Eucalyptus forest plantation assessment of vegetation health using satellite remote sensing techniques

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Abstract. Early examination of the water condition of the plants utilizing remote sensing technology can be used to assess the health of the vegetation in the Eucalyptus forest plantation. To preserve a sustainable wood supply and wooded region that is necessary to human life and vital wood supplies, the forested region should be protected from disease and environmental damage. Disease and environmental impacts are two of the most critical challenges in Eucalyptus forest management. To calculate the vegetation index and identify land cover in the research region, remote sensing with Catalyst Professional software based on Object Analyst (OBIA) tools was utilized. The NDVI (Normalized Difference Vegetation Index) is a valuable index for assessing early vegetation health. For atmospheric correction and haze removal, the image was first pre-processed with ATCOR tools. Second, the image was converted to NDVI using algorithm library tools. In addition, for land cover classification in the area, an OBIA based on Support Vector Machine (SVM) was utilized, followed by an accuracy assessment. Using ArcGIS software, zonal statistics were used to calculate the NDVI value for each land cover category. According to the method, the map produced roads, plantations, buildings, low-density vegetation, oil palm, and open area classifications. Based on accuracy assessment in OBIA, plantation, oil palm, and open area were all 100% accurate, whereas low-density vegetation and oil palm were 100% accurate according to the user. Producer accuracy was lowest on roads, whereas user accuracy was lowest in open areas. Non-vegetated land is difficult to classify at this site, according to the accuracy assessment results. The map improved accuracy since the study used a lower segmentation scale factor of 50, which produced fine vectors ascribed for classification. The average NDVI for oil palm area was 0.71, and 0.69 for plantation. Because it was difficult to classify open areas and roads, the NDVI for the class was low, at 0.37 and 0.22, respectively. From land use classification, the plantation was classified (37%), low-density vegetation area (28%), and oil palm (21%). Others make up only 2 to 7% of the site's overall area. According to the study, NDVI is a useful indicator for assessing the health of vegetation in areas where NDVI values are larger than 0.70 and presents pf mixed landscape and non-vegetated features. A higher NDVI value implies that the plant is in good enough shape to conduct photosynthetic activities thus producing biomass for sustaining vegetation health. This type of inquiry can forecast more indices to produce higher accuracy of land use maps for the Eucalyptus plantation. At the same time, this type of research can assist forest managers in detecting large areas in their plantation for vegetation health assessment such as for early disease detection.
1. Introduction
In forestry plantations, satellite remote sensing plays a critical role in determining vegetation status. First and foremost, land usage should be recognized and classified swiftly and properly in this sector. The Object Analyst tools (OBIA) provided in the Catalyst (PCI Geomatica) program can be used in remote sensing post processing. Eucalyptus is a forest plantation species that is extremely useful in terms of providing income opportunities and ensuring the socioeconomic development of society in Sabah and Malaysia in general. Sabah Softwood Berhad (SSB), a private firm that pioneered the development and commercialization of fast-growing timber species and forest plantations, has provided an opportunity for research on the role of the plantation. The health of a eucalyptus plantation can be assessed by first defining land use categories, then using vegetation indicators to produce a final health assessment.

OBIA was used in many research to classify land use types in forest plantations. A study by [1] used object-based classification with a WorldView-2 satellite picture for mangrove classification. When working with high-resolution satellite images, OBIA is quite effective. Moreover, a study by [2] used LIDAR (Light Detection and Ranging) for basic land cover characterization. A recent study [3] used OBIA to map soil classes in the Brazilian Cerrado. The study concluded is a promising and useful technique for digital predictive mapping of soil classes that can contribute to increased reproducibility of conventional soil maps. Meanwhile, in Nepal, OBIA is being used to map landslides using open source [4]. Meanwhile, [5] used this technique on the coastal area of Ingrid Christensen Coast, Princess Elizabeth Land (eastern Antarctica). Meanwhile, as proven in [6, 7, 8, 9, 10], NDVI has been employed in several studies to distinguish vegetation from non-vegetation and mangrove vegetation from non-mangrove vegetation. As a result, NDVI is an excellent tool for assessing early water stress in this plantation. Meanwhile, NDVI has been utilized to estimate biophysical features of forests in studies such as [11, 12] and a study of [12] was conducted for assessing the NDVI-MODIS index that was conducted at the global level. Moreover, in detail, in a global context, NDVI has been used to estimate Gross Primary Productivity (GPP) in a variety of settings, including tropical forest types of Amazon [13, 14, 15, 17, 18].

