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Object Oriented Analysis for Updating Vegetation Features using ALOS Imagery

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Abstract

Image segmentation as basis for object oriented analysis promises high classification accuracy as it also takes structural, textural, contextual and spectral information into account.
In this study, vegetation features were extracted on the basis of classification results acquired using the object oriented image analysis and pixel based approaches using fusion of ALOS imagery (PRISM & VNIR) with a spatial resolution of 2.5 m. The main objective of the study is to evaluate the performance of the object oriented image analysis on extracting vegetation features compared to the traditional pixel based classification as an alternative approach for updating the Indonesian topographic map. Beside the accuracy assessment, cost and time assessment was also performed in this study.

The results showed that the object oriented image analysis gave higher accuracies (overall, producer's, user's and KHAT) for all obtained classes than those achieved by pixel based classification. Cost and time reductions in the map updating process were also achieved by this approach compared to manual interpretation of aerial photographs that is currently performed to update the Indonesian topographic map.

This study illustrates that object oriented analysis in combination with fusion of ALOS AVNIR and ALOS PRISM images has the potential for updating topographic maps for several reasons: it gives a good classification accuracy compared to pixel based approach; it is much more time and cost effective than the existing updating approach; it has great possibilities to be applied over large areas; it generates good quality object delineation and it allows manual corrections in an easy and friendly manner to enhance classification results. Even though considered having a good potential, application of this method over large areas in operational ways should be further explored.

Keywords: Object oriented analysis, segmentation, classification, ALOS imagery

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1. INTRODUCTION

1.1 Background

Having accurate and updated topographic maps is essential for natural resources and environmental management activities, especially for developing countries like Indonesia. The topographic map in Indonesia is provided by the National Coordinating Agency for Surveys and Mapping. Rupa Bumi Indonesia (RBI) is the Indonesian topographic or base map and presently contains 7 feature types/layers for the whole area of The Republic of Indonesia at the scale of 1: 10.000, 1:25.000, 1: 50.000, and 1: 250.000 (Bakosurtanal, 2009).

Most of the existing digital topographic maps of Indonesia were produced based on data dated from more than 10 years ago. There is a need to have an automated procedure for updating maps to reduce time and cost compared to the manual updating process. Especially considering Indonesia is the largest archipelagic country in the world where a huge area should be covered by the map.

The fast development of image data acquisition and processing at different temporal, spectral and spatial resolutions, may answer this challenge. Recently, the research division of this agency has been working on the utilization of brand new high resolution Advanced Land Observing Satellite (ALOS) images to support its mapping activities. One of the applications is utilizing this image data for map updating. ALOS is a Japanese high-resolution Earth observation satellite launched in 2006. As it is well known, ALOS has 3 different sensors in its satellite that makes this system very unique. The first one is a panchromatic sensor, known as PRISM. The second one is a 4-band (visible and near-infrared) optical multispectral sensor, named AVNIR-2. The last one is an L-band synthetic aperture radar (SAR), called PALSAR.

The characteristics of ALOS data can be seen in table 1.1.

Table 1.1 PRISM and AVNIR characteristic (source: Remote Sensing Technology Center of Japan, 2009).

Sensor	PRISM	VNIR
Spatial resolution	2.5m (at Nadir)	10m (at Nadir)
Number of bands	1 (Panchromatic)	4
Swath Width	70km (Nadir only) / 35km (Triplet mode)	70km (Nadir only)
Wavelength	0.52 to 0.77 micrometers	Band 1 : 0.42 to 0.50 μm Band 2 : 0.52 to 0.60 μm Band 3 : 0.61 to 0.69 μm Band 4 : 0.76 to 0.89 μm
Bit Length	8 bit	8 bit

The vegetation and built-up features in Rupa Bumi Indonesia (topographic map) were generated by visual interpretation using aerial photographs acquired in 1996. There is a large time gap between the time of data source and the present condition. So far, revisions on vegetation features for large scale maps were done also by visual interpretation of aerial photographs which are time and cost consuming.

Pixel based digital classification has not been used in the updating process because it generally resulted in a "salt and pepper" look of the classified image. An extensive manual editing to the classification result is needed to make it useful in the mapping process.

Recent development on remote sensing techniques is considering the neighbouring pixel to help the analysis which is called object oriented image analysis approach. This approach has been yielding better classification results particularly for high-resolution data or an image which has heterogeneous objects and great/large local brightness (Hajek, 2006, Blaschke and Stroble, 2001, Phillai et al., 2005).

This study focuses on assessing the capability of object oriented analysis for extracting vegetation features using ALOS images as an alternative approach in updating vegetation and man-made features on a topographic map. To have a better evaluation of the method, a pixel based approach was also performed as a comparison.

1.2 Problem definition

Visual interpretation using aerial photographs, which has been implemented to update man-made and vegetation features gives generally a good result. However, this process is labor intensive, time and cost consuming. The interpretation results also seem to be very general. The small and detailed patches mostly are presented as a general polygon.

More and more high resolution satellite images are available as an alternative to substitute aerial photographs as data source for mapping activities. The large amount of available data is also supported with the development of software and hardware to analyze the data.

The pixel based approach is a well known method to classify remote sensing images and it is widely implemented. Some researchers argue that this method ignores any spatial concept (Blaschke and Stroble, 2001). Phillai et al. (2005) mentioned some drawbacks in using traditional algorithms and pixel based methods to classify high-resolution data such as "inconsistent result" and "salt and pepper", which reduce the reliability of a classified image.

Recent development in remote sensing is the object oriented image analysis which takes structural, textural, contextual and spectral information into account in the analysis (Benz et al., 2004, Hajek, 2006; Yan et al., 2006).
As opposed to pixel based analysis, which operates directly on a single pixel, object oriented analysis is based on pixels grouped into meaningful image objects which are created by taking the textural, contextual and spectral information into account and using multiple scales for generating objects of different size (Definiens, 2007). The object oriented analysis comprises two parts. The first one prepares image objects by segmentation and the second one allows their classification. Many researches have been conducted regarding the land cover classification using object oriented analysis. The result shows that the overall accuracy of object oriented classification is higher than the pixel based one beside the increase of user's and producer's accuracy of most classes (Mansor et al., 2002, Phillai et al. 2005, Whiteside and Ahmad, 2005).

The capability of this approach to be implemented as an alternative approach to update topographic maps has not been tested by the Indonesian mapping agency. On the other hand, ALOS is considered by the agency as a high resolution satellite image which may give great support to mapping activities, especially to updating topographic maps. Unfortunately the utilization of this data is still limited since it are new satellite data.

The question that arises is how feasible is it to use the object oriented approach for updating the topographic map using ALOS data. This question can be answered by accessing the accuracy of the classification result. To have a better assessment, at least two methods are needed to make a comparison, in this study a pixel based approach will also be performed. How big the accuracy is improved using the object oriented approach can be judged from the comparison result.

1.3 Research objectives and research questions

The main research objective is to determine the capability of object oriented analysis and how feasible is it to be implemented as an alternative approach to update topographic maps using ALOS. The capability will be measured by assessing the accuracy of the classification result compared to the accuracy of a pixel based classification result. How big the accuracy is improved using the object oriented approach can be judged from the comparison result. Beside the accuracy, this study also tries to assess operating cost and time of the proposed and existing approaches.

The research questions:
- How accurate is the classification result using an object oriented approach?
- Does an object oriented approach better classify land-cover than a pixel based classification?
- How cost and time effective is this approach compared to the existing approach?

