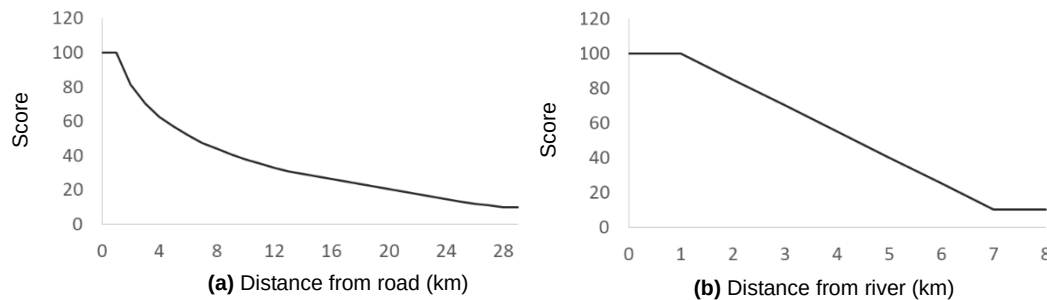
The driving force of natural forest cover change was identified without using typology. However, a developed model for the entire West Kalimantan region is similar to the results obtained during the natural forest cover change typology test. This study had approximately 17 natural forest cover change driving force factors or variables (Table 1). All variables were analyzed to find the correlation between the independent variable of x and the dependent variable of y (Table 2).

Table 2. A correlation value of driving force with natural forest cover change rate

Variable	Mathematic Equation	R
x ₁	$y = 0.02\ln(x) + 0.0068$	0.4277
x ₂	$y = 0.0369x + 0.0528$	0.2343
x ₃	$y = 0.0524x + 0.0511$	0.2358
x ₄	$y = -0.0096\ln(x) + 0.0326$	0.7401
x ₅	$y = -0.0078x + 0.0568$	0.8552
x ₆	$y = -0.019\ln(x) + 0.0621$	0.9227
x ₇	$y = -0.017\ln(x) + 0.1447$	0.3807
x ₈	$y = -0.022\ln(x) + 0.1317$	0.6813
x ₉	$y = -0.013\ln(x) + 0.0775$	0.6680
x ₁₀	$y = -0.007\ln(x) + 0.0551$	0.3693
x ₁₁	$y = 0.0391\ln(x) + 0.0841$	0.7171
x ₁₂	$y = -0.018\ln(x) + 0.0856$	0.8441
x ₁₃	$y = -0.017\ln(x) + 0.0678$	0.8844
x ₁₄	$y = 0.0238x^{-0.311}$	0.2512
x ₁₅	$y = -0.005\ln(x) + 0.0295$	0.3317
x ₁₆	$y = -0.01\ln(x) + 0.0474$	0.8752
x ₁₇	$y = -0.022\ln(x) + 0.1478$	0.9446

Information: y = rate of natural forest cover change (ha/year)

There were at least 10 variables of the driving force of natural forest cover change in West Kalimantan that were significant, with its R being more than 0.50 and the detail as follows: distance to the road (x₄), distance to the river (x₅), distance to the settlement (x₆), distance to the regency/city capital (x₈), distance to the sub-district capital (x₉), distance to the forest edge in 2015 (x₁₁), distance to the plantation land in 2009 (x₁₂) and 2015 (x₁₃), slope class (x₁₆), and the elevation (x₁₇). Data standardization was done on the variables mentioned above (Figure 2).



