Extraction of Complex Plantations from VHR Imagery using OBIA Techniques

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Abstract
The study aimed to extract complex plantation using Object Based Image Analysis (OBIA) techniques. GeoEye-1 image covering Pa Khlok sub-district, Phuket Thailand was used, and thirteen vegetation indices calculated and analyzed with the aim of exploring plantations coverage in the area. Five plantation classes were identified including young coconut, mature coconut, young rubber, mature rubber and oil palm, with another five non-plantation classes assigned to water, built-up land, bare ground, mangrove forest and all other, using rule based techniques. Results support also the idea of mixed plantations in heterogeneous patterns with mixed and missing classes, as experienced in traditional pixel based classification. OBIA techniques can be used successfully to classify complex plantation structures in the study area, with values of 88% and 79% for overall accuracy and kappa coefficients of 0.85 and 0.75 in empirical (development) rules set images and validation images, respectively.

1. Introduction

Remote sensing imagery effectively captures characteristics of the Earth's surface, but it takes an experienced interpreter's knowledge about shape, texture, patterns, and site context to derive information about land use activities from land cover information (Anderson et al., 1976). The mapping of multi crop agriculture and forest lands is verified through either visual analysis of the imagery or pixel based analysis. The difference in crop percent canopy closure, soil moisture, biomass, or the difference in row spacing or orientation might cause one crop to have dramatically different reflectance properties due to the influence of the background soil or understory materials present (Jensen, 2007). Discrimination of plantation types in complex land cover may be difficult with traditional pixel based classification methods, using spectral information only. Sometimes plantations are mixed with natural forest or mixed with other crop types and it is not too easy to identify and separate plantation from natural forest using pixel based methods. Traditional pixel based classification has limitations in spatial resolution, spectral and temporal interpretation. A "salt and pepper" effect can occur and produces inaccuracies in the classification, particularly when pixel based classification is applied to high resolution images (Kim et al., 2011, Li and Shao, 2012 and Pu et al., 2011). However, poor spectral resolution is a main disadvantage of very high resolution images and pixel based classification does not perform well to classify vegetation types. Object based image analysis (OBIA) became a major research method with the increased availability of high resolution images (Blaschke, 2010). OBIA works more like the human eye-brain combination does (Addink et al., 2012). The object's color (spectral information), size, texture, shape and topological relationship with other image objects are interpreted and analyzed. The benefits from using OBIA over pixel based methods are described in many publications (Blaschke, 2010 and Navulur, 2007). In general, OBIA can take advantage of all dimensions of remote sensing including spectral (multispectral and panchromatic bands), spatial properties (object area, length, width and direction), morphological (shape parameters, texture), contextual (relationship to neighbors, proximity analysis) and temporal (time series) (Navulur, 2007). Additionally, it can incorporate proven methods or techniques used for

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image analysis such as supervised classification, fuzzy logic, and rule-based classification, some GIS functionality for thematic classification, and can extract features from the same scene at different resolutions. OBIA is widely applied in remote sensing field such as forestry (Hay et al., 2005, Heumann, 2011, Polychronaki and Gitas, 2012 and Yang et al., 2013), agriculture (Moran et al., 1997 and Vieira et al., 2012), landscape ecology (Dronova et al., 2012, Dupuy et al., 2012 and Yang et al., 2013) , disasters (Martha et al., 2012 and Stumpf and Kerle, 2011) and in GIS applications (Benz et al., 2004, Camara et al., 1996 and Dadon et al., 2008). Vegetation indices (VIs) have been developed and applied to biophysical parameter studies such as leaf area index (LAI), percentage green cover, chlorophyll content, green biomass, and absorbed photosynthetically active radiation (APAR) (Bannari et al., 1995 and Jensen, 2007). The most of them derived from the near infrared and visible bands. Normalized Difference Vegetation Index (NDVI) is the one of the most widely used to assess the vegetation cover and has been well demonstrated over the past two decades. However, there are many disadvantage of NDVI. NDVI is nonlinear ratio-based which can be influenced by additive noise effects such as atmospheric path radiance and very sensitive to canopy background (Jensen, 2007). Therefore, many studies have proposed to combine in various ways the reflectance of different channels for eliminating disturbances from exterior factors (sensor calibration, atmosphere, viewing, and illumination geometry) which were developed in order to satisfy quite specific applications in remote sensing: crop yield, forest exploitation, vegetation management, vegetation detection in inundated regions, etc. (Bannari et al., 1995). Almost all high resolution satellites have very limited spectral resolution which normally included Red, Green, Blue, and Near Infrared (NIR) regions. Therefore, VIs which can be applied for the high spatial resolution but low spectral resolution, such as GeoEye-1, was very limited number. The list of indices for remote sensing has been reviewed and collected by the IDB project (Henrich, 2011). There are many studies that combine VIs into OBIA techniques to achieve better result as it can help to extract the vegetation pattern, structure and identify the crop types by the reflectance characteristics (Chen et al., 2012, Mitri and Gitas, 2013 and Peters et al., 2011). Complex plantation is an important form of land use in the tropical countries, and the area under plantation crops have expanded rapidly in the past decades. Identification of complex plantation using remote sensing approach was found to be quite delicate due to the complex structure, different age and thus development, pattern and its dissimilarity of crop types (Hansen and Schjoerring, 2003 and Moran et al., 1997). This issue can be a problem when trying to identify the types of vegetation using limited spectral resolution satellite images. Coconut, rubber, and oil palm trees have been referred to as woody agricultural crops which are mainly grown in the equatorial high monsoon regions including Indonesia, Malaysia, India, Sri Lanka and Thailand. Complex plantation land use has evolved rapidly in many parts of Thailand, especially rubber and oil palm trees. This expansion has brought along a detrimental cascade of environmental effects including increasing threats to biodiversity and reduction in forest carbon stock. The spatial extent of rubber, oil palm and its evolution currently is unknown. In this dynamic situation accurate, meaningful and current data on land use are essential for management. Therefore, the main objective of this paper is to examine the ability of OBIA methods using very high resolution image from GeoEye-1 satellite for classifying complex plantation land use in a part of Pa Khlok sub-district, Phuket province, Thailand.