2. METHODOLOGY

2.1 Study area

A subset (6652x2017 pixels) from a 2.5m ALOS image is taken as the study area. The coordinates are ranging in latitude from approximately 9267120 to 9272174 and in longitude 698000 to 714660 (WGS84 UTM 48S). On the ground it covers the center of Bogor city (figure 2.1). The study is located in Bogor Municipality, West Java, Indonesia. This area covers 4 sheets of RBI 1:10.000 or equal to 4.583 km x 18.332 km (figure 2.2).
The dominant land cover types are: human settlement, dry agricultural land and mix garden.

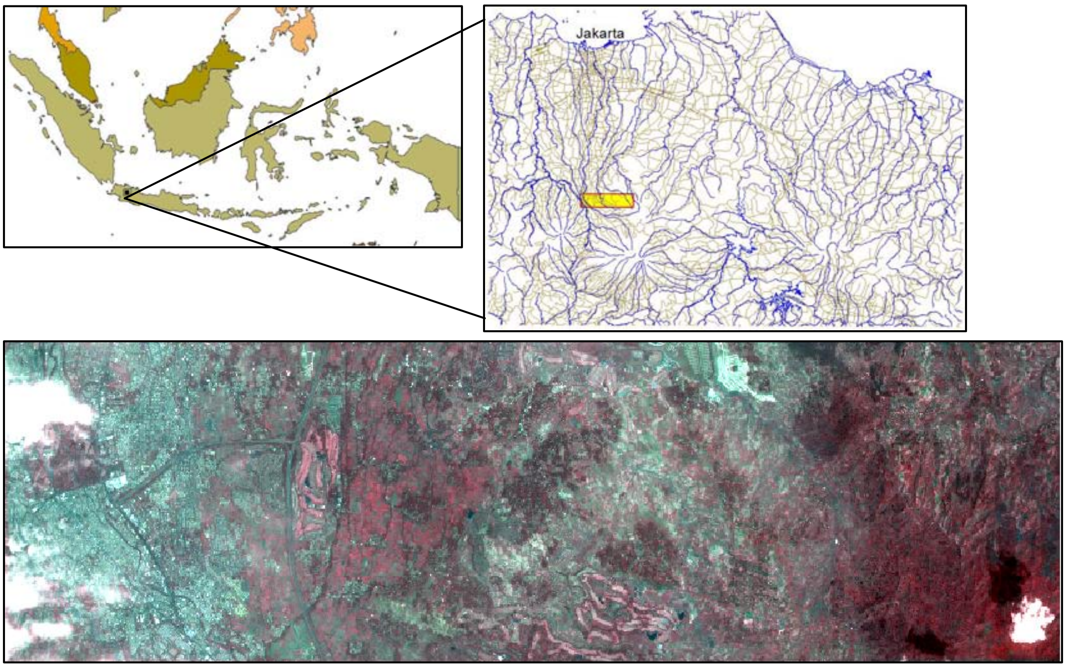
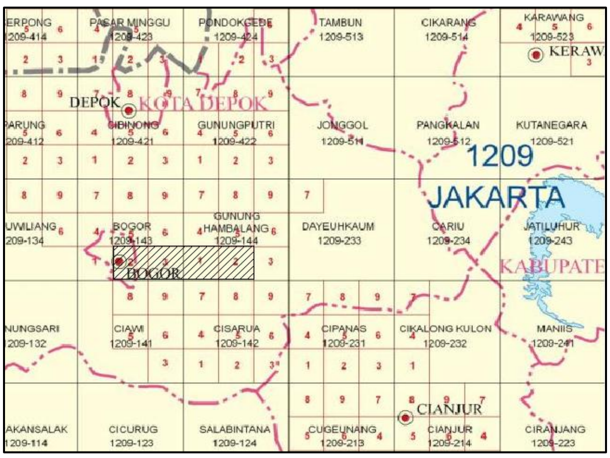


Figure 2.1 ALOS image (AVNIR) of the study area.



Study area

Figure 2.2 Rupa Bumi Indonesia Index

2.2 Materials

ALOS AVNIR and PRISM images were acquired on the 24th August 2006 and 9th October 2006, respectively. Geometrical correction was performed before applying a sharpening algorithm since there was still a mismatch between both images. Miss-registration of images results in a blurry pan-sharpened image. The correction was based on the topographic map 1: 10.000.
Training area and reference for each intended class for the accuracy assessment were taken from an existing land cover map and then verified in the field in May 2009. Even though there is a time interval of almost three years, no significant changes were happened.

For the object oriented analysis the eCognition 4.1 software package was used and ER Mapper 7.0 software was used for the pixel based supervised classification.

2.3 Methods

2.3.1 Class definition

The existing land cover classes on the topographic map (RBI) were used as the guidance for the classification of ALOS images (figure 2.3).

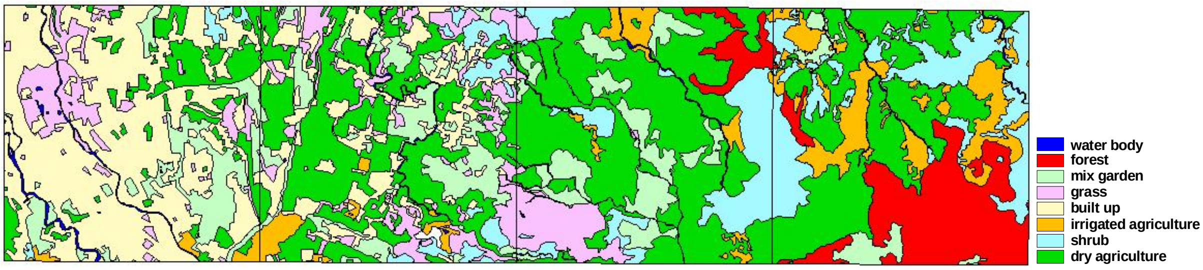


Figure 2.3 Existing vegetation and man-made features of the study area.

2.3.2 Image Fusion

In order to improve interpretability of the image, the PRISM 2.5 m resolution and AVNIR 10 m resolution images were fused. Image fusion is a combination of two or more images to obtain a better quality image. The increase in quality of the information leads to better processing such as classification or segmentation accuracies (Pohl, 1999).
There are 2 types of image fusion technique; a color related technique which involves color composition of three bands like Red-Green-Blue or Intensity-Hue-Saturation and a statistically based technique which uses arithmetic operations such as band ratios (Kumaran and Shyamala, 2002).

In this study, pan-sharpening was used to fuse PRISM 2.5 m resolution and AVNIR 10 m resolution. This data fusion technique provides not only spatial enhancement using a panchromatic band but also recombination and optional enhancement of the color information provided by the selected multispectral image bands (Han et al., 2008). The algorithm retains the high spatial information from the panchromatic band while maintaining the basic spectral information of the original multispectral data.

There are many pan-sharpening algorithms available in commercial packages. In this study, four image fusion algorithms were applied using RSI ENVI image processing software as implementation tool (figure 2.4). The algorithms are: Hue-Saturation-Value (HSV) sharpening, Brovey transform, Gram-Schmidth spectral and Principal Components (PC) spectral sharpening. The description of the algorithm of these techniques will not be discussed in this thesis since information on this can be found in existing literatures on image processing.

