object-oriented classifier for detection Tropical Deforestation using LANDSAT ETM+ IN Berau, East Kalimant, Indonesia

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Abstract

Forests are very important natural resources, and tropical rain forests are even more important due to the abundance of biodiversity. But the rate of deforestation in the tropics is alarmingly high because of the rapid population growth and economic development. The use of satellite remotely sensed data and image analysis (i.e. classification) has proven its effectiveness in detecting tropical deforestation. In this research, two sets of Landsat-7 ETM+ data acquired on 26 August 2000 and 16 August 2002 were used in this research. The Object-oriented image analysis, which is implemented through software eCognition, was used for image classification. The GIS software ILWIS was used for integrated analysis of classification results and other geographic data. Two projects were created in eCognition. First one was applied on fused data set that covers a relative small and cloud free area on both images. Eight classes were classified, namely *dense forest*, *moderate dense forest*, *sparse forest*, *heavily logged area*, *less heavily logged area*, *old conversion area*, *new conversion area* and *cloud and shadow*. The overall accuracy for this classification is 81.3% and KIA (Kappa Index of Agreement) is 78.1%. The second project was applied on original data set and two thematic layers. Seven classes were classified, namely *illegal logging*, *legal logging*, *slightly logged area*, *non-forest*, *unlogged area*, *moderate dense forest* and *sparse forest*. The overall accuracy is 76%, and the KIA is 70.4%. These classification results and the classification process revealed the great potential of using Object-oriented image analysis to extract information from satellite image to detect tropical deforestation.

1. Introductions

Forests are very important natural resources, and tropical rain forests are even more important due to the abundance of biodiversity. But the rate of deforestation in the tropics is alarmingly high because of the rapid population growth and economic development.

Tropical countries, like Indonesia, cannot afford to stop logging natural forests because they need the timber to generate revenue and to open more land for agriculture to produce food in order to support their people and economy. On the other hand, timber-consuming countries, including developed and developing ones, are not rich enough or generous enough to help tropical countries to stop logging tropical forests. As a matter of fact, they are quite enjoying the quality products from these precious tropical forests.

Sustainable forest management (SFM) is a concept or practice that satisfies the needs of both producer and consumer countries. Further more it can be an answer to the increasing environmental concerns of professionals, the public, and the media worldwide. SFM can be considered as a compromise between ban of logging and uncontrolled logging.

Indonesia's forests are very important, not only to Indonesia but also to the whole world, due to its capability of supporting biodiversity and ameliorating climate. However, the sustainability of forest management in Indonesia, in general, is far from desired (Brown, 1999). The certification of SFM is considered an important method to push the forest management towards sustainable manner. In order to efficiently carry out SFM certification and monitor the already certified forest management unit's performance, objective, unambiguous and timely information about the target forest areas is needed. For the frequent information acquirement on large and, usually, remote forest areas, only depending on field survey is not feasible both in terms of money and time. Therefore, the remote sensing data and techniques must be considered. In fact it is the only way to obtain timely information for large and remote tropical rain forest. Theoretically, there is no doubt that remote sensing data can be a useful tool in supporting the acquirement of this information.

Many studies have been carried out on the use of remote sensing products to detect tropical deforestation using traditional supervised Maximum Likelihood Classification. But extra classification capability such as object detection classification has not been used in classifying tropical deforestation.

Object-oriented image analysis is different from conventional pixel base image analysis e.g. Maximum Likelihood Classification, which analyses the image based on image objects rather than pixels. As an example to Object-oriented image classifier, eCognition is one of the software to implement this concept. It is a powerful and versatile technology for multiscale analysis of earth observation data, particularly suited for the analysis of very high resolution optical and radar data. It can handle even complex problems, which require the consideration of local context information. Object-oriented image such as eCognition is based on the concept that important semantic information necessary to interpret an image is not represented in single pixels, but rather in meaningful image objects and their mutual relations. Therefore, the image classification is based on attributes of image objects rather than on the attributes of individual pixels. Therefore, Object-oriented classifier can deliver results noticeably better than conventional methods. It leads to higher classification accuracy and to better semantic differentiation.

