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Algorithm for detecting deforestation and forest degradation using vegetation indices

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Abstract

In forestry sector, the remote sensing technology hold a key role on forest inventory and monitoring their changes. This paper describes the algorithm for detecting deforestation and forest degradation using high resolution satellite imageries with knowledge-based approach. The main objective of the study is to develop a practical technique for monitoring deforestation and forest degradation occurred within the mangrove and swamp forest ecosystem. The SPOT 4, 5, and 6 images acquired in 2007, 2012 and 2014 were transformed into three vegetation indices, i.e., Normalized Difference Vegetation Index (NDVI), Green-Normalized Difference Vegetation index (GNDVI) and Normalized Green-Red Vegetation index (NRGI). The study found that deforestation was well detected and identified using the NDVI and GNDVI, however the forest degradation could be well detected using NRGI, better than NDVI and GNDVI. The study concludes that the strategy for monitoring deforestation, biomass-based forest degradation as well as forest growth could be done by combining the use of NDVI, GNDVI and NRGI respectively.

Keywords: *deforestation, forest degradation, GNDVI, NDVI, NRGI*

1. Introduction

The spatial, temporal, radiometric and spectral resolution variations provided by satellite sensor have opened great opportunities in the use of satellite imagery for deforestation and forest degradation monitoring. Some tropical countries with large forest areas and having a very high dynamics of changing has been relying on the use of remote sensing data to obtain information related to forest conditions, standing stocks and changes through remote sensing based forest inventory and monitoring activities such as Brazil, Indonesia etc. Previous studies successfully described how a deforestation and forest degradation could be detected using remote sensing for 10 years interval [1], as well as examination on the use of NDVI for at least as long as 3 decades for identifying deforestation and forest degradation in Brazil [2]. Other studies [3-6] successfully examined the use of Landsat images for detecting forest degradation on selective logging by implementing spectral mixture analysis and classification of spectral curves, the use of Landsat MSS for detecting deforestation, investigation of deforestation on regional scale using NDVI approach, as well as estimation of the forest loss using radar images.

Since 1996, IPCC has developed Greenhouse Gas (GHG) monitoring method, which was later revised to Good Practice Guidance (GPG2000) in 2000, and then became GPG2003 in 2003, and eventually became the National Greenhouse Gas Inventories (2006GL) in year 2006, which combines the LULUCF sector and agriculture into Agriculture, Forestry and Other Land Use (AFOLU). In 2011, the UNFCCC ruled that the revised IPCC 1996 Guidelines related to GPG2000 and GPG2003 should be used by developing countries to estimate to estimate anthropogenic emissions and removals. The method to measure the historical carbon emission from forest degradation can be found in the review of [7]. Other authors [8] also showed an alternative method to estimate the above ground carbon of forest using lidar and multispectral imagery. As we all knew, the high rate of deforestation in tropical countries has alarmed many

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countries due to reduced biodiversity, the extinction of germ plasm sources and the excessive accumulation of CO2 in the atmosphere, which will eventually lead to significant increases in the temperature of the earth, and trigger climate change. Some researchers say that the highest greenhouse gas emissions come from forest conversion into other non-vegetated forest uses. In developing countries, particularly, forest degradation is also become a fundamental problem. It has been reported by ITTO [9] in 2000 that the total area of degraded forest in 77 countries are about 800 million hectares (ha) where 500 million ha of them are degraded from primary to secondary forest.

In tropical ecosystems, particularly in the region with high economic growth, the forest ecosystems are suffering from many other land use pressures and conversion. To anticipate the unauthorized forest conversion, then the automated, practical and fast monitoring technique is required to provide accurate and comprehensive estimation by ecosystem type and its geographic location. In this study, the authors focused on the development of deforestation and forest degradation monitoring techniques. The monitoring system for detecting forest condition could be found in several studies such as Maselli [10-13]. At global level, it was mentioned that NOAA-AVHRR-based NDVI closely correlated with forest ecosystem variation [10]. Other studies [14, 15] used NDVI as an indicator of forest degradation. At the tree-crown level, the use of spectral indices had been examined for detecting defoliation of Eucalypts [16] and the use of NDVI trend to detect forest cover changes [17]. In some studies, it were pointed out that some methodological and sensors were implementable for monitoring of the forest degradation using remote sensing in tropical forest [18-23]. The use of satellite data of LISS III for monitoring deforestation and degradation had also been reported [24]. In more detailed level, Da [25] reported the use of remote sensing data to asses the forest dynamic change at household level data. The use of NDVI for monitoring land degradation in arid environment has been also examined [26]. Now, the use of high spatial resolution and hyper-spectral imageries for detecting change is also a highlighted issue [27, 28].

