RUBBER AGROFOREST IDENTIFICATION USING OBJECT-BASED CLASSIFICATION IN BUNGO DISTRICT, JAMBI, INDONESIA

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Abstract

Jungle rubber is a form of rubber-based agroforestry system, which possesses unique vegetation characteristics among other types of land cover in Jambi province, Indonesia. Similar in structure to rubber plantation in the installation phase as a result of very extensive management by farmer, it rapidly develops a vegetation structure close to that of secondary forest of similar age. Due to the rapid loss of primary forest in Sumatra, jungle rubber has an important role to play in conservation of the original forest flora. However the current spatial extent of jungle rubber and its recent evolution is unknown. This paper focuses on the identification of rubber agroforest through remote sensing data in Jambi, Sumatra, Indonesia. It compares two different approaches to land cover classification. The standard purely pixel-based approach is confronted to an object-based method. The latter relies on the information contained in an image object, which represents spectral homogeneity as well as the shapes of real objects on the satellite image. The object-based classification, applied through a hierarchy of scales, gave better accuracy and with regards to mixed vegetation structures such as in agroforestry systems, it is more capable of extracting specified features related to complexity and age.

1. INTRODUCTION

Rapid deforestation has taken place for decades in many parts in Indonesia including in Bungo District, Jambi Province. Land cover changes study using multitemporal remote sensing data has shown that 30 years ago the area was nearly covered by forest. A land cover type in Bungo district, which has replaced forest, is rubber agroforest (RAF), which is also termed as *jungle rubber*. The first planting event of jungle rubber was reported in 1918 by an agricultural extension officer, who observed rubber trees that had been planted in slashed and burned fields, but that were managed (or unmanaged) as though 'wild', along with other natural vegetation (Joshi, et.al., 2002). Jungle rubber is a form of rubber-based agroforestry system, which possesses unique vegetation characteristics. It is similar in structure to rubber plantation in the installation phase as a result of very extensive management by farmer, but rapidly develops a vegetation structure close to that of secondary forest of similar age. Due to the rapid loss of primary forest in Sumatra, jungle rubber has an important role to play in conservation of the original forest flora.

The spatial extent of jungle rubber and its evolution remains unknown. Identification attempt of RAF using remote sensing approach was found to be quite delicate due to the unique structure and its similarity to monoculture rubber and forest. Development of object-based approach was considered to be an alternative to a conventional pixel-based classification. This study tried to use both pixel and object-based approach to identify RAF and assess the results produced by each method.

2. DESCRIPTION OF STUDY AREA

Bungo district is a lowland peneplain area located in the western part of Jambi Province Indonesia, covering an area of 4550 km2 and divided into 8-sub districts. The ground altitudes of the area range from 100 m to 1250 m asl. Most part of the district is covered by smallholder rubber plantation privately owned by local people. Natural forest still exists at the southwestern part of the district in conjunction with Kerinci Seblat National park (Figure 1).

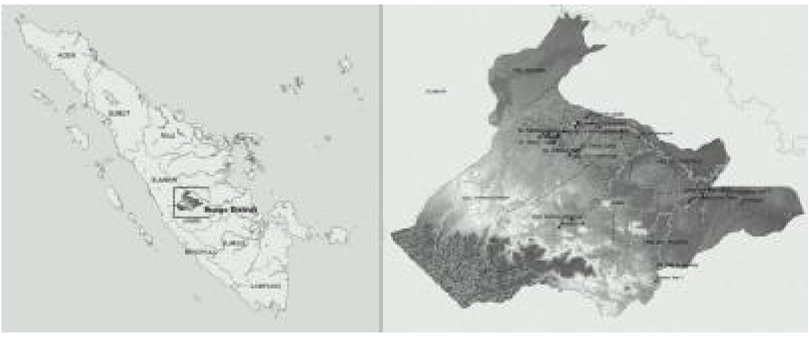

Figure 1. Bungo district in Jambi Province, Sumatra Indonesia

3. METHODS

3.1 DATA AND MATERIALS

Landsat Enhanced Thematic Mapper (ETM) image taken in March 24^{th} 2002 was used in this study. The image was geometrically corrected using 68 ground control points (GCP) and the root mean square error for each GCP was maintained to be around 1 pixel. Training area for classification process was collected for all land cover types during a fieldwork using GARMIN 48 GPS receiver. Training and reference areas of RAF were also used as biodiversity measurement plots where biophysical data of RAF were gathered. Information regarding age of RAF was obtained through interview with the owners of the RAF patches. Image pre-processing and pixel-based classification was carried out using PCI Geomatica version 8.3, while the object-based approach was carried out using eCognition version 3.0.

