Sriwijaya Journal of Environment
Article
ojs.pps.unsri.ac.id

The Rapid Changes of the Landscape Structure of the Meranti-Dangku Tropical Lowland Forest in the South Sumatra Province, Indonesia

Zulfikhar[1,2*], Hilda Zulkifli[3], Sabaruddin Kadir[4], and Iskhaq Iskandar[5]

[1]Graduate School of Environmental Science, University of Sriwijaya, Jl. Padang Selasa, Bukit Besar, Palembang, Sumatra Selatan, 30139, Indonesia.
[2]Technical Staff in South Sumatra Provincial Government, Indonesia.
[3]Department of Biology, Faculty of Mathematics and Natural Sciences, University of Sriwijaya, Kampus Inderalaya, Ogan Ilir, Sumatra Selatan, 30662, Indonesia.
[4]Department of Soil Science, Faculty of Agriculture, University of Sriwijaya, Kampus Inderalaya, Ogan Ilir, Sumatra Selatan, 30662, Indonesia.
[5]Department of Physics, Faculty of Mathematics and Natural Sciences, University of Sriwijaya, Kampus Inderalaya, Ogan Ilir, Sumatra Selatan, 30662, Indonesia.

**Corresponding Author: zulfikhar.zl@gmail.com*

Article history

Received	Received in revised form	Accepted	Available online
12 December 2016	15 February 2017	25 February 2017	15 March 2017

Abstract: The fragmentation of forest vegetation cover can be measured quantitatively, using tools that can characterize the geometry and spatial properties of the patch or patches of mosaic, which depicts the forest loss and the changes in the temporal pattern. The aims of this paper are to observe the process of the forest fragmentation, to find out the changes of spatial patterns of habitat continuum by applying the spatial dynamics change analysis of the forest fragmentation phases, and to provide the comprehensive approach in determining the rapid change of the forest landscape structure in the spatial transformation process, based on the decision tree models. We find three phases of the forest fragmentation were identified, namely dissection, dissipation, and attrition. This study shows that the production forest area and a wildlife conservation area that contiguous or borders, has the same phases in the process of fragmentation of the forest, but both have a difference of the magnitude of forest loss. We find there are at least five effects of forest fragmentation to the landscape structure, those are increasing in a number of habitat patches, decreasing in a size of habitat patches, reduction in a habitat amount, increasing in a dispersion and interspersion of patch types, and reduction in a size of spatial connectedness between patches.

Keyword: fragmentation, landscape metrics, spatial transformation.

Abstrak (Indonesian): Fragmentasi penutupan vegetasi hutan dapat diukur secara kuantitatif, menggunakan alat-alat yang dapat mengkarakterisasi geometri dan properti spasial patch atau mosaik patch-patch, yang menggambarkan kehilangan hutan dan perubahan-perubahan dalam pola temporal. Studi ini bertujuan untuk (1) mengamati proses fragmentasi hutan, (2) mengetahui perubahan pola spasial habitat kontinum dengan menerapkan analisa perubahan dinamika spasial pada fase-fase fragmentasi hutan, dan (3) memberikan pendekatan yang komprehensif dalam menentukan perubahan yang cepat dari struktur lanskap hutan dalam proses transformasi spasial, berdasarkan model pohon keputusan. Hasil studi ini menunjukkan bahwa ada tiga fase fragmentasi hutan yang teridentifikasi, yaitu pembedahan (dissection), pemecahan (dissipation) dan penghilangan (attrition). Studi ini juga menunjukkan bahwa kawasan hutan produksi dan kawasan konservasi satwa liar yang berdekatan atau berbatasan, memiliki fase-fase yang sama pada proses fragmentasi hutan, namun keduanya memiliki perbedaan pada besaran hilangnya hutan. Setidaknya ada lima dampak fragmentasi hutan pada struktur lanskap; meningkatnya jumlah patch habitat, penurunan ukuran patch habitat, penurunan jumlah habitat, meningkatnya dispersi dan interspersi jenis patch, dan pengurangan dalam ukuran konektivitas spasial antar patch.

Kata kunci: fragmentasi, metrik lanskap, transformasi spasial

1. Introduction

Meranti-Dangku landscape is the tropical natural lowland forest and essential ecosystems remaining in South Sumatra which has undergone changes of forest vegetation cover very quickly (Figure 1.). The rate of deforestation in Meranti-Dangku landscape from 1989 to 2013 is in the range of 4.32 to 12.75 % per year, much larger than the average loss of the old-growth forests cover in Sumatra from 2000 to 2012, which is the average area of 1.75 % per year (100.416 ha per year) [1].

The forest fragmentation of the landscape of Meranti-Dangku can be measured quantitatively, using tools that can characterize the geometry and spatial properties of the patch or patches of mosaic, which depicts the spatial landscape structure on a particular point in time [2]; [3], and can describe the quantitative dimensions of sustainability [4], in the region of the landscape [5] .

The land use change and forest fragmentation caused by human activity, such as the logging and utilization of natural forest, agricultural development, livestock, mining, settlement, and development of the infrastructure, where all of activities are relevant to environmental issues and ecological phenomena [6]–[9]. Many cases that arise because of human activity, has conflicts with wildlife, suspected as the cause of the main occurrence of loss of habitat and endangered species[10].

Abdullah has found that there are three main components of the forest fragmentation, namely Attrition, or the loss of original habitat patches; Shrinkage, or the reduction of the size of habitat patches; and the Isolation, or increasing the distance between patches of habitat [11].

The aims of this paper are to observe the process of the forest fragmentation, to find out the changes of spatial patterns of habitat continuum by applying the spatial dynamics change analysis of the forest fragmentation phases, to provide the comprehensive approach in determining the rapid change of the forest landscape structure in the spatial transformation process, based on the decision tree models. This is a new approach in determining the dominant phase of the forest fragmentation, from the perspective of the biodiversity conservation and forest restoration, in the production forest and wildlife conservation areas.

2. Experimental Sections

Description of Research Site

This research area is in the tropical lowland forest ecosystem, namely Meranti-Dangku landscape (Figure 1). Geographically, it is located at UTM Zone 48S; 26900-37000 Easting and Northing 9765000-9710000, with an area of 209.619 ha. The Meranti-Dangku lanscape is located in the Production Forest Management Unit covering an area of 157.228 ha and in the Dangku Conservation Forest Management Unit covering an area of 52.392 ha.

Figure 1. The location of the research area, the tropical lowland forest ecosystem of Meranti-Dangku landscape, District of Musi Banyuasun, South Sumatra Province, Indonesia

Image Analysis

The Satellite imagery data that used in this research is the Landsat 5 Thematic Mapper (TM), sourced from the National Institute of Aeronautics and Space (LAPAN), presented as Table 1. We conducted an analysis based on the changes of the closure of the vegetation and land use from a series of satellite imagery map on a medium resolution. The change detection method of the land cover type "again-being" is done in post classification (post-classification comparison = PCC), namely the analysis of the comparison of the results of the land cover classification for the time t_1 and t_2 [12].

Table 1. Types of satellite imagery and date of acquisition used in this study.

No.	Sattelite Imagery	Data type	Path-Row	Date of Acquisition
1	Landsat 5. TM.	L1, T.	125 - 062	September 6, 1989.
2	Landsat 5. TM.	L1, T.	125 - 062	March 19, 1995, and September 11, 1994 (subset for cloud cover free).
3	Landsat 5. TM.	L1, T.	125 - 062	Mey 25, 2000.
4	Landsat 5. TM.	L1, T.	125 - 062	Mey 15, 2006.
5	Landsat 5. TM.	L1, T.	125 - 062	November 9, 2009.
6	Landsat 5. TM.	L1, T.	125 - 062	August 7, 2013.