2. Methodology

2.1 Data and Materials

Two overlapping sections from GeoEye-1 with 2 m resolution in GeoTiff 11-bits standard format taken on 14th March 2009 covering 2 sq.km and 4 sq.km were extracted, respectively, over the Pa Khlok sub-district of Phuket province, Thailand (Figure 1). Four multispectral original bands (Blue: 450-510 nm, Green: 510-580 nm, Red: 655-690 nm, and NIR: 780-920 nm) were applied for pre-processing (after geometric correction using rational polynomial coefficient (RPCs) method) and after that 13 vegetation indices were calculated (Table 1). The first subset image (2 sq.km) was used for development of the rules set and the partially overlapping second section (4 sq.km) was used for validation the rules set. Visual assessment from, Google street view from 2012, GeoEye-1 Panchromatic band with 0.5 m resolution in the same date of dataset and land use maps from 2009 at 416 sample points (Table 2) were used for accuracy assessment in this study.

2.2 Image Segmentation

In OBIA approach, an image is segmented into homogeneous patches based on scale, color (spectral information), and shape (Laliberte et al., 2007). The GeoEye-1 images were segmented using eCognition® software.

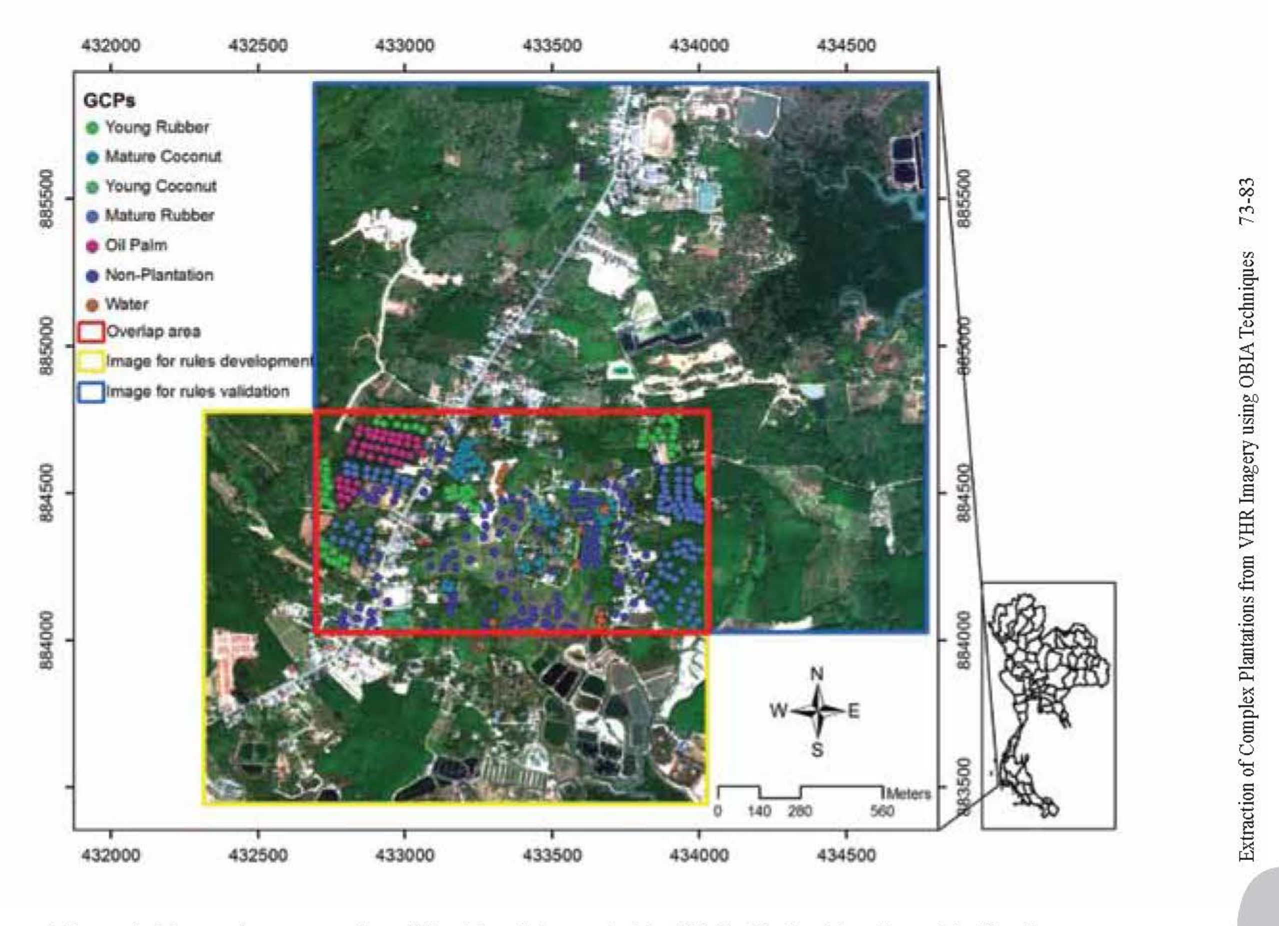


Figure 1: True color composite of GeoEye-1 image in Pa Khlok, Phuket Province, Thailand

Table 1: Vegetation indices used in this study