Object-oriented classifier is based upon contiguous, homogeneous image regions that are generated by initial image segmentation. Connecting all the regions, the image content is represented as a network of image objects. These image objects act as the building blocks for the subsequent image analysis. In comparison to pixels, image objects carry much more useful information. Thus, they can be characterized by far more properties than pure spectral or spectral-derivative information, such as their form, texture, neighbourhood or context. Classifying an image using Object-oriented approach means classifying the image objects either based on sample objects (training areas) or according to class descriptions organized in an appropriate knowledge base. The knowledge base itself is created by means of inheritance mechanisms.

The objective of this research is to assess the effectiveness of the use of Object-oriented Classifier in detecting tropical deforestation in Berau, East Kalimantan, Indonesia, using Landsat ETM+ images.

2. Study area

Labanan forest concession area, which was selected as the study area for this research, is located between latitude 2°10' N and 1°45' N, and longitude 116°55'E and 117°20' E (Figure 1). It is in Berau regency, one of four regencies in East Kalimantan province, Indonesia. Labanan forest concession area covers 8100 ha production forest. Inhutani I, a state owned forest concession company, has managed this area for more than 30 years and selective logging has been applying since 1970s (Fauzi, 2001). At present, Inhutani I is carrying out the Berau Forest Management Project (BFMP), which is jointly financed by the Government of Indonesia (GOI) and the European Commission (EC). Inhutani I has managed the Labanan concession as an international showcase of forest management, at the request of the ministry. They have already achieved ISO 14001 certification for the concession management and are currently seeking Forest Stewardship Council (FSC) and LEI certification (BFMP, 2002). Remotely sensed and other ancillary data such as Landsat ETM+ images and various maps and records of temporary or permanent forest sampling plots are available and accessible. All these facts made Labanan concession area an ideal place for carrying out this research.

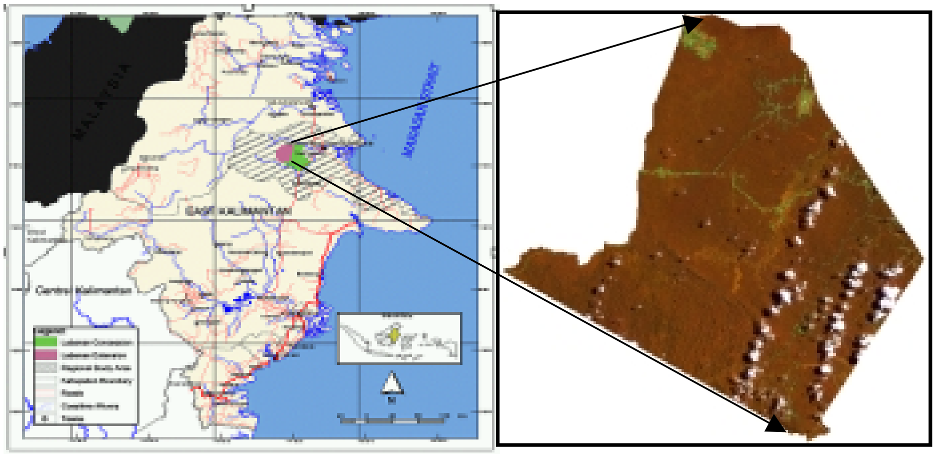


Figure.1 Location of the study area, map source: (BFMP, 2000)

The study area has a typical tropical climate; the annual rainfall is about 2000 mm and every month receives more than 100 mm rainfall in most years. A high botanical diversity characterizes the Berau area. Lowland mixed dipterocarp forest dominates the natural vegetation of East Kalimantan. The logging system adopted here is called RKL or five-year working plan. The whole production area was arbitrarily divided into square blocks of 100 ha each from which they selectively log 1000 ha per year. Since 1995, natural boundary of watershed has been used as logging boundary (Hussin, 2002).