In change detection studies that have been done previously, none of them has a study related to the development of algorithms to detect forest cover changes, especially deforestation and forest degradation. While remote sensing technology is developing very rapidly, particularly the ability of spatial resolution and temporal resolution. Spatial resolution has arrived at the ability to detect objects up to sub-meters, while the temporal resolution of high spatial resolution sensor had been capable to acquire the data at every 1 to 3 days (revisit time). In this regard, the authors examined the algorithm for detecting deforestation and forest degradation. In this study, deforestation detection was analyzed using conventional vegetation indices such as NDVI and GNDVI, while detection of forest degradation was done with the modified vegetation index. The main objective of the study is to provide a practical technique for monitoring deforestation and forest degradation, particularly within the mangrove and swamp forest ecosystem. This study is expected to be a factor in the development of forest cover change detection methods, such as deforestation and forest degradation, especially on mangrove forest ecosystems which became one of the important ecosystems in the tropics. This algorithm will help detect changes in the mangrove region semi-automatically using high-resolution satellite imagery.

2. Research Method

2.1. Date and Study Site

For ground data collection, the study was conducted from February 2015 to mid 2016, at two different sites, in Kubu Raya Regency, West Kalimantan as shown in Figure 1. Geographically, the study sites is located between 109^{o}18’0” E and 109^{o}42’0” E and between 0^{o}30’00” and 0^{o}55’00”. The data processing and analysis was carried out at the Remote Sensing and GIS Laboratory, Forest Management Department, Faculty of Forestry, Bogor Agricultural University.

2.2. Data, Software and Hardware

The main data used in this study are medium-resolution image, i.e., SPOT 4 and 5 acquired in 2007 and 2012 as well as high-resolution image SPOT 6 recorded in 2014, covering mangrove and swamp forest ecosystem in Kubu Raya District, West Kalimantan Province. The SPOT 6 data has 6 m spatial resolution, whereas SPOT 4 and 5 images have 10 m spatial resolution. The other supporting data that are used were field observation data including forest condition, standing stock, geographic coordinate point, year of land clearing, terrestrial-based standing stock, administrative boundary and the base map of West Kalimantan. The algorithm for detecting the deforestation and forest degradation, starting from the image pre-image processing to image processing was used ERDAS imagine software and operated at the desktop computer. The establishment image vegetation indices, examination of deforestation criteria, degradation and growth were done by utilizing the capability of ERDAS "modeler", while the statistical analysis for each synthetic image was processed using the statistical functions of the Microsoft excel.

2.3. Criteria for Detecting Deforestation between 2007, 2012 and 2014

Observations of deforestation on mangrove forests has been observed using both the visual interpretation and digital analysis. The vegetation index derived from NIR and R bands could enhance the contrast between cover classes experiencing the biomass and/or chlorophyll changes. The use of spatial technology for monitoring biomass or carbon stock could be found in the work of Nyamugama and [29]. In this study, the deforestation information was derived by examining several threshold values for “bare-land” and “forest cover” that express “the changes” and “no change”. The algorithm for detecting deforestation was done by using “knowledge-based" approach with multilevel slice classification method. The forest and land cover classes, such as mangrove forests, swamp forests, shrubs/bushes, Nypahs, water bodies, barren land, clouds and cloud shadows were derived in the image of 2007, 2012 and 2014.