3.2 LAND COVER CLASSIFICATION

The land cover classes to be differentiated are: forest, old RAF, mature RAF, monoculture rubber, young rubber, oil palm plantation, young oil palm, herb and shrub, cleared land, rice field, settlement and water body. Emphasis was given to differentiating RAF from the classes similar to it, and to discriminating it into two classes which implies differences in complexity: old RAF (> 30 yrs) and mature RAF (10-30 yrs). Figure 2 shows a simple illustration of RAF, compared to forest and monoculture rubber.

a b c

Figure 2. An illustration of (a) forest ,(b) RAF, and (c) and monoculture rubber *(illustration by Wiyono)*

Hierarchical classification approach was implemented for both pixel-based and object-based approaches. This approach possesses several advantages since it offers more consistency owing to its ability to accommodate different levels of information, starting with structured broad-level classes, which allow further systematic subdivisions into more detailed subclasses. Another advantage of the structure is that non-parametric and parametric information can be incorporated into the decision rule of each level.

3.2.1 Pixel-based classification

Pixel-based classification was conducted in 4 hierarchical levels shown in Figure 3 (left). At each level, different classification procedures were utilized to identify specific type of land cover. Masking was conducted to the results at one level to be able to incorporate them into the next level of the hierarchies. Classification procedures used in pixel-based classification included simple threshold method and maximum likelihood classifier (MLC). MLC procedure was applied mainly to distinguish RAF from forest and monoculture rubber. The spectral channels to be used as input for the classification procedure varied, depending on the land cover to be identified, guided by spectral variability assessments conducted prior to classification routines.

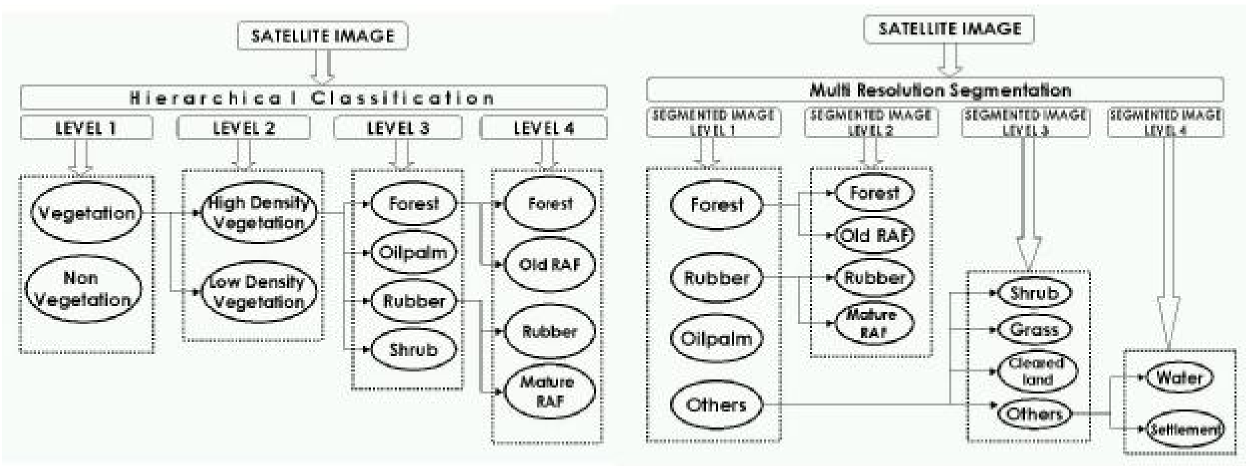

Figure 3. Classification scheme of pixel-based classification (left) and object-based classification (right)