Two Landsat-7 ETM+ satellite image acquired on August 26, 2000 and 16 August 2002, which were used for this research. The 7 bands were resampled to the panchromatic image acquired at the same time. Then, the fusion technique of RGB and IHS transformation was used to integrate this multi spectral data set with panchromatic image (ITC, 2001). This resulted in a sharpening of image due to the higher spatial resolution of the panchromatic image, and the resolution of the resulting image became 15 meters (Lillesand & Kiefer, 2000). According to Franklin (2001), the striking enhancements for visual interpretation can be achieved using above-mentioned method. In fact, the result of our fusion operation confirmed this conclusion. Much more detailed information could be drawn visually from this fused image than that from separate original data. In the same time the image of the original 30 meters spatial resolution were used and compared with the enhanced 15 meters resolution.

3. Methodology

Two classification projects were implemented in this research. The first classification project contains two subsets of fused images of 2000 and 2002. Altogether 3 levels were constructed (Figure 2). Segmentation is the first operation in any eCognition project, which is a process to subdivide the image into separated homogenous areas according to the given segmentation parameters. Different segmentation parameters result in different objects size. The parameters used in this research were basically obtained through tries according to different segmentation purposes. The first segmentation of this project, which considers band 4, 5 and 7 of two images, was made for level 2. This segmentation is aimed to get objects that represent the conversion areas and selectively logged areas properly. The second classification project (Figure 3) contains not only two subsets of original images of 2000 and 2002, but also two thematic layers (boundary and RKL map). For image data, the panchromatic band was included and band 6 was excluded. eCognition distinguished two basic types of data: image layers and thematic layers. The image layers contain continuous information, while the information of thematic layers is discrete. The two types of layers have to be treated differently in both segmentation and classification (Definiens Imaging GmbH, 2001). Altogether 4 levels were constructed in this project.

