Identification of Multistrata Vegetation using High Resolution Satellite Imageries in Sumberjaya, Lampung, Indonesia

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By

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Abstract

Coffee farming practices in Sumberjaya, Lampung, Indonesia, have environmental implication to the soil and water conservation in the area, especially with regard to soil erosion. The types of coffee gardens which include the vegetation structure complexity and the canopy cover become the initial aspect of identification before further studies related to its configuration along with other land cover types on the landscape is further explored. High resolution satellite images have potential for such detailed level of identification taking into account different remote sensing approaches to be applied in fulfilling the objectives. Two properties of remotely sensed data, spectral and spatial properties are the starting point in the application of the methods which eventually leads to the integration of both properties. Both approaches are realized through various techniques of image enhancements and image segmentation, followed by supervised classification procedures. Various transformations based on spectral pixel values are explored, *i.e.* PCA, NDVI, IHS and resolution enhancement with image fusion. In addition, spatial approach, namely textural analysis and segmentation, are applied. This latter approach is useful in taking into account the high variability of spectral values in neighboring pixels, which is inherent to the high resolution satellite images.

The results show that for a detailed classification of coffee gardens in the study area, with standard pixel-based classification a reasonably good accuracy is obtained. Integration of the pixel-based approach and the spatial-based approach of segmentation using majority rules gives an increased overall accuracy. However, the discrimination of several classes of coffee gardens with moderate canopy density and variable density of shade tress, is not fully satisfactory. Ways to improve their classification are indicated.

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1 Introduction

1.1 Background

The vast coffee farming practices in Sumberjaya catchment, Lampung, Indonesia have been occupying 60 % of the area in 1990 (Syam, *et al.* 1997). Along with the development of coffee farming systems, ricefield cultivation, occupying the river valleys of the area has also been maintained by the farmers. The dominance of coffee systems and ricefield characterizes the landscape configuration in Sumberjaya catchment. Through time changes take place and the biggest reduction of coffee gardens took place during the reinforcement of reforestation program by forestry authority starting in mid 1970s. *Calliandra* was introduced for the replanting program at about 6000 ha. During late 1990s farmers who lost their lands started to return and open up the reforested areas and rejuvenated the old coffee stumps. The extent of conversion is up to the hilly areas into the remaining natural forests. The land conversion to coffee gardens on steep slopes up to100 % or more and into the protection forest, brought concerns in relation to soil and water conservation in the area from the Forestry Department.

A study is conducted by the International Centre for Research in Agroforestry-Southeast Asia Programme (ICRAF SE Asia) in collaboration with other organizations, in which it seeks to take an overall look at the effects of coffee farming practices to the soil and water conservation in the catchment by taking into account the land use changes in the area. The project also tries to develop a negotiation support model which incorporates the concerns of all the stakeholders in the area, towards a more environmentally sound watershed management. One part of the project is trying to study the configuration of vegetation cover in the landscape and its role in the extent of erosion in the area. And since coffee gardens are the major vegetation cover, their presence in different types, related to vegetation complexity and management aspects, becomes the initial issue of the investigation.

Remote sensing technology in the monitoring of land cover has been widely known. Included in the utilization of this technology is various vegetation and crop studies. The provision of data by satellite images relevant to these studies has proven to be of significant importance, and the progress in terms of more sensors, better spatial, spectral and temporal resolution provided by remote sensing technology gives more reliable data. The availability of high spatial resolution down to 4 m and 1 m resolution is expected to provide opportunities to explore various image processing and GIS methods for the study concerning coffee gardens and other vegetation types existing in Sumberjaya.

1.2 Research objectives and questions

The main objective of this study is to identify and inventory multistrata vegetation with the emphasis of coffee gardens as the major crop in Sumberjaya area using remotely sensed data.

In order to reach the objectives, three specific questions have been developed

1. How many types of vegetation classes can be differentiated in Sumberjaya area ?
2. To what extent the vegetation strata, with the emphasis of coffee gardens as the major crop, can be differentiated ?
3. What approach(es) can optimally be applied in reaching the objectives using available data and resources ?