The study's goal is to assess vegetation health of Eucalyptus plantation using NDVI index and assessed based on land use map created using the OBIA technique. The NDVI was used to analyze land use to determine the early state of vegetation health in the research region. The NDVI value of healthy vegetation was high, while the NDVI value of unhealthy vegetation was low.

2. Methodology

2.1. Study area
This research was conducted at the Brumas Tree Plantation, Brumas (Latitude 4°35'36", Longitude 117°45'31", Elevation 200 to 600 meters above sea level) (figure 1). It is located in the southern part of Sabah, and the plantation area is approximately 18,000 hectares, with Eucalyptus pellita species dominating the area, followed by F. moluccana, other high value species (for conservation area). Tanjung Lipat type (clay texture 25 percent to 35 percent) dominated the soil type in the area, followed by Kumansi type (>40 percent clay).

2.2. Satellite data
The study employed a WorldView-2 satellite image based on the below characterization. The satellite is one of the high resolution satellites with 1.84 m resolution for multispectral that is used for many applications [19, 20]. Using WorlView-2 derived indices, a bronze bug that caused damage in plantation forest was successfully detected. Moreover, the satellite was selected for biomass study [21] in wetland vegetation forest. The satellite is also popular in the susceptible mapping of landslide risk [22]. Figure 2 shows the bandwidths of the satellite employed in the study.
Figure 1. Sabah Softwoods Tree plantation (upper) and study area where OBIA was carried out (lower).
3. Satellite Image Pre-processing

3.1. Atmospheric Correction
The study used Catalyst Professional software, formerly known as PCI Geomatica's Atmospheric Correction wizard, which allows users to execute a variety of atmospheric corrections in the simplest and fastest method possible. The wizard automatically in most of the required parameters using image information and walks the user through each key step. The software's focus application was used to prepare data, and then ATCOR ground reflectance tools were used to analyze atmospheric correction. The general flowchart of the approaches used in the study is shown in figure 3.

3.2. Geometric Correction
The study used ArcGIS software 10.7.1 for geometric correction. The image was geocoded as Borneo in RSO format. After that, the research area position was verified by comparing the map location to the epsg.io/map website because the web is available to all users.

3.3. Index Calculation
Catalyst Professional program based on Focus tools was used to calculate the indexes. To calculate the Normalized Difference Vegetation Index (NDVI) value utilising spectral bands of red and near-infrared, picture bands were first entered into an algorithm librarian using VEGINDEX tools. The index employed in the study has the following equation (1):

$$NDVI = \frac{(\text{Near-infrared band} - \text{Red band})}{(\text{Near-infrared band} + \text{Red band})} \quad [23]$$

(1)
NDVI is an index that is very useful for detection of early heath assessment for canopy vegetation demonstrated in the various region South America, China, Mediterranean, dry semi-arid region, a coastal area in Turkey and also tropical region [14, 15, 17, 18, 24, 25, 26, 27].

**Figure 3.** Flowchart of the study using OBIA.

### 3.4. OBIA

**3.4.1. Segmentation and attribute statistics.** Based on this data, segmentation is performed with a scale of 50, a shape of 0.5, and compactness of 0.5. After that, the study calculates statistical attributes for the segmentation image's attribute. Meanwhile, the scale can be modified to fit the land cover types, such as a lower scale for a city with buildings. However, in forest areas with few land cover categories, a greater scale is required for segmentation in order to construct a larger polygon for the features. For zonal histogram analysis, the segmentation was transformed into an ArcView shapefile.
3.4.2. Training sites editing. In this process training sites for land use samples were collected for the plantation which was oil palm, buildings, roads, open area and low-density vegetation.

4. Supervised classification

Unsupervised and supervised classification are classification methods that can be used with satellite images. The technique is utilized for larger and substantial change identification in low resolution images, also including land cover mapping [28]. SVM was employed in a study [29] to map urban area change detection in Algeria's capital. The Support Vector Machine (SVM) classifier was used in this work to classify the training site classes. Much research adopted supervised SVM because of its ability to manage features such as in urban areas with diverse land cover.