3.2.2 Object-based Classification

The initial step of object-based classification is image segmentation, which forms a set of image-object primitives to be used in the classification process (Definiens, 2001). The objects were formed by defining a **scale factor** which controls the resulted size of image objects, and **homogeneity criteria** which define the proportion of spectral and shape information used in segmentation process. Due to the nature of vegetation patches in the area, which have more variability on spectral, compared to the shape variability, which is mostly irregular, at all levels, the importance of spectral variation is emphasized over shape variation. This was done through inputting bigger proportion of spectral compared to shape in the segmentation parameter setting. The process was carried out to form four levels of object's scales by utilizing bands 3, 4, 5, and 7 as the input bands, emphasizing on the variation of vegetation in the satellite image. Four levels of segmentation results were used as a basis for hierarchical classification.

For each level in hierarchical classification, training areas scaled-up from pixel unit to object unit was used. The hierarchical classification started by identifying broad-level classes which were visually and spectrally easy to distinguish. These broad-level classes still had inherent heterogeneity as they include land cover types similar in spectral values. These undifferentiated classes were further separated in the next level of hierarchy through interpretation of statistical parameters (i.e. means, standard deviations) of the class' spectral features based on their training objects. Hierarchical structure of object-based classification is shown in Figure 3 (right).

3.2.3 Accuracy Assessment

Accuracy assessment was conducted for both classified image produced by pixel-based and object-based approach by forming an error matrix between reference points and the classified image, which shows the magnitude of omission/commission errors in the classified image.

4. RESULTS AND DISCUSSION

4.1 Spectral Signature of Rubber Agroforest

Spectral signatures were represented by a set of spectral-response curves compiling all types of vegetation in the study site. Figure 4a shows the spectral curve of RAF compared to rubber and forest. As initially assumed, old RAF's signature was found between the signatures of forest and monoculture rubber. Mature RAF's response curve is mixed with the rubber's curve and old RAF's response appears to be mixed with forest's, indicating that spectral information alone was not sufficient to distinguish RAF from monoculture rubber.

4.2 Pixel-Based Classification

Results from pixel-based classification showed that, some of old RAF is mixed with patches of forest due to its complex structure, high variations of species and low density of rubber trees. The patches of mature RAF were mixed with monoculture rubber class due to the dominance of rubber trees in the patches. Maximum likelihood classifiers using band 7,5,4, and 3 were used at the final level to separate the classes of RAF from forest and monoculture rubber. The final result of this method is shown in Figure 6b. RAF classes appeared along the river in small patches size ranging from 0.5 to 250 ha. This result appeared unsatisfactory, as there are many pixels of RAFs, misclassified as forest or monoculture rubber. It was estimated about 31% of old RAF were misclassified as forest or monoculture rubber.

4.3 Object-based Classification

Results of segmentation process at the first level can be seen in Figure 5a. The objects at this level were classified into forest, rubber, and oil palm.

Old RAF, despite the high mixture of non-rubber species, usually still has lower variations of species compared to natural forest, which made the standard deviation of RAF lower compared to forest. For mature RAF, the species variation is higher compared to monoculture rubber due to the addition of non-rubber species, this caused the standard deviation value of mature RAF higher than that of monoculture rubber. Figure 4b shows comparison of spectral variations represented by standard deviation of training objects of RAF classes compared to forest, rubber and oil palm. The graph shows that RAFs are completely inseparable at the visible wavelength (band1-3 of Landsat ETM), but could be well-separated around the infrared length. It is also shown that forest has the highest spectral variations and oil palm has the lowest one.

At the second level of segmentation (Figure 5b), RAF patches were distinguished from forest and monoculture rubber, and thus from forest and rubber classes from the previous level, through evaluations on means and standard deviation values of image objects. Trials were conducted on matching the statistical analyses results with the training objects in the respective levels, and across levels as well. The combination of standard deviation and means value proved to be able to capture the differences of RAF's spectral responses from forest and monoculture rubber while at the same time maintain the spectral homogeneity of its own class.