The method used in the satellite image analysis is the Object Base Image Analysis (OBIA), and the processing of the image analysis using the eCognition Developers 64 software (Trimble). The pre-requisites for classification is the segmentation of the image, which is a subdivision of the image into a separate area [13] [14]. In the settings of the scale parameters, colors and shapes, and the data processing are using the multi-resolution segmentation algorithm, with the scale parameter = 10, the color and shape factor = 0.1, and the compactness and smoothness = 0.5 [15], [16].

In ground thruthing for the checking of the land use type classification are using the Global Positioning System (GPS), Garmin Oregon 550 series, the work map, and the draft of the land use type classification map from a satellite imagery. Observations of the field towards planned of 620 random point, 510 points which were taken as examples and training area, and 444 points used to test the accuracy of the mapping of the land cover type. In selection of the location of training area, with attention to the representativeness of the type of the land use classification, and the road accessibility.

The classification of an objects is done by using the method of the nearest neighbor classifiers, based on the user-selected samples, which is the training area obtained from field survey (ground truth), and the land use type classification for the interpretation of image analysis is using the Standar Nasional Indonesia (SNI) [17].

The calculation of the accuracy of an image analysis is using the matric error, against the map of object-based classification results, which are include overall accuracy (accuracy overall), the accuracy of the producer (producer accuracy) and the accuracy of the user (user ' accuracy) for the each class of the closure, and the accuracy of the Kappa [12], [18].

Forest Cover Change

The forest cover change rate per year on each sub-landscapes for the period between the 2004 year's acquisition of Landsat data is calculated following the formula [19] :

$$P = \left(\frac{100}{t_2} - t_1\right) ln\,(\frac{A_2}{A_1}) \qquad (1)$$

Where P indicates percent of forest loss per year, A_1 and A_2 are the forest cover area in t_1 and t_2, and t_1 dan t_2 indicate year-i data acquisition of Landsat imagery.

Indicators of Forest Landscape Structure

In this research, the dynamics change of landscape metrics of forest is investigated using 14 indicators, i.e. 7 indicators of landscape metrics that are used in determining the composition of the landscape and the level of fragmentation of forest landscape (Table 2), and 7 indicators of landscape metrics that are used in determining the level of the configuration of the changing of landscape connectivity and the occurrence of forest habitat isolation (Table 3). These definitions are following the definitions of Forman [20]. The generation of the indicators were conducted by using software FRAGSTATS 4.ver 2. [21].

We analyzed the behavior of each measure of forest fragmentation in three regions of sub-landscape against the series of years of data acquisition of satellite imagery. We examined the relationship between the percentage of forest loss in the series of years of data acquisition with all landscape metrics indicators. This calculation was based on a regression techniques, in order to know the variable predictors of the forest landscape metrics indicators [7], and to know the significant differences in the values of the size of the fragmentation occuring in the three areas of sub-landscape [23].

Table 2. Landscape metrics indicators of the composition and level of forest landscape fragmentation, based on McGarigal [22].

No	Metric Indicator	Definition	Rank of Value and Unit
1.	Percent of Landscape (PLAND)	Quantify the abundance of a proportional forest patch type in the landscape. More precisely by measuring the composition of the landscape rather than the broad classes of patches, to compare between the landscape of any size.	0 <PLAND ≦ 100 (%)
2.	Number of Patch (NP)	The number of patches to a certain type of patch is a simple measure of the level of subdivision or the fragmentation of forest patch types. The amount of information a particular type of patch will be more meaningful if the added information about the area, distribution, or a density of patch.	NP ≥ 1, unlimited (no unit)
3.	Largest Patch Index (LPI)	Quantifies the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance, equals the percent of the landscape that the largest patch comprises. Note, total landscape area (A) includes any internal background present.	0 < LPI ≦ 100 (%)
4.	Edge Density (ED)	Edge Density reported long edge per unit area basis to facilitate a comparison between the different sizes of landscapes. Edge Density is equal to the sum of the lengths (m) all segments of banks involving the same type of patch and divided by the total area of the landscape.	ED ≥ 0, unlimited (meter/ha)
5.	Landscape Shape Index (LSI)	The index of the shape of the landscape provides a standard measure of total edge or edge density that adjusts to the size of the landscape. LSI increase without limit as the landscape becomes more irregular and/or as the length of the edges in the landscape that matches the type of patch is increased.	LSI ≥ 1, unlimited (no unit)
6.	Effective Mesh Size (MESH)	Based on the cumulative patch area distribution and is interpreted as the size of the patches when the corresponding patch type is subdivided into S patches, where S is the value of the splitting index.	Sel size ≦ MESH ≦ total landscape area (m2)
7.	Shannon's Diversity Index (SHDI)	The measure of the patch community diversity used in landscape ecology, which is determined by the proportion of the distribution of different types of land use cover in the landscape. SHDI increases as the number of different patch types increases and/or the proportional distribution of area among patch types becomes more equitable.	SHDI ≥ 0, unlimited, (no unit)

We analyzed the behavior of each measure of forest fragmentation in three regions of sub-landscape against the series of years of data acquisition of satellite imagery. We examined the relationship between the percentage of forest loss in the series of years of data acquisition with all landscape metrics indicators. This calculation was based on a regression techniques, in order to know the variable predictors of the forest landscape metrics indicators [7], and to know the significant differences in the values of the size of the fragmentation occuring in the three areas of sub-landscape [23].

Identifying of the spatial transformation process of landscape pattern

The identification of the phases of forest fragmentation on each area of sub-landscape are based on the decision-tree model [24]. All decisions are based on the area (a), the perimeter (p), or the number of patches (n), before (a_0, p_0, n_0) and after (a_1, p_1, n_1) transformations of the landscape, as well as comparation of the area before and after transformation, $t_{obs} = a_1/a_0$. Furthermore, the flow charts of the decision tree model was translated into matrix as show in Table 4.

The decision tree model can be used to determine the ten spatial transformation processes. However, in this study the fragmentation of forest is mainly related to the degradation of forest cover, in such that this study research will only use five spatial transformation

 http://dx.doi.org/10.22135/sje.2017.2.1.8-18

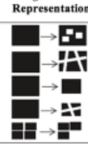
process, namely: reduction of the number of patches (attrition), reduction of patch size (shrinkage), subdivision of patches using equal-width lines (dissection), breaking up of patches into smaller parcels (fragmentation), and gap formation (perforation) [24].

Table 3. Landscape metrics indicators of the configuration of the landscape, changes, and occurrence of connection isolation landscape habitat, based on McGarigal [22].

