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Tropical deforestation monitoring using NDVI from MODIS satellite: a case study in Pahang, Malaysia

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Abstract. Malaysian tropical forest vegetation cover type has experienced a continuous degradation and defragmentation during the past two decades. This study examined the tropical forest land cover density and conditions using Normalised Difference Vegetation Index (NDVI) observations derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imageries specifically in Pahang, Malaysia. Prior to classification, the images were geometrically corrected to a common map projection. A set of 1294 random spatially distributed points was analysed to investigate the accuracy assessment of the NDVI classification. The results show that 96% of the total area were classified as the forest cover type in 2002 and only 87% in 2015. It was found that a total of 8.9% (0.22 mHa – 250m) and 6.6% (0.16 mHa – 1km) forest were degraded from the study area, mostly happens at the southern region. The four images classifications are having 70 – 90 % accuracy (Kappa coefficient= 0.4 to 0.5) and shows that imagery with higher resolution (250-m) has a better assessment. In conclusion, MODIS imagery can obtain information about the forest vegetation and can be more broadly applicable with various method combinations for forest degradation investigation.

1. Introduction

The assessment of vegetation dynamics from satellite-derived primarily to characterize the type, amount, and condition of vegetation present within a scene. The drastic changing of landscape and forcefully the surrounding ecosystem would lead to major possible consequences in the entire ecology such as flood, water quality degradation, land slide, and global warming.

Forest usually covers a vast area and remoted from human settlement that it is difficult to see the changes from horizontal surface view. The existing remote sensing services make it possible for us to monitor the changes using less cost, time, and labor. Forest land cover changes is an issue of global that can cause a shift in climate, carbon, water availability, and ecological behavior [1]. The Food and Agriculture Organization (FAO) has widely assessed the forest state globally since 1950s. Hansen et al. [2] had estimated that the global net forest loss area was about 1.5 million km² from 2000 to 2012 (excluding the forest gain during those period) based on tree cover density. Based on the report by Geist and Lambin [3], the tropical regions are on pressure for forest loss exerted from the demographic, economy, and social changes. Malaysia is one of the top 50 countries which experienced largest deforestation rate, which 50% of the deforestation was caused by oil palm plantation [4]. The Malaysian's forest loss shows a growing trend for the past 15 years especially after 2009 [5]. Abundant of studies regarding the transition of forest and grasslands to other Land Use/Land Cover (LULC) are due to anthropogenic conversion such as urbanization [6,7], timber harvesting [8], and



agricultural expansion [9]. Forest monitoring usually do not require a rapid mapping for monitoring because they never have major changes happened unless there is big events such as thunderstorm, ice storm [10], fire [11,12], and drought [13,14], however it still need our attention as it is exposed to human activities.

Data availability offered by optical remote sensing can be accounted for a more than four decades with only a few seems to dominate on the analysis of LULC (e.g., Landsat since 1972, the Landsat Thematic Mapper (Landsat TM) since 1983, Satellite Pour l'Observation de la Terre (SPOT) since the mid-1980s, and MODIS since 1999) [15]. Due to the different resolution, each system can often be used for different scale of land mapping. Regional and national-scale mapping usually used medium-to-high spatial resolution systems such as Landsat or SPOT, while for global coverage, a lower resolution products are utilized such as SPOT VEGETATION for the Global Land Cover 2000 dataset [16], Advanced Very High Resolution Radiometer (AVHRR) for the University of Maryland Global Land Cover Classification [17], Medium Resolution Imaging Spectrometer (MERIS) for GLOBCOVER [18], or the MODIS global land cover product [19]. The frequent temporal resolution enables constant analyses even though its lack of details in lower resolution. Majority of forest study used medium to coarse resolution satellite data [20]. Higher resolution imageries are better used for details localize analysis because it can reduce mixed-pixel problems. Therefore, this study will utilize remotely sensed images from MODIS that has been extensively used in environmental monitoring which can indicate the vegetation density and conditions [17,19,21,22,23].