To distinguish between vegetation cover and non-vegetation cover, the study examined the used of the standard vegetation index and it modifications. There are three indices were examined, namely the Normalized Differenced Vegetation Index (NDVI), Green Normal Differentiated Vegetation Index (GNDVI) and Normalized Green-Red Vegetation Index (NRGI), computed with the following formula:

$$NDVI = (NIR-R)/(NIR+R) \quad (1)$$

$$GNDVI = (NIR-G)/(NIR+G) \quad (2)$$

$$NRGI = (G-R)/(G+R) \quad (3)$$

where *NIR* is infrared *R* is red band and *G* is green band. Therefore, the first step of this deforestation detection is to separate water bodies, bare soil and vegetation by examining the most optimal threshold value of NDVI (THN) at each pixel values of NDVI image (X1):

If X1 < THN1 Then “Water body”
Else if X1 ≥ THN1 && X1 < THN2 then “Bare land”
Year 2012: $NRGI_{Mangrove} > NRGI_{Swamp\ Forest} > NRGI_{Nypa} > NRGI_{Bushes} > NRGI_{water\ bodies} > NRGI_{bare\ land}$

furthermore, this study examine the threshold value of GNDVI (THG) at every pixel value of GNDVI (X2) with the following decision rules:

If X2 < THG1 && X1 = “water body” Then “water body”
Else if X2 ≥ THG2 && X1 = “vegetation “Then “vegetation”
Else “bare land/cloud/cloud shadow”
If X2 > THG1 && X1 > THN1 Then “calculate biomass change or volume change”

then, deforestation and afforestation detections from two difference dates, i.e. DT1 for date 1 and DT2 for date 2 are formulated using the following formula:

If DT1 = “Forest” && DT2 = “Bare land” Then “Deforestation”
Else if DT1 = “Bare land && DT2 = “Forest” Then “Afforestation”
if DT1 = DT2 Then “No-change”
Else “undefined”

the "*undefined*" changes are defined as other changes including cloud and cloud shadow classes. The change from a water body to bare land or vice versa is frequently due to the influence of the tides or the season (dry or rainy) at the acquisition time.

2.4. The Forest Degradation Criteria and Regrowth

Forest degradation is defined as changes in forest quality in terms of decreasing stand volume, forest biomass and/or biological and non-biological environment quality. Many studies have suggested that remote sensing is able to provide accurate information regarding the biomass and volume of forest stands. The forest degradation examined in this study was defined as a forest having a degraded or decreased biomass volume. If the change is negative beyond the threshold limit then it is called "*degradation*", otherwise the positive change is called "*growth*". The small negative changes that belongs within the threshold limit is called as "*somehow degradation",* conversely, the small positive change is referred to as *"somehow growth".* Mathematically detected forest degradation and standing growth are as follows:

If (BT2 -BT1) > -1 && (BT2 -BT1) < 0 && Then "somehow degradation"
Else If (BT2 -BT1) ≤ -1 Then "degradation"
Else If (BT2 -BT1) > 0 && (BT2 -BT1) < 1 Then "somehow growth"
Else If (BT2 -BT1) > TH Then "growth"
Else "No-change"

An area is categorized as degraded, or otherwise as grows if the biomass changes are more than or equal to 15% of the original biomass volume. The BT2 and BT1 values are the biomass volume values in the second year (T2) and the previous year (T1) obtained using the biomass estimation model using the NRGI variable. The estimation model was already developed in our previous researches.

3. Results and Analysis

3.1. The Separability Analysis of Forest and Land Covers

In monitoring deforestation and forest degradation, consideration of the spectral capability of each band becomes a very crucial task. Referring to the separability analysis using the original band of SPOT 4 and 6 images, namely Green, Red and NIR, it is recognized that the high inter-class separability are occurred between vegetation with bare land, vegetation with water bodies and or between water bodies with bare land. This is in line with the study results of [30], where the NIR and Red band hold a significant role on discriminating green vegetation and burnt vegetation. The separability analysis on the SPOT and TM images could also be found in [31].