No	Metric Indicator	Definition	Rank of Value and Unit
1.	Radius of Gyration Distribution (GYRATE_AM)	The size of an expansion patch; so is affected by the size of the patch and patch density, gives the size of the continuity of the landscape (also known as the correlation length) that represents the average landscape traversability for an organism that is limited to remain in a single patch; in particular, gives the average distance an organism can move from a random starting point and traveling in a random direction without leaving the patch.	GYRATE ≥ 0, unlimited (meter)
2.	Contiguity Index (CONTIG)	Assess the size of spatial connectedness or transmission the patch of forest in forest patches of other individuals. CONTIG equals 0 for a one-pixel patch and increases to a limit of 1 as patch contiguity or connectedness increases. Note, 1 is subtracted from both the numerator and denominator to confine the index to a range of 1.	0 ≤ CONTIG ≤ 1 (no unit)
3.	Perimeter-Area Fractal Dimension (PAFRAC)	Reflecting the complexity of the shape in the entire range of spatial scales (patch size), it is only meaningful if the relationship between perimeter and area is linear over the full range of patch sizes, PAFRAC approaching 1 to form with a perimeter of simple (box) and approaching 2 to shape with perimeter are very complicated, and vice versa.	1 ≤ PAFRAC ≤ 2 (no unit)
4.	Mean Nearest Neighbor Distance (MNND)	Simple in the context of the size of the patch, which has been used extensively to measure the insulation patches, defined using the Euclidean geometry as simple as the shortest straight line distance (m) between the Centre of the nearest neighbor of the patch and the same class.	MNND> 0, unlimited (meter)
5.	Connectance Index (CONNECT)	Defined on the number of functional joinings between patches of the same type, where each patch pair is either connected or not based on user-specified distance criteria; reported as a percentage of the maximum possible connectance given the number of patches. Note, connectance can be based on either Euclidean distance or functional distance.	0 ≤ CONNECT ≤ 100 (%)
6.	Patch Cohesion Index (COHESION)	Measures the physical size of the connectedness of the same patch type. Patch cohesion increases as type patch become more clumped or aggregated in its distribution; It is, therefore, more physically connected. COHESION increases monotonically as the proportion of the landscape comprised of the focal class increases until an asymptote is reached near the percolation threshold.	0 < COHESION < 100 (%)
7.	Contagion Index (CONTAG)	When a single class occupies a very large percentage of the landscape, contagion is high, and vice versa. Contagion is affected by both the dispersion and interspersion of patch types. Low levels of patch type dispersion (i.e., the high proportion of like adjacencies) and low levels of patch type interspersion (i.e., inequitable distribution) of pairwise adjacencies results in high contagion, and vice versa.	0 < CONTAG ≤ 100 (%)

The multiple regression analysis was done to determine the predictor variables and the coefficient of regression, as well as the weighted of each variable roles against the process of the forest fragmentation, which is expressed in various indices.

Table 4. The spatial transformation process of the forest fragmentation phases extracted from the flow chart of the decision tree model [24].

No.	Total Patch Habitat (a)	Number of Patches (n)	Total Edge (p)	Spatial Transformation Process	Diagrammatic Representation
1	$a_1 < a_0$	$n_1 = n_0$	$p_1 > p_0$	Perforation	
2	$a_1 < a_0$	$n_1 > n_0$	$p_1 > p_0$	Dissection	
3	$a_1 < a_0$	$n_1 = n_0$	$p_1 < p_0$	Shrinkage	
4	$t_{obs} < t$	$n_1 > n_0$	$p_1 < p_0$	Dissipation	
5	$a_1 < a_0$	$n_1 < n_0$	$p_1 < p_0$	Attrition	

Noted : a_1 – total patch area; p_1 – total edge; n_1 – number of patches. a_0, n_0 dan p_0 refer to the state before transformation, where as a_1, n_1 and p_1 refer to the state after transformation at time t+1, $t_{obs} = a_1 / a_0 > 0$. The definition is based on Bogaert and Abdullah [11], [24].

Fragmentation Index

Calculation process of fragmentation index is performed with the multiple regression analysis to determine the variable predictors, in which the percentage of the forest cover loss as the dependent variable, while the entire indicators of landscape metrics as an independent variables. The variables do not have a significant correlation with other variables are not used in the regression techniques. The multiple regression analysis produces predictor variables and coefficient of regression, which is a value of each indicator of landscape metrics as a variable fragmentation.

The value of the total score of fragmentation, based on the value of each variable multiplied by the value of the coefficient of regression, was calculated with the following formula:

$$Wfg = \sum_{i=0}^{n} Wfg_i . fg_i \qquad (2)$$

where *Wfg* indicates the value of total score of fragmentation, wfg_i indicates the weighted of each variables, and fg_i indicates score variable fragmentation of the *i*th.

Re-scaling the Value of Fragmentation Variables

To provide an explanation of how the values of indicators of landscape metrics and the value of total score of fragmentation can be created in the graph, we conducted re-scaling against all off scoring, which results in a value interval. So it can be shown in simple form, as the graphic of the dynamics of forest fragmentation phase. In order to determine the standard of the fragmentation level, then the total score of fragmentation is transformed (re-scaling) into value of the forest fragmentation index, with a value interval from 1 to 5, using the equation as follow (modified from Sharifi, [25]:

$$Ind_{Frag} = 1 + \frac{(Score\ total\ input - Score\ total\ min)}{(Score\ total\ max - Score\ total\ min)} \times (Ind_{Frag}max - Ind_{Frag}min) \qquad (3)$$

where *Ind_Frag* indicates the fragmentation index: (1 – 5), *Score total input* indicates the value of total score entered, *Score total max* indicates the value of largest total score, *Score total min* indicates the value of smallest total score, *Ind_Frag max* indicates the largest fragmentation index (5), and *Ind_Frag min* indicates the smallest fragmentation index (1).

3. Results

Deforestation and forest fragmentation

A series of forest cover maps representing a profile of change throughout our study period, based on the TM Landsat Imagery for acquisition of period: 1989, 1995, 2000, 2006, 2009 and 2013 are presented at Figure 2. The land cover types based on the interpretation of Landsat imagery year 2013 are defined as the secondary natural forest (173.722 ha), forest plantation (14.114 ha), shrub (68.052 ha), mixed dryland agriculture (76.332 ha), open land (11.030 ha) and palm plantations (3.226 ha).

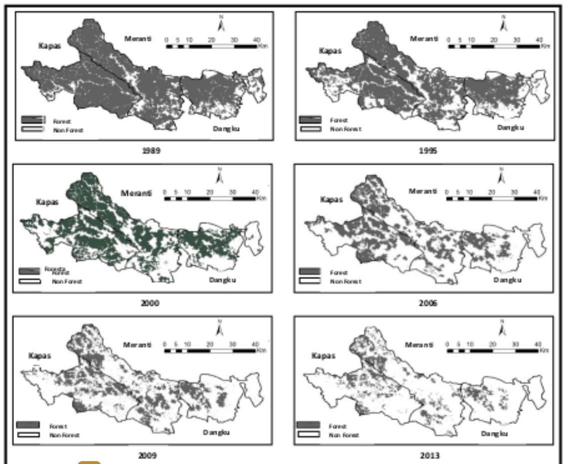


Figure 2. A series of the forest cover maps representing a profile of change through our study period, base on the TM Landsat Imagery.

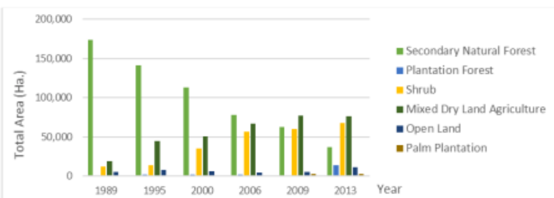


Figure 3. A total areal of land cover classification, based on the TM Landsat Imagery

The land cover types from the moderate resolution of the Landsat TM data in 1989, 1995, 2000, 2006, 2009 and 2013 with six land cover types are shown in Figure 3, which shows a tendency of the decreasing in the area of the secondary natural forest, and has turned, which is dominated by the mixed dry land agriculture and shrub.

Table 5. Total areas of secondary natural forest in each sub-landscape by the years of the acquisition of Landsat imagery

Sub Landscape	Total Area (Hectars)	Secondary Natural Forest Cover											
		1989		1995		2000		2006		2009		2013	
		Ha	%	Ha	%	Ha	%	Ha	%	Ha	%	Ha	%
Kapas	71,893	65,100	90.55	50,375	70.07	40,580	56.45	31,047	43.19	22,410	31.17	13,304	18.51
Meranti	85,335	71,950	84.32	61,035	71.52	49,777	58.33	33,789	39.60	29,324	34.36	17,118	20.06
Dangku	52,392	36,672	69.99	30,141	57.53	22,849	43.61	12,972	24.76	10,733	20.49	6,444	12.30

Table 5 indicates the occurrence of the total area of change and percentage of natural secondary forest closure as the process of the deforestation and degradation of natural forests from 1989 to 2013 on the respective of sub-landscape. In the rest of our analysis, we used this database for the calculation of the spatial analysis of the forest fragmentation phases.