Tropical regions country such as Malaysia faces lack of available data of optical imagery due to high cloud coverage that reduces useful observations. Finn et al. [24] discussed that the optical sensor provides information based on spectral reflectance of lithology or rock composition. Similarly, Mou et al. [25] has also highlighted that optical imagery reflects the chemical characteristics of the scene and follows a perspective imaging geometry. The data applications can be disturbed with varies of noise such as the clouds, atmospheric transparency (water vapor, dust, chemical, etc.), satellite position, and other noises and supposedly reduce the values and increase difficulty in application [26]. This study used data composition and treatment to reduce the limitations for data availability for the study area.

Finally, having information about forest land cover is necessary for making useful environmental planning and monitoring to conserve the environment. Hence, this study assesses the changes in tropical forest vegetation cover of Pahang state from 2000 to 2015 using NDVI classification methods.

2. Study area

The spatial context for this study is the largest state in Peninsular Malaysia which cover high forest density area located on, 2 - 5°N latitude and 101 - 104°E longitude (Figure 1). The region consists of 11 districts in a total of 36,137 km² land area. Having the most extent area in Peninsular, Pahang forest were mixed with all types of forest that existed in other tropical region. The eastern boundary is formed by the South China Sea and the western boundary majority at a high altitude extent including the Main Range (Banjaran Titiwangas), Banjaran Tahan, and Banjaran Pantai Timur. Currently, there is about 1.4 million hectares are categorized under Permanent Reserve Forest (PRF) classification, while 0.5 million hectares were classed as other forest lands under PERHILITAN, State Land Forest, and PRF inclusion areas. All the PRF classes were distributed in eight districts, which includes dry inland forest, peat swamp forest, mangrove forest, and plantation.

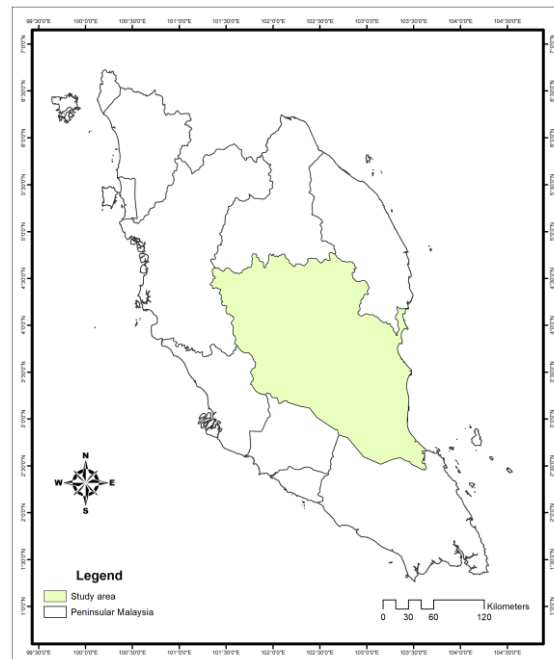


Figure 1. Peninsular Malaysia and study area

3. Material and methods

Spectral and temporal based classification techniques are manipulated to achieved the same goal, which is an accurate land cover classification; yet different in terms of method. Both have specific goals depending on the objective of the study. When choosing a data source for temporal classification, factors such as time scale and sensor resolution are the few concerns because it may affect the data availability from the features of the satellite to captures the scenes of target area. Firstly, 16-day NDVI with 250-m and 1-km resolution for year 2002 and 2015 were calculated from geometrically corrected MODIS MOD13Q1 (250-m) and MOD13A2 (1-km) products. Two resolution of MODIS imagery was used to classified the forest land use cover area using the NDVI values and were compared with cloud free composite (year 2012 to 2015) Landsat satellite images. The MODIS data used in this study are summarized in Table 1.