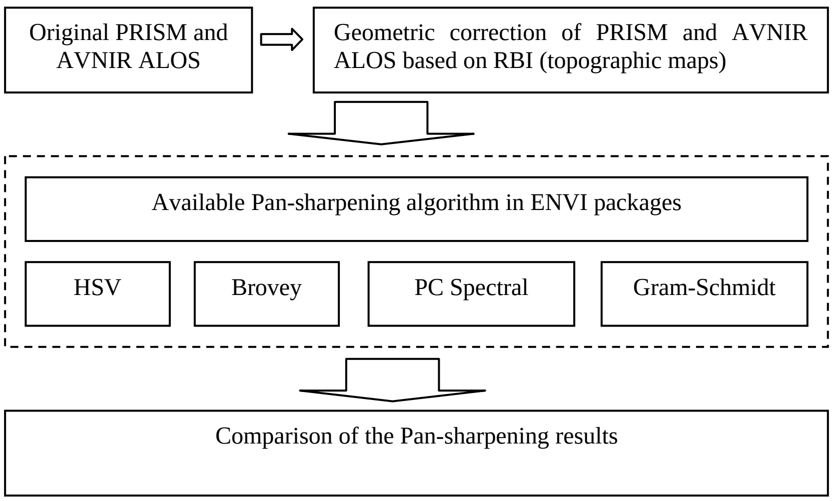


Figure 2.4 Image fusion process.

The best fusion result was used as source for extracting the vegetation features. Evaluation on selecting the best fused result was based on qualitative visual inspection by considering the color recovery and sharpness of the pan-sharpened images. Based on this visual evaluation, the result of PC Spectral pan-sharpening was selected.

2.3.3 Pixel based supervised classification

A pixel based classification method, either supervised or unsupervised, has been the conventional method for land cover mapping. Pixel based classification of multispectral data based on the single pixel, assigns a pixel into land cover classes basically according to the spectral information. Since classification using this approach is only based on the spectral information, the results are often showing a pepper and salt look because of confusion between classes in case of a high resolution image or an image with complex surface features.

In this study, a pixel based supervised classification was performed using fused AVNIR and PRISM images. It was a standard supervised classification using the maximum likelihood algorithm with ER Mapper software (Lillesand et al., 2004). Training areas are selected according to the field check representing nine land cover classes. These homogeneous areas are identified in the source image to create training areas for all of the intended classes.

2.3.4 Object oriented classification

As opposed to the pixel based analysis, which operates directly on a single pixel, object oriented analysis is based on pixels grouped into meaningful image objects. The groups are created by taking the textural, contextual and spectral information into account and by using multiple scales for generating objects of different size (Definiens, 2007). The object oriented analysis comprises two parts. The first one is preparing image objects by segmentation and the second one is the classification of the created objects.

Segmentation is the automatic subdivision of a digital image into segments that are rather homogeneous inside and have a certain shape and size. This segment is used to initially classify the generated image object by its physical properties (color, texture and form). Defining a suitable size and shape of image object primitives is the most important step for having a successful image analysis. What should be considered is that the result of the image segmentation is strongly depending on the image data and purpose of study. There are no standards for defining the segmentation parameters. As rule of thumb, good object primitives are as large as possible, yet small enough to be used as building block for the object to be detected in the image (Definiens, 2007).

In Definiens and its predecessor eCognition software, the generation of image object size is controlled by the scale parameter. This scale controls the average image object size by determining the upper limit or maximal allowed heterogeneity throughout the segmentation process. The larger the scale the more objects can be fused and the larger the size of the objects. The software uses multi-resolution segmentation which basically works as a bottom up merging technique starting with objects of one pixel. In numerous iterative steps, smaller image objects are merged into bigger ones (Benz et al., 2004). The process stops when the smallest growth of an object exceeds a user-defined threshold which is an arbitrary value (a scale parameter). The scale parameter is determined by a systematic trial and error approach. The quality of the image objects is validated by visual inspection.

eCognition Professional 4.0 was used for object oriented segmentation and classification. Segmentation was conducted at two levels to create hierarchical image objects (figure 2.5).

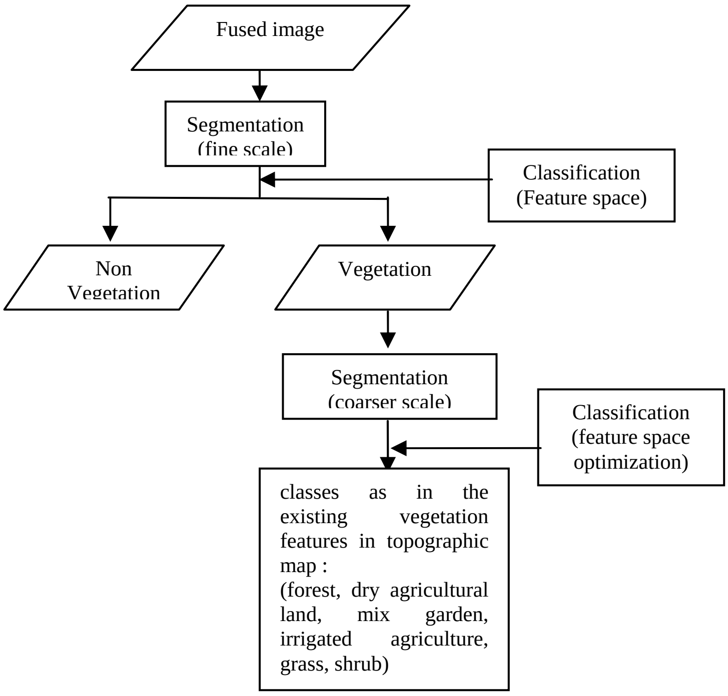


Figure 2.5 Object oriented classification of the study

At the first level, fused data were segmented at a fine scale to obtain vegetation and non-vegetation areas. At the second level, the vegetation areas were again segmented at coarser scale. The image objects then were classified into the same classes as the existing vegetation features on the topographic map, namely: forest, dry agricultural land, mix garden, paddy field, grass and shrub.

Using the same training areas as in supervised pixel based classification, the object oriented classification was performed based on nearest neighbor classification. The classification was based on a given feature space and samples representing the aimed classes. The algorithm searches for the closest sample object in the feature space for each image object. The image object will be assigned to class A if an image object's closest sample object belongs to class A (Definiens, 2007).
Defining which features should be used for the class description to classify objects into a certain class is an important step. This step was done by using the feature view window. The feature view window displays all image objects based on their feature values. By identifying visually what is presented on the screen, features which have the possibility to separate classes can be identified. Feature space optimization helps to find the features that best separate classes. The tool analyzes and calculates separability of intended features. The combination of optimum features then can be determined by the class separation distance.

Table 2.1 shows features that were used to classify the segmented image in this study. The features were spectral (mean, SD and ratio) and texture (GLCM and GLDV) features. GLCM is Grey Level Co-occurrence Matrix and GLDV is Grey-Level Difference Vector. Both are texture measurements.

Table 2.1 Spectral and texture features used in the classification

Feature	Band
Mean	Green, Red, NIR, Max. difference, brightness
Standard Deviation (SD)	Green
Ratio	Green, Red, NIR
GLCM Homogeneity	Red
GLCM Dissimilarity	All directions
GLCM Mean	Red
GLCM Standard deviation	All directions
GLDV Angular 2nd Moment	Green, all directions
GLDV Entropy	Blue, Green
GLDV Mean	Blue, Green, NIR, all directions
GLDV contrast	Red

2.3.5 Accuracy assessment

The classification accuracy for both classifications was undertaken using the matrix of confusion. Overall, user's and producer's accuracies were determined by means of error matrices as well as the KHAT statistic (Congalton and Green, 1999). The accuracy was assessed using reference from ground information in the field and also from finer spatial resolution images (pan-sharpened IKONOS) which have a spatial resolution of 1 m. 215 samples were generated with a stratified random sampling to cover all obtained classes (McCoy, 2005). 32 samples were used as training area

The flow chart of the study can be seen in figure 2.6.