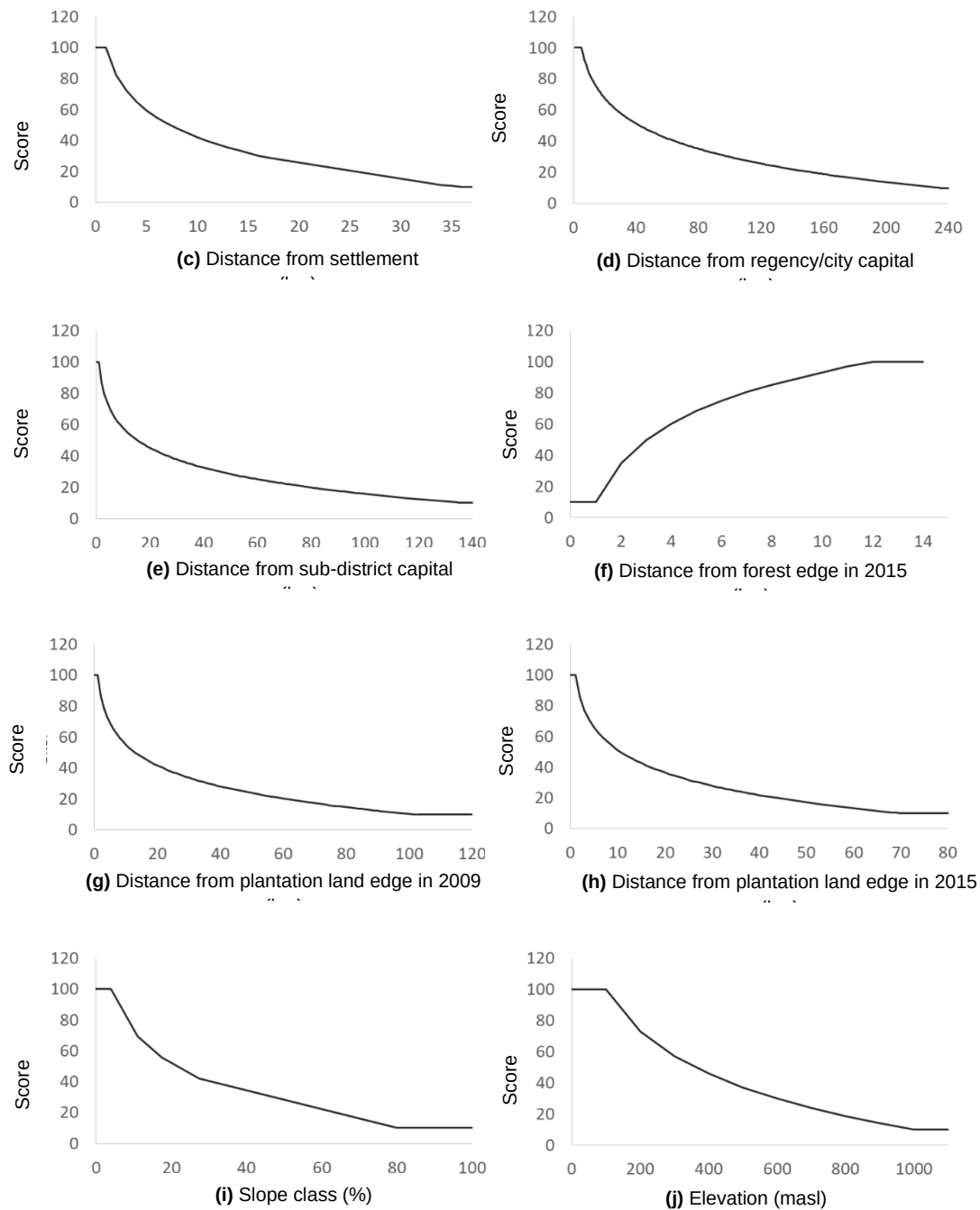


Figure 2. Driving force of natural forest cover change score

Spatial Model of Natural Forest Cover Change Rate

There were 10 variables identified as the natural forest cover change driving force. Correlation tests between x variables were done to prevent multicollinearity. The multicollinearity test shows several variables that are not bound to each other, and the other variables are independent. The chosen variable combinations are those with R value of less than or equal to 0.70 in order to prevent multicollinearity. Correlation matrix of chosen x dependent variables and y variable are shown in Table 3 below.

Table 3. Correlation matrix of chosen x dependent variables and y variable

	y	x ₄	x ₅	x ₆	x ₈	x ₉	x ₁₁	x ₁₂	x ₁₃	x ₁₆	x ₁₇
y	1.00										
x ₄	0.83	1.00									
x ₅	0.69	0.87	1.00								
x ₆	0.85	0.98	0.83	1.00							
x ₈	0.91	0.69	0.52	0.73	1.00						
x ₉	0.92	0.84	0.69	0.87	0.99	1.00					
x ₁₁	-0.74	-0.93	-0.98	-0.89	-0.57	-0.74	1.00				
x ₁₂	0.94	0.80	0.64	0.84	0.95	0.99	-0.69	1.00			
x ₁₃	0.92	0.86	0.70	0.89	0.90	0.98	-0.75	0.97	1.00		
x ₁₆	0.61	0.80	0.96	0.76	0.45	0.63	-0.94	0.58	0.63	1.00	
x ₁₇	0.71	0.91	0.98	0.87	0.55	0.73	-1.00	0.68	0.73	0.96	1.00

Model development of the natural forest cover change rate was conducted based on the variable combinations that fulfilled the statistical requirement of the multiple regression model, which produced equations shown in Table 4 below.