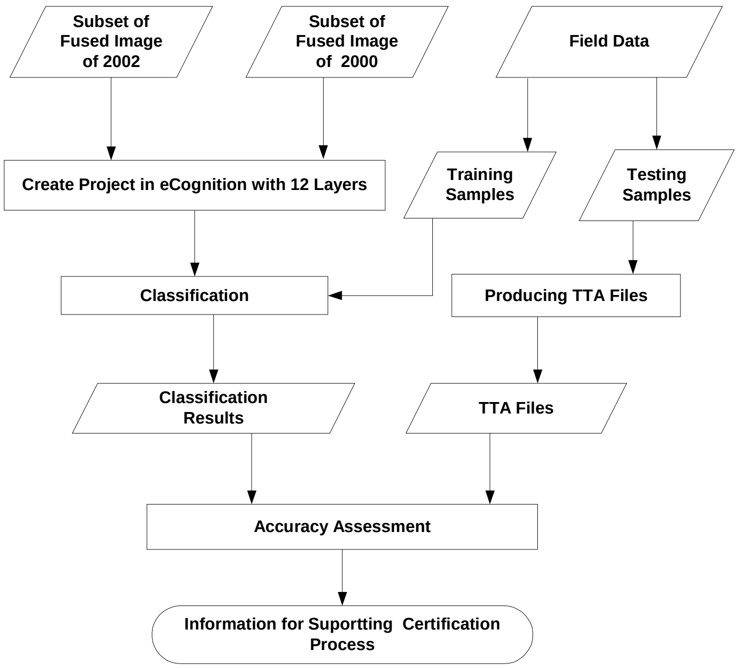


Figure 2. Process involved in fused data classification and accuracy assessment

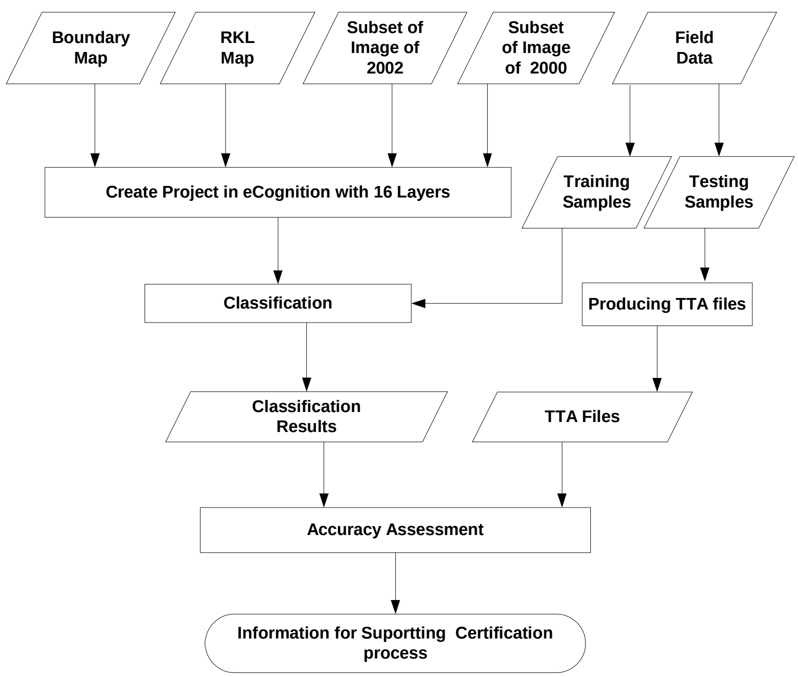


Figure 3. Steps involved in original data classification and accuracy assessment

4. Results and Discussions

4.1 Classification result of fused data set

The classification result of fused data (15 meters spatial resolution) is shown in Figure 4. The accuracy assessment result is shown in Figure 5.

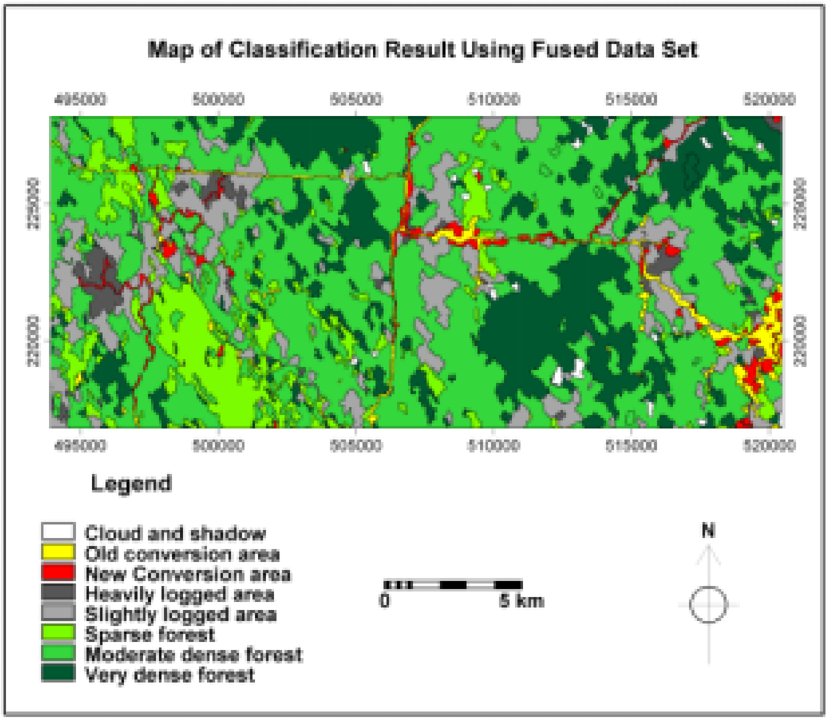
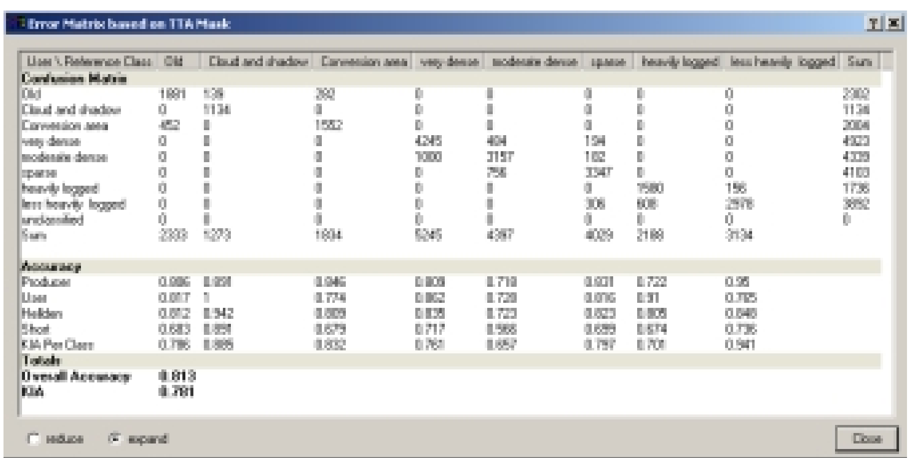