In the 2007 image, the low separability (less than 1600) are only between shrubs and swamp forests, whereas for 2012 imagery, low separation was occurred between mangrove and shrubs. In the 2014 image, low class-to-class separation occurs between cloud and water bodies; as well as between mangrove forests and swamp forest and between bare land and shrubs. Based on the inter-class separation approach, it was found that the inter-class separation among 8 classes, using the original data (the R, G and NIR bands), the average of Transformed Divergence (TD) are 1951, 1909 and 1903, for 2007, 2012 and 2014 respectively. However, average of separation increases when the synthetic band NDVI, GNDVI and NRGI are applied having TD around 1986, 1968 and 2000 as shown in Table 1. From the individual separation of using the original bands, the separation classes between water bodies and cloud shadows is very low at the 2014 images. In contrast, using the vegetation index, the inter-class separation was improved significantly, and all classes had an inter-class separation above 1600.

3.2. The Spectral Analysis of NDVI, GNDVI and NRGI

In general, the use of synthetic images using NDVI, GNDVI and NRGI images could increase the inter-class separation, particularly between vegetation and non-vegetation classes (such as water bodies, bare soils, clouds and cloud shadows). Theoretically, the dense vegetation will have high value of NDVI, GNDVI and NRGI, close to one, whereas the water body value is close to minus one. From land spectral analysis at the 2007, 2012 and 2014 acquisition date as shown in Figures 1-3, that the NDVI and GNDVI improve separation between water bodies and vegetation. At all dates, consistently, NDVI shows its superiority to GNDVI in distinguishing vegetation cover classes, water bodies, clouds, cloud shadows and bare soils. However, when viewed from the separability between the vegetation cover class and the water body, it is seen that GNDVI gives wider average values compared to NDVI. In other words, to distinguish water bodies, bare land and vegetation as well as cloud or cloud shadow, then NDVI is better than GNDVI. The ratio between NIR and R in NDVI increases the separability between classes of water bodies, bare land and vegetation. While GNDVI shown its superiority particularly in classifying vegetation and non-vegetation classes. The GNDVI is a modification of NDVI where the Red (R) band is replaced with Green (G).

Table 1. Average of TD and Number of class-pair with TD less than 1600 using original band and synthetic band of SPOT 4, 5 and 6

Year	TD_avg with original band	Number of class-pair with TD < 1600	TD_avg with NDVI GNDVI, NRGI	Number of class-pair with TD < 1600
2007	1951	1	1986	0
2012	1909	3	1969	0
2014	1903	1	2000	0

The NDVI, GNDVI and NRGI bands have unique brightness values patterns. The NDVI and GNDVI images are superior on distinguishing the water bodies and non-water bodies than NRGI. To distinguish shadows from cloud shadows, the NDVI provides better separation than GNDVI. The NRGI could not classify vegetation and non-vegetation cover accurately. Furthermore, the GNDVI image easily separate water bodies and non-water body classes, better than NDVI. This study shows that the NRGI images are not sensitive to the vegetation and non-vegetation classes such as bare land, water bodies, clouds and cloud shadows. However, as shown in Figures 1-3, the NRGI of 2007, 2012 and 2014 consistently gradation of biomass volume classes. The observations in Figures 1-3 show that NRGI could distinguish variations of forest biomass classes or forest potential classes, better and more consistent than either GNDVI or NDVI. Based on the NRGI sequence, the order of NRGI and biomass values is as follows:

$$NRGI_{mgrv} > NRGI_{swf} > NRGI_{sbh} > NRGI_{Nypa}$$

this is in line with the sequence of biomass volume:

Mangroves > swamp forest > bush / shrub > Nypa.

based on the above considerations, then the algorithm for deforestation and degradation detection using synthetic channels could be formulated as follows:

a) The threshold value of NDVI could be used to classify vegetation and non-vegetation covers, such as vegetation, water bodies, bare land, cloud and cloud shadow categories. Based on the value of its separation, the classes could be easily distinguished. NDVI easily differentiate cloud shadows and water bodies, where these two classes are difficult to separate on the original channel as shown in Figures 1-3. The sequence of NDVI values from dates 2007, 2012 and 2014 in this study are:

$$NDVI\ Vegetation > NDVI_{cloud\ shadow} > NDVI_{clouds\ /\ bare\ land} > NDVI_{water\ bodies}$$

b) In the GNDVI images, the separation between the vegetation and non-vegetation classes is similar with those obtained from the NDVI. However, if it is examined precisely, the separation between water bodies and vegetation using GNDVI is better than NDVI. Thus, water body detection could be well assessed using GNDVI values, better than NDVI. This concludes that the GNDVI threshold is useful to differentiate the class of water bodies and non-water body classes.