Spectral region/Vegetation index (VI)	VI adapted to GeoEye-1	Reference
Normalized Difference Vegetation Index (NDVI)	$\frac{(NIR-Red)}{(NIR+Red)}$	(Rouse et al., 1973)
Differenced Vegetation Index MSS (DVIMSS)	$2.4NIR-Red$	(Richardson and Wiegand, 1977)
Green leaf index (GI)	$\frac{2Green-Red-Blue}{2Green+Red+Blue}$	(Hunt et al., 2011)
Transformed Vegetation Index (TVI)	$\sqrt{NDVI+0.5}$	(Hunt et al., 2011)
Chlorophyll vegetation index (CVI)	$NIR\frac{Red}{Green^2}$	(Hunt et al., 2011)
Visible Atmospherically Resistant Index Green (VARIG)	$\frac{Green-Red}{Green+Red-Blue}$	(Hunt et al., 2011)
Chlorophyll Red-Edge (CRE)	$\left(\frac{NIR}{Red}\right)^{-1}$	(Gitelson et al., 2006)
Chlorophyll Green (CG)	$\left(\frac{NIR}{Green}\right)^{-1}$	(Gitelson et al., 2006)
Coloration Index (CI)	$\frac{Red-Blue}{Red}$	(Maimouni et al., 2011)
Atmospherically Resistant Vegetation Index 2 (ARVI2)	$-0.18+1.17\left(\frac{NIR-Red}{NIR+Red}\right)$	(Kaufman and Tanre, 1992)
Spectral Polygon Vegetation Index (SPVI)	$0.4\left(3.7(NIR-Red)-1.2(Green-Red)\right)$	(Main et al., 2011)
Diff800_680 (D680)	$NIR-Red$	(Hunt et al., 2011)
Diff800_550 (D550)	$NIR-Green$	(Hunt et al., 2011)

Table 2: Number of Ground Control Points (GCPs) in each class

Class Name	Number of GCPs
Mature Coconut	52
Young Coconut	14
Mature Rubber	90
Young Rubber	78
Oil Palm	40
Non-Plantation	126
Water	16
Total	**416**