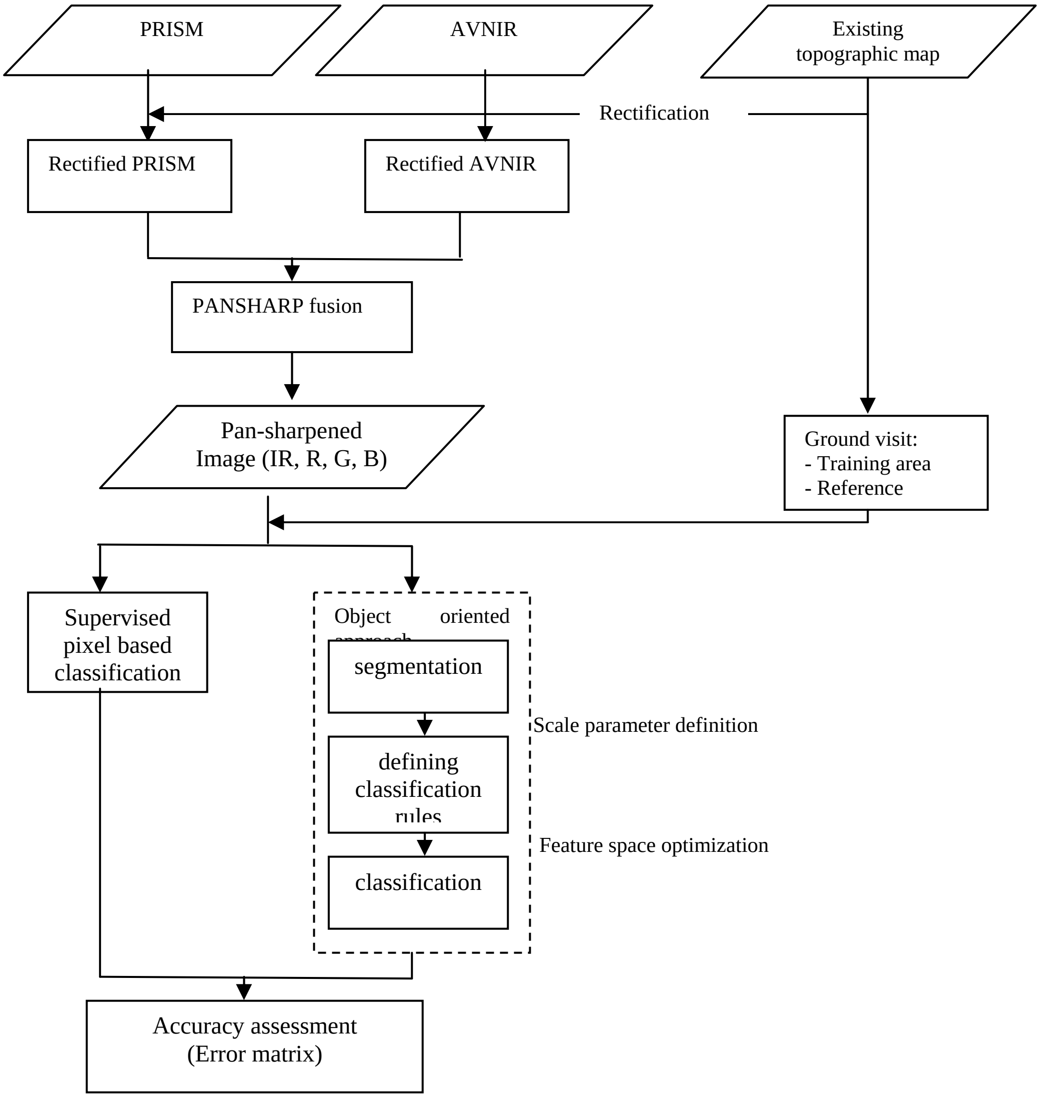
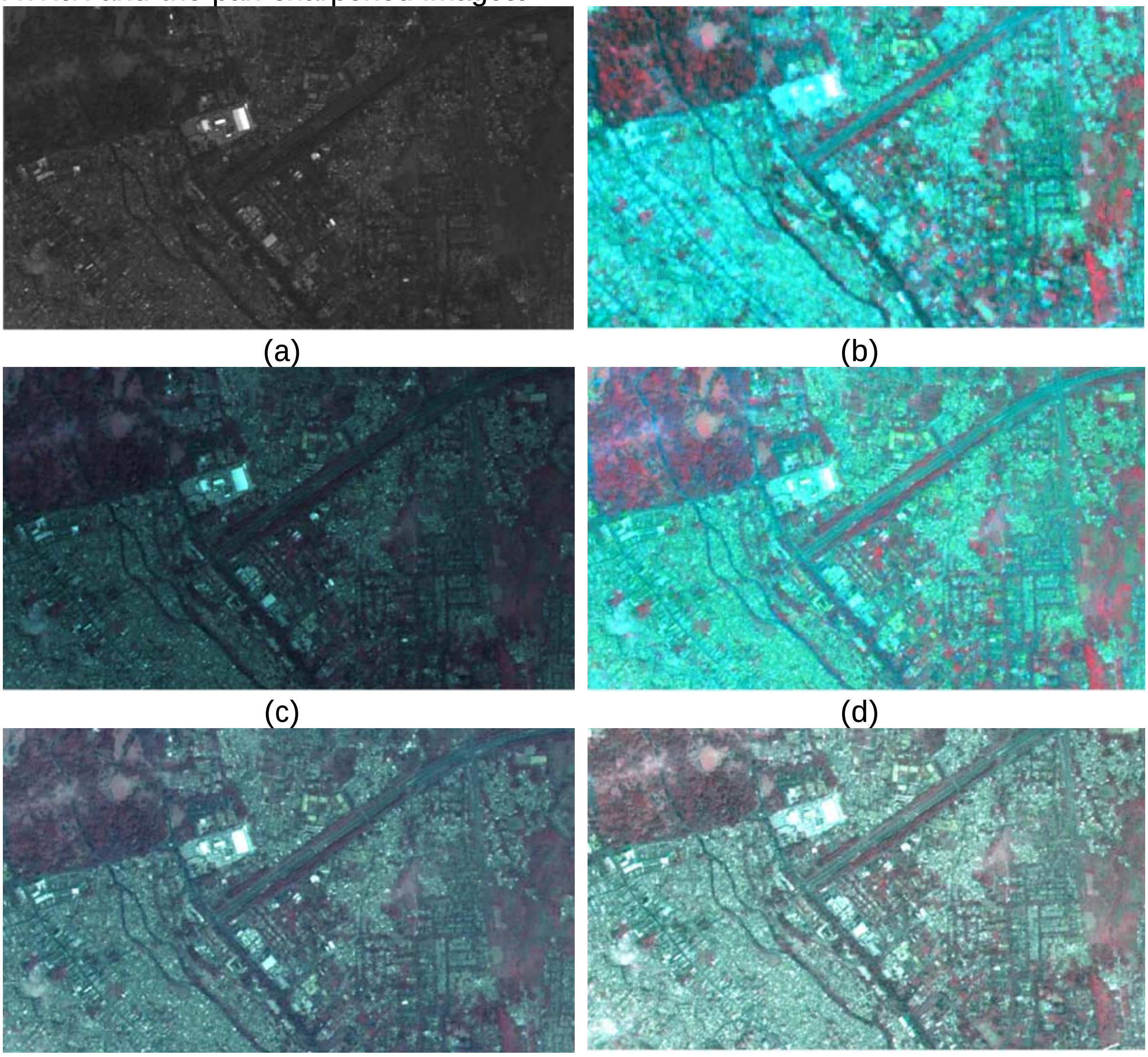


Figure 2.6 General process of the study

3. RESULTS AND DISCUSSION

3.1 Image fusion

The fusion resulted in a pan-sharpened ALOS image with a 2.5 m resolution and 3-4 multispectral bands. Figure 3.1 shows a sub-scene of the PRISM, AVNIR and the pan-sharpened images.