c) Particularly for vegetation sub-classes, the NRGI provides consistent and accurate estimation of biomass and volume contents. From the data time series examined, the NRGI values on the 2007, 2012 and 2014 images consistently show that the sequence of NRGI values as follows:

$NRGI_{Mangrove} > NRGI_{Swamp\ Forest} > NRGI_{Bushes/Nypa} > NRGI_{water\ body}$

d) Following the classification using NDVI the GNDVI, the NRGI image could be used to detect forest type and other cover classes such as mangrove, swamp forests and shrubs/nypa. In this study nypa and bush could not be well distinguished, because this non-woody vegetation, have a similar biomass content. From the image of 2007, 2012 and 2014, the study found the ability of NRGI in determining stand biomass having the sequence as follows:

Year 2007: $NRGI_{Mangrove} > NRGI_{Swamp\ Forest} > NRGI_{Bushes} > NRGI_{Nypa} > NRGI_{water\ bodies} > NRGI_{bare\ land}$
Year 2012: $NRGI_{Mangrove} > NRGI_{Swamp\ Forest} > NRGI_{Nypa} > NRGI_{Bushes} > NRGI_{water\ bodies} > NRGI_{bare\ land}$
Year 2014: $NRGI_{Mangrove} > NRGI_{Swamp\ Forest} > NRGI_{Bushes} > NRGI_{Nypa} > NRGI_{water\ bodies} > NRGI_{bare\ land}$

all the NGRI sequence as mentioned above then could be summarized as follows:

Potential mangroves> swamp forest potential> potential shrub / bushes> Nypa potential.

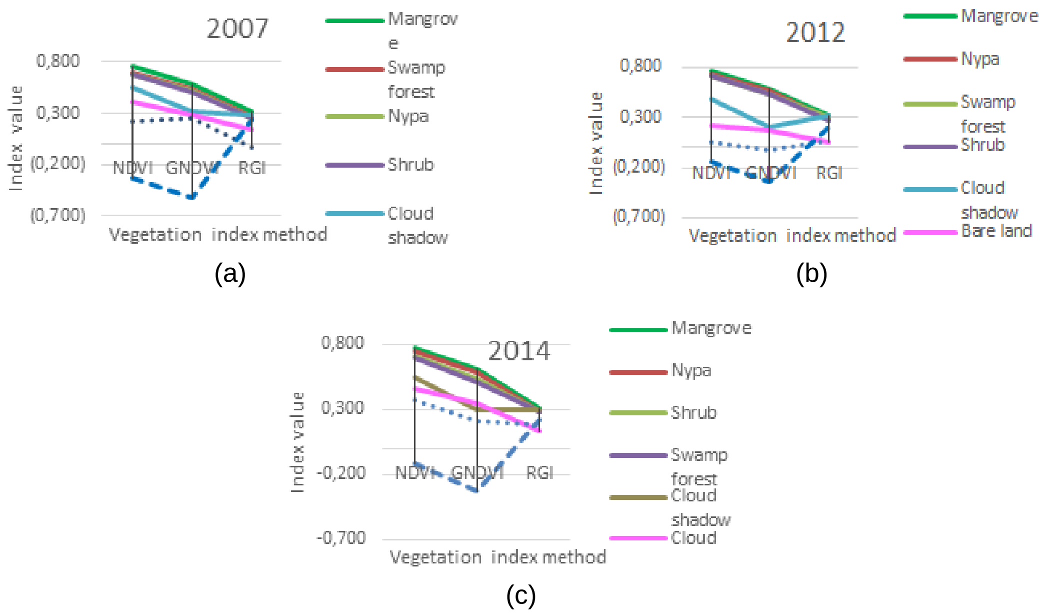


Figure 1. The values of NDVI, GNDVI and NRGI for each cover class in (a) 2007 (b) 2012 and (c) 2014

