Estimating feature extraction changes of Berkelah Forest, Malaysia from multisensor remote sensing data using and object-based technique

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Abstract

The study involves an object-based segmentation method to extract feature changes in tropical rainforest cover using Landsat image and airborne LiDAR (ALS). Disturbance Index (DI) derived from Tasseled Cap Transformation and Normalized Difference Vegetation Index (NDVI) are the variables for object-based segmentation process. The classification is categorized into two classes; disturbed and non-disturbed forest cover using Nearest Neighbor (NN), Random Forest (RF) and Support Vector Machine. The result shows overall accuracy ranging from 88% - 96% and kappa ranging from 0.79 – 0.91 for each classification method used. Mcnemar's Test p-value (<0.05) is applied to check the classification for each method used which is RF 0.03 and SVM 0.01. The accuracy increases when the integration of ALS in Landsat image ($Spectral_{Landsat}$; and and $Spectral_{Landsat}$ + $Height_{ALS}$) is compared to Landsat image alone. The higher resolution image is useful to detect small changes and help to improve the lower resolution imagery.

Keywords: Object-based segmentation, Airborne LiDAR, Remote Sensing, Random Forest, Support Vector Machine

1. Introduction

The 1960s is the beginning of the commercial logging and leading to cause of the huge depletion and degradation of forest lands in Malaysia. A study from University of Maryland revealed the condition of Malaysia's forest between 2000 and 2012. Satellite images are used to record the loss and gain of forest (Hansen et al., 2013; Song et al., 2015; Hadi et al., 2018). The result shows Malaysia is one of three countries in the world with the highest national rates of deforestation which is over 75% canopy has lost with an amount of 4.72 million hectare of forests (Yong et al., 2014).

Factors that can lead to deforestation and forest degradation can be either direct or indirect drivers. Direct causes involve industrial logging, natural forest clearance for other land uses (e.g. palm plantation, dams, mining and quarrying industries), urban development or infrastructure projects (e.g. roads and highways, building factory, resorts and hilltop bungalows). Indirect causes include legislation and policies related to jurisdictions over land and forestry involving national and state legal with power from different levels and actors of federal and state (Yong et al., 2014).

The complexity of forest that provides functional systems of interacting and is interdependent biological, physical and chemical component produces a combine of climate, soil, tree and plant species distinctive effecting to hundreds of variance forest type around the world (Mohd Zaki et al., 2016). Tropical rainforest in Malaysia requires year round high temperature, abundant rainfall, dense and lush known as a vital storehouse of biodiversity on the planet and can be found near the equator (Latif and Blackburn, 2011), holds the most extensive forest in the world with the vast diversity of the tree with layered canopies (Mohd Zaki et al., 2016); and crucial role as a carbon sink, which absorbs carbon dioxide from the atmosphere (Mohd Zaki et al., 2018). Therefore, remote sensing is an important tool offering information for an achievement of sustainable and efficient forest management. Light Detection and Ranging (LiDAR) has found useful in various application such as a 3D model of cities, delineation of tree crown (Latif and Blackburn, 2011), analyses of vegetation cover (Latif et al., 2012), and deriving forest canopy structure (Saeidi et al., 2014).

Malaysia's forest was alarmed by unsustainable logging activities. However, there is no one single method to monitor forest degradation at regional to country scales using multi-resolution optical, synthetic aperture radar (SAR) and Airborne LiDAR data because of the specific nature of the degradation type or process and the timeframe over which it is observed (Mitchell et al.,2017). Mapping forest degradation details is more difficult compared to deforestation mapping (Herold et al., 2011). Approaches in monitoring forest degradation reviewed by Mitchell involve detection and characterization of degradation (e.g. forest disturbance mapping, identification of canopy gaps and clearings, proxies) and quantification of carbon stock changes (e.g. tracking of secondary forest dynamics, canopy height change, above-ground biomass change) (Mitchell et al.,2017).