5. Accuracy assessment

Based on the vector layer created during segmentation, all segmented polygons were assigned the roles of trained and accurate polygons. Before using the maps and categorization findings for scientific study or policy decisions [30], the developer should evaluate their accuracy. Based on a study by [31], an assessment for land use map obtained from satellite data of this study was calculated for producer's and user's accuracy. Meanwhile, KAPPA analysis is used to measure agreement or correctness, with scores ranging from +1 to -1. According to the, KAPPA statistics are a type of KHAT statistics. Positive KHAT values are expected, however, because there should be a positive correlation between the remotely sensed categorization and the reference data. A study [32] classified the possible KHAT ranges as follows: a value more than 0.80 (i.e. 80 percent) denotes strong agreement; a value between 0.40 and 0.80 (i.e. 40–80 percent) represents moderate agreement; and a value less than 0.40 (i.e. 40 percent) shows poor agreement.

5.1. Land use index analysis

Land cover of the study area that was created for land use map assigned to NDVI value using zonal histogram tools derived from ArcGIS software.

Figure 4. OBIA training site dialogue in collecting feature classes for the classification process.
6. Results

6.1. Land use map

The final land use map for the study showed six land cover types for the area. The land cover is an open area, oil palm, low density vegetation, buildings, plantation, and roads.

| No. | Land use class              | Area  | Pixel | Percentage (%) |
|-----|-----------------------------|-------|-------|----------------|
| 1   | Open area                   | 6,766,669 | 7     |
| 2   | Oil Palm                    | 21,358,343 | 21    |
| 3   | Low-density vegetation      | 28,557,355 | 28    |
| 4   | Buildings                   | 5,343,873  | 5     |
| 5   | Eucalyptus plantation       | 37,333,886 | 37    |
| 6   | Roads                       | 1,804,601  | 2     |

Table 2. Area and pixels assessment for the land use map

The area covered 37% of the overall site, and other vegetation landscapes were classified with 21% for oil palm and 28% for low density vegetation area. Within the site are roads with 2%, buildings 5% and finally open area 7% (table 2).

6.2. Accuracy assessment

For Producer's accuracy showed plantation scored 100%, similarly for oil palm and open area, whereas buildings scored 81.25% and low-density vegetation scored 94.12%. For user accuracy assessment low density vegetation and oil palm scored 100%, whereas roads scored 80%, plantation 94.12%, open area 76.92 and the lowest accuracy for this was 61.90 for building class.

| Class Name                | Producer Accuracy (%) | Producer 95% Confidence Interval Lower (%) | Producer 95% Confidence Interval Upper (%) | User Accuracy (%) | User 95% Confidence Interval Lower (%) | User 95% Confidence Interval Upper (%) | KAPPA statistic |
|---------------------------|-----------------------|--------------------------------------------|--------------------------------------------|-------------------|----------------------------------------|----------------------------------------|-----------------|
| Roads                     | 25.00                 | 0.66                                       | 49.34                                      | 80.00             | 34.94                                  | 100.00                                | 0.76            |
| Eucalyptus plantation     | 100.00                | 96.88                                      | 100.00                                     | 94.12             | 79.99                                  | 100.00                                | 0.93            |
| Buildings                 | 81.25                 | 59.00                                      | 100.00                                     | 61.90             | 38.75                                  | 85.06                                 | 0.54            |
| Low-density vegetation    | 94.12                 | 79.99                                      | 100.00                                     | 96.88             | 100.00                                 | 100.00                                | 1.00            |
| Oil palm                  | 100.00                | 95.45                                      | 100.00                                     | 95.45             | 100.00                                 | 100.00                                | 1.00            |
| Open area                 | 100.00                | 97.50                                      | 100.00                                     | 76.92             | 58.80                                  | 95.04                                 | 0.71            |

Table 3. Accuracy assessment of the land use classification in the study

Figure 4 shows a land use map for all land covered classified using object-based classification. Low density vegetation showed the lightest color and plantation showed the darkest green colour on the map. The open area appeared in pink color as it also holds the brighter land which much reflected back the reflectance of the land.