Figure 4. The classification result of fused data set



User \ Reference Class	Old	Cloud and shadow	Conversion area	very dense	moderate dense	sparse	heavily logged	less heavily logged	Sum
Confusion Matrix									
Old	1881	139	282	0	0	0	0	0	2302
Cloud and shadow	0	1134	0	0	0	0	0	0	1134
Conversion area	452	0	1552	0	0	0	0	0	2004
very dense	0	0	0	4245	404	194	0	0	4923
moderate dense	0	0	0	1000	3157	102	0	0	4339
sparse	0	0	0	0	756	3347	0	0	4103
heavily logged	0	0	0	0	0	0	1580	156	1736
less heavily logged	0	0	0	0	0	306	608	2978	3892
unclassified	0	0	0	0	0	0	0	0	0
Sum	2333	1273	1834	5245	4387	4029	2188	3134	
Accuracy									
Producer	0.806	0.891	0.846	0.809	0.719	0.831	0.722	0.95	
User	0.817	1	0.774	0.862	0.728	0.816	0.91	0.765	
Hellden	0.812	0.942	0.809	0.835	0.723	0.823	0.805	0.848	
Short	0.683	0.891	0.679	0.717	0.566	0.699	0.674	0.736	
KIA Per Class	0.786	0.886	0.832	0.761	0.657	0.797	0.701	0.941	
Totals									
Overall Accuracy	**0.813**								
KIA	**0.781**								

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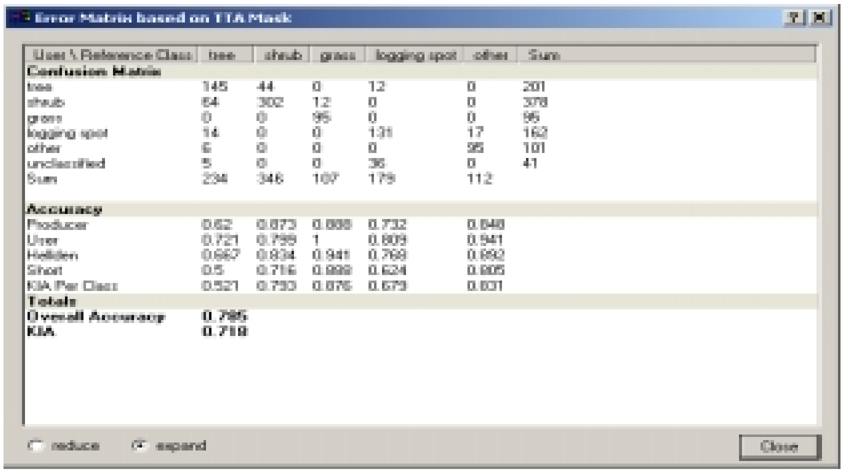
Figure 5. Accuracy assessment result of fused data set

Because the final classification result was derived from its sub level i.e. level 1, the accuracy assessment of level 1 is also important. In fact this assessment was done before its up level's classification was carried out. Figure 6 shows the accuracy assessment result of level 1.