Forest disturbance can be detected by the time series image of satellite remote sensing. Recognizing the changes within a time series is the first phase in order to identify the drivers and processes (Verbesselt et al., 2012). However, direct estimate changes unable to detect due to the attribute of time series (e.g. a combination of seasonal, gradual and abrupt ecosystem changes occurring in parallel, noise, residue geometric errors, atmospheric scatter and cloud effects (Wolfe et al., 1998; Roy et al., 2002; de Beurs and Henebry, 2005). Pixel-based Break detection For Additive Seasonal Trends (BFAST) monitor is used to detect changes in near real-time with statistics and econometrics literature to evaluate the stability of linear regression models (e.g. examining exchange rate dynamics. Another approach is a transformation of Landsat satellite image is applied to integrate multispectral reflectance measurements and improve the disturbance detection. For example, Tasseled Cap transformation (Crist and Cicone, 1984) which is provides orthogonal indices such as brightness (B), greenness (G) and wetness (W). This technique describes the spectral variation from those indices across the solar reflective spectrum measured using Landsat imagery. After the transformation occurred, identification and classification of land cover changes and disturbance can be automatically performed by thresholding and image arithmetic methods (Healey et al., 2005; Hilker et al., 2009). Disturbance Index (DI) is derived from Tasseled Cap transformation and will be used to detect changes in tropical rainforest.

Classification value will be affected by the sensitivity to changes of the object properties (e.g. types or numbers of objects) encountered and the sensitivity to the rates of managing needed. Single classification method is used to overcome a limited set of object types but go against the simple alterations in the physical characteristics of object (Cain et al., 1989). Since 1980s, remote sensing classification techniques have developed to produce land use land cover at various scales. Image pixel analysis is used as a basic unit which is each pixel is labeled as a single land use land cover. Based on the image pixel, unsupervised k-means and ISODATA, supervised (e.g. Maximum Likelihood, SVM, RF, decision tree) and hybrid classification have been developed (Li et al., 2014). When the technique is performed especially to heterogeneous regions, the size of pixel is bigger than the object size. In addition, each pixel contains mixture of other types of land use land cover. Therefore, the sub-pixel method had developed such as spectral mixture and fuzzy classification and can be applied in forestry application (Adam et al., 1986; Wang, 1990; Roberts et al., 1998). In the appearance of high quality data (e.g. very high resolution, VHR), object based technique had developed (Blaschke, 2010; Oreopoulos, 2013). High performance computing systems and efficient software algorithms are able to provide better performance for segmentation and feature extraction from multiscale and multispectral remotely sensed imagery which are combining raster-based with vector-based task (Blaschke, 2010). Image segmentation from object-based method is the process of dividing an image into homogenous parts which contains similar pixels and differ to another part of object (Pal and Pal, 1993; Myint et al., 2011).

Therefore, the issues had improved by the appearance of solution such as multisensor or multispectral concept in classification (Cain et al., 1989). Object-based image analysis approach is used in this study to extract feature from Landsat satellite imagery combine with the ALS surface model (ALS-Landsat). In this paper, the objectives are 1) to produce different resolution images by resampling Landsat image (30 meter resolution) into 1 meter and 15 meter; 2) to extract feature changes by object-based segmentation using multisensor data (CHM, DI, NDVI); and 3) to classify the integration of multisensor data by two classes (Disturbed non-Disturbed) using NN, RF, and SVM.

2. Materials and Methods

2.1. Study Area

This study was carried out in the Berkelah Forest Reserve (Figure 1) located at the central part of Peninsular Malaysia, Pahang at 3°44’25.73” N , 102°57’35.71” E. This forest is mixed dipterocarp lowland forests and a type of evergreen tropical moist forest. Berkelah provide the main production of forest where the most areas have been managed for timber production by selective felling.

The sample plot is designed using Landsat OLI satellite image of 26 June 2016 and Google Earth. Sample plot coordinate location is recorded using Garmin GPS and will be used in the accuracy assessment of Airborne LiDAR point clouds. Differential GPS will be used to measure the ground control point (GCP).