The wetness of soil background condition at the sparse vegetation either in mangrove or swamp forest ecosystem would influence the value of the vegetation index. As shown in this study, the NRGI value of shrub is higher than Nypa for the year 2007 and 2014, whereas for the year 2012 Nypa is larger than shrub. The successful use of vegetation indices for recognizing land cover classes in wetlands could be found in [12, 13]. It was also found an index associated with drought are Modified Vegetation Water Supply Index (MVWSI) and relative precipitation index (RPI) [11]. It is recognized that MVWSI has simpler calculation and provide more stable result, hence more easily realized in application.

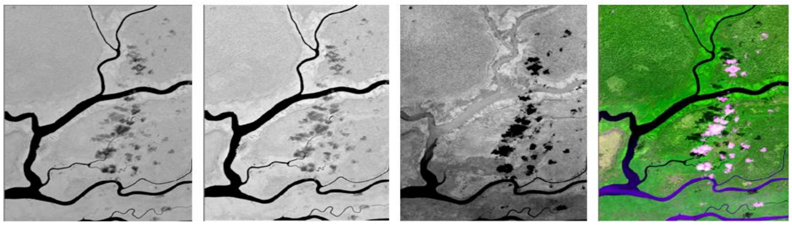


Figure 2. The appearance of (a) NDVI, (b) GNDVI, (c) NRGI and (d) Composite MIR-NIR-R image of SPOT 6

As shown in Figure 2, each index provides various levels of contrast. The NDVI and GNDVI show similar object variations, both capable to distinctly distinguish between water bodies and vegetation as shown in Figures 2 (a) and (b). However, GNDVI gives better separation between water bodies and vegetation compared to the NDVI. Yet, the NDVI produces better separation than GNDVI in terms of increasing the separability between the bare land and clouds as well as cloud shadows. In Figure 2 (c) water bodies have various variable NRGI values ranging from very dark to gray (compare with Figures 4 (a) and 4 (b)). In other words, the NRGI is not able to clearly identify the water bodies and non-water body. As shown, there is a stream with dark tones and bright tones, and this might contribute to misclassification. However, the NRGI could consistently differentiate the sequence of biomass potentials for each forest cover class such as mangroves, swamp forests, vegetation in ecotone (shrub and Nypa).

As the findings discussed above, we may conclude that the vegetation index values obtained using NDVI, GNDVI and NRGI have a potential capability to detect deforestation and forest degradation. The selection of threshold limits of each threshold could be done by two methods, namely by the average method and nearest neighbor method. The order of NDVI values by land cover from 2007 to 2014 is presented in Tables 2-4.

Furthermore, based on the threshold values of each vegetation index examined, a decision-making flow diagram for detecting deforestation and forest degradation is developed as shown in Figure 3. Figure 4 shows one example of the forest degradation detection based on biomass stock. The biomass estimation projection model used was the NRGI-based model already developed our previous research. Forest degradation due to the decrease in biomass content or growth due to increased biomass could be detected well using the algorithm examined in this study, particularly when the image is in excellent quality (free of clouds, cloud shadows, no stripping/banding or haze). The presence of haze on one image may lead to misclassification and mis-identification. The presence of haze in the second-year causes changes to be detected as degradation, otherwise the presence of haze or thin clouds in previous imagery will cause the change as growth. Detection of changes that resemble "noise" in the river or shoreline less than 2 pixels is mostly due to miss-registration.