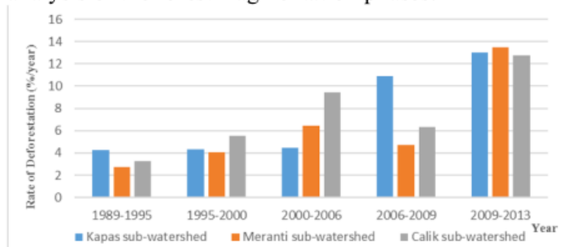


Figure 4. Rate of deforestation (%/year) on the each of the sub-landscape, in the period between series of years of data acquisition of satellite imagery

Figure 4 indicates the occurrence of the deforestation (% per year) on the each of the sub-landscape, during various time interval between 1989 and 2013. It is shown that during the period of 2006 – 2009, there was a decrease in the deforestation rates in the Meranti and Dangku sub-landscape. However, the deforestation rate again increase during 2009 – 2013 period, in which all three sub-landscapes show a comparable rate of deforestation.

Patterns of Change of the Landscape Structure

Quantitative analysis of landscape structure during the period of 1989 to 2013 is presented in Table 6. The algorithms used to analyze the landscape structure is based on the level of class, in particular for the indicator of Shannon's Diversity Index at the level of Landscape. Then, the results from the quantitative analysis of landscape structure were extracted, in particular for the data from forest cover type. Finally, the result from the extraction were used in the analysis of the forest fragmentation phases.

Table 6. Characteristics of the muti-temporal landscape metrics indicators based on the composition and configuration of the forest landscape in each sub-landscape.

YEARS	FOREST LOSS (%)	TOTAL EDGE (m)	PLAND (%)	NP (patch)	LPI (%)	ED (m/ha)	LSI	MESH (m2)	SHDI	GYRATE_MN (m)	CONTIG_AM	PA-FRAC	ENN_MN (m)	CON-NECT (%)	COHE-SION (%)	CON-TAG (%)
Kapas Sub-landscape																
1989	9.44	1,139,460	90.56	60	89.87	15.85	11.16	58,065	0.42	246.39	0.99	1.30	120.13	2.60	99.99	81.03
1995	29.95	1,275,000	70.05	132	67.38	17.74	14.20	32,651	0.95	177.06	0.98	1.28	120.86	0.97	99.95	65.92
2000	43.56	1,463,580	56.44	212	19.08	20.36	18.16	4,288	1.14	211.32	0.97	1.27	140.35	0.50	99.68	58.42
2006	56.81	1,013,460	43.19	236	16.42	14.10	14.38	3,654	1.19	135.46	0.97	1.30	122.26	0.55	99.71	58.34
2009	68.81	1,723,020	31.19	976	4.64	23.97	28.75	556	1.24	79.00	0.93	1.33	140.72	0.11	98.92	53.32
2013	81.50	1,433,580	18.5	771	3.54	19.94	31.07	198	1.42	84.16	0.91	1.31	145.34	0.13	98.42	45.88
Meranti Sub-landscape																
1989	15.69	1,550,160	84.30	62	89.87	18.17	14.44	58,961	0.58	382.17	0.98	1.28	103.19	2.33	99.98	74.22
1995	28.48	1,428,180	71.55	143	67.38	16.74	14.44	17,192	0.85	218.29	0.98	1.29	150.34	0.74	99.86	69.19
2000	41.67	1,615,020	58.31	195	19.08	18.93	18.09	8,360	1.05	241.01	0.97	1.24	146.72	0.65	99.76	65.88
2006	60.40	1,555,140	39.60	390	16.42	18.22	21.14	1,767	1.17	144.96	0.96	1.28	102.05	0.39	99.50	57.85
2009	65.64	1,951,860	34.39	906	4.64	22.87	28.46	1,427	1.19	89.62	0.94	1.30	132.22	0.11	99.29	55.52
2013	79.94	1,760,740	20.09	721	3.54	20.87	34.00	401	1.39	99.29	0.91	1.33	137.08	0.13	98.89	53.20
Dangku Sub-landscape																
1989	30.00	1,075,560	70.01	67	63.64	20.53	14.04	21,262	0.86	282.47	0.97	1.29	187.88	0.77	99.92	60.23
1995	42.47	799,680	57.56	235	52.76	15.26	11.51	14,598	0.99	100.97	0.98	1.30	141.00	0.43	99.86	53.79
2000	56.39	848,220	43.62	154	41.42	16.19	14.02	8,989	1.24	112.93	0.97	1.29	162.87	0.62	99.88	54.58
2006	75.24	582,180	24.73	208	11.70	11.11	12.78	879	1.26	112.44	0.96	1.25	163.92	0.62	99.39	54.95
2009	79.51	604,440	20.55	406	11.06	11.54	14.56	760	1.32	65.09	0.95	1.32	176.65	0.17	99.36	62.89
2013	87.70	665,880	12.35	277	5.23	12.71	20.67	169	1.34	90.76	0.91	1.36	185.55	0.37	98.74	58.88

In the Kapas sub-landscape, based on the indicators of landscape composition and the level of forest landscape fragmentation shown in Table 6, all data from 1989 to 2013 show a decrease in the percentage of extensive forest patch against the vast landscape (PLAND) from 90.56% to just 18.5%, and the largest patch index (LPI) plummeted from 89.87% to 3.54% due to the increasing number of patches, and the effective mesh size of patch (MESH) also decreased from 58, 064.78 m2 to being only covering 198.20 m2. Meanwhile, the number of patches (NP) rose significantly from 60 units to become 771 units,

In the Meranti sub-landscape, the landscape structure showed a decrease in the percentage of extensive forest patch against the vast landscape (PLAND) from 84.30% to just 20%. The largest patch index (LPI) plummeted from 89.87% to 3.54% due to the increasing number of patches, and the effective mesh size of the patch (MESH) also decreased from 58, 961.19 m2 to 400.88 m2. On the other hand, the number of patches (NP) rose significantly from 62 units to 721 units.

In the Dangku sub-landscape, the landscape structure showed a decrease in the percentage of extensive forest patch against the vast landscape (PLAND) from 70.01% to a 12%, the largest patch index (LPI) decreased from 63.64% to 5.23% due to the increasing number of patches, and the effective mesh size of patch (MESH) also decreased from 21,261.76 m2 to 168.51 m2. Meanwhile, the number of patches (NP) rose significantly from 67 units being 277 units.

Forest Fragmentation Index

Note that the fragmentation is a spatial transformation process having several phases or levels. Therefore, in order to get a single fragmentation index based on a combination of several landscape metrics a different natural landscapes, and using multi-temporal data, several regression models have been developed. In this study, the percentage loss of forest cover from 1989 to 2013 was used as the dependent variable, while indicators of landscape metrics are designed as the independent variables.

Table 7. Analysis of Variant (ANOVA) of the Multiple Regression Models of Forest Fragmentation Index.

No.	Sub-landscape	Multiple Regression Models	$df_1;df_2$	F	Significant (p)	R^2
1.	Kapas	*Y = 129.768 + 0.16 (NP) – 0.126 (LPI) – 1.382 (CONTAG)*	3;2	21.836	0.044	0.970
2.	Meranti	*Y = 416.869 – 0.110 (NP) – 0.083 (LPI) – 2.300 (CONTAG) – 226.719 CONTIG.*	4;1	2.062	0.050	1.000
3.	Dangku	*Y = 933.009 + 0.008 (NP) – 0.437 (LPI) + 40.485 (SHDI) – 9.111 (COHESION).*	4;1	3.193E3	0.013	1.000

The results of multiple regression analysis of forest fragmentation index of each location, showed that the independent variables are statistically significant in predicting a dependent variable *($p \leq 0.05$)*, with high deterministic's (R^2) (Table 7). Note that all locations have the same independent variables, namely NP and LPI. In addition, the Kapas and Meranti sub-landscape have similar independent variables, namely CONTAG. Figure 5 provides an explanation of how the values of indicators of landscape metrics can be created in the graph in the same scale. Then, we do re-scaling from 1 to 5 against the values of landscape metrics. The result shows the dynamics of forest fragmentation phase in the Kapas sub-landscape. It could be different from the forest fragmentation process in the Meranti and Dangku sub-landscapes.