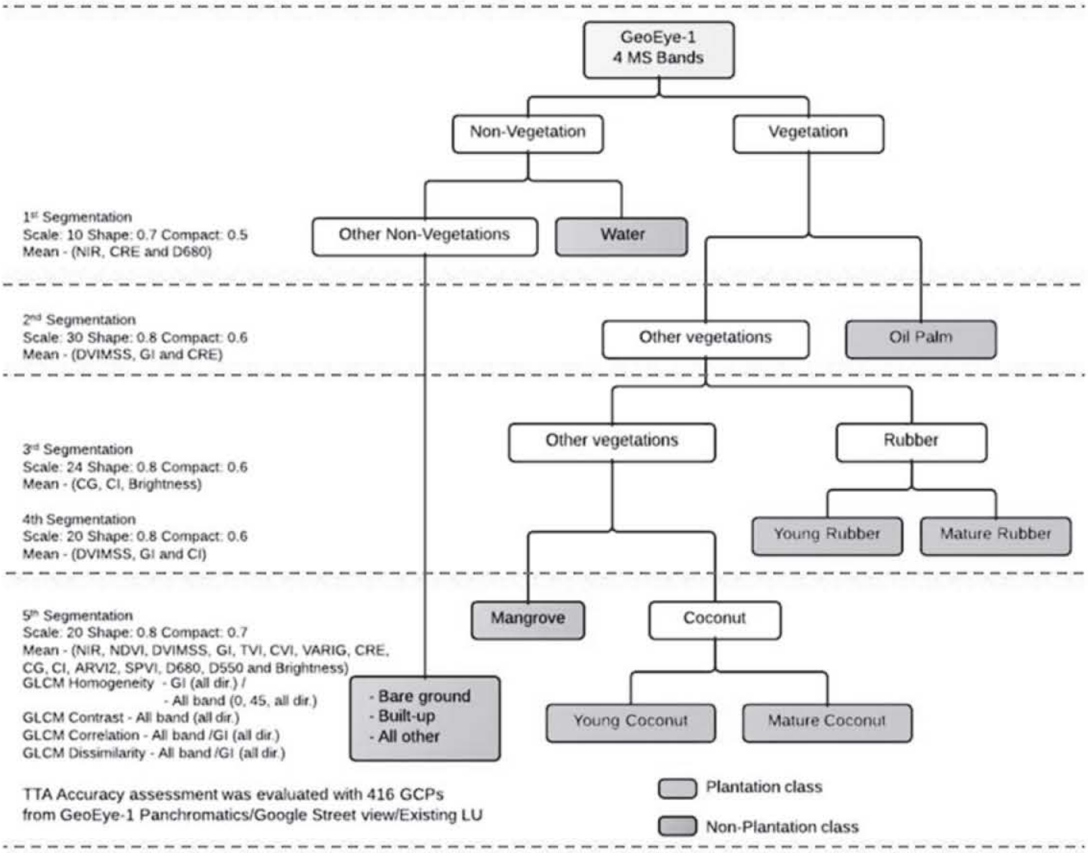


Figure 2: Classes schema outline

The different scales of segmentation were set in multi-resolution segmentation for simultaneous representation of imagery information at different scales. Multi-level segmentation was adjusted to get the best fit with objects of interest. Segmentation levels were implemented using the parameters reported in Table 3 and Table 4. Rule sets in the selected study area were developed and tested with a focus on extracting coconut, oil palm and rubber at plantation parcel level. The selected parameter for assigning classes shown summarized in Table 3 were chosen using a recursive visual selection process by fitting the interest object which was compared to Google street view, Geoeye-1 Panchromatic band with 0.5 m resolution and existing land use map. Ten classes including young coconut, mature coconut, young rubber, mature rubber, oil palm, mangrove forest, tree, bare ground, built-up, and water bodies were established using "Assign class" algorithm. Four multispectral bands and thirteen vegetation indices (Table 1) were used for radiometric and texture analysis. Figure 2 shows the outline of identifying classes. In the initial segmentation (1st segmentation) process "Vegetation" and "Non-Vegetation" were assigned. Afterward oil palm plantations were extracted from other crops in the second segmentation.

Table 3: Spectral and texture features used in this study

Category	Name	Image layer
Object spectral features pixels	Mean	each image layer (excepted ; Blue, Green and Red)
	Brightness	-
Shape	Area	-
Textures	GLCM Homogeneity	All image layers (all, 0° and 45° dir.) and GI (all dir.)
	GLCM Dissimilarity	All image layers (all dir.) and GI (all dir.)
	GLCM Correlation	All image layers (all dir.)
	GLCM Contrast	All image layers (all dir.)
Object texture based on class related feature	Related border to neighbor objects	-

The third and fourth segmentations were initialized for "mature rubber" and "young rubber" plantations. "Young coconut", "mature coconut" plantations and the rest object classes were segmented in the fifth segmentation. Meanwhile, the spectral and texture features in Table 3 were applied to distinguish and clean misclassification objects time to time. The selected spectral and textural features were applied and the information of them was described in (Blaschke, 2010). More details, meanings and equations for each of those features can be accessed in (Definiens, 2007). The vegetation indices were analyzed separately in ERDAS Imagine software® and were added as input image layers due to their ability to differentiate green vegetation areas, and texture analysis to capture the generally well-defined patterns of plantations.

2.3 Sampling Data and Accuracy Assessment

In this study, spectral values from panchromatic GeoEye-1 with 0.5 m resolution and multispectral GeoEye-1 with 2 m resolution were extracted at 416 points of ground reference data (Figure 1) using stratified random sampling technique to determine the accuracy assessment in the overlap area for using in the accuracy assessment step. The ground reference data was picked up by visual selection randomly. Overall accuracy and kappa coefficients were assessed the accuracy of thematic maps classified from GeoEye-1 image. The overall accuracy has the advantage of being directly interpretable as the proportion of pixels classified corresponds to probabilities related to a given thematic map's reported commission and omission accuracy, while the kappa coefficient has been used to assess statistical difference between classifications. For each classification, a confusion matrix was presented, along with its overall accuracy with 95% confidence intervals.