Table 2. Threshold Values using Average and Nearest Method for NDVI in 2007, 2012 and 2014) for Each Class

Land cover	NDVI 07	Land cover	NDVI 12	Land cover	NDVI 14
Mangrove	0.7655	Mangrove	0.7619	Mangrove	0.7737
Swamp forest	0.7008	Nypa	0.7378	Nypa	0.7472
Nypa	0.6852	Swamp forest	0.7135	shrub	0.7152
Shrub	0.6728	Shrub	0.7101	Swamp forest	0.6952
Thr-avg	0.6267		0.6101		0.6418
Thr-nnb	0.6100		0.5998		0.6230
Cloud shadow	0.5473	Cloud shadow	0.4895	Cloud shadow	0.5508
Thr-avg	0.4290		0.3139		0.4851
Thr-nnb	0.4763		0.3562		0.5062
Bare land	0.4054	Bare land	0.2228	Cloud	0.4615
Cloud	0.2159	Cloud	0.0539	Bare land	0.3771
Thr-avg	(0.0076)		(0.0003)		0.1555
Thr-nnb	(0.0550)		(0.0425)		0.1344
Water body	(0.3259)	Water body	(0.1389)	Water body	(0.1083)

Remarks: Thr-avg: average-based threshold; Thr-nnb: nearest-neighbour threshold

Table 3. Threshold Values using Average and Nearest Method for GNDVI in 2007, 2012 and 2014) for Each Class

Land cover	GNDVI07	Land cover	GNDVI12	Land cover	GNDVI14
Mangrove	0.5897	Mangrove	0.5874	Mangrove	0.6078
Swamp forest	0.5349	Nypa	0.5743	Nypa	0.5905
Nypa	0.5213	Shrub	0.5423	Shrub	0.5389
Shrub	0.5034	Swamp forest	0.5288	Swamp forest	0.5063
Thr-avg	*0.4264*		*0.3819*		*0.4562*
Thr-nnb	*0.4094*		*0.3672*		*0.4289*
Cloud shadow	0.3154	Cloud shadow	0.2056	Cloud	0.3515
Bare land	0.2793	Bare land	0.1715	Cloud shadow	0.2981
Cloud	0.2446	Cloud	-0.0259	Bare land	0.2115
Thr-avg	*-0.1192*		*-0.1112*		*-0.0200*
Thr-nnb	*-0.1368*		*-0.1827*		*-0.0578*
Water body	-0.5183	Water body	-0.3395	Water body	-0.3271

Table 4. Threshold Values using Average and Nearest Method for NRGI in 2007, 2012 and 2014) for Each Class

Land cover	NRGI07	Land cover	NRGI12	Land cover	NRGI14
Mangrove	0.3206	Mangrove	0.3160	Mangrove	0.3132
Cloud shadow	0.2802	Cloud shadow	0.3157	Cloud shadow	0.3023
Swamp forest	0.2654	Swamp forest	0.2966	Swamp forest	0.2916
Thr-avg	*0.2722*		*0.2938*		*0.2930*
Thr-nnb	*0.2608*		*0.2901*		*0.2892*
Shrub	0.2562	Nypa	0.2837	Shrub	0.2869
Nypa	0.2549	Shrub	0.2728	Nypa	0.2805
Water body	0.2315	Water body	0.2105	Water body	0.2268
Bare land	0.1422	Cloud	0.0797	Bare land	0.1800
Cloud	-0.0303	Bare land	0.0533	Cloud	0.1314