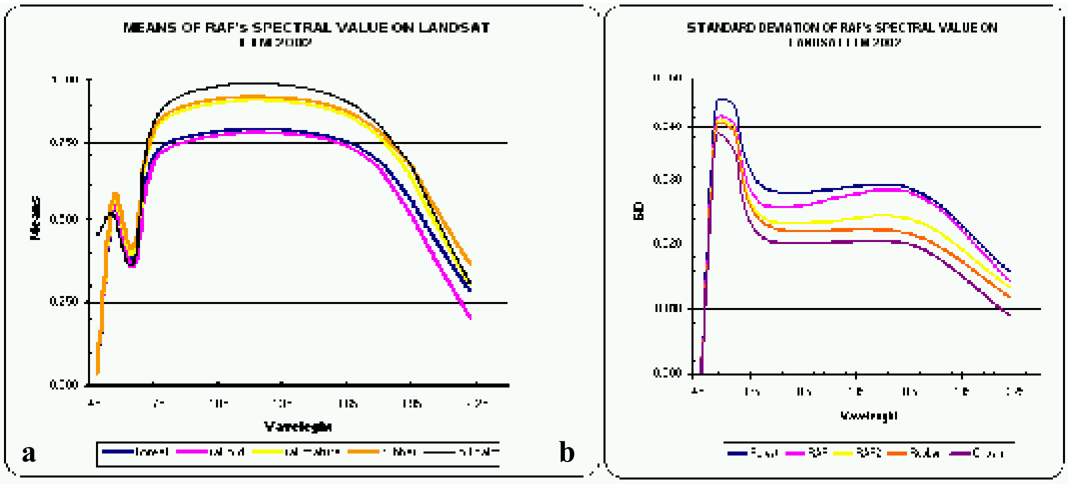

Figure 4. (a) Means value of RAF (b) standard deviation of RAF ; compared to forest, rubber and oilpalm

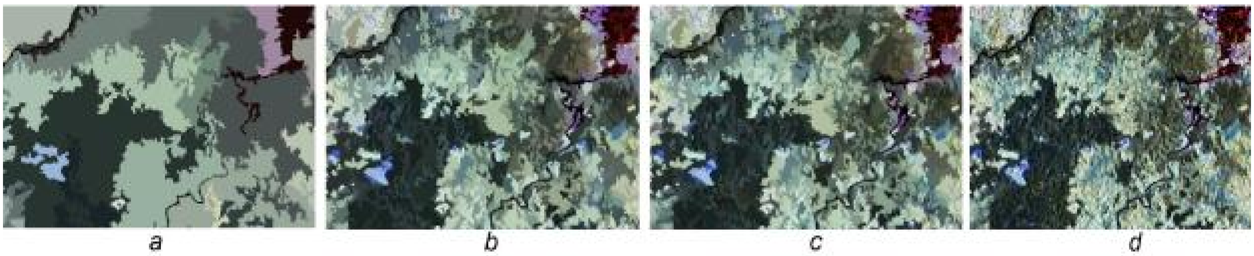

Figure 5. Subsets of segmentation results of Landsat ETM 2002

Figure 6 shows the classification subsets of classification results compared to the original image. RAF patches were found along the river, close to settlement areas and in sparse patches in the middle of smallholder rubber. Approximately 533.79 km^2 of RAF were identified by pixel-based approach, while object-based identified 615.52 of RAF area. Visually, the pixel-based classified image has 'salt and pepper effects' caused by the spatially-independent labeled individual pixels, and this didn't capture the inherent variability of RAF patches in the field. In the object-based approach, the labeling on individual pixel based on maximum likelihood rule was overruled by the pixel aggregation into objects in the initial stage (segmentation). Later, labeling rule by taking into account the inherent spectral variation within objects assisted the object discrimination into different classes. The other land cover types such as river and settlement were also better classified in this approach, as seen in Figure 6. These classes were classified by focusing on spatial features such as size, shape and length of image objects, and the classification was done to the segments in lower levels, levels 3 and 4 (Figure 5c and 5d).