3. Results and discussions

3.1 Image Segmentation

Primarily, visual interpretation was used to identify the crop types in each input image layer (Figure 3). Figure 3(a) to 3(q) show the gray scale color of each input image layer from development rules set image which can identify the crop type differently. This step was very helpful to observe the ranges of image object values and to setup the rules set criteria for the object classification steps. As the vegetation patterns and the spectral responses in each band were very similar, multi-scale and multi-segmentation were applied in several processes to extract the desired objects and classes. First, Non-vegetation were distinguished as Built-up, Water, Mangrove forest, and Bare ground. Then all plantations were assigned using all possibility techniques such as shape, texture, spectral from original bands and vegetation indices to identify Young Coconut, Mature Coconut, Young Rubber, Mature Rubber, and Oil Palm plantations. All spectral bands and the calculated vegetation indices were added for the input layer in segmentation and classification steps. Table 4 shows the algorithm parameters and input image layers which varied and depended on the result of each segmentation step. Seventeen image layers (including 4 original MS bands and 13 VIs) were used. The selected VIs was very useful for vegetation extraction and identifies the plantation patterns (Figure 3). Mainly, Green leaf index (GI) was very useful for creating image object boundaries and identifying the patterns of the plantation. The initial segmentation stage, pixel level classification was used for creating objects from the pixels. After the image was segmented into suitable image objects, the image was classified by assigning each object to a class based on features and criteria set. Later the object level from the period step was applied.

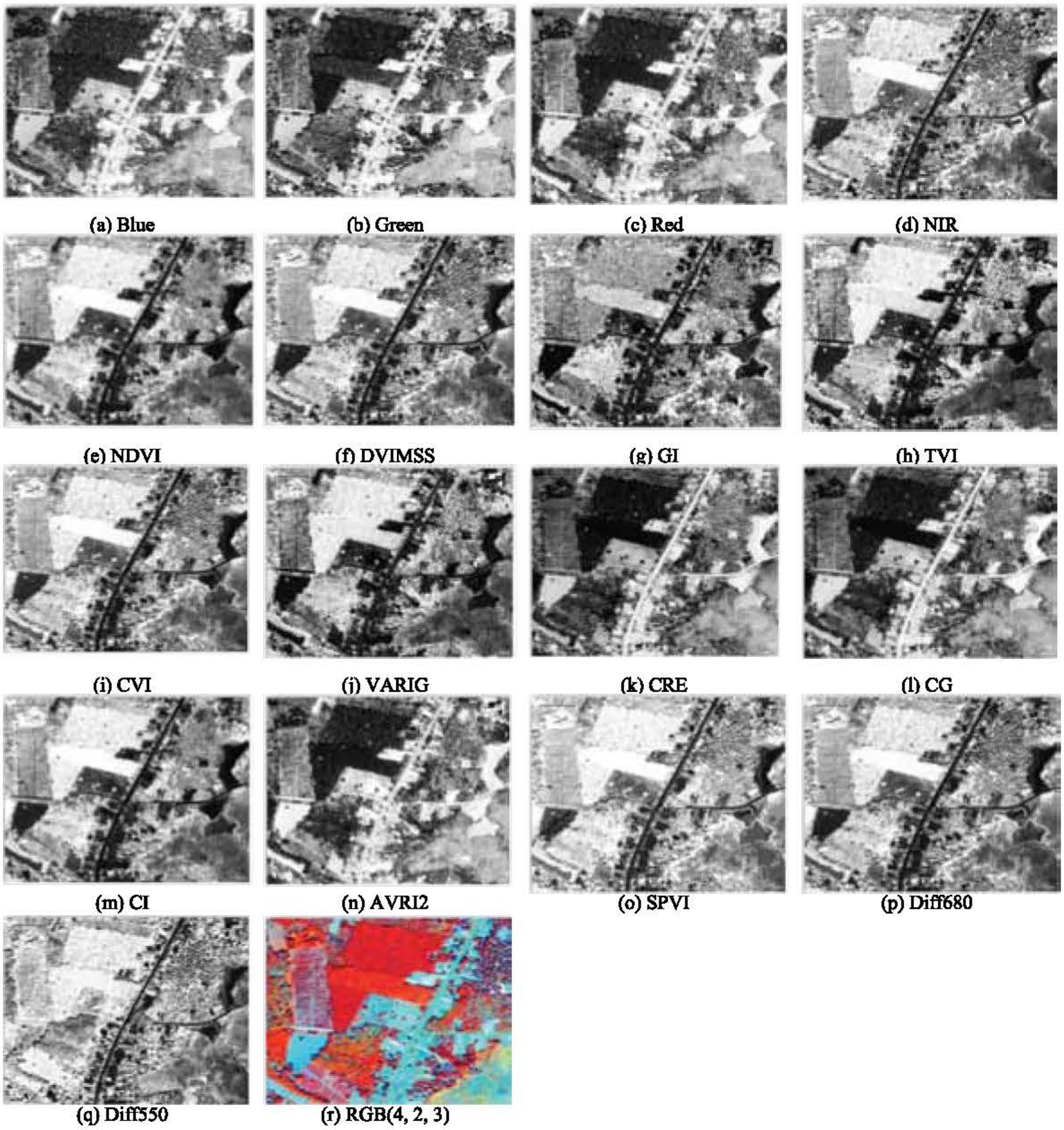


Figure 3. Example screenshots of 4 MS bands and 13 vegetation indices in the study area

"Non-vegetation", "Coconut", "Rubber" and "Oil Palm" classes were assigned between 1st and 4th segmentation steps using "Mean" object value feature (Figure 2). However, young crop stage in coconut or rubber plantation could not be extracted from mature crop stage because of the complex patterns of plantations (Figure 4(b)). Gray level co-occurrence matrix (GLCM)) and possibility techniques such as "GLCM homogeneity" , "GLCM contrast", "GLCM dissimilarity", "GLCM correlation", "Area", "Merge region", and "Related border to neighbor objects" were utilized to help distinguish the plantation growing stages time to time, especially, in the last segmentation step. Sample snapshots of the segmentation results are show in Figure 5.