[Figure 1 here]

[Figure 2 here]

2.2. Landsat NDVI

Level-1 data products (Table 1) generated from Landsat 4-5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) are downloaded from the USGS server. Level-1 Precision and Terrain (L1TP) corrected data that have well-characterized radiometry and considered suitable for time-series analysis. All Landsat data were standard terrain corrected, geometrically and atmospherically corrected maintained by the USGS (Frantz et al., 2016, Hamunyela et al., 2017). Cloud and cloud-shadows in Landsat-5 and Landsat-8 images were masked using the Fmask cloud-shadow mask product.

[Table 1 here]

Landsat data delivered as digital numbers and are converted to absolute units of radiance or reflectance (Young et al., 2017) to obtain radiometric consistency (Griffiths et al., 2013). The equation is:

$$L = \text{Gain x DN} + \text{BIAS} \tag{1}$$

where, L represent spectral radiance measured over spectral bandwidth of a channel, DN is a digital number value recorded, Gain is slope of response function ((L_{max} – L_{min})/255), Bias is intercept of response function (L_{min}), L_{max} is radiance measured at detector saturation in $mWcm^{-2}sr^{-1}$ and L_{min} is the lowest radiance measured by detector in mWcm-2sr-1 (Bruce & Hillbert, 2006).

Guyot & Gu, 1994 stated the conversion from DN to a top of atmosphere (TOA) reflectance is required for an accurate production of normalized difference vegetation index (NDVI) (Bruce & Hillbert, 2006). The equation is:

$$\rho\lambda = (\pi d^2 \quad L\lambda) / (E0\lambda \cos\theta s) \quad (2)$$

where, $\rho\lambda$ represent the reflectance as a function of bandwith, d is earth-sun distance correction, $L\lambda$ is the radiance as a function of bandwith, $E0\lambda$ is an exoatmospheric irradiance and θs is solar zenith angle.

Plants show high reflectance in Near Infrared (NIR) and high absorption in Red spectrum. NDVI value varies from -1 to 1. Therefore, 0.6 to 1.0 represent tropical rainforest or dense vegetation. Formula for NDVI is:

$$NDVI = (NIR - Red) / (NIR + Red) \quad (3)$$

2.3. Airborne LiDAR Scanning (ALS) point cloud

Airborne LiDAR data were acquired on 12 November 2014 using Dornier Do228-101 G-ENVR. Leica ALS50-II is used for capturing airborne LiDAR data. This site captured about 20 lines plus cross in 3 hours 10 minutes duration. Full-waveform ALS data are provided from Airborne Research and Survey Facility (ARSF). The data consists of full-waveform ALS data with total of 20 flight lines and supplied as Las 1.3 point cloud. In this paper, all the flight lines were combined into one LAS dataset in ArCCatalog tools (Bayracki et al., 2015; Kharee et al.,2017). Automatic statistics were calculated for all LAS files to identify the returns, attributes and classification codes provided. The data have performed basic classification values follow that of the American Society of Photogrammetry and Remote Sensing (ASPRS) standard Airborne LiDAR point classes. Most points will have default classification (1) but some may have been identified as noisy points and given classification of (7). The attributes from the statistics indicate the minimum and maximum of return values which is the last return is 4. Therefore, the last return values will be used for generating digital terrain model (DTM) represent the ground or bare earth elevation model which is excluded vegetation, buildings or non-ground objects and the first return values will be used for generating digital surface model (DSM) represents the non-ground objects or forest cover above the ground layer.