6.3. Land use and NDVI index

NDVI calculated showed a mean value from 0.22 to 0.71. Oil palm showed the highest value, 0.71 NDVI and roads scored lower NDVI 0.22.
Figure 5. Land use map using SVM method developed in the study.
Table 4. NDVI value for all the land use classes obtained for the Eucalyptus plantation area in the Sabah Softwoods Berhad plantation site.

| Land use Class          | Mean NDVI |
|-------------------------|-----------|
| Open area               | 0.37      |
| Oil palm                | 0.71      |
| Low-density vegetation  | 0.58      |
| Buildings               | 0.40      |
| Eucalyptus plantation   | 0.69      |
| Roads                   | 0.22      |

7. Discussion

The land use map for the Eucalyptus plantation area in the Sabah Softwoods Berhad plantation site was created using OBIA's PCI programme. Oil palm, Eucalyptus plantation, and open area were identified by OBIA as having better producer accuracy for distinguishing land cover between vegetation and open land. Roads received the lowest score, possibly due to similarities with building elements. However, the vegetation region received a high accuracy score based on the producer's accuracy. Users concentrated on acquiring accurate vegetation classification, which resulted in high scores for Eucalyptus plantations and oil palm. The user accurately marked open area features based on field trips, resulting in a score of roughly 76.92 percent for open area features and around 80.00 percent and 61.92 percent for other non-vegetated areas, respectively.

Because NDVI was split by land use categories, oil palm had the highest mean value of 0.71, followed by Eucalyptus plantations with 0.69. Oil palm had a high value, indicating that it dominated around 21% of the plantation's healthy, very profitable crop. The crop is critical for the corporation because, aside from forest species, it is a key contribution to the company's revenue generating. Forest plantations, on the other hand, had an average value of 0.71, indicating that 37 percent of the land was covered with healthy vegetation. The forest and oil palm showed healthy crown cover, and there was no evidence of disease affected in the plantation at high resolution utilizing a WorldView-2 image with an area of 1.84 m on the ground for each satellite pixel.

NDVI showed its capability for early vegetation health assessment using NDVI mean value. Interestingly, NDVI can be an indicator of drought which was demonstrated in many studies elsewhere and also in the tropical region [7, 33]. Therefore, NDVI was applied in forest fire susceptibility mapping by [34]. This index showed its capability respective to vegetation greenness and healthiness varied upon environmental circumstances [35] however it has been used in many areas in spite of its long-term availability [36].

NDVI in the natural forest tends to have a higher value than oil palm or another crop such as rubber demonstrated in a study by [37] in Hainan Province, China. NDVI that was tested in a tropical forest in Brazil, Ethiopia and Vietnam showed NDVI value over 0.75 observed for 13 years from 2000 to 2013 [38]. Our findings demonstrated a very outstanding agreement with Brazil forest, which could be due to the implementation of accurate pre-processing techniques employed on the WorldView-2 satellite data in this study.

Low-density vegetation showed a big gap between full density forest plantation, which is supported by another study because NDVI differences for different land use types depend on season, leaf structure and color of the leaves presented in a study by [39]. This showed low-density vegetation is a good proxy to the NDVI value for forest plantation and oil palm plantation.

8. Conclusion

For the research area, NDVI was found to be a good early detection index for vegetation health problems in plantations. This study discovered that NDVI is a suitable predictor for assessing vegetative health in Eucalyptus plantations. Simultaneously, extensive research has revealed that NDVI can be utilized as a
forerunner for analyzing vegetation status. Higher NDVI indicated that the vegetation was in a healthier state and capable of conducting photosynthetic activities. More activity means more biomass gain for the area. Meanwhile, lower NDVI indicates that the land use has a poorer health quality. On the other hand, this study increased its use in the most highly profitable plantation areas in tropical areas. Meanwhile, for all of the land cover identified for the study, OBIA produces a fair accuracy agreement. Because of the increased accuracy, zonal histogram demarcation for NDVI data has become more efficient and meaningful. This research can be used in other tropical crop plantations, and it has also been shown to be effective in detecting early problems with vegetation health elsewhere.

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