3.2 Accuracy Assessment

The main purpose of the study was focused simply on plantation extraction. The accuracy assessment of classification result was evaluated in young coconut, mature coconut, young rubber, mature rubber, oil palm plantations, Non-plantation and water classes based on the ground truth references (Table 2) within homogeneous regions.

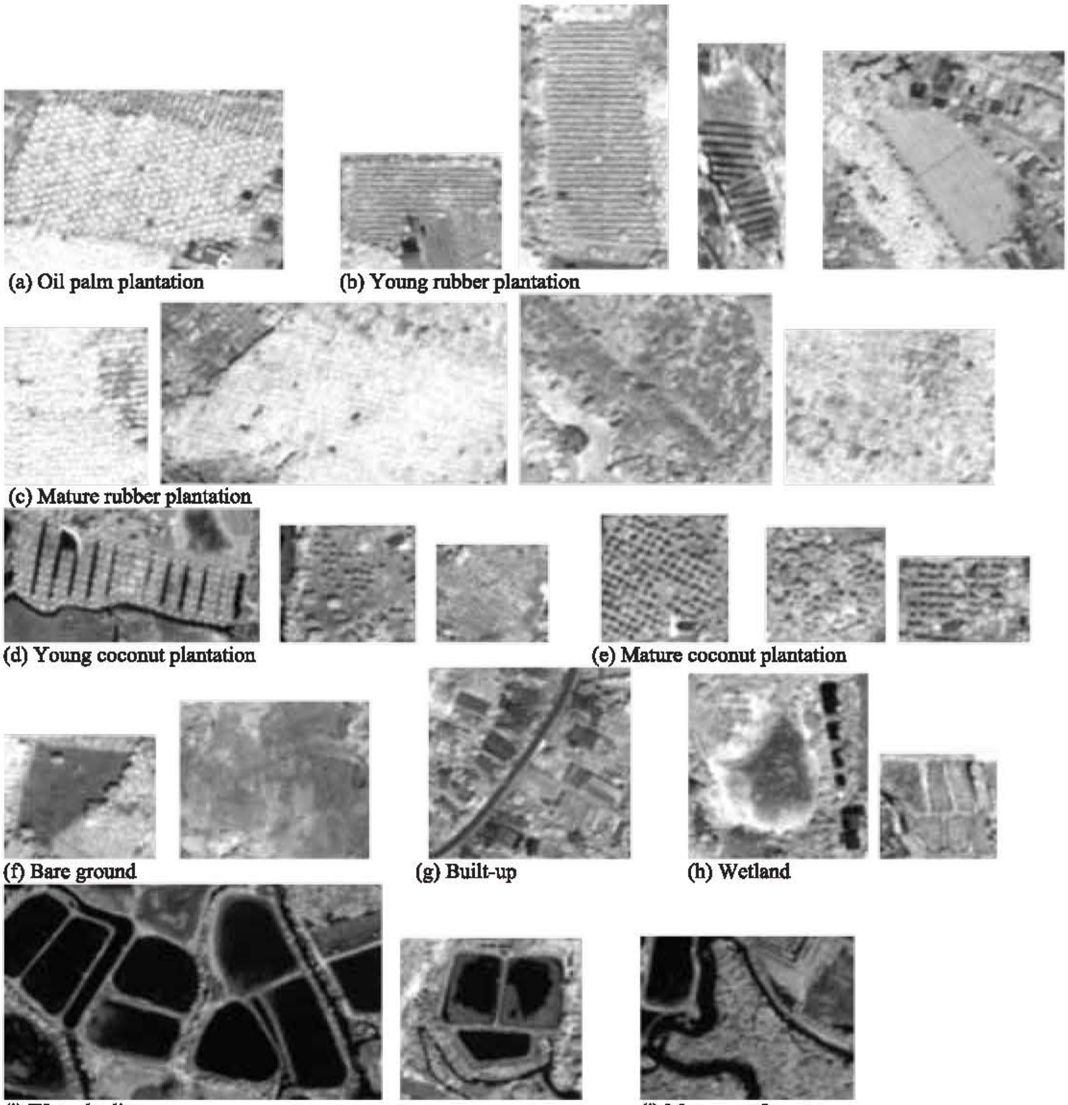


Figure 4. Example of screenshots from NIR band of plantation patterns in the area