Table 1. Description of Modis satellite image data

Image	Path/row	Resolution	Date of acquisition	Cloud cover (%)
MODIS MOD13A2	28	1-km	12-07-2002	5
			26-06-2015	5
MODIS MOD13Q1	28	250-m	12-07-2002	8
			26-06-2015	5

The data originally imported as single band (red and NIR band) floating point images and was exported into TIFF (.tif) format before composite into a single image. Both Near-Infrared (NIR) and red band reflectance were extracted from the MODIS data and composited together. The MODIS image was then projected into Kertau RSO Meter coordinate system for further analysis. The scientific output was selected from Band Arithmetic function to produce values within the range of -1.0 to 1.0. The values of NDVI were calculated from NIR and red band reflectance. The NDVI was then reclassified into 4 classes based on the standard value. The NDVI value for different land use are as in Table 2.

Table 2. NDVI value classes summary

NDVI Value	Land Use Type
< 0.1	Barren rock, sand or snow
0.2 – 0.5	Shrub and grassland
0.6 – 0.9	Temperate and tropical forest, dense vegetation, and crops at their peak growth stage

Forest boundary was developed from the topological maps indicates the forest and non-forest area to differentiate the forest dense vegetation and crops vegetation at their peak of growth. The boundary was used as the mask for the NDVI and forest changes analysis. Finally, a series of random points were generated for accuracy assessment, and validated using land use map. The area for vegetation coverage were calculated using (2):

$$\text{Area}_a = \text{Number of cell}_a \times \text{Area of cell (width} \times \text{length)} \quad (2)$$

where,

Area_a = area of a vegetation, m^2

Number of cell_a = total count of cells/pixels for a vegetation

Area of cell = the width times the length of the cell ($x \times y$)

4. Results and discussion

Different surface will reflect, transmit, and absorb a relative amount of radiances according to their characteristic [27]. The index takes advantage of the contrast of NIR and red bands characteristics (~ the chlorophyll pigment absorptions in the red band and the high reflectivity of plant materials in the NIR band. In other words, a healthy vegetation (more chlorophyll pigment) or high greenness vegetation tends to have a high NDVI mean. A green dense vegetation reflects very small amount of red light, while bare land and water reflects a bigger amount. Bare soil NDVI values usually assumed close to zero and generally chosen from the lowest observed NDVI values, while water will give negative values. The NDVI values actually indicates the vegetation health where it is highly related with water variability for the region. In other words, if the region were poured with high precipitation, the NDVI values should be higher or directly proportional relationship. As reported by Muhaimed and Al-HednySuhad [28], the rainfall and NDVI were statistically correlated and shows a significance correlation within range of 0.70 – 0.83. However, study by Badamasi et al. [29] provide a preliminary evidence that the mean annual rainfall and mean NDVI having an inverse relationship. This give an idea that it is not clear what could be responsible for the observed patterns in vegetation cover change using NDVI [30]. As mention in Table 2, the NDVI for tropical and temperate forest and crops at the peak growth stage are in the same value range of 0.6 to 0.9. The possibilities of the selected area are in the crops vegetation extent were reduced using the forest mask data. Figure 2 shows the distribution of NDVI value classes within the study region.

The summaries from Figure 3 and Table 3 describe the forest type vegetation is declining with an overall net loss area of 0.22 and 0.16 million hectares. The forest type vegetation has progressively been degraded from 2002 to 2015 with -8.91% (-0.016 mHa/yr) and -6.63% (-0.011 mHa/yr) with respect of 1 km and 250 m resolution. There is only a small difference between the two moderate resolutions. The difference is due to the number of pixels involves in the analysis, where high resolution image tends to have more pixels than the moderate resolution of the same area. The high resolution imageries can capture more data and improve the accuracy and have a better agreement with real data.