Error Matrix based on TTA Mask

User \ Reference Class	tree	shrub	grass	logging spot	other	Sum
Confusion Matrix						
tree	145	44	0	12	0	201
shrub	64	302	12	0	0	378
grass	0	0	95	0	0	95
logging spot	14	0	0	131	17	162
other	6	0	0	0	95	101
unclassified	5	0	0	36	0	41
Sum	234	346	107	179	112	
Accuracy						
Producer	0.62	0.873	0.888	0.732	0.848	
User	0.721	0.799	1	0.809	0.941	
Hellden	0.667	0.834	0.941	0.768	0.892	
Short	0.5	0.716	0.888	0.624	0.805	
KIA Per Class	0.521	0.793	0.876	0.679	0.831	
Totals						
Overall Accuracy	**0.785**					
KIA	**0.718**					

reduce expand Close

Figure 6. Accuracy assessment result for level 1

It is clear that the accuracy of level 1 is lower than the final result. This is reasonable, because the segmentation scale parameter for level 1 is very small (3). This resulted in a large amount of small homogenous objects, and they server as primitive information carriers. In fact, among these classes in level 1, only some classes have contribution to the final classification result. So the overall accuracy is not as important as that of some specific classes. In this case the most important class is '*logging spot*', and followed by '*tree*', '*bush*', '*grass*' '*water*' and '*other*'. The accuracy assessment of '*water*' was included in the class of 'other', so the '*water*' was not in error matrix.

From Figure 5, it can be noted that the final classification result has an overall accuracy 81.3% and a KIA (Kappa index of agreement or kappa coefficient) 78.1%. Congalton (1996) stated, "Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement (Brandon & Bottomley, 1998). According to this standard, the accuracy achieved in this classification project represents moderate agreement.

By crossing the map of classification result with slope map and followed by producing attribute map. The logged area_ slope map was produced From this map it can be found that there were very few logged areas, including heavy and slightly logged, on the steep areas. It means that the regulation of "**selective logging excludes slope greater than 40% area**" was observed very well.

The classification result was also crossed with the elevation map that shows the areas with an elevation higher than 400 meters above see level. It was found that only 0.09% of logged areas was located in high elevation areas. So it can be concluded that the regulation of "**selective logging excludes the area with an elevation higher than 400 m**" was observed very well also. The reason for this finding is similar as that of steep slope areas.

From the classification map we can see the class '*old conversion area*' which means the forest area was converted to other land cover before the 2000 image was acquired. The class of '*new conversion area*' means the area that was forest in 2000 image, but was not forest area in 2002 image. The area of each class can be easily obtained from the map's statistics table, and can be seen in a very clear way.

4.2. Classification result of original data set

The classification result of original data set (30 meters spatial resolution) is shown in Figure 7. First of all, it must be clarified that the class '*illegal logged'* and '*legal logged'* are two sub classes of '*heavily logged area'*, and they are separated according to the location. The '*illegal logged*' is the *heavily logged area*s that are located in the protected area or in RKL 7. So the accuracy assessment was done to the class '*heavily logged area*', not the two sub classes. The accuracy assessment result is shown in Figure 8.

Because the final classification result was derived from its sub-level i.e. level 1, the accuracy assessment of level 1 is also important. In fact this assessment was done before its up level's classification was carried out. Figure 8 shows the accuracy assessment result of level 1. Note that the class '*logging spot'* has a quite good accuracy. This is important because this class contributes a lot to the classification of '*heavily logged area*' and '*slightly logged area*', and these two classes are more relevant to the assessment of Forest Management Unit performance.