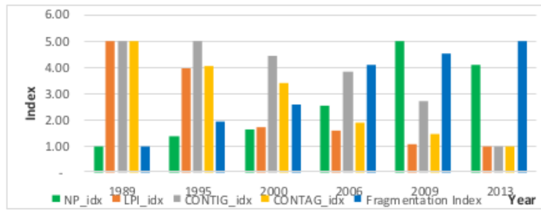


Figure 5. Forest fragmentation index of the predictor variables of the landscape metric indicators in the Kapas sub-landscape.

Using a similar procedure, we could obtain the fragmentation index of the predictor variables of the landscape metric indicators in other sub-landscapes, namely the Meranti and Dangku sub-landscape as shown in Figure 6 and Figure 7, respectively. Note that the dynamics of forest fragmentation phase in each sub-landscape has different characteristics in which each sub-landscape has its own typical characteristic.

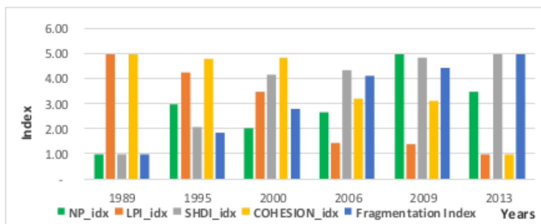


Figure 6. Same as in Figure 5 except for the Meranti sub-landscape

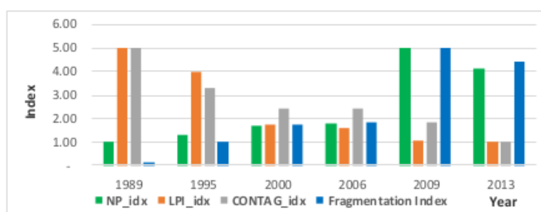


Figure 7. Same as in Figure 5 except for the Dangku sub-landscape.

Forest Fragmentation Phases

The identification of forest fragmentation in the Kapas sub-landscape was conducted for a period of 1989 to 2013. There were three criteria used in the identification process, the total of habitat patches, number of patches and total edge (Table 4). The results are presented in Figure 8. It is shown that the forest fragmentation phases based on the landscape-pattern changes during the period of observation are Dissection – Dissection – Dissipation – Dissection and Attrition, respectively.

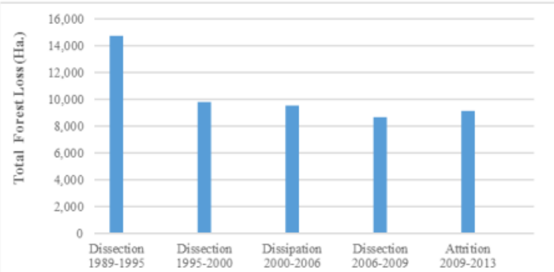


Figure 8. Identification of the magnitude of forest fragmentation phases in Kapas sub-landscape.

The identification of forest fragmentation in Meranti sub-landscape made between observation data in a period of 1989 to 2013, with reference to the criterion in Table 4, namely a total of habitat patches, a number of patches and total edge, presented in Figure 9. The pattern changes of the each forest fragmentation phase in year of periods of observation are Dissipation – Attrition – Dissipation – Dissection and Attrition.

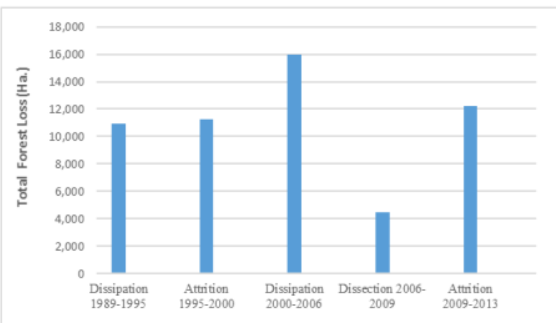


Figure 9. Same as in Figure 8 expet for the Meranti sub-landscape.

The identification of forest fragmentation in Dangku sub-landscape made between observation data in a period of 1989 to 2013, with reference to the criterion in Table 4, namely a total of habitat patches, a number of patches and total edge, presented in Figure 10. The pattern changes of the each forest fragmentation phase in year of periods of observation are Dissipation – Attrition – Dissipation – Dissection and Attrition.

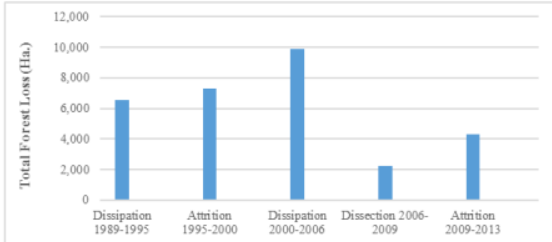


Figure 10. Same as in Figure 8 except for the Dangku sub-landscape.

Spatial transformation process and forest fragmentation phases

The calculation of the multiple regression models of forest fragmentation index (Table 7) and the spatial transformation process based on the decision tree model (see Figure 8, 9 and 10), on each phase of the fragmentation of forests, were implemented at the each research location, e.g. the Kapas, Meranti and Dangku sub-landscape, and it was formulated in Table 8.

Table 8. The spatial transformation process on the phases of forest fragmentation

Forest Fragmentation Phases						Magnitude of Forest Loss	
Year	Phases	Key Indicators of the Landscape Metrics *)				Ha	%
Kapas sub-landscape							
1989-1995	Dissection	n1>n0	lpi1<lpi0	cont1<cont0	ctg1<ctg0	14,725	22.62
1995-2000	Dissection	n1>n0	lpi1<lpi0	cont1<cont0	ctg1<ctg0	9,795	19.44
2000-2006	Dissipation	n1>n0	lpi1<lpi0	cont1<cont0	ctg1<ctg0	9,533	23.49
2006-2009	Dissection	n1>n0	lpi1<lpi0	cont1<cont0	ctg1<ctg0	8,637	27.82
2009-2013	Attrition	n1<n0	lpi1<lpi0	cont1<cont0	ctg1<ctg0	9,106	40.63
Meranti sub-landscape							
1989-1995	Dissipation	n1>n0	lpi1<lpi0		ctg1<ctg0	10,915	15.17
1995-2000	Attrition	n1<n0	lpi1<lpi0		ctg1<ctg0	11,258	18.45
2000-2006	Dissipation	n1>n0	lpi1<lpi0		ctg1<ctg0	15,988	32.12
2006-2009	Dissection	n1>n0	lpi1<lpi0		ctg1<ctg0	4,465	13.21
2009-2013	Attrition	n1<n0	lpi1<lpi0		ctg1<ctg0	12,206	41.62
Dangku sub-landscape							
1989-1995	Dissipation	n1>n0	lpi1<lpi0	shd1>shd0	coh1<coh0	6,531	17.81
1995-2000	Attrition	n1<n0	lpi1<lpi0	shd1>shd0	coh1<coh0	7,292	24.19
2000-2006	Dissipation	n1>n0	lpi1<lpi0	shd1>shd0	coh1<coh0	9,877	43.23
2006-2009	Dissection	n1>n0	lpi1<lpi0	shd1>shd0	coh1<coh0	2,239	17.26
2009-2013	Attrition	n1<n0	lpi1<lpi0	shd1>shd0	coh1<coh0	4,289	39.96

*Note : (a) total patch area, (n) number of patches, (co) patch cohasion index,(shd) shannon's diversity index, (cont) patch contiguity index, (ctg) contagion index, (lpi) largest patch index, (p) total edge, (>) increase, (<) decrease, *) refers to Table 6 and Table 7.*

Table 7 shows the form of the multiple regression model of forest fragmentation on the respective research location. Figure 5, 6, and 7 shows the magnitude of the role of each variable and the level of forest fragmentation in the index, in the lapse of the time period, while Figure 8, 9, and 10 indicate the magnitude of the forest fragmentation phase in the interval of time period.