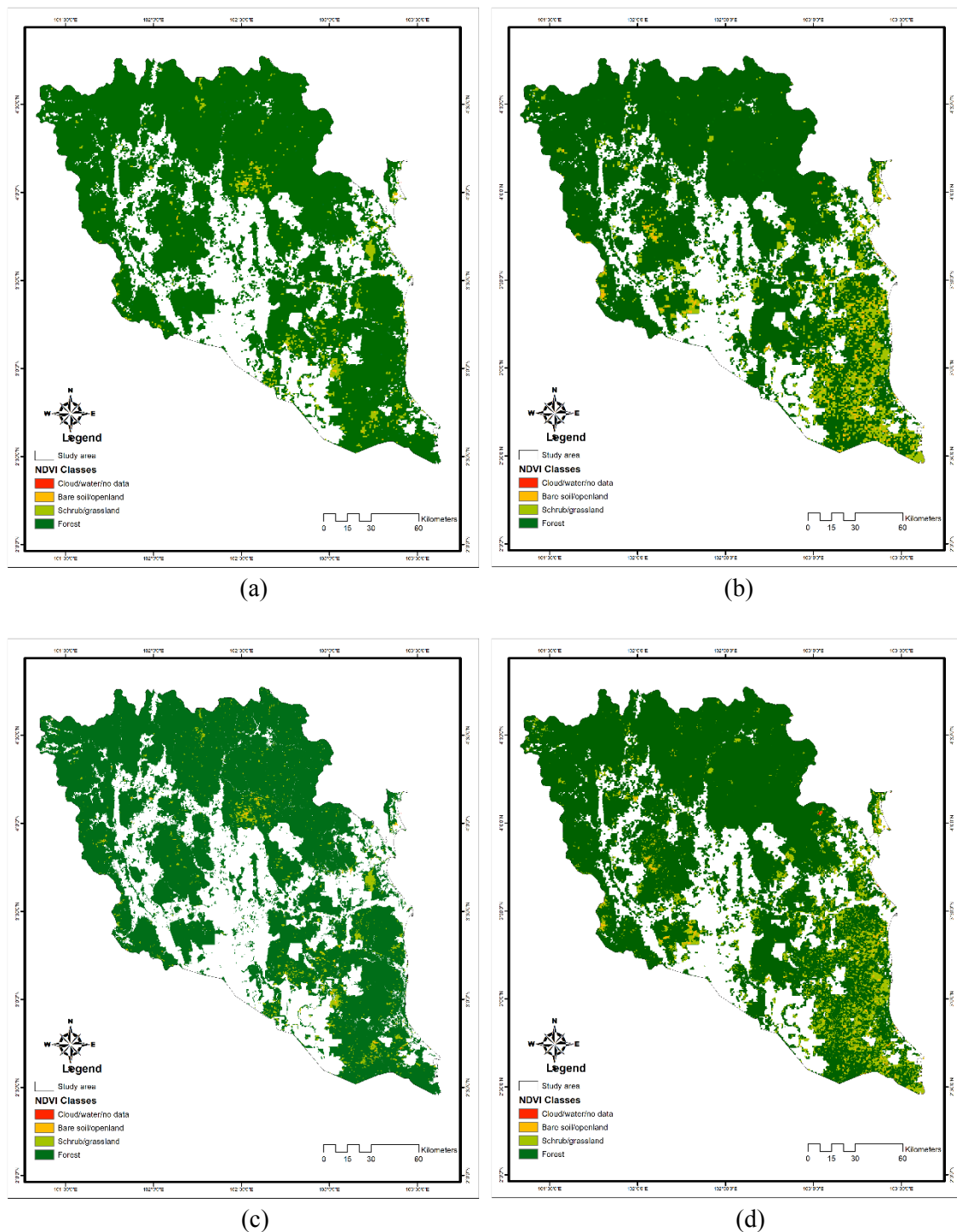


Figure 2. NDVI classification of study area. 1 km resolution: 2002 (a) and 2015 (b), and 250m resolution: 2002 (c) and 2015 (d)