(a) (b)

(c) (d)

(e) (f)

Figure 3.1 Image fusion of ALOS images, original panchromatic (a), original multispectral (AVNIR) (b), result of HSV sharpening (c), result of Brovey sharpening (d), result of Gram-Schmidt sharpening (e) and result of PC-Spectral sharpening (f).

Comparison of the pan-sharpened results to determine the best result was based on two criteria: color recovery and sharpness of the result image as the pan-sharpened image should be similar in color with the original AVNIR ALOS image and should also be as sharp as the original panchromatic (PRISM) ALOS image.

At a glance, Brovey transform seems to be the best result. The result shows a bright color similar to the multispectral image. However, from sharpness point of view, the result is blurred. HSV sharpening produces a dark image, but the color recovery is poor. Gram-Schmidt sharpening and PC spectral sharpening gave almost the same result. Sharpness of both images is very good. The difference is that PC spectral sharpening gave a better color contrast. Another advantage using this algorithm is that it may use any number of selected input bands. Brovey Transform and HSV algorithms can only allow three bands to be fused. Based on the visual comparison on sharpness and color recovery, the best result in this study was obtained from the PC spectral algorithm and the fused image using PC spectral sharpening was used as the source data for the classification process.

3.2 Pixel based classification results

The ALOS fused image was classified with the Maximum Likelihood algorithm. It can be seen that the pixel based classification contains many small groups of pixels (grainy) or individual pixels (figure 3.2).

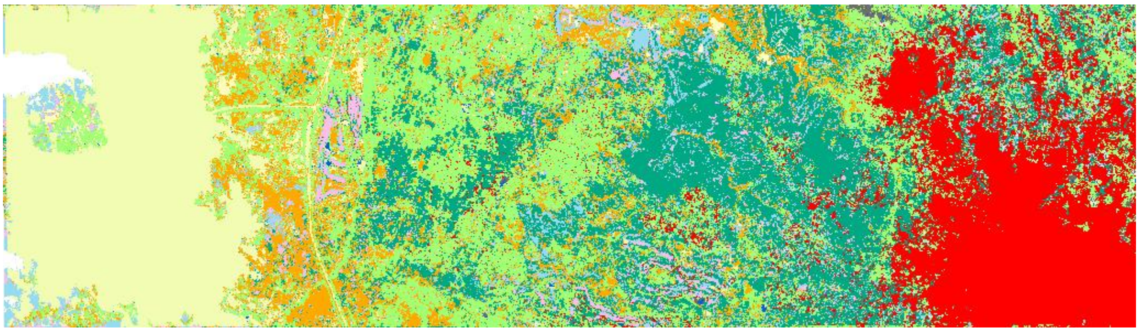


Figure 3.2 Pixel based classification result

Table 3.1 Summary of confusion matrix for the accuracy of pixel based classification.

	Accuracy	
Class name	Producer's (%)	User's (%)
Built up	45	68
Shrub	29	36
Forest	100	75
Grass	71	88
Mix garden	71	72
Irrigated agriculture	100	23
Dry agriculture	56	66
Water body	69	100
	Overall accuracy = 63%	
	KHAT = 0.60	

Some classes show very poor accuracy such as shrub and irrigated agriculture. Shrub was confused with other classes especially grass. Both classes have relatively the same tone, which makes it difficult to differentiate the classes only by their digital value.

The poorest accuracy is found for the irrigated agriculture class with 23 % user's accuracy although it has producer's accuracy of 100%. It means that even though 100% of the irrigated agriculture has been identified correctly as "irrigated agriculture", only 23 % of the areas identified as the said class are actually "irrigated agriculture" on the ground. Irrigated agriculture is confused with the other classes, especially dry agriculture since some parts in the image also have the same tone and pattern. The vegetations are the same, the difference is only the watering practice in the field (figure 3.3).

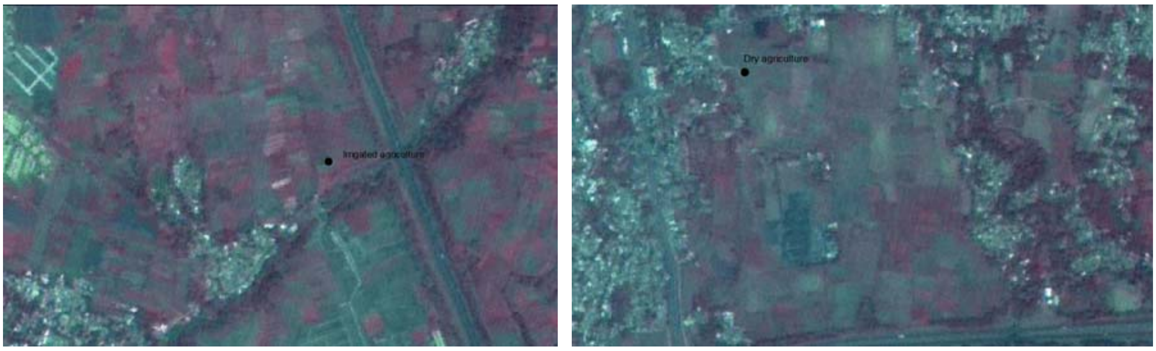


Figure 3.3 Example of irrigated agriculture (left) and dry agriculture (right) in the image which have similar tone and texture.

3.3 Object oriented classification results

In this study, segmentation is conducted at 2 levels using different scales to construct hierarchical image objects. First level of segmentation aims to separate vegetation and non-vegetation (built-up and cloud) (figure 3.6). This level was segmented using a scale parameter of 50 (shape 0.2 and compactness 0.5).

An example of a feature which has the possibility to separate vegetation and non-vegetation can be seen in figure 3.4**.** The feature (GLCM Mean all directions Red) showed that non-vegetation is visually distinguishable and it is used in the feature space for the classification since the combination of the features has the highest separation distance.

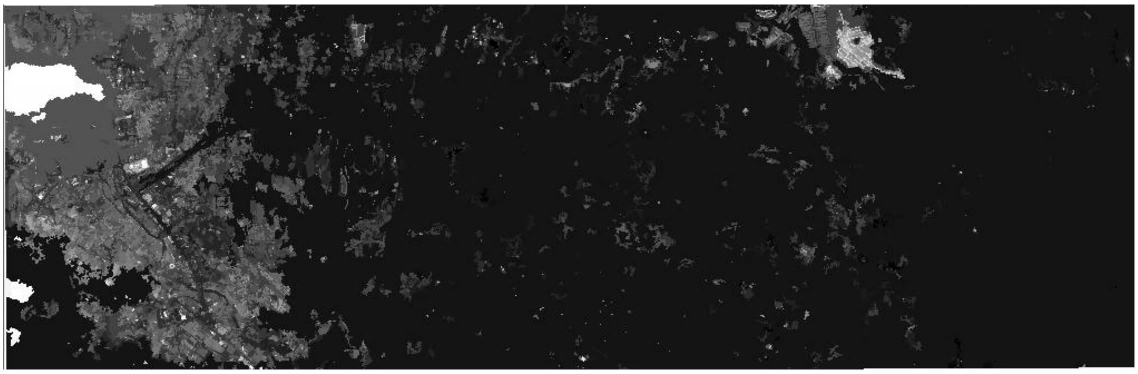


Figure 3.4 Feature of GLCM mean all dir Red which has high possibility to distinguish vegetation and non-vegetation.