Table 4. Equation model of analysis results of multiple linear regression

No	Variable	Mathematic equation	R ² (%)	P-value < 0.05	
				x _i	x _j
M1	x ₄	$y = 0.020 + 0.00048x_4$	68.48	0.000	-
M2	x ₅	$y = 0.021 + 0.00048x_5$	48.20	0.000	-
M3	x ₆	$y = 0.020 + 0.00047x_6$	72.60	0.000	-
M4	x ₈	$y = 0.011 + 0.00038x_8$	82.62	0.000	-
M5	x ₉	$y = 0.017 + 0.00040x_9$	88.00	0.000	-
M6	x ₁₁	$y = 0.079 - 0.00053x_{11}$	54.24	0.000	-
M7	x ₁₂	$y = 0.018 + 0.00042x_{12}$	88.05	0.000	-
M8	x ₁₃	$y = 0.019 + 0.00043x_{13}$	84.74	0.000	-
M9	x ₁₆	$y = 0.021 + 0.00049x_{16}$	37.09	0.000	-
M10	x ₁₇	$y = 0.020 + 0.00054x_{17}$	51.10	0.000	-
M11	x ₄ , x ₈	$y = 0.013 + 0.00022x_4 + 0.00027x_8$	90.22	0.000	0.000
M12	x ₅ , x ₈	$y = 0.012 + 0.00021x_5 + 0.00031x_8$	89.47	0.000	0.000
M13	x ₅ , x ₉	$y = 0.016 + 0.00014x_5 + 0.00035x_9$	90.51	0.000	0.000
M14	x ₅ , x ₁₂	$y = 0.017 + 0.00011x_5 + 0.00037x_{12}$	89.45	0.000	0.000
M15	x ₅ , x ₁₃	$y = 0.018 + 0.00007x_5 + 0.00040x_{13}$	85.25	0.027	0.000
M16	x ₈ , x ₁₁	$y = 0.038 + 0.00030x_8 - 0.00023x_{11}$	89.82	0.000	0.000
M17	x ₈ , x ₁₆	$y = 0.011 + 0.00033x_8 + 0.00027x_{16}$	88.70	0.000	0.000
M18	x ₈ , x ₁₇	$y = 0.012 + 0.00031x_8 + 0.00023x_{17}$	89.31	0.000	0.000
M19	x ₉ , x ₁₆	$y = 0.016 + 0.00037x_9 + 0.00011x_{16}$	89.35	0.000	0.000
M20	x ₁₁ , x ₁₂	$y = 0.030 - 0.00012x_{11} + 0.00037x_{12}$	89.45	0.000	0.000
M21	x ₁₂ , x ₁₆	$y = 0.017 + 0.00039x_{12} + 0.00008x_{16}$	88.68	0.000	0.006
M22	x ₁₂ , x ₁₇	$y = 0.017 + 0.00037x_{12} + 0.00011x_{17}$	89.22	0.000	0.000
M23	x ₁₃ , x ₁₆	$y = 0.018 + 0.00042x_{13} + 0.00004x_{16}$	84.86	0.000	0.290

Discussion

Scoring results of the significant variables in Figure 2 show a synchronization between the independent variable (x) and natural forest cover change rate within the score range of 10-100. A score of 10 indicates low natural forest cover change, and a 100 indicates high natural forest cover change (Mulyanto, 2004). The driving force of distance to the road towards natural forest cover change rate (Figure 2a) shows that the closer the forest area and road are, the more change will occur as the score will decline until it reaches the distance of 28 km from the road. Several studies mentioned that more changes would appear to come up when the distance between both the forest area and the road is close (Febriani *et al.*, 2017; Ahmad *et al.*, 2016; Kumar *et al.*, 2014; Bax, 2016; Wyman and Stein, 2010; Mulyanto and Jaya, 2004; Kaimowitz, 2002). As for the distance to the river variable (Figure 2b), the closer a forest to a river is, the higher the change rate will be, and the score will decline linearly until the distance reaches 7 km to the river. Commonly speaking, in West Kalimantan, rivers are meant to become the locals' transportation routes, making it easier for the people to utilize the forest land for their plantations. Several studies also mentioned that forest loss happened because it was close to the river (Febriani *et al.*, 2017; Bax *et al.*, 2016; Wyman and Stein, 2010).