2.4. Canopy Height Model

The digital surface model (DSM) and the digital terrain model (DTM) are the raster format data and the difference between this two raster will derive the canopy height model. The R-statistic computational is used to explore CHM value for decision making and presentation of the data by producing the boxplot and histogram graph.

$$CHM = DSM - DTM \tag{6}$$

[Figure 3 here]

2.5. Disturbance Index

Change detection in tropical rainforest land cover is performed using Disturbance Index (DI) derived from Landsat Tasseled Cap component (Brightness, Greenness and Wetness). The DI keeps the normalized spectral distance of any given pixel from a nominal “mature forest” class to a “bare soil” class (Healey et al., 2005). The DI is computed as a linear combination of the three normalized Tasseled Cap values (Healey et al., 2005; Hilker et al., 2009):

$$DI_{\text{Landsat}} = Br - (Gr + Wr) \tag{7}$$

where Br, Gr, Wr are the normalized (Brightness, Greenness and Wetness) with mean and standard deviation.

$$Br = (B - B_{mean}) / B_{std} \tag{8}$$

$$Gr = (G - Gmean) / Gstd \tag{9}$$

$$Wr = (W - Wmean) / Wstd \tag{10}$$

2.6 Data Fusion

LiDAR surface models and Landsat data will be performed fusion technique by Principal Componenet Analysis (PCA) to evaluate differences in classification accuracy over a range of spatial resolutions. This research carried out classification at different (1 meter, 15 meter and 30 meter) resolutions. Therefore resampling of Landsat image into 1 meter, 15 meter is performed using nearest neighbor (NN) resampling to minimize loss of original pixel values at finer resolutions (Raptis et al., 2003; Gardner et al., 2008; Singh et al., 2012). PCA will be performed to combine LiDAR surface models and Landsat TM data into different types of composite images: 1) $\text{Spectral}_{\text{Landsat}}$; and 2) $\text{Spectral}_{\text{Landsat}}$ + $\text{Height}_{\text{ALS}}$.

2.7 Object-based Segmentation

Images for reference and forest cover changes are obtained from the BFAST model and will be used for further segmentation and classification by the object-based method. In object-based method by eCognition Developer software, the parameter will be adjusted based on the condition of satellite image such as the study area and the segmented object. Multiresolution segmentation parameter setting includes the scale, shape, compactness; thematic layer used and image layer weight. Segmentation object selection is performed on two fusion model with specific condition of threshold in order to establish training sample. Threshold setting for disturbed area is set using: DI > 2 (Healey et al.,2005; Masek et al., 2008 ; Hilker et al., 2009), NDVI < 5.0 and H < 2.

2.8 Change detection of Landsat time series

There are main steps in classifying changes in each pixel using BFAST method (DeVries et al., (2015). A history model of Landsat time series is fitted by calculating the reverse-order-cumulative sum (ROC or CUSUM) of residuals (Verbesselt et al., 2012). To define the end of the stable history period, ROC statistical algorithm perform moving backwards in time, from the starting moment of the monitoring period, and evaluates a cumulative prediction error until the season-trend model breaks down. The stable history should be long and constant enough to detect the changes in forest cover accurately for at least two years with an optimal temporal resolution of 16 days (Verbesselt et al., 2012). Moving sum (MOSUM) statistic approach is applied to detect breakpoints for monitoring structural change. This method is applied to evaluate the stability of the previous observation model when performing the new observations. In this case, when the model does not remain stable for new observations, a disturbance is detected. The residuals value of MOSUM will be assessed where the value close to 0 indicates that the model remains stable while the structural change will be occurred when the values deviated from 0 and exceeds 95% confidence interval of the calculated residuals from the history period.

2.9 RF and SVM Regression and Classification

Training sample for two fusion models is tested using machine learning RF and SVM classification algorithm using Rstudio statistical software. Disturbed area will be classified on Landsat image selected from BFAST model based on training sample created in during segmentation process. Dependent variable of two classes is established as 'disturbed' or 'not disturbed' and act as a factor in RF and SVM model. Training classification model will be used to perform prediction to classify all cells in the Landsat imagery.