Besides, there is a new existence of water catchment area located at $103^{\circ}1'45''\text{E}$ and $4^{\circ}2'56''\text{N}$. As we can see in Figure 2b and Figure 2d, the location was classified in the lowest NDVI class (<0.02) and described as cloud or water area. The image was visually compared with the optical imageries of Landsat and surprisingly, despite of its non-existence in 2002, there is about a 10 km^2 coverage of

water storage area in that location. The location was then identified as Sungai Bakah and Sungai Cereh. A set of points sample were randomly distributed to test the NDVI classification accuracy. The accuracy for both 250-m resolutions are significantly higher with 89.43% for 2002 and 74.71% for 2015 compared to 1-km resolution imageries. Overall Kappa coefficient for all images ranging from 0.4 to 0.5 (refer Table 4).

Table 3. Change area and rate of change between 2002 and 2015

Class cover/Resolution	Net change (ha)		% changes		% annual rate of change	
	1-km	250-m	1-km	250-m	1-km	250-m
Forest	-224027.07	-160488.02	-8.91	-6.63	-0.64	-0.47
Shrub/grassland	197387.87	141295.90	7.71	5.87	0.55	0.42
Bare soil/open land	30592.11	18663.12	1.20	0.77	0.09	0.06

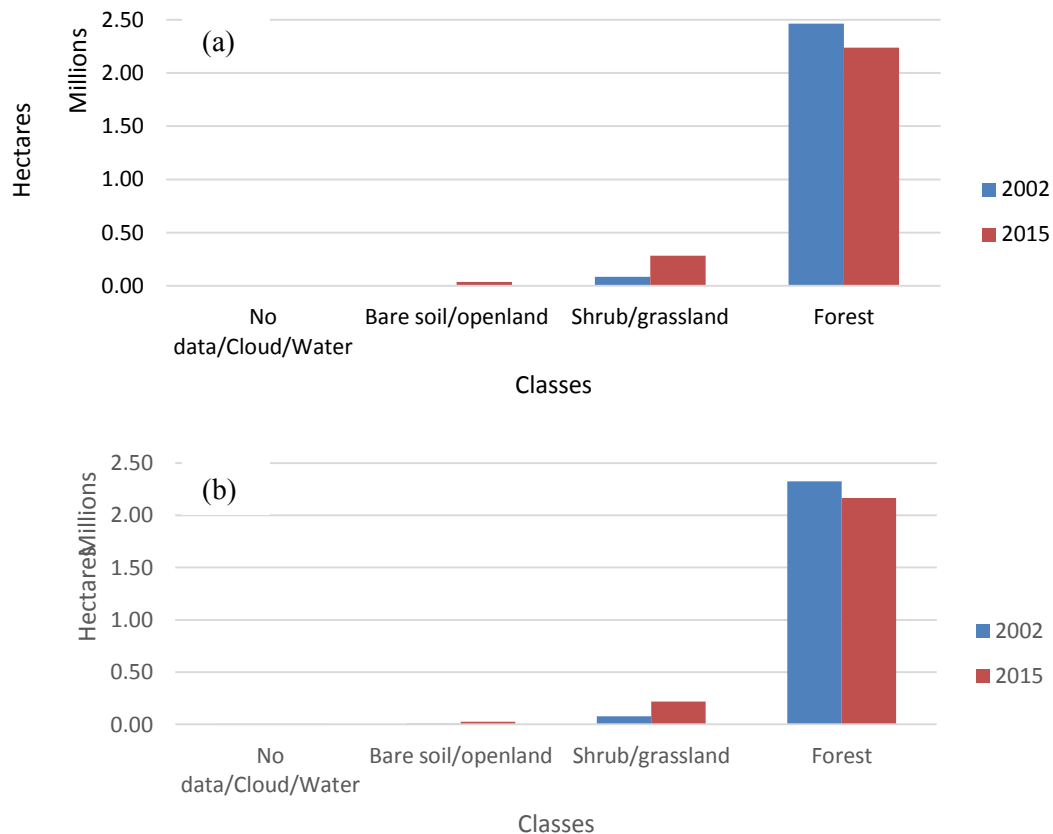


Figure 3. Distribution of vegetation cover from 2002 to 2015. (a) 1 km resolution, and (b) 250m resolution