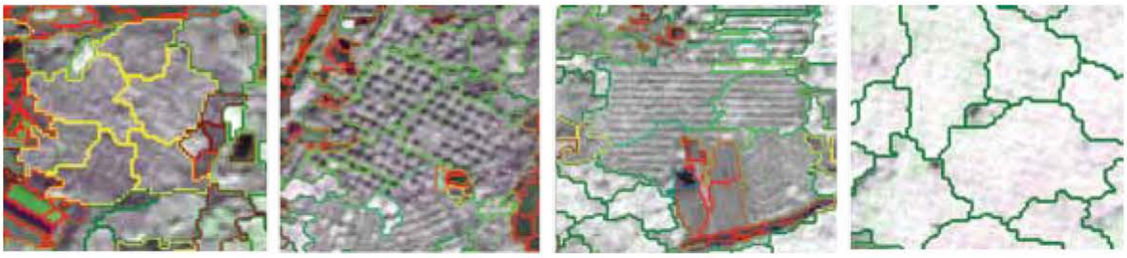
An error matrix based on Training or Test Areas (TTA) Mask in eCognition® software was evaluated for the rule set development image section and the rule set validation image section. Error matrix based on TTA mask was generated to compare the classification results with ground truth references. Comparison of the overall accuracy and kappa coefficients for each image by using the error matrix is presented in Table 5. The results of accuracy assessment with 88% and 79% for overall accuracy and 0.85 and 0.75 kappa coefficients values of development and validation rules set images, respectively. The development rules set image showed higher overall accuracy and kappa statistics than the validation rules set image as the rules set in young coconut could not be properly computed and also misclassification of each crop stage (young and mature plantations) could be found in validation rules set image. However, Kappa value between 0.61 – 0.80 is substantial and greater than 0.81 is almost perfect (Kumar, 2006). The results thus show very good overall accuracy and kappa statistics. The rules set developed in this study seems to be transferability, nevertheless, the accuracy assessment should be further checked for the other classes.

Table 4: Algorithm parameters used for this study

Segmentation	1st	2nd	3rd	4th	5th
Scale parameter	10	30	24	20	20
Shape	0.7	0.7	0.8	0.8	0.8
Compactness	0.5	0.6	0.6	0.6	0.7
Layer Weight					
GeoEye-1 Blue band	1	0	0	0	0
GeoEye-1 Green band	1	0	0	0	0
GeoEye-1 Red band	1	1	1	1	1
GeoEye-1 NIR band	1	2	2	2	2
Normalized Difference Vegetation Index (NDVI)	1	0	0	0	0
Differenced Vegetation Index MSS (DVIMSS)	1	1	0	0	1
Green leaf index (GI)	1	1	0	0	1
Transformed Vegetation Index (TVI)	1	1	2	2	1
Chlorophyll vegetation index (CVI)	1	0	0	0	0
Visible Atmospherically Resistant Index Green (VARIG)	1	1	0	0	1
Chlorophyll Red-Edge (CRE)	1	1	0	0	2
Chlorophyll Green (CG)	1	0	0	0	0
Coloration Index (CI)	1	1	0	0	1
Atmospherically Resistant Vegetation Index 2 (ARVI2)	1	0	0	2	0
Spectral Polygon Vegetation Index (SPVI)	1	1	0	0	1
Diff800_680 (D680)	1	0	0	2	0
Diff800_550 (D550)	0	0	0	2	0

Table 5: Accuracy assessment of development rules set image and validation rules set image using error matrix based on TTA mask

Classes/Accuracy	Development rules set image			Validation rules set image		
	Overall accuracy = 0.88 Kappa Coefficient = 0.85			Overall accuracy = 0.79 Kappa Coefficient = 0.75		
	Producer	User	Kappa	Producer	User	Kappa
Young Coconut	1.00	0.74	1.00	0.00	0.00	-0.01
Mature Coconut	0.85	0.90	0.82	0.94	0.80	0.93
Young Rubber	0.74	0.98	0.69	0.46	1.00	0.40
Mature Rubber	1.00	0.86	1.00	1.00	0.74	1.00
Oil Palm	1.00	1.00	1.00	1.00	1.00	1.00
Non-plantation	0.92	0.84	0.91	0.92	0.84	0.91
Water	0.94	1.00	0.93	0.94	1.00	0.93



(a) (b) (c) (d)

Figure 5. Sample snapshots of the segmentation results: (a) Young coconut (b) Mature coconut (c) Young rubber and (d) Mature rubber