2.10 Accuracy assessment

DEM appeared as raster surface format. Therefore, DEM were converted into a sample containing attributes such as coordinates (X, Y) and elevation in table format using spatial analyst tools in ArcMap software. R^2 were obtained from the graph between ALS point and ground control point. The evaluation will be based on the value of RMSE in equation 7,

$$\text{RMSE} = \sqrt{} \ (\sum \text{ni=1 (ZLiDARi} - \text{ZGCPI)2} \ / \ \text{n}) \qquad (11)$$

where n is the number of samples, ZLiDARi is the terrain elevation obtained from the discrete and full waveform LiDAR DEM and the ZGCP is terrain elevation obtained from the field GCP (Salleh et al., 2015). Error matrix based on samples is used for segmentation and classification accuracy evaluation. Error matrix, total accuracy and kappa statistics report are generated for an accuracy assessment.

2.11 Mcnemar's Test p-value

In order to determine the performance of classification used in this research, Mcnemar's test is calculated from error matrices of the two classes based on standardized equation below:

$$Z = (f12 - f21) / \sqrt{(f12 + f21)} \quad (12)$$

where f12 represents the number of samples that are misclassified by the prediction sample but correctly classified by the tested sample, while f21 represents the sample that are correctly classified from the tested sample but misclassified from the prediction sample. Accuracy of confusion matrices is statistically significant ($p < 0.05$) if the value of Z more than 1.96 (Foody, 2004).

3. Results

In this study, CHM from ALS will be used as one of the parameter for detecting any disturbance appeared on the Landsat image. Figure 4 shows the positive correlation (R^2=0.99) between elevation point of ALS and elevation point on the ground measurement. Many studies proved the effectiveness of ALS data for an accurate estimation of forest attribute. ALS has been used to derive precise and accurate information on forest structural characteristics (Maltamo et al., 2014). For the extraction of canopy height information from image-based point clouds, a high-quality digital terrain model (e.g. full-waveform ALS) data is highly recommended (White et al., 2013 & Straub et al., 2013). In forestry, observation of tree height value on a ground measurement has proven more difficult in a denser forest area (Birdal et al., 2017). The complex forest structure such as a higher density of forest cover, steepness slope and unreachable of the study area will provide advantages to the use of ALS data in forestry application. Figure 5 shows the image classification of forest land cover generated from ALS raster-based image alone. The land use land cover is classified into 3 classes. The values of height are filtered based on histogram and boxplot of CHM. The minimum height of canopy is considered above 0 and more than 1.3 meter where the grassland and shrubland are identified while the high density of vegetation cover is considered above 6 meter. Based on the histogram plot of CHM, values of height more than 30 is considered as outliers such as multi-path reflection, moving objects and animals, snow, rain, or dust.

[Figure 4 here]

[Figure 5 here]

NDVI of time series Landsat image is derived and will be used for two analyses. Firstly, NDVI of time series is applied in BFAST model to predict the existence of breakpoints between time series in order to fit the models of changes detection. The ordinary least square residuals based moving sum (MOSUM) is applied to check if the breakpoints are happening in the time series (Zeileis, 2005). The residuals value of MOSUM where the value close to 0 indicates that the model remains stable during year 2007 to 2010 while the structural change is occurred when the values deviated from 0. Figure 6 shows the model does not remain stable when the model fluctuate away starting in year 2011 which is it represents the appearance of disturbance. Landsat time series in the year between 2007 and 2018 has plotted in Figure 7 using NDVI value. Second analysis, Landsat image in which breakpoints was detected in year 2011 will be further discussed in segmentation and classification analysis to extract the feature changes of Landsat image integrate with ALS data. In addition, Landsat image in the year of 2009 is selected as a reference image which is the image lies within the stable period detected in BFAST model and also contain lower percentage of cloud cover. Based on the prediction model in Figure 8, the period between 2007 and 2010 is considered to be a stable history period of time. This interval is shown in Figure 8 on the left side of the black dotted line. The monitoring period is lied on the right side of the graph. The continuous black line represents the historical data. Based on the historical data, the blue line describes the prediction of the model. The continuous red line represents a new data from the monitoring period. From the prediction of BFAST monitor, changes are detected in the year 2011 highlighted by the vertical red dotted line shown in graph Figure 8.