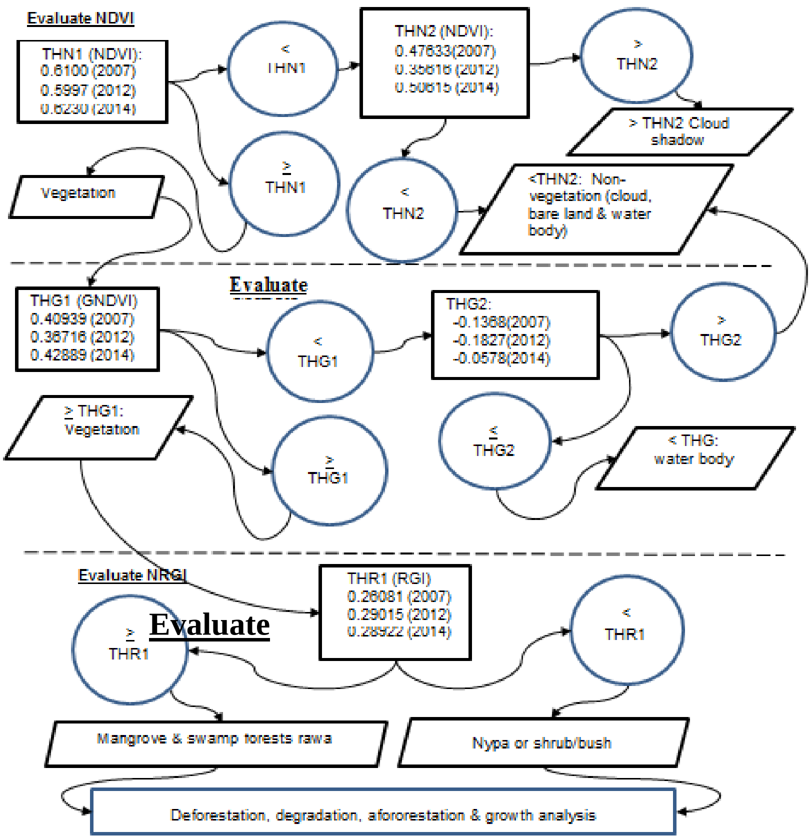
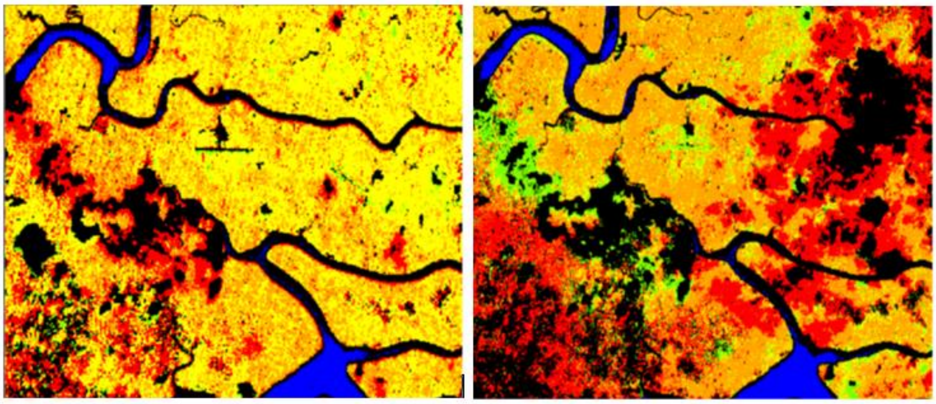


Figure 3. The flow diagram for detecting deforestation and biomass-based forest degradation using remote sensing approach



Row	Histogram	Class Names	Color	Red
0	240166	Background (/Bad data)		0
1	184716	Water body		
2	247131	Degraded forest		
3	66068	Slightly degraded f.		
4	434471	Stable forest (veg)		
5	345225	Some veg growth		
6	222007	Significant growth		

(a)

Row	Histogram	Class Names	Color	Red
0	2033718	Background (/Bad data)		
1	2187640	Water body		
2	3718744	Degraded forest		
3	2101224	Slightly degraded f.		
4	5825458	Stable forest (veg)		
5	1130834	Some veg growth		
6	2313260	Significant growth		

(b)

Figure 4. Example of detecting forest degradation between two dates (a) 2007-2012 and (b) 2012-2014

4. Conclusion

The study concludes that the algorithm for detecting deforestation and forest degradation should include the use of NDVI, GNDVI and NRGI derived from SPOT 4/5 and/or SPOT 6. The algorithm is started by detecting deforestation using both NDVI and GNDVI, respectively, then followed by using the NRGI. Deforestation could be well detected and identified when the NDVI and GNDVI are used respectively, but it could not be accurately identified when NRGI is applied. Conversely, forest degradation is only well identified using the NRGI index. The study found that NRGI image has advantages over NDVI and GNDVI in terms of estimating the above ground biomass and is recommended for use in monitoring degradation and standing growth. The NDVI and GNDVI indices are not sensitive to changes in biomass or standing forest volume, so those two indices could not be used to detect degradation and/or growth of stands accurately.

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