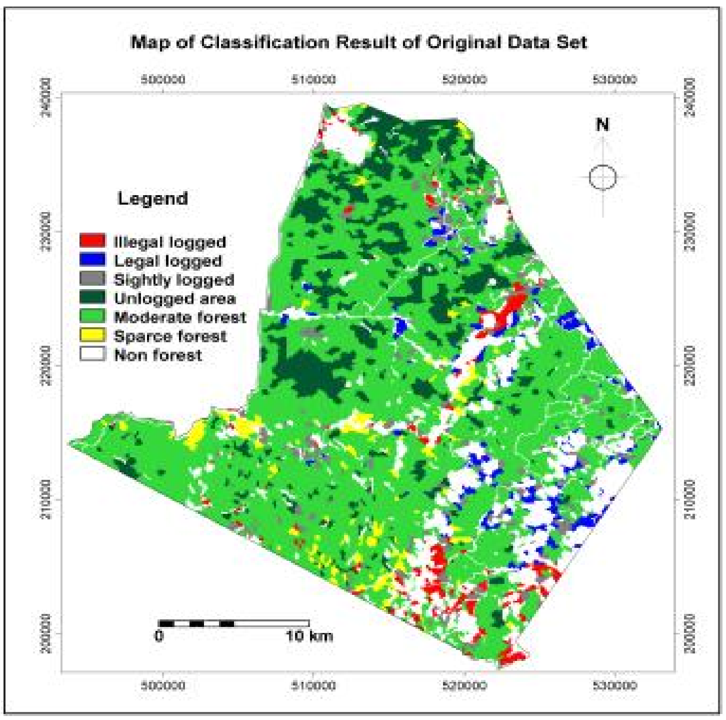


Figure 7. The classification result of original data set (30 meters spatial resolution)

Error Matrix based on TTA Mask

User \ Reference Class	non foreset	logging spot	tree	sapling or bush	water and other	Sum
Confusion Matrix						
non foreset	0	4	0	0	0	12
logging spot	0	80	0	0	0	80
tree	24	0	250	84	40	398
sapling or bush	0	0	0	138	0	138
water and other	0	12	0	0	16	28
unclassified	0	0	0	0	0	0
Sum	32	96	250	222	56	
Accuracy						
Producer	0.25	0.833	1	0.622	0.286	
User	0.667	1	0.628	1	0.571	
Hellden	0.364	0.909	0.772	0.767	0.381	
Short	0.222	0.833	0.628	0.622	0.235	
KIA Per Class	0.236	0.81	1	0.521	0.254	
Totals						
Overall Accuracy	**0.75**					
KIA	**0.63**					

reduce expand Close

Figure 8. Accuracy assessment result of classification of original data set.

Error Matrix based on TTA Mask

User \ Reference Class	non forest	heavily logged area	slightly logged area	unlogged	sparse forest	moderate dense forest	Sum
Confusion Matrix							
non forest	2288	176	0	0	684	0	3870
heavily logged area	0	1579	282	0	0	0	1860
slightly logged area	0	0	1316	0	0	0	1316
unlogged	144	0	0	2462	518	0	3124
sparse forest	314	0	0	0	1992	0	2306
moderate dense forest	0	0	0	652	1732	4390	6774
unclassified	0	0	0	0	0	0	0
Sum	2746	1756	1598	3114	4846	4390	
Accuracy							
Producer	0.833	0.899	0.824	0.791	0.411	1	
User	0.745	0.848	1	0.788	0.864	0.648	
Hellden	0.787	0.873	0.903	0.789	0.557	0.786	
Short	0.649	0.774	0.824	0.652	0.386	0.648	
KIA Per Class	0.8	0.897	0.81	0.748	0.327	1	
Totals							
Overall Accuracy	**0.76**						
KIA	**0.704**						

reduce expand Close

Figure 9. Accuracy assessment result for level 1.

From Figure 9, it can be found that the final classification result of original data has an overall accuracy 76% and a KIA (Kappa index of agreement or kappa coefficient) 70.4%. According to the standard this kappa coefficient value represents moderate agreement.

At this point in the research it is necessary to compare the results of the two classification of the fused and un-fused data sets. Fused data set covers a relatively cloud free area on both images. Base on the results of the preliminary analysis it was concluded that the use of fused data is not essential and even not necessary. More research is needed to verify whether fused data can really improve the classification accuracy or not.