[Figure 6 here]

[Figure 7 here]

[Figure 8 here]

In multispectral Landsat (2011 image), downscale process is performed to test the ability of different resolution by resampling the 30 meter resolution images into 1 meter and 15 meter using interpolation technique. After the process takes place, each of the resolution images is combined with ALS image to perform segmentation and preliminary classification; and the segmented object is constructed for training sample. When using object-based segmentation, any object on the ALS-Landsat image can be clearly identified by the shape generated from multi-resolution segmentation process. The shape of each object will be segmented based on the user interpretation by determine proper scale. In this study, the crown of trees segmented represents the forest canopy. The logging track also clearly segmented by this technique compared to pixel-based which can give mixture information of land use land cover in a single pixel on an image (Li et al., 2014). NDVI, DI and CHM are used in this step to assign the class into two categories such as forest cover (Undisturbed area) and non-forest cover (Disturbed area).

The result in Table 2 represents the overall accuracy and kappa coefficient between two types of data condition, 1) $Spectral_{Landsat}$; and 2) $Spectral_{Landsat}$ + $Height_{ALS}$. It indicates the result of accuracy assessment and kappa coefficient for preliminary classification of NN using different resolution of Landsat image after segmentation process takes place. 1 meter fusion data using ALS-Landsat produced the highest total accuracy (95%) improving on Landsat alone by 1%. 15 meter fusion data using ALS-Landsat also perform better in total accuracy (94%) improving on Landsat alone by 3% while 30 meter Landsat alone and fusion of ALS-Landsat show an increase from 88% to 93%. The accuracy increases as well as kappa, when the higher or finer resolution of image is applied during segmentation. In comparison between spectral Landsat and spectral Landsat with Height ALS, the accuracy and kappa also increases. It shows that the lower the resolution image, the lower the accuracy of image classification. The 1 meter and 15 meter fusion using NN, RF and SVM classifier produce total accuracies more than 85% which is the accepted minimum standard for total accuracy in land cover mapping investigations (Anderson 1976; Rogan et al., 2003; Singh et al., 2012).

[Table 2 here]

The result in Table 3 compared the classification using different machine learning algorithm; RF and SVM method. The classification is performed using training sample constructed from previous segmented object of 1 meter resolution. The fusion of Landsat and ALS approach perform better than Landsat alone in classification accuracy. 1 meter fusion data using ALS surface models and RF classifiers produced the highest total accuracy (96%) compared to SVM (93%). The RF classifiers performed better than SVM classifier. Mcnemar's test (p-value <0.05) for RF classifier is 0.03 and 0.01 for SVM respectively. The total forest cover in the study area (2011) is decreased comparing with reference image (2009) from 83% to 76% (RF) and 79% (SVM) showing that there are the changes detected between the years (Table 4). Disturbance map is presented in Figure 9 between 2009 and 2011 of the classification images.

[Table 3 here]

[Table 4 here]

[Figure 9 here]

4. Discussion

Analysis of NN, RF and SVM classifications produced from ALS-Landsat fusion revealed the increasing in accuracy at different resolution and vegetation cover classification. The contribution of height information extracted from ALS surface model (CHM) to differentiate the vertical feature classes with minimal vertical structure. Based on the omission and commission statistic between two classes (forest and non-forest cover), the accuracy of forest cover is slightly decreased when ALS is fused with Landsat at all resolution of images. ALS surface model did not entirely enhance the forest surface. The accuracy of classification involving ALS will be affected by the quality or processing technique involved (Singh et al., 2012). For example, the spaces existed between ALS tiles is considered to be a potential cause of error found into fusion data. Therefore, misinterpretation in classification may be occurred due to some missing point of ALS data.