1.3 Description of the study area

1.3.1 Sumberjaya catchment

Sumberjaya catchment is located in the western part of Lampung Province, Sumatera, Indonesia (Figure1.1). The island is the third biggest island in the country and is located in the western part of the archipelago. It is part of a bigger catchment, Way Besai catchment. Sumberjaya catchment nearly coincides with the administrative boundary of *Kecamatan* Sumberjaya (Sumberjaya sub-district). It covers an area of approximately 541.9 km^2 . (Budidarsono *et al*, 2000). The elevation ranges from 500 to 2000 m asl. The soils on which coffee garden dominates are moderately developed soil (Inceptisol) with fine texture and somewhat stable to weak aggregates. The color of the soil is pale to reddish , which indicates low organic matter content, low soil fertility and somewhat low pH. (Fahmudin & Kusworo, 2000, cited in Budidarsono *et al*, 2000). The soil in this area is prone to erosion due to the undulating and hilly physiography, high intensity and high annual rainfall ($\pm$ 2000 mm) and weak consistency (Budidarsono *et al*, 2000).

Figure 1.1 The location of Sumberjaya catchment, in Lampung Province, Sumatera.

1.3.2 Coffee gardens in Sumberjaya catchment

1.3.2.1 Historical perspectives

Since early 1900 extensive deforestation has taken place in Sumberjaya catchment. The first migrant settlers and main actors of forest clearing in this catchment was Semendo people from the north (South Sumatera). They clear-cut the land and slopes and planted the cleared area with coffee . After a rapid decline of harvesting, they abandoned the plots and let them grown by secondary growth. Commonly, after a period of 15-30 years they reopened those plots and the same cycle repeated.

Sundanese and Javanese from Java started to join the migration in Sumberjaya in 1950s, along with government transmigration program, which basically focused on redistributing the dense population in Java to other islands in the country. With their knowledge of irrigated ricefield cultivation, these spontaneous migrants came to the valley bottoms to utilize the lands for ricefield cultivation (*sawah*). Intrigued by the high price of coffee, Javanese and Sundanese started also the coffee farming practices. As Semendo people had done for years, Javanese and Sundanese went up to the slopes and opened the lands for coffee. This led to a massive deforestation starting in early 1970s to 1990s. Forest cover decreases from 57% to 11% from 1970 to 1990 (Lumbanraja *et al*, 1998, cited in Verbist, 2000).

Starting from 1970s, the government of the Republic of Indonesia through its regional forest authority offices, has implemented the reforestation program in the area to ensure the watershed protection. In recent decades the program even included the destruction of coffee gardens and eviction of the settlers occupying areas destined as state forest zone. However, in late 1990s, while the reform spirit dominated the political situation in the country, farmers who had lost their lands in the reforestation program returned to the area and encroached the slopes to restart planting coffee. The reforestation program introduced tree species like pine, *sungkai, sonokeling, Calliandra* and *Gmelina*. Therefore, in some areas some of these species are found in between the coffee plots or even used as shade trees in the coffee gardens.

1.3.2.2 The growth of coffee gardens areas

Coffee gardens as the major land cover in Sumberjaya catchment change in terms of areas and percentage of areas compared to the other land covers in the area. As in the last ten years the statistics of Sumberjaya sub-district shows that the areas of coffee gardens in 1999 become twice as big as that in 1990 (99.2 %). Figure 1.2 shows the growth of coffee garden areas from 1990 to 1999 in Sumberjaya sub-district (*Dinas Perkebunan*, Lampung Province, 1990-1999).

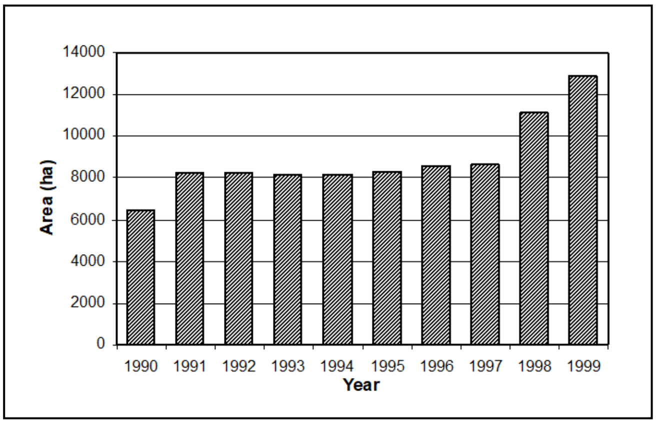


Figure 1.2 The growth of coffee gardens areas in Sumberjaya Sub-district *(Kecamatan* Sumberjaya*)*, 1990-1999 (*Dinas Perkebunan*, Lampung Province, 1990-1999)