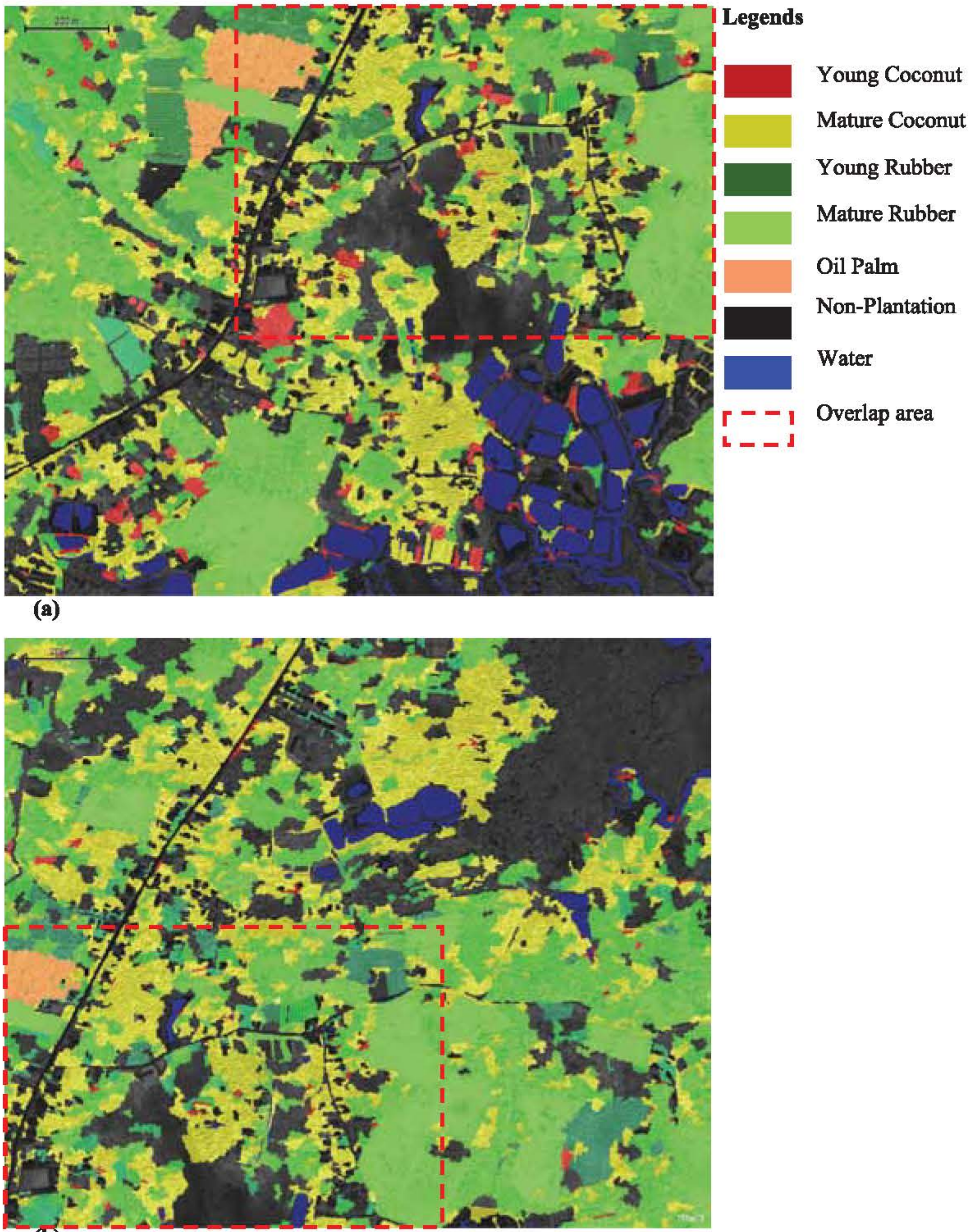


Figure 6: Classification results in rule set (a) development area and (b) validation area

The Figure 6 shows the results of classification using OBIA in rules set development image and rules set validation image. The red rectangular dashed line outlines the overlap area between both images used for the accuracy assessment for mentioned plantation classes. Oil palm plantation can be properly extracted from other plantation types in both images. However, misclassification can be found in the results since the crop textures were very similar. The rules set can be extracted the in main crop categories (coconut, rubber and oil palm) in validation image better than extracted in each growing stage (Young coconut, Mature coconut, Young rubber and Mature rubber). Since the dimension of input image layers can be affected on the object boundary in the segmentation steps. The delineation of object boundaries were not the same as in development rules set image and these affected the variation statistics range of each object between the two dataset. However, the object based classification techniques seem to be a valuable tool for extracting crop type level (coconut, oil palm and rubber plantations) but it may not be useful for extracting in the each crop growing stage level (young and mature plantations).

4. Conclusions

This study presented complex plantations extraction including young coconut, mature coconut, young rubber, mature rubber, and oil palm plantations in two part of Pa Khlok area, Phuket, Thailand using GeoEye-1 multi-resolution images with 2 m resolution. The methodology was based on the OBIA concepts and image segmentation. Separation of complex plantations such as mixed coconut, rubber trees and oil palm at object level requires not only the textural information to enable differentiation but also context relationships, such as object area and shape, adding further information to object based classification. Thirteen vegetation indices and 4 original multispectral responses from GeoEye-1 imagery were used to support the classification in OBIA techniques. The extraction methodology for complex plantation patterns using OBIA techniques has been demonstrated to be useful for the similar complex plantation pattern in other areas. However, different spatial, spectral and temporal condition should be concerned and explored further.

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