A combination of 6 features (GLDV Entropy Green, Ratio NIR, Stddev Green, GLDV Ang. 2nd moment, GLCM StdDev and GLCM Mean Red) was the optimum one to separate vegetation and non-vegetation with a separation distance of 1.876 (figure 3.5). Spatial distribution of vegetation and non-vegetation can be seen in figure 3.6.

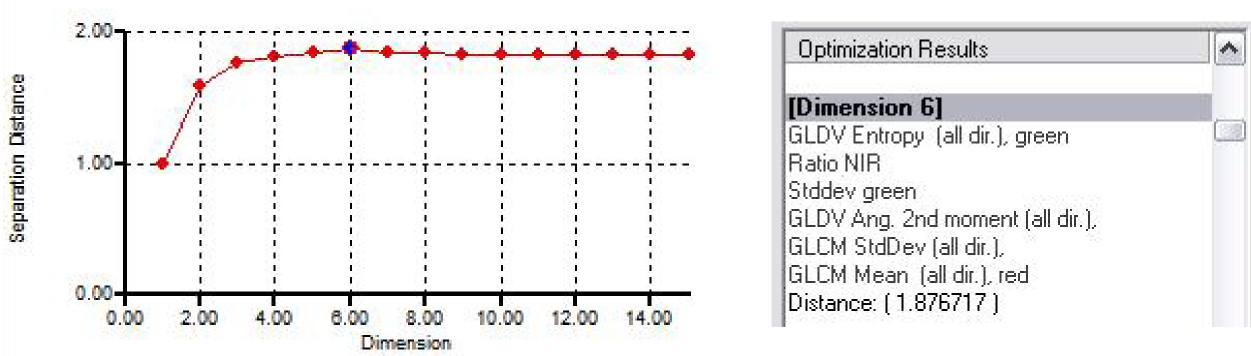


Figure 3.5 Optimum feature space to separate vegetation and non-vegetation (left) and optimum combination of features (right)

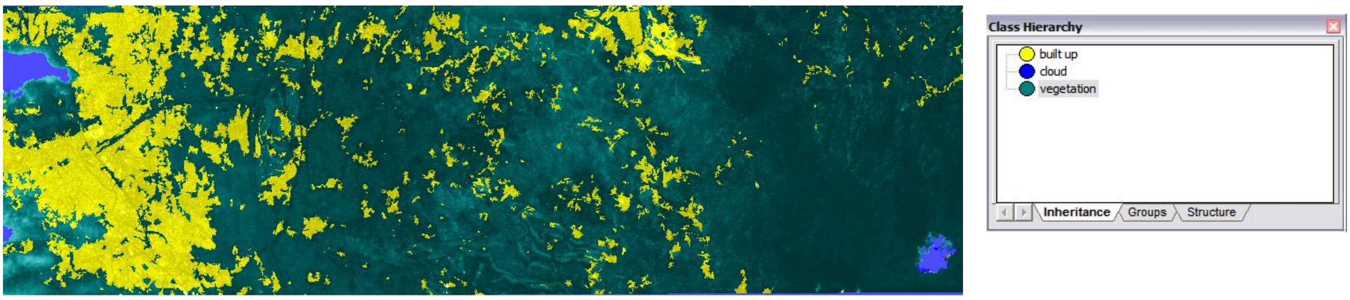


Figure 3.6 Spatial distribution of vegetation

The second level segmentation aims to separate the vegetation areas into six classes: the same as the existing vegetation classes in the topographic map (figure 3.8). After several testing, a scale parameter of 90 (shape 0.1 and compactness 0.7) was chosen to segment the vegetation class. The parameters

were determined by trial and error until the desired objects are isolated. The quality of the image objects is validated by visual inspection. This level was segmented only within vegetation areas by using a coarser scale parameter and by classification based segmentation tools.
Based on feature space optimization, a combination of 14 features was used in the feature space to classify the resulting segments. This combination has the highest separation distance (1.207) among other combinations (figure 3.7). The resulting map with the 6 vegetation classes, built-up and water is shown in figure 3.8.

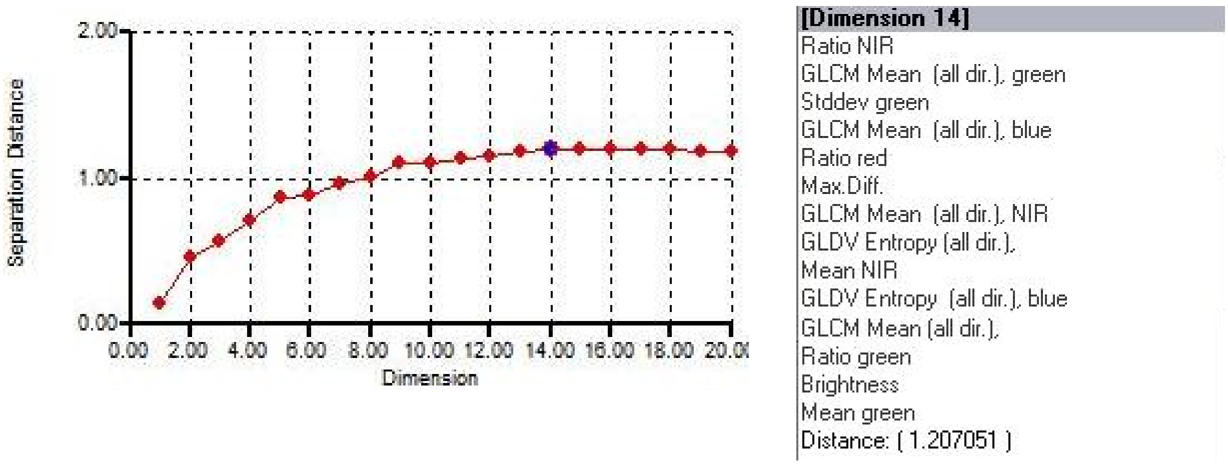


Figure 3.7 Separation distance and features combination used to classify segments of level 2.