4. Discussion

Monitoring of forest fragmentation

During 1989 to 2000, the production forest in the Kapas and Meranti sub-landscape was managed by the concessionaire with the Selective Cutting System. These two areas show a deforestation average of about 4.32 - 4.08 % per year (Figures 3 and 4.). During 2000 to 2006, the production forest area was managed by state-owned enterprises, and failed in implementing the industrial forest plantation silviculture with the Slash Line Planting System. As a result, the rate of deforestation rose to 4.48 - 6.46 % per year (Figure 4). The concessionaire permit was revoked in 2005, and then the deforestation in 2006 to 2009, especially in Kapas sub-landscape, rose dramatically up to 10.87% per year. This rapid increase mainly due to the change of the status of the forest area into an open access area.

In 2007 the Central Government issued a new forest concession license of *Acacia* industrial plantation for pulp and paper industries. In 2009 the illegal logging could be suppressed by district forestry service, which caused a drop in the rate of deforestation to 4.72%. However, from 2009 to 2013 the deforestation rate increase to more than 13.00% per year. This increase is partly due to the conversion of the secondary natural forest into an *Acacia* forest plantation. In addition, the increase of deforestation rate may be caused by the illegal logging and encroachment was out of control.

The Dangku sub-landscape is a wildlife conservation area. During 1989 to 2009, the deforestation rate in Dangku sub-landscape was about 3.27 - 6.31 % per year. However, during 2009 to 2013, the deforestation rate increased drastically by about 12.75% per year. [1] concluded that the loss of the old-growth forests cover in the Sumatra from 2000 to 2012 is covering an area of about 1,205,000 ha (21.3%) or average area of 100,416 ha/year (1.75%). This proves that the rate of loss of the remaining lowland natural forest of the South Sumatra is far above the average rate of loss of the natural forests of Sumatra.

Spatial transformation process of landscape structure

The discussion on the rapid changes of the landscape structure of the Meranti-Dangku tropical lowland forest implied the sensitivity to the spatial arrangement that should have been attributed to the shape and size of patches. The ecologists are interested in the spatial distribution of the patches, because many ecological processes, including the animal behavior, seed dispersal, and climatic factors are potentially influenced by this component of landscapes (Hargis, 1998). In the absence of such parameters, then, the ecologists improve their understanding of the ecological processes by applying the several metrics indicators to any given investigation [26].

The spatial transformation process, such as dissection, dissipation and attrition have affected on the patch type dispersion and patch type interspersion of pairwise adjacencies, in such that they become high, while the patch cohesion index of similar type was declined. Here, the largest patch index decreases and improves the diversity index of the path type. As the result of the conversion process, part of the largest patch type has changed into other patch types.

The dissection occurs when the largest patch is broken up into a smaller size, while the dissipation phase occurs when the largest patch is breaking up into smaller parcels. In this case, the contagion is affected by both the dispersion and interspersion of pairwise adjacencies of patch types. The contagion index has strong correlation with the patch cohesion index, where it indicators measure the physical size of the connectedness of the same type patch. Likewise, contagion index has strong correlation with the patch contiguity index, where it assesses the size of spatial connectedness or transmission the patches of the fragmented forest. The multiple regression shows that the fragmentation of the forests affected by the increase in the number of patch, as well as the decrease in the largest patch index and the contagion index [7]. This in a sustainable way will affect the shape of the landscape and increase the complexity of the structure of the landscape.

The change of patch type after the process of dissection, dissipation and attrition, will increase the patch type diversity, whereas the patch type change will effect the growing of dispersion and interpersion. We found that all of fragmentation phases, namely dissection, dissipation and attrition, indicated by decreasing of the largest patch index, will cause a change in the dispersion and interspersion of pairwise adjacencies of patch type.

We found specific characteristics of the Dangku sub-landscape, where the forest fragmentation phases is a function of increasing number of patches and the diversity of the patches type, as well as decreasing in the largest patch and the inter-patch cohesion. There are strong correlation between reducing of largest patch index and increasing of patch type diversity, where the patch type diversity increase because of some number of patch converted into another patch type. In addition, a very strong correlation between the number of patches and the patch connectivity, suggests that a reduction in the number of patches are highly sensitive to the change of the physical size of the connectedness of the same patch type.

In the whole area of research, the number of patches continue to change, so that we do not find the process of perforation (gap formation) and shrinkage (reduction of patch size). The perforation and shrinkage process can only be observed if there are no additional or reduction of the number of patches.

Forest Fragmentation Phases

The pattern change occurring in each forest fragmentation phase suggests the association of each phase with the tendency of a part of patches of particular sizes to be converted into another patch type. The different magnitude of forest loss in each phase of fragmentation affects the uncertainty level associated with the research of natural forest. The quantification of fragmentation index in this research differs from a single fragmentation index, in particular the selection of the level of fragmentation at a specific time (i.e. a specific year) [11].

We did an inter-correlation analysis, among the indicators of landscape metrics. Then, we selected the variables having significant inter-correlation. In order to find key indicators of landscape metric affecting forest loss or forest fragmentation, a multiple regression analysis was applied to the percentage of forest loss as a dependent variable.

A primary impact of the habitat fragmentation is an increase in the patch edge of the habitat. Meanwhile, the fragmentation of dissection and dissipation caused a decrease in the index of patch contiguity and patch cohesion. Both indexes, patch contiguity and cohesion, have a high positive correlation with the mean nearest neighbor distance (MNND). Note that, the MNND provides an information on the spacing between patches in a cluster, regardless of the patch type. This suggests that habitat fragmentation poses a multiplier effect and influences the balance of forest ecosystems.

The research on the forest fragmentation in the Kapas, Meranti and Dangku sub-landscapes indicated that the number of a patch and area of habitat patch is the main criteria for determining the phases of forest fragmentation. This result is in agreement with previous study by Boygaert (2004).

In the Kapas and Meranti sub-landscapes, there are at least five effects of the forest fragmentation process, namely (a) an increase in the number of habitat patches, (b) a decrease in the sizes of habitat patches, (c) a reduction in the habitat amount, (d) a reduction in contagion values of habitat patches, and (e) reduction in contiguity values of habitat patches. Meanwhile, previous study proposed an additional effect, which was an increase in the isolation of patches [27].

As the big patches of the landscape were broken, where the phases of fragmentation are dissection, dissipation, or attrition, then a small patches will fill the remaining space, and this will result in slightly higher of edge density and slightly lower of contagion values, and this is in accordance with Hargis [7].

The Kapas sub-landscape have the fragmentation phases of Dissection – Dissection – Dissipation – Dissection – Attrition. From 1989 to 2000 there was a process of subdivision of the forest patches, which devided the area using an equal-width lines (dissection), indicated by a forest logging for road construction. From 2000 to 2006, the fragmentation continous with the process of breaking up of the forest patches into the smaller parcels (dissipation). Then, from 2006 to 2009 there was the process of subdivision of the forest patches using an equal-width line (dissection), while from 2009 to 2013 has been going on the reduction of the number of patches (attrition), indicated as converted to other land use type. The magnitude of forests loss in the period 1989 to 2013 shows a continued declination, from 14.725 ha to 9.106 ha, but the magnitude of total forest loss is higher than in the Meranti and Dangku sub-wtershed.