Two projects were constructed in this research using eCognition. The classification process and results demonstrated that: (1)The multi temporal image data can be put into one project and can be simultaneously considered for image analysis, like what was done in both projects; (2) eCognition can classify image objects not only according to layers' original spectral attributes, many customized features can be used also for better classification results, for instance, the '*ndvilike*', the '*ratio of band 4-band 3*' used in this research; (3) It can incorporate the objects' other property into classification, for

example the shape index used in project of original data set; (4) It can classify image based on the objects' contextual information, like the heavy logged area means that the relative area of logging spot is larger than certain amount; (5) It can incorporate thematic layers into classification project for meaningful semantic differentiation, for example, the classification of *illegal logged area*.
All of these cannot be easily done using conventional pixel-based image processing techniques.

A recent research by Fauzi (2001) was taken for discussion and comparison purpose, because our research did not incorporate conventional pixel-based classification methods as parts of the research. Fauzi conducted a research on detecting logged over forest in the same study area. He classified the forest to *unlogged* and *logged over forest*, and *logged over forest* was further classified as *highly degraded* and *low degraded forest*. Among the methods deployed by his research, neural network classification using input from Landsat-7 ETM+ data and DEM gave the best classification accuracy, which was 74.4%, while the maximum likelihood classifier gave an overall accuracy 64.2%. From Fauzi's results, it can be found that the effect of salt-and-pepper (scattered pixels) is quite strong, which is one of the drawbacks of pixel-based classification methods. Further more, it can be found that, from error matrices, the accuracy assessment was only done to 2 classes, i.e. *unlogged forest* and *logged over forest*, and the user accuracy of *unlogged forest* for both classifiers are below 50%. This analysis does not imply that Fauzi's research quality is low. As a matter of fact, he did very good research because he is an Indonesia and very familiar with study area. In fact, the only problem is that what pixel-based classifiers can deliver is relatively limited. Compared the classification results achieved in this research with pixel-based classification processes, it can be found that Object-oriented image analysis has much more potential for achieving desired results than what is possible for pixel-based methods. In fact the eCognition's potential has not been fully reflected in the classification results of this research, one reason is that the research topic does not need to do so.

eCognition is specially good for high resolution image analysis. The images used in this research are medium (30m) resolution and with considerable amount of cloud cover. Even under this unfavourable situation, the classification results are quite satisfactory. So its potential should not be underestimated. More researches should be done on its potential for the classification of tropical rain forest in order to support forest certification process more effectively. Although this research achieved some quite satisfactory classification results, the author would like to suggest the readers of this thesis that please pay more attention to the concepts rather than the specific methods and results. eCognition provides huge amount different possibilities for image processing. The specific method used in this research is only one of them. Depending on different application, even different aspects of same application, the image processing methods can be adjusted very flexibly to suit the specific purposes. As to the classification results achieved in this research, although they are sufficient for assessing some of the indicators and institutional regulations, there is still much room for improvement. Please note that only one short fieldwork was carried out for this research, and further more, the fieldwork was not carried out in a very purposive way. The main reason for this is lack of knowledge on tropical rain forest and image analysis techniques before going to the field. Moreover, in order to achieve very accurate classification result, interactive field check is also essential.

5. Conclusions

- The data fusion technique used in this research is not essential and even not necessary for the information extraction to support forest certification process. More research is needed to verify whether fused data can really improve the classification accuracy or not. Here the data fusion technique specifically refers to the technique of RGB and IHS transformation, which was used to integrate multi spectral data with panchromatic data in this research.
- Object-oriented image analysis, which is implemented by eCognition software, is the suitable image processing method for the information extraction to support forest certification process, although it is not very easy to use. Many functions provided by it are not available yet in other pixel-based techniques, and some of these functions are especially useful for assessing forest management.

- Landsat-7 ETM+ data can play an important, but also crucial role for detecting tropical deforestation when used with object oriented classification by achieving high classification accuracy. However, it achieved low accuracy when classified with Maximum Likelihood. It also plays an important role in supporting forest certification process in Indonesia.

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