4.4 Accuracy assessment

An accuracy assessment was conducted using 580 reference points collected using GPS receiver. The overall accuracy is 70.1% for pixel-based approach and 90.6 for object-based classification. Calculation of Kappa accuracy resulted in 0.685 for pixel-based classification result and 0.89 for object-based classification. From Table 1, it is seen that applying hierarchical object based approach improves the accuracy of old RAF and mature RAF by 10 % and 7 % respectively.

Table1. Results of Accuracy Assessment on pixel-based and object-based approach

No	Classes	Pixel Based	Object Based
1	Forest	0.73	0.95
2	Old RAF	0.68	0.75
3	Mature RAF	0.60	0.67
4	Monoculture rubber	0.80	0.90

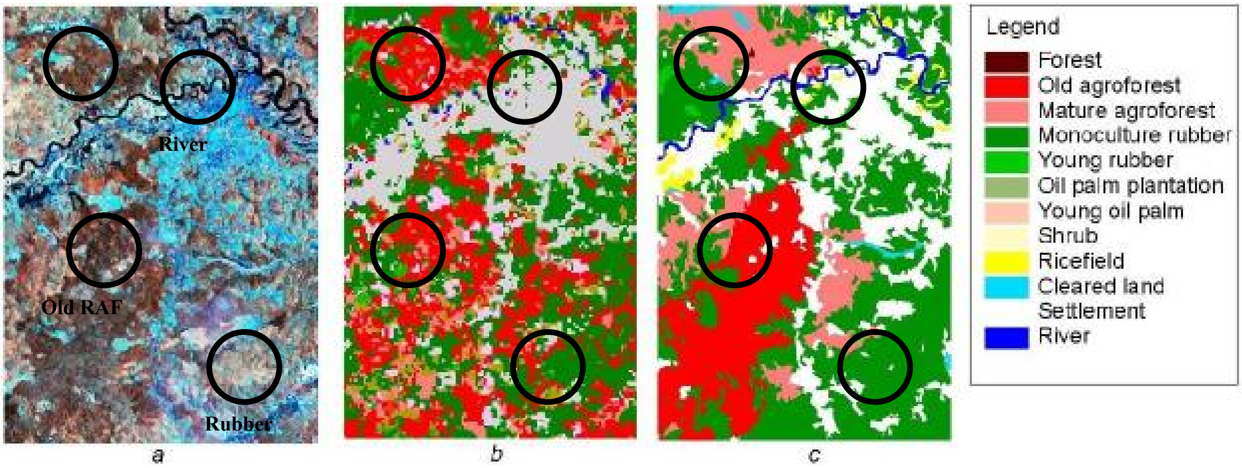

Figure 6. Subsets of classification results; (a)Original image, (b) pixel based classification result, and (c) object based classification result

5. CONCLUSION

This study shows a higher ability of object-based classification to distinguish rubber agroforest from other classes with spectral values and variations close to it. The classification results from object-based approach proved to have higher accuracy compared to the one produced by pixel-based approach. This results show promising prospects for the monitoring role of Remote Sensing on complex vegetation structures in agroforestry systems in conjunction with the assessments of their environmental values, e.g. biodiversity preservation, watershed and soil conservation

6. ACKNOWLEDGEMENT

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7. REFERENCE

Chavez, Pat S. 1996. *Image Based Atmospheric Corrections Revisited and Improved*. Photogrametric Engineering and Remote Sensing. 62:9, 1025-1036.

Definiens Imaging. 2001. *Ecognition Object Oriented Image Analysis, User Guide*. Definiens Imaging. Munchen, Germany.

Joshi, L, et.al. 2002. *Jungle Rubber : A Traditional Agroforestry System Under Pressure*. International Centre for Research in Agroforestry South East Asia Regional Research Programme.

Vincent, G., L. Joshi and Susilowati (accepted). *Sources of variability in rubber productivity in Indonesian agroforests : a case study from Jambi province (Sumatra).* Agroforestry Systems.