We found a unique result in the Meranti and Dangku sub-landscape, whereas during the period from 1989 to 2013 both sub-landscapes have similar amplitude and phase of forest fragmentation: Dissipation – Attrition – Dissipation – Dissection – Attrition. However, in each stage of the forest fragmentations, both sub-landscapes have different the measure on reduction of the number of patches, and the magnitude of total forest loss. In addition, both these locations have a different in the inter-correlation characteristics and the predictor variables of the multiple regression models of forest fragmentation. At both of adjacent locations, showed have similarity in the pattern of drivers and pressures of deforestation, although with different levels of intensity.

Despite having undergone various phases of the forest fragmentation, but the value of the patch cohesion index in Kapas, Meranti and Dangku sub-landscape remains high (Table 5), more than indicating over 98,42%. This indicates that the physical size of the connectedness of the current forest patch is still high, where the type of the remaining forest patches becomes more clumped or aggregated in its distribution. It is, therefore, physically more connected.

However, the fragmentation of the forest produces a large number of small-sized patch, where some fauna species probably could not cross the area of the non-habitat, will be limited by the large number of other patches type with small size. Each patch of habitat would be too small to sustain the local population, or perhaps also against individual territory, so it would be reduced of the opportunities to survive, and would be reduced to the overall population size.

4. Conclusion

In this research, to find the magnitude of the lost of forest in the process of fragmentation, it would be better if preceded by doing a review of the pattern of spatial structure of forest landscape change, as well as exposing the properties of the unknown, rather than simply evaluating the change on closure of the forest. Thus, we will find the behavior of the spatial forest fragmentation processes.

When some locations have the same of amplitude and phases of the fragmentation of the forest, but at each stage and each location of the forest fragmentation have the distinction of size of the reduction of the number of patches and the magnitude of the total forest loss, then this research found the difference in the characteristics of the inter-correlation and predictor variables of fragmentation of the forest. We convinced that at these locations have the same drivers and pressures that influence the patterns of deforestation.

We affirm that the core-set of the landscape metrics is not have like it. Of the three locations of this study area have a different core set metrics, where the other metrics may be more appropriate to another location; and metrics should be always be used critically, aware of the usefulness and limitations of the resulting range of the metric-derived values.

The understanding of the relationship between series of the forest loss rate and the spatial transformation process based on the decision tree models provides a more comprehensive approach in the determining of the rapid change of the forest landscape structure of the forest fragmentation phases, and can be complemented to the Protocol of the Forest Monitoring.

The landscape ecology approaches to be adopted in the Protocol of Conventional Forest Inventory and Monitoring, so the planning and management of the habitat could be based on the quantitative analysis of spatial changes of landscape structure of the forest. Needed more research for to find the linkages between the dynamics of the spatial change in the tropical forest fragmentation and its effect on the forest biodiversity.

Acknowledment

This study is part of the first author's dissertation in the Graduate School of Environmental Science, University of Sriwijaya. The last author is supported by the Ministry of Research, Technology and Higher Education through "*Hibah Kompetensi (No. 023/Sp2H/LT/DPRM/II/ 2016)*".

References

[1] B. A. Margono, P. V Potapov, S. Turubanova, F. Stolle, and M. C. Hansen, "Primary forest cover loss in Indonesia over 2000–2012," *Nat. Clim. Chang.*, vol. 4, no. June, pp. 1–6, 2014.

[2] M. J. Fortin, M. R. T. Dale, and J. Hoef, "Spatial analysis in ecology," *Encycl. Environmetrics*, vol. 4, pp. 2051–2058, 2002.

[3] J. Sun, Z. Huang, J. Southworth, and Y. Qiu, "Mapping fractality during the process of deforestation in an Amazon tri-national frontier," *Remote Sens. Lett.*, vol. 4, no. March 2013, pp. 37–41, 2013.

[4] A. Botequilha Leitão and J. Ahern, "Applying landscape ecological concepts and metrics in sustainable landscape planning," *Landsc. Urban Plan.*, vol. 59, no. 2, pp. 65–93, Apr. 2002.

[5] R. R. Claggett and J. S. Tilley, "A Landscape Indicator Approach to the Identification and Articulation of the Ecological Consequences of Land Cover Change in the Chesapeake Bay," *Situ*, no. June, 2007.

[6] R. T. T. Forman, "Some general principles of landscape and regional ecology," *Landsc. Ecol.*, vol. 10, no. 3, pp. 133–142, 1995.

[7] C. D. Hargis, J. A. Bissonette, and J. L. David, "The behavior of landscape metrics commonly used in the study of habitat fragmentation," *Landsc. Ecol.*, no. 1992, pp. 167–186, 1998.

[8] B. Goodwin and L. Fahrig, "How does landscape structure influence landscape connectivity?," *Oikos*, vol. 3, no. June, pp. 552–570, 2003.

[9] M. Martínez-Ramos, I. A. Ortiz-Rodríguez, D. Piñero, R. Dirzo, and J. Sarukhán, "Anthropogenic disturbances jeopardize biodiversity conservation within tropical rainforest reserves," *Proc. Natl. Acad. Sci.*, vol. 113, no. 19, pp. 5323–5328, 2016.

[10] H. S. Alikodra, Zulfikhar, L. B. Prasetyo, H. Zulkifli, M. Wijayanti, T. Partomihardjo, H. Soedjito, A. Yanuar, A. Rafiastanto, Y. Hastiana, I. Imanda, W. Novariano, and Sunarto, *The Concept Towards the Development of Essential Areas of a Wildlife Corridor. Harapan Forest – Dangku Wildlife Conservation Area, South Sumatra Province*, I. Palembang: Sriwijaya University Press, 2013.

[11] S. A. Abdullah, "Quantifying forest fragmentation spatial process in the developing State of Selangor, peninsular Malaysia," *J. Land Use Sci.*, vol. 4248, no. November, pp. 1–16, 2016.

[12] W. Liu and Q. Zhou, "Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison," *Int. J. Remote Sens.*, vol. 25, no. 5, pp. 1037–1050, 2004.

[13] Frochn, A. R.C., D.C., Lane, C.R., And, and M. Reif, "No Title," *Int. J. Remote Sens.*, vol. 32(5), p. pp.1471-1489, 2011.

[14] T. Blaschke, "Object based image analysis for remote sensing," *ISPRS J. Photogramm. Remote Sens.*, vol. 65, no. 1, pp. 2–16, 2010.

[15] R. C. Weih and N. D. Riggan, "Object-based classification vs. pixel-based classification: Comparitive importance of multi-resolution imagery," *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*, vol. XXXVIII, pp. 1–6, 2010.

[16] A. S. Laliberte, A. Rango, K. M. Havstad, J. F. Paris, R. F. Beck, R. McNeely, and A. L. Gonzalez, "Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico," *Remote Sens. Environ.*, vol. 93, no. 1–2, pp. 198–210, 2004.

[17] B. S. Nasional, "Metode penghitungan perubahan tutupan hutan berdasarkan hasil penafsiran citra penginderaan jauh optik secara visual," 2014.

[18] I. Vorovencii, "Assessment of some remote sensing techniques used to detect land use/land cover changes in South-East Transilvania, Romania,"

Environ. Monit. Assess., vol. 186, no. 5, pp. 2685–2699, May 2014.
[19] J. Puyravaud, “Standardizing the calculation of the annual rate of deforestation,” *Ecol Manag.*, vol. Vol. 177, pp. 593–596, 2003.
[20] R. T. T. Forman, “Some general principles of landscape and regional ecology,” *Landsc. Ecol.*, vol. 10, no. 3, pp. 133–142, Jun. 1995.
[21] K. McGarigal and B. J. Marks, “FRAGSTATS: spatial pattern analysis program for quantifying landscapesStructure,” *Gen. Tech. Rep. PNW-GTR-351. U.S. Dep. Agric. For. Serv. Pacific Northwest Res. Station. Portland, OR*, vol. 97331, no. 503, p. 134, 1994.
[22] McGarigal K, C. SA, N. MC, and E. E., *FRAGSTATS: Spatial pattern analysis program for categorical maps, Comp. software prog.* Univ. Mass., Amherst., 2002.
[23] Slonecker and E.T., “A Landscape Indicator Approach to the Identification and Articulation of the Ecological Consequences of Land Cover Change in the Chesapeake Bay Watershed, 1970-2000.,” 2008.
[24] D. Bogaert, J., Cuelemans. R. And Salvador-Van Eysenrode, “A Decision tree algorithm for detection of spatial processes in landscape transformation,” *Environ. Manage.*, vol. 33, pp. 62–73, 2004.
[25] M. van Sharifi, Herwijnen and and W. H. van T. van Den., *Spatial Decision Support Systems.* Enschede, the Netherlands: International Institute for Aerospace Survey and Earth Sciences (ITC), Enschede, 2007.
[26] K. H. Ritters, R. V. O’Neill, C. T. Hunsaker, J. D. Wickham, D. H. Yankee, S. P. Timmins, K. B. J. And, Jackson, and B.L., “A factor analysis of landscape pattern and structure metrics,” *Landsc. Ecol.*, vol. 10, pp. 23–39, 1995.
[27] L. Fahrig, “Effects of habitat fragmentation on biodiversity,” *Annu Rev Ecol Evol Syst*, vol. 34, pp. 487–515, 2003.

40-86-3-PB.pdf

ORIGINALITY REPORT

8%

SIMILARITY INDEX

PRIMARY SOURCES

1	Elisa Wildayana, M. Edi Armanto. "Utilizing Non-Timber Extraction of Swamp Forests over Time for Rural Livelihoods", Journal of Sustainable Development, 2018 Crossref	110 words — 2%
2	Saiful Arif Abdullah. "Quantifying forest fragmentation spatial process in the developing State of Selangor, peninsular Malaysia", Journal of Land Use Science, 2014 Crossref	91 words — 1%
3	Agus Dwi Saputra, Dedi Setiabudidaya, Dwi Setyawan, M. Yusup Nur Khakim, Iskhaq Iskandar. "Burnscar analysis using normalized burning ratio (NBR) index during 2015 forest fire at Merang-Kepahyang peat forest, South Sumatra, Indonesia", AIP Publishing, 2017 Crossref	39 words — 1%
4	André Botequilha Leitão, Jack Ahern. "Applying landscape ecological concepts and metrics in sustainable landscape planning", Landscape and Urban Planning, 2002 Crossref	34 words — 1%
5	K.J. Koffi. "Spatial Pattern Analysis as a Focus of Landscape Ecology to Support Evaluation of Human Impact on Landscapes and Diversity", Landscape Ecological Applications in Man-Influenced Areas, 2007 Crossref	34 words — 1%

6	de Barros Ferraz, S.F.. "Landscape dynamics of Amazonian deforestation between 1984 and 2002 in central Rondonia, Brazil: assessment and future scenarios", Forest Ecology and Management, 20050103 Crossref	27 words — < 1%
7	Abdullah F. Alqurashi, Lalit Kumar. "Investigating the Use of Remote Sensing and GIS Techniques to Detect Land Use and Land Cover Change: A Review", Advances in Remote Sensing, 2013 Crossref	16 words — < 1%
8	Iosif Vorovencii. "Assessment of some remote sensing techniques used to detect land use/land cover changes in South-East Transilvania, Romania", Environmental Monitoring and Assessment, 2013 Crossref	15 words — < 1%
9	Iskhaq Iskandar, Putri Adia Utari, Deni Okta Lestari, Qurnia Wulan Sari et al. "Evolution of 2015/2016 El Niño and its impact on Indonesia", AIP Publishing, 2017 Crossref	15 words — < 1%
10	Saiful Arif Abdullah, Nobukazu Nakagoshi. "Changes in landscape spatial pattern in the highly developing state of Selangor, peninsular Malaysia", Landscape and Urban Planning, 2006 Crossref	14 words — < 1%
11	Zs. Ladányi, V. Blanka, B. Meyer, G. Mezősi, J. Rakonczai. "Multi-indicator sensitivity analysis of climate change effects on landscapes in the Kiskunság National Park, Hungary", Ecological Indicators, 2015 Crossref	12 words — < 1%

12 Wenli Huang, Huiping Liu, Qingzu Luan, Mu Bai, Xiaodong Mu. "Monitoring Urban Expansion in Beijing, China by Multi-Temporal TM and SPOT Images", IGARSS 2008 - 2008 IEEE International Geoscience and Remote Sensing Symposium, 2008 — 11 words — < 1%
Crossref

13 C. Huang. "Sensitivity of landscape metrics to classification scheme", International Journal of Remote Sensing, 7/1/2006 — 9 words — < 1%
Crossref

14 Kamlisa Uni Kamlun, Renate Bürger Arndt, Mui-How Phua. "Monitoring deforestation in Malaysia between 1985 and 2013: Insight from South-Western Sabah and its protected peat swamp area", Land Use Policy, 2016 — 9 words — < 1%
Crossref

15 Knight, Elly. "Impacts of Habitat Fragmentation by Agriculture on Breeding Songbirds in the Okanagan Sagebrush Shrubsteppe.", Proquest, 2014. — 9 words — < 1%
ProQuest

16 "Verifying Treaty Compliance", Springer Science and Business Media LLC, 2006 — 8 words — < 1%
Crossref

17 Fahrig, Lenore. "Effects of Habitat Fragmentation on Biodiversity", Annual Review of Ecology Evolution and Systematics, 2003. — 8 words — < 1%
Crossref

18 Fanhua Kong, Haiwei Yin, Nobukazu Nakagoshi, Yueguang Zong. "Urban green space network development for biodiversity conservation: Identification based on graph theory and gravity modeling", Landscape and Urban Planning, 2010 — 8 words — < 1%

Crossref

19 Femke Van den Berghe, Monique Christina Johanna Paris, Michael Brent Briggs, Wenche Kristin Farstad et al. "A two-step dilution tris-egg yolk extender containing Equex STM significantly improves sperm cryopreservation in the African wild dog (Lycaon pictus)", Cryobiology, 2018 — 8 words — < 1%
Crossref

20 Laliberte, A.S.. "Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico", Remote Sensing of Environment, 20041030 — 8 words — < 1%
Crossref

21 Lele, N.. "Assessing forest fragmentation in northeastern region (NER) of India using landscape matrices", Ecological Indicators, 200809 — 8 words — < 1%
Crossref

22 M. A. Mulders. "Structured approach to land cover mapping or the Atlantic zone of Costa Rica using single date TM data", International Journal of Remote Sensing, 11/1/1992 — 8 words — < 1%
Crossref

23 Manuel A. Hernández-Ruedas, Víctor Arroyo-Rodríguez, José Carlos Morante-Filho, Jorge A. Meave, Miguel Martínez-Ramos. "Fragmentation and matrix contrast favor understory plants through negative cascading effects on a strong competitor palm", Ecological Applications, 2018 — 7 words — < 1%
Crossref

24 Zelang Miao, Wenzhong Shi, Alim Samat, Gianni Lisini, Paolo Gamba. "Information Fusion for Urban — 6 words — < 1%

Road Extraction From VHR Optical Satellite Images", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2016

Crossref