The study by Lepers et al. [9] categorised the loss of forest cover in Southeast Asia into three main categories: forest degradation into secondary vegetation by intensive logging, conversion of forest areas into large-scale plantations, and expansion of small-holder dominated farming areas. Across the 14 year periods, most of changes take place at the southern parts (refer Figure 2) of Pahang in the Pekan and Rompin districts, and also some in the western region. The tropical forest below 100 m elevation are the most impacted based on the NDVI measurement. Lowland areas tend to be preferred more than highland area in term of cost and benefits for conversion purposes. From a visual evaluation on high-resolution satellite images and land use maps, the forested area in 2000 mostly has been

converted into agricultural area and secondary vegetation. Hamdan et al. [31] mentions that the region is having vast expansion of oil palm with 36% from a total deforestation in 2000 to 2010. They mention that the overall rate of forest exploitation was 0.01 mHa/yr from the ten years of evaluation, with majority of assessed forest loss was due to conversion of forest to oil palm plantation. This supports that tropical forest is facing deforestation, area reduction, and loss of forest ecosystem due to agricultural activities [20,32].

Table 4. Accuracy table for both resolutions

1-km resolution	Accuracy	Kappa coefficient	Magnitude
2002	87.8%	0.4	Fair
2015	70.2%	0.5	Fair
250-m resolution			
2002	89.4%	0.4	Fair
2015	74.7%	0.5	Fair

Furthermore, it could be observed that the northern part has a consistent greening throughout the whole periods. The northern regions were covered with National Parks and more than half of the state's Permanent Reserve Forest (PRF). These areas were restricted for any development or land clearing activities to help in preserving the natural ecosystem. Even though they were classified as protected, they were also risked for logging and cutting. Shchur et al. [33] conduct a study at a protected forests area in Western Siberia and find out that higher percentage of forest disturbance occurs inside the protected area region as a result from clear cuts, selective logging, and strip cuts. They suggest that the conditions happened due to existence of high value tree species (Scots pine) within the protected areas. Tropical forest also covered with valuable tree species. Local government give conditional permissions to extract the logs under monitoring to avoid overexploiting of the vegetation. In Malaysia itself, an amount of 4.0 million cube (m³) of selected wood-based from a total of more than 20 tree species products were exploited annually [34]. Although some of the logging or wood extraction were reported or legalized (licensed), it is hard to control illegal logging and deforestation due to its remote location. In term of this, a very high resolution such as LIDAR and new technology using drone are more suitable to analyse more detail features up to less than 1-m resolution.

5. Conclusion

In this study, NDVI classification was used to investigate the forest vegetation cover changes in 14 years. As an overall conclusion, there are changes happening to the forest vegetation cover type in the study area, particularly a negative changes and it prove that the forest has been degraded and deforested into other land cover. The NDVI analysis from a MODIS satellite data revealed that there were changes of 8.9 % and 6.6 % respectively for 1-km resolution and 250-m resolution in the study area. The accuracy assessment shows a higher resolution imagery data (89% and 74%) have a better accuracy than a moderate resolution (87% and 70%). The products of this study also reveals that agriculture expansion is one the main reason for reduction of tropical forest area other than tree cutting. The regions at the lowland area are quite suitable and more considerable for conversion in sense that it will involve lower costs and workloads during the process. LULC classification in tropical region is a bit challenging because of the cloud covers and type of vegetation existed. A pre-condition (such as forest mask) must be applied before the classification to take place to reduce the effects. NDVI method using MODIS data is only a part of remote sensing application for forest land use analysis. The application of NDVI analysis in this study can be improve using combination of different remote sensing platforms and various methods to provide deep details and more reliable results.

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