A study of land use change in West Lampung area, where Sumberjaya catchment is located, was conducted by Syam *et al*, 1997. This study shows that plantation areas (which are mostly coffee in the context of this area) grew from 0 % in 1970 to 60 % in 1990. The development of plantation areas implies a land conversion from forest, as it can be seen from the decrease of forest areas from 69% in 1970 to 30 % in 1990. Figure 1.3 shows the land cover changes from 1970 to 1990 in the district of West Lampung as area percentage. (Syam *et al*, 1997)

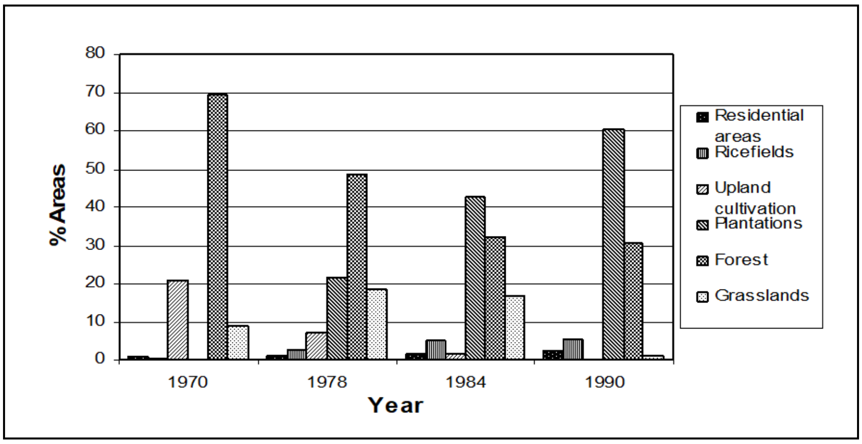


Figure 1.3 Area percentages of various land cover types in West Lampung, 1970-1990 (Syam *et al*, 1997)

1.3.2.3 Coffee garden typology

As reported by Budidarsono *et al*, 2000, the coffee farming practices in Sumberjaya fall into different classes based on three categories:

1. **Vegetation Structure complexity**

   Based on this category coffee gardens fall between two extremes: simple mono culture coffee system and complex agroforest coffee system

2. **Management intensity**

Three types of management are found in Sumberjaya with the characteristics described below:

a. Traditional-Pioneer system, characterized by:
- Without fertilizer and other external farm input, extensive system
- Short productive lifetime cycle. When the yield is decreasing to an unacceptable level, farmer will abandon the plot or hand over to others, and open new plots. This implies shifting cultivation technique.
- Weeding and cleaning are intensively done in the first five years
- Monoculture coffee, without shade trees

b. Semi intensive system

In many cases it is done by migrants who bought old coffee gardens from other farmers. The main characteristics are:
- Low external input technology : fertilizer application of 100-300 kg/ha/yr
- Weeding, cleaning the buds and pruning (to keep the trees not higher than 2 m)
- Productive life time is kept as long as possible, with efforts of: replanting, the use of "*rorak*" (holes in the ground to trap litter and sediment)
- Shade tree is not a must

c. Intensive system
- Intensive measures to increase productivity, like high rate of fertilization of 1 ton /ha/yr
- Crop care activities include grafting and tree rejuvenation

3. **Tenurial Security**

Two patterns are recorded in Sumberjaya:
- Coffee planted on privately owned lands
- Coffee planted on state forest land

The criteria under 'vegetation structure complexity' and 'management intensity' will be used as the bases by the author to define the different classes of coffee gardens in this thesis (Section 3.1.1.)

1.4 Environmental impacts of coffee farming practices

Coffee gardens in Sumberjaya cover most of the area regardless the slopes. Land conversion to coffee plots exists up to the mountainous area in the boundaries of the catchment as well as at the foothills around Bukit Rigis (located in the center of the catchment). Coffee gardens are located up to the slopes of > 100% . As described in the previous section, the management of the coffee farming requires intensive maintenance including fertilization as well as weeding.

Research on plot erosion measurement was done in the area (Sinukaban *et al*, 2000) and the result shows that clean weeded coffee gardens have the highest soil erosion compared to the other land use classes (unweeded coffee gardens, multistrata coffee gardens, reforestation areas of *Calliandra* and natural forest). Unweeded coffee gