Vegetation Indices for Selective Logging Detection in Tropical Forest of East Kalimantan

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Abstract: Selective logging is currently a widely adopted management practice throughout the tropics. Monitoring of spatial extent and intensity of such logging is, therefore, becoming an important issue for sustainable management of forest. This study explores the possibility of using vegetation indices and Landsat 7 ETM+ image for this purpose. Two dataset acquired on 2002 and 2000 of Labanan concession area East Kalimantan, Indonesia were used. Three different vegetation indices (MSAVI, SAVI and NDVI) slicing and differentiating methods were tested. The results showed that the MSAVI is superior with overall accuracy of 77% and kappa 0.64.
Keywords: Selective logging, Vegetation indices.

1. Introduction

Tropical forest, one of the most important natural resources of the world is facing continuous depletion due to various reasons. Clearing of the forest area for other use is one of the main reasons. An area of 16.1 million ha of forests were lost every year during the 1990s, of which 15.2 million ha were in the tropics [1]. Though clear felling is still a big reason of forest depletion, it is no longer main management option in the most of the areas. Studies have shown that selective logging has become dominant practice in Brazilian Amazon [2]; similarly it is commonly used silvicultural practice in the natural production forest of Indonesia [3].

Illegal logging that is considered as a serious threat for sustainable management of forest in Indonesia [4] is also carried out generally in selective way, as the illegal loggers are only interested with timber quality and easy accessibility [5]. Monitoring of spatial extent and intensity of selective logging is, therefore, becoming a very important for sustainable management of forest. But it is not an easy task to track out such logging in the ground over the vast area of dense tropical forest.

Remote sensing techniques as an efficient way of evaluating larger spatial extent could be a better choice to monitor selective logging as canopy damage is highly correlated with timber volume removed across the wide range of tropical environment [6]. But, the possibility of using image data to detect selective logging is poorly studied [2]. However, felling of single tree creates an average of about 400 m^2 of opening in canopy in such forest [7]. It shows that the canopy could be quite different for some period though it is recovered in short period of time due to high growth rate of tropical forest. Therefore, there is a possibility of detecting newly logged points using medium resolution image data.

Many studies have shown that different vegetation indices are quite sensitive to measure the amount of green vegetation cover [8, 9]. We report on a field based study to test sensitivity of most commonly used Normalized Difference Vegetation Index (NDVI) and other some specialized vegetation indices (VIs) i.e. Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI), which are reported more sensitive to measure canopy gap fraction [8] against the canopy damage done by selective logging using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data.

2. Methodology

2.1 Study Site

The study area is located in the Indonesian province of East Kalimantan, in the district of Berau (1°45′-2°10′N, 116°55′-117°20′E), in Labanan concession area managed by Inhutani I, a state owned company. The Labanan area consists of undulating to rolling plain with isolated masses of high hills and mountains. The elevation of the area ranges from about 10 to 1000m from mean sea level [10]. The forest of the Labanan area is known as lowland mixed *Dipterocarp* forest. Based on management system, the Labanan concession area has been divided in to seven compartments known as RKL locally. Each RKL has been further subdivided in to five annual coups and logging has been taking place progressively since 1976. At present, the logging is going on in RKL six.

2.2 Field Data

A fieldwork was carried out in September 2002 to collect the ground data. To measure forest variables altogether 50 randomly selected 500 m^2 circular plots (about 25m diameter nearly a pixel of ETM+ image) were laid considering each RKL as a stratum. Geographical coordinates were recorded for each plot along with other forest variables. Newly logged points (NLP) were purposely found and the geographical coordinates were recorded using Global Positioning System (GPS) receiver. Care was taken to minimize the error of GPS recording. Besides, GPS coordinates were recorded on road and other totally open area.

As the main aim of this study was to detect the selective logging and it was realized that the logging could not be evenly distributed, there is possibility of existing undisturbed pixels (as the totally unlogged or protected area) adjoining to the logged points. Similarly, it was also realized beforehand that the effect of selective logging in spectral pattern would no longer exist after one growing season [2]. Therefore, the objective was fixed to detect the 'NLP'**.** To compare the different indices, other two classes were also considered. The other were 'Unlogged area'**,** where no sign of recent logging was found and 'Road/Highly degraded' means main road and logging road, skids etc, where the damage is quite higher than that of the selective logging creates. After defining the classes the ground truths should be regrouped accordingly. Therefore, the sampling plots where recent logging was recorded were also considered as newly logged points in addition of those purposefully found NLP.

2.3 Satellite Image Analysis

Landsat ETM+ imagery of the area (Path 117, Row 59) was acquired on September 26, 2000 and September 16, 2002. In the beginning, the images were carefully georeferenced and registered to each other. ERDAS IMAGINE 8.5 was used for the purpose and the total root mean square error was achieved about seven meters. The image were not fully cloud free and as the clouds create a lot of disturbances to analyze the image, the clouds as well as shadows were digitized and masked beforehand and used for the analysis.

Though the date of acquiring was not much different, both images were converted in to reflectance as the process normalized the sun elevation difference, earth sun distance difference etc [11]. Moreover it is necessary to have reflectance to calculate different VIs [9]. The procedure and formulae given by NASA [12] were used to calculate the reflectance from the images. The VIs were then produced using the following formulae.

$$\text{NDVI}=\frac{\rho_{NIR}-\rho_R}{\rho_{NIR}+\rho_R}$$

$$\text{SAVI}=\frac{\rho_{NIR}-\rho_R}{\rho_{NIR}+\rho_R+L}(1+L)$$

$$\text{MSAVI}=\frac{2\rho_{NIR}+1-\sqrt{(2\rho_{NIR}+1)^2-8(\rho_{NIR}-\rho_R)}}{2}$$

Where, ρ_{NIR} and ρ_R are the reflectance in band four and three of ETM+ image and L is a constant and the value is 0.5.

To identify the area affected by selective logging in first step, a simple criterion that the VI should be less than mean after the logging even of a single tree with in one pixel was considered to slice the VI maps of 2002 in following three classes. High = more than $\mu-1sd$, Medium = from $\mu-1sd$ to $\mu-2sd$, Low = Less than $\mu-2sd$. Where, μ and sd are the mean and standard deviation of histograms of VI maps. The high value areas were considered as 'unlogged area'; medium as NLP and low as 'road or highly degraded', water body etc. Though, it could be logical to assume the VIs of the NLP in the above mentioned range, all points with such values can not be considered as NLP, because, there could be many other reason to get the value on that range.

In second step, therefore, the 2002 VI maps were subtracted from 2000 VI maps to detect the change. The resulting maps were also sliced in three classes as Positive, Negative and No change. To determine the threshold for change, the mean value of the histogram of the change maps was taken in to account. As the mean of change map was found negative in all cases, the area that has more negative value than the mean was considered the negative change. All positive values were considered positive change and rest as unchanged area. Finally, the sliced 2002 VIs maps were crossed with sliced change maps. Out of nine classes of crossed maps, the class *Negative change x Medium* was considered as 'NLP'. The classes *Negative change x Low* and *No change x Low* were categorized as 'Highly degraded / Road'. All remaining categories were considered 'Unlogged area'.

Both results of slicing and differentiating were tested against ground truth collected during fieldwork. Confusion matrices were prepared and overall accuracy (OA), kappa statistics (KA) and class mapping accuracy (CA) for each class were calculated for comparison.

3. Results and Discussion

Figure 1 shows the result of slicing of MSAVI (a), SAVI (b) and NDVI (c) in a part of RKL6 where official logging was going on. It can be noted here that more area is identified as NLP in case of MSAVI and least in case of NDVI. Similarly, more pixels have been identified as highly degraded in case of MSAVI than the others. As this is the part of newly logged area, the result of MSAVI can be considered closer to reality.

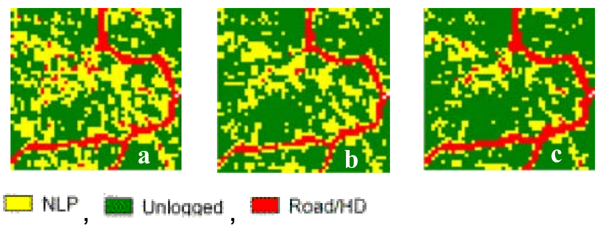

Fig 1 The result of vegetation indices slicing (a) MSAVI, (b) SAVI and (c) NDVI to detect selective logging

The analysis of error matrices showed similar result. Table 1 shows the summary of the performance of different VIs. The OA 71.56 % as well as KA 0.56 is much higher in case of MSAVI than other two indices. The OA and KA was found 55.05 and 0.28 in case of SAVI and it was almost similar (57.80% OA and 0.35 KA) in case of NDVI. Similarly, MSAVI showed the higher CA for classes NLP and unlogged than the other two. However, NDVI showed interesting nature with very low 13.73% CA for NLP and much higher 77.27% for road/highly degraded than the MSAVI and SAVI. The z test showed that the kappa value for MSAVI is significantly different than other two (z = 51.48 and 29.67 with SAVI and NDVI respectively much higher than the threshold value of 1.96 in α 0.05 level).

Table 1 Summary of accuracy matrices of different indices in first step.

	OA %	KA	CA NLP %	CA Road/HD %	CA Unlogged %
MSAVI	71.56	0.54	52.38	44.00	65.38
SAVI	55.05	0.28	26.56	36.36	48.61
NDVI	57.80	0.35	13.73	77.27	47.56

The figure 2 shows the maps resulting from second step that includes the procedure of differentiation of 2000 VI maps of a part of RKL1 with a road either side of which a lot of illegal logging was observed during fieldwork. It can be seen from the maps that the NDVI has performed differently, detecting very few logged points and differentiating road much better than others. But, the qualitative difference between MSAVI and SAVI is difficult to realize in this case though few more pixels have been identified by MSAVI in highly degraded category.

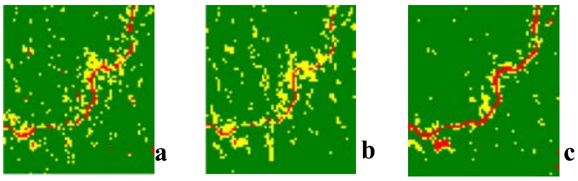

Fig 2 The result of second step (a) MSAVI, (b) SAVI (c) NDVI

The analysis of accuracy matrices, however, proved the superiority of MSAVI over the SAVI and NDVI in second step (Table 2) too. Both OA 77.38% and KA 0.64 are much higher in case of MSAVI. Similarly, the CAs are also higher except than the Road/HD. NDVI showed better performance to detect the road/highly degraded category as in the first step. The high difference in kappa values shows obvious superiority of MSAVI, which was proved by z test also (z >20 in both case). But the difference between SAVI and NDVI was not found significant by the same test (z =1.89, p > 0.05).

Table 2 Summary of accuracy matrices in second step

	OA%	KA%	CA NLP%	CA Road/HD%	CA Unlogged%
MSAVI	77.38	0.64	57.5	47.37	75.06
SAVI	60.71	0.35	31.82	31.25	56.14
NDVI	57.14	0.32	13.16	68.75	48.48

The better performance of MSAVI over other indices is a nice agreement with Qi *et al* [9]. They have reported that NDVI generally overestimate the percentage vegetation cover and become saturated after certain level and therefore cannot represent a small change in vegetation cover. Similar reporting has been done by Baret *et al*.[8]. They compared various vegetation indices to measure the canopy gap fraction and found the better performance of MSAVI than NDVI. The nature of NDVI overestimating vegetation cover gives the idea why NDVI was able to separate road better than MSAVI, although MSAVI showed better overall performance.

In short, it can be concluded that the MSAVI is superior to other indices compared here and can be used for the purpose of detection of newly carried out selective logging with reasonable accuracy. As this procedure doesn't need field data, it could be a quicker cheaper option to monitor the logging in the large area.

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