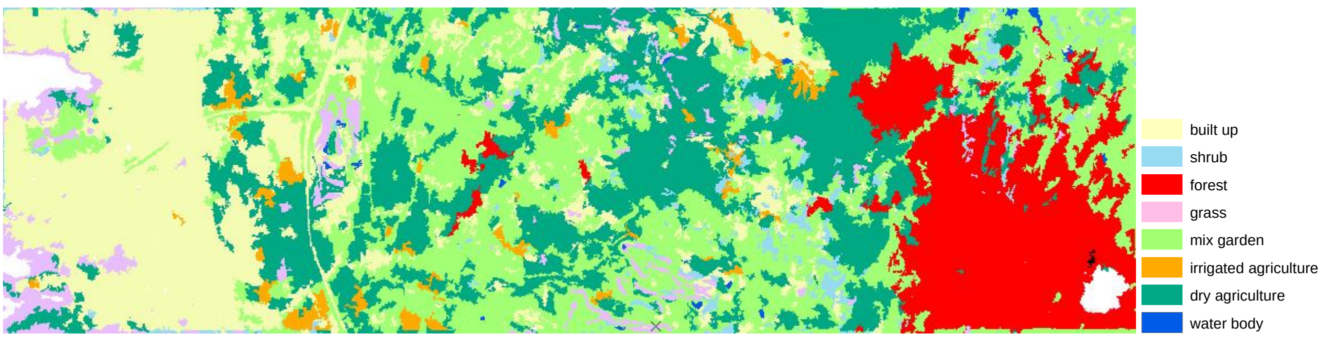


Figure 3.8 Object oriented Classification results of level 2

Accuracy assessment in table 3.2 shows a satisfactory result as all classes have a high accuracy. Forest was classified correctly by having 100% producer’s and user’s accuracy. Shrub has better accuracy compared to pixel based classification with 86% and 81% for producer’s and user’s accuracy, respectively. Texture information which is used as the feature space in the classification can be the reason for this high accuracy. It is difficult to distinguish shrub and grass by using the tone only; texture information is helpful to better differentiate those two classes.

Even though giving a satisfactory result, this object oriented analysis is still a preliminary study for updating topographic maps using ALOS imagery. Operational ways to use the approach for large areas should be further explored.

Table 3.2 Summary of confusion matrix for the accuracy of object oriented classification.

Class name	Accuracy	
	Producer's (%)	User's (%)
Built up	93	81
Shrub	86	81
Forest	100	100
Grass	85	100
Mix garden	90	96
Irrigated agriculture	100	85
Dry agriculture	94	97
Water body	100	100
	Overall accuracy = 92%	
	KHAT = 0.91	

3.4 The comparison of pixel based and object oriented analysis results

Figure 3.9 is an example of a classified image by a pixel based and an object oriented approach. It can be clearly seen that the object-based approach results are smoother and yield homogeneous polygons compared to the pixel based approach, which appears blurred because of the grainy effect.

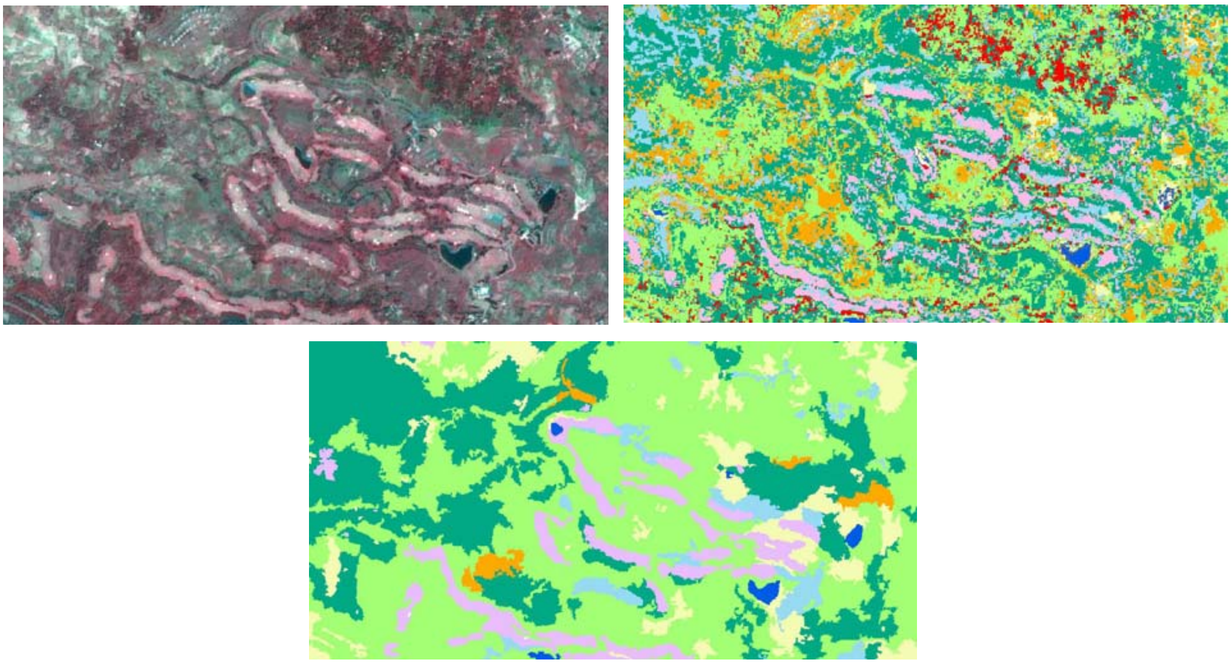


Figure 3.9 Example of classification results. Fused image (upper left), classified by pixel based (upper right) and classified by object oriented method (bottom).

The classified image derived from object oriented analysis is closer to human visual interpretation. A visual comparison of both results shows the difference between classifications. Generally, the distribution of the classes is similar or has the same pattern. The visual difference is obvious in the heterogeneous area, such as buildings which mix with garden or trees.

eCognition software allows the manual correction of the classification results in an easy and friendly manner. This is a very quick and easy part during the visual control. Based on the segmentation result, wrongly classified image objects are clearly identified and easily corrected. Some corrections have been made in this study. This advantage has improved the classification accuracy.

Object oriented approach has several advantages compared to pixel based approach such as: image object can be more easily integrated or overlaid with other vector data (GIS ready); segmentation of an image into objects is similar to how humans comprehend the landscape; image objects have useful features (texture, shape, relations with other objects) that single pixels lack (Hay and Gastilla, 2006). Those aspects influence the accuracy of the classification. From the results of the confusion matrix, it can be concluded that the object oriented classification obtained a higher overall accuracy than the pixel based classification, 92% and 63% respectively. This was also the case for the individual accuracies and the KHAT statistic.

The accuracy was evaluated by stratified random points which is generally recognized to be more trustworthy than an evaluation using homogeneous areas (Gao and Mas, 2008). It may not be true for the pixel based approach because of the great variation in local brightness. In object oriented analysis great brightness variation of a certain class is merged to become one homogeneous image object. Since pixel based approaches do not take the surrounding pixels into account, the accuracy of a pixel based approach could be underevaluated.

3.5 Prospect for updating topographic maps

The other advantage of using the object oriented analysis beside the higher accuracy result is in the cost and time effectiveness, which makes this approach more attractive than the existing approach used at BAKOSURTANAL to update the map.

A comparison was made on cost and time of map producing. Calculation of data source cost and processing times spent for map producing were performed for both existing and proposed approaches. The comparison was based on the presently valid work unit prices (Bakosurtanal, 2006).

3.5.1 Data source

Although the source data of the existing topographic map of the study area were aerial photo's, airborne InSAR data has been the main source data for mapping activities in BAKOSURTANAL in the last few years. It means that updating and revising topographic maps will most probably also use that source. In this study, the data source cost estimation for the existing approach refers to the real survey cost mapping for airborne inSAR (Klaar and Amhar, 2001). Data source cost for mapping at scale of 1:25.000 is US$ 26/km^2. For the study area (4.583 km x 18.332 km), the source data would cost US$ 2182.74. Another reference, as a comparison, Konecny (1999) mentioned that land use mapping cost using aerial photographs for 1: 10.000 is US$ 520/km^2 and US$ 150-180/km^2 for 1: 25.000 scale topographic maps.