The preference of classifier for any classification process is depend on the type of data in order to handle a very big dimensionality and volume of data. Multisource data delivers considerable dimensionality with increased volume of data, then, increases the chances of Hughes phenomenon which is against the efficiency of classification algorithms use. In classification process, the higher number of training sample is required to estimate the classifier parameters and avoiding in decreasing the accuracy due to Hughes phenomenon which is the number of training sample is lower than the number of input features (Dalponte et al., 2009). Random Forest classification for land cover analysis shows that these techniques perform better with a large number of training samples (Kulkarni and Lowe, 2016). In addition, overall accuracy of mapping for ALS-Landsat using NN, RF, and SVM classifier improved with increasing spatial resolution and number of input bands without data dimensionality issues. SVM and RF shows a similar performance (Ghosh et al., 2014) when ALS-Landsat fusion with higher spatial resolution image is used. However, in a spectral resolution context, SVM classifier are able to interpret non-linear discrimination function using the real passages than the reduced of spectral resolution (Dalponte et al., 2009) due to their effectiveness in working with high complexity of the decision boundary and its high robustness to the original spectral passages (e.g. outliers and signal-to-noise ratio). Random Forest methods have been proved to improve classification accuracy (Gislason et al., 2006). For a computational time, both RF and SVM classifier are flexible and competent to manage higher dimensional data with minimum processing time.

In detecting changes in time series Landsat using BFAST model, a disturbance is detected when the model remain unstable when a prediction is observed. However, the accuracy of the simulation model in predicting the time of disturbance was not evaluated due to the previous research study purposes such as the simulation has been developed to be a fast system, a variety of uses, useful to function as a disturbance alert system within recently obtained time series observations data and the objective of case study to analyze the effect of ongoing drought on vegetation changes (Verbesselt et al., 2012). For the stable history period in time series data, the ROC is an automated technique only to detect a structural change. BFAST was not directly produce information of the disturbance sources. However, the detected disturbances of NDVI time series can be described by using DI. When the structural change was detected, the history period is determined (image Landsat 2007 - 2010). The 2011 image Landsat is considered as a disturbed image and will be used to detect feature changes using DI. DI has provided a useful method to determine the spatial extent of changes in land cover (Healey et al., 2005). The studies from (Healey et al., 2005 and Masek et al., 2008) proved this technique is an effective tool for mapping changes in land cover and disturbance of forest (Hilker et al., 2009). Automatic detection of disturbance using this algorithm can be effectively used in masking cut blocks but require further modifications (Coops et al., 2006; White et al., 2007). When using the coarser spatial resolution imagery (Hilker et al, 2009) in raster based detection algorithm, the detection of disturbance area occurred in pixelated mode compared to the original images of Landsat with the DI map, it shows intense delineation of disturbed events. The image contrast when using DI for two forest conditions (disturbed and undisturbed) is differ from ecosystem to ecosystem. Forest scenes having bright contrast possibly contain a large hardwood or ground component. It indicates smaller spectral change when cleared than darker conifer stands (Figure 10). Spectral distance between cleared and non-disturbed forest is smaller when the structure of forest are relatively open.

[Figure 10]

4. Conclusion

The finer spatial resolution provides better performance to detect changes in fusion ALS-Landsat image. Then, a different resolution images produce by resampling Landsat image (30 meter resolution) into 1 meter and 15 meter is required in order to identify the suitable approach that can be applied for change detection analysis. Extracting feature changes using multi-sensor data (CHM, DI, NDVI), object-based segmentation is a useful technique in extracting the feature on an image before and after fusion of ALS-Landsat. The number of training sample constructed must be larger and enough to apply into a classifier. In classifying the integration of multi-sensor data by two classes (Disturbed non-Disturbed), NN technique provide acceptable standard of total accuracy. Machine learning regression and classification such as RF and SVM also provide effective algorithms to classify the training sample of segmented object. Disturbance area can be identified using time series of satellite image. The period of time to be tested must be in a long period for better detection of any structural changes occurred within the selected time. Satellite image (e.g. Landsat) can be utilized in detecting changes in a smaller scale of a large coverage area. However, to detect feature changes of a larger scale in a small particular study area, a higher spatial and spectral resolution image is required to produce better quality of classification map. Future work to replace the Landsat image with different sensors which contain higher resolution of data is considered.

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