Distance to the settlement variable (Figure 2c) shows that the closer a forest to a settlement is, the higher the forest cover change rate will be, as the score will decline until the distance reaches 36 km from the settlement. One factor causing deforestation is the closeness of the settlement to the forest area (Ahmad *et al.*, 2016; Setiawan *et al.*, 2015; Kumar *et al.*, 2014; Arekhi, 2011). Moving on, the distance from the regency/city capital and sub-district capital variables (Figures 2d and 2e) show that the closer a forest is to the capital, the higher the forest cover change rate will be as the score will decline until it reaches a distance of 235 km from regency/city capital and 137 km from sub-district capital.

Now as for the distance from the forest edge variable (Figure 2f), it shows that forest cover change from the forest edge up to 1 km from it is relatively small, while the forest cover change rockets from a distance of 2 km up to 12 km where it reaches a score of 100%. Thus the natural forest cover change into non-natural forest area during the 2009-2015 period could reach 12 km from the original forest edge in 2009, or 6 years before the study. Study results of adjacency between forest edge with deforestation (Purwanto *et al.*, 2015). Distance from the plantation land edge variable, either in 2009 (Figure 2g) or 2015 (Figure 2h), shows that the closer a forest to the plantation land edge is, the higher the natural forest cover change rate will be. The change rate will decline along with the distance from the forest to the plantation land edge. The research on the proximity of relation between deforestation with plantation land edge has been done in several studies on various locations (Wijaya *et al.*, 2015; Febriani *et al.*, 2017; Romijn *et al.*, 2013).

The case of slope class is very influential towards natural forest cover change (Figure 2i). The Figure shows that the more flat the slope, the higher the cover change rate. Almost all locals prefer to do their activities in gentler slope regions such as farmlands, plantations, and settlements. Studies on slope class with land cover change have been conducted in several places (Purwanto *et al.*, 2013; Wijaya *et al.*, 2015; Ahmad *et al.*, 2016). The graph of elevation above sea level variable, shown in Figure 1j, tells that the lower an elevation in a region is, the higher the forest cover change will be, and vice versa. This specific condition is hugely related to the environment in West Kalimantan where the swamp and mangrove forests belong. Several studies on elevation towards forest cover change have also been done in various places besides mentioned places (Purwanto *et al.*, 2013; Wijaya *et al.*, 2015; Ahmad *et al.*, 2016; Kumar *et al.*, 2014; Prasetyo *et al.*, 2009).

Based on the analysis results of multiple linear regression on variable combinations (Table 4), 13 models were chosen, with their R^2 being $> 85.00\%$ and their P -value being < 0.05 . The standardization process successfully transformed the non-ratio data type into a ratio data type. By using the standardized data, the study obtained spatially mathematical models that are reliable in estimating the rate of forest cover change, namely (a) $y = 0.017 + 0.00040x_9$ with SR of 17.3%, and R^2 is 88.0%; and (b) $y = 0.011 + 0.00033x_8 + 0.00027x_{16}$, with SR of 18.9%, and R^2 is 88.7%. The study concludes that the most significant factor affecting the natural forest cover change in the study site is the proximity from the regency capital (x_8), proximity from the sub-district capital (x_9), and slope class (x_{16}).

Conclusion

The spatial mathematical model for estimating the rate of natural forest change in the tropical region could be established using various attribute data types. Data standardization was crucial for transforming the non-ratio to ratio data types, such as scoring. From the standardized variables, this study found 10 dominant factors that are closely related to natural forest cover change, namely the distance from the road (x_4), distance from the river (x_5), distance from the settlement (x_6), distance from the capital city of the regency (x_8), distance from sub-district capital (x_9), distance from forest edge in 2015 (x_{11}), distance from plantation land in 2009 (x_{12}), distance from plantation land in 2015 (x_{13}), slope class (x_{16}), and elevation (x_{17}). To estimate the rate of natural forest cover change spatially, the best spatial mathematical model (simple and accurate) is y (ha/year) = $0.017 + 0.00040x_9$ with an average deviation of 17.3% and R^2 of 88.0%. This study concludes that the most significant variable influencing the rate of natural forest cover change is the proximity from sub-district capital (x_9). Therefore, a spatial mathematical model can facilitate the government in monitoring forest cover.

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