In this study, ALOS imagery is proposed to be the source for updating the topographic map. Each scene of ALOS PRISM image (35 km x 35 km) and ALOS AVNIR image (70 km x 70 km) costs JPY ¥ 25000 (US$ 250). Because of the pan-sharpening process that fuses these two images, a total of US $ 500 will be needed.

3.5.2 Processing

According to BAKOSURTANAL's standard work unit price (Bakosurtanal, 2006), the cost to generate a thematic layer per sheet at the scale 1: 25.000, equal to 13.75 km x 13.75 km, is IDR 2700000 or US$ 272.7 and it takes 90 working hours. The process includes interpretation, classification and digitizations (table 3.3).

Table 3.3 Cost calculation for visual interpretation per map sheet (source: Bakosurtanal, 2006)

Processing unit	Time (hour)	Cost/hour (IDR)	Total cost (IDR)
Interpretation and data analysis	35	30000	1050000
Thematic classification	40	30000	1200000
Digitizations	15	30000	450000
Total	90		2700000

Cost assessment for object oriented analysis can be estimated based on BAKOSURTANAL's work unit prices for digital analysis activity which is IDR 759000/scene or US$ 76.6/scene. In this assessment, SPOT imagery was used as standard reference image for it has the same spatial resolution of 2.5 m (panchromatic) and 10 m (multispectral) and relatively the same coverage (60 km x 60 km) (Bakosurtanal, 2006). It includes geometric/radiometric correction, classification and post classification (table 3.4). It takes 46 working hours.

Table 3.4 Estimation cost for object oriented processing (source: Bakosurtanal, 2006)

Processing unit	Time (hour)	Cost/hour (IDR)	Total cost (IDR)
Geometric correction	5	30000	150000
Classification	21	17000	357000
Post classification	21	12000	252000
Total	46		759000

The comparison of the tables showed a reduction of almost 50% in processing time for object oriented compared to the manual updating process.

3.5.3 Total Production Cost

Both calculations on the data source and processing are summarized in table 3.5. This table clearly shows that object oriented approach in combination with ALOS data is more time and cost effective compared to the existing updating approach.

Table 3.5 Summary cost calculation for proposed and existing approaches

Item (US$/km^2)	ALOS + Object oriented	Aerial photo/inSAR + visual interpretation
Data source	0.1	150 (AP) or 26 (inSAR)
Processing cost	0.021	1.44
Total cost	0.121	151.44 (AP) or 27.44 (inSAR)

The ALOS image has a number of advantages such as high frequency of revisit (46 day), large coverage, cost effective compared to other high resolution imagery. These advantages give a great promise for using this type of images extensively in Indonesia. Large coverage of ALOS image may cover huge area of Indonesia in an effective manner. Especially in cases where it is difficult to take aerial photograph from airplane and for inaccessible or isolated islands.

Considering the performance of the object oriented analysis on classifying land cover and the advantages of ALOS imagery, the combination of those may give great possibilities to be applied for updating topographic maps for the whole Indonesian areas.

Good quality of land cover delineation is essential to have an accurate map. This challenge can be answered by object oriented analysis. Segmentation in object oriented analysis is able to delineate boundaries between classes with a better quality compared to visual interpretation. Humans have a visual limitation on delineating objects as compared to a machine. Visual interpretation generally gives a general delineation of objects while object oriented analysis gives more precise boundaries, the objects are distinguished and delineated very well based on their boundaries (figure 3.10).

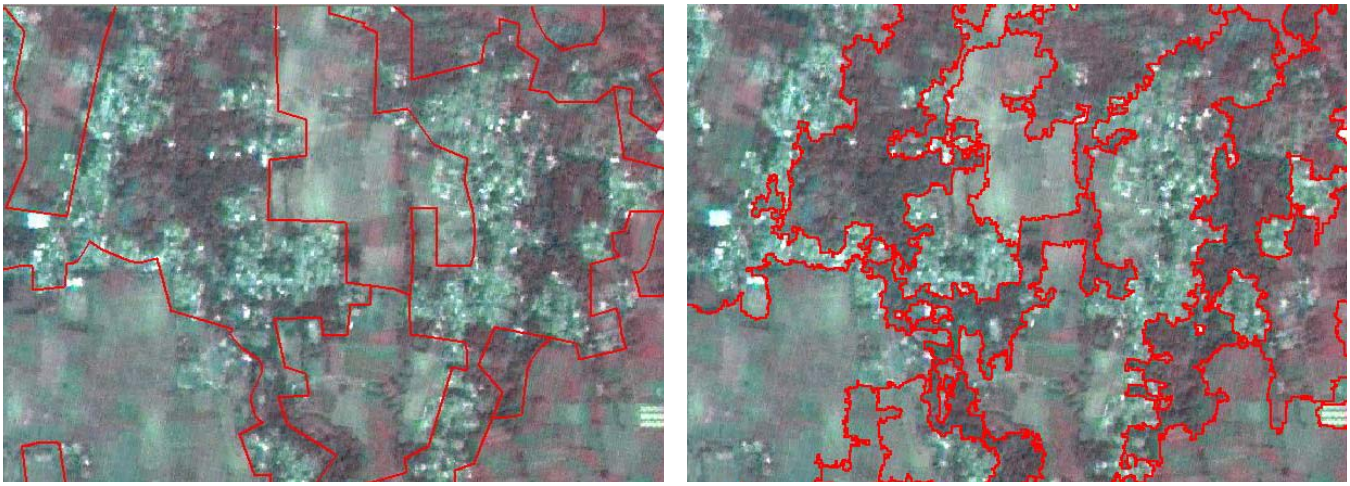


Figure 3.10 Comparison of objects delineated by visual interpretation (left) and by computer (right)

With the promise of high classification accuracy, time and cost effectiveness, the combination of object oriented analysis and ALOS imagery can be considered as the potential approach for updating topographic maps in the future.

Even though fusion of ALOS imagery, 10 m x 10 m multispectral + 2.5 m x 2.5 m panchromatic, according to the mapping specification of topographic maps is only suitable for updating topographic maps 1:25000 (BAKOSURTANAL, 2003), it was found that this approach could be used to update land cover on 1: 10000 scale topographic maps since detail and class definition of land cover features for both scales are the same.

4. CONCLUSION

The main objective was to present a possible approach for updating topographic maps in Indonesia. An object oriented approach in extracting land cover classes on the fused image of ALOS-AVNIR and ALOS-PRISM was tested. The best fused image was created using the PC-spectral sharpening algorithm and both pixel based and object-oriented classification were performed on this fused image to produce a map of the 8 main land cover types in the study area. Comparison of the accuracy assessment result shows that the object oriented image analysis gave a higher overall accuracy (92%) than that produced by the pixel based approach (63%).

The use of ALOS imagery instead of the more expensive aerial photo's or airborne InSAR data gives a tremendous reduction in cost. Using ALOS imagery as the data source will cost only US$ 0.121 per km^2 compared to US$ 151.44 for aerial photo's or US$ 27.44 for InSAR data. Also reduction of almost 50% in processing time was achieved compared to the manual updating process.

Object oriented analysis in combination with fusion of ALOS AVNIR and ALOS PRISM showed a promising technique for updating topographic maps for several reasons:

- It gives a better classification accuracy compared to the pixel based approach;
- It is much more time and cost effective than the existing updating approach;
- It has great possibilities to be applied over large areas (whole Indonesia areas);
- It delineates objects better than a visual interpretation;
- It allows manual corrections in an easy and friendly manner to enhance classification results.

However, the finding presented here should support classification of large areas. Moreover, operational ways to use the object oriented approach to update topographic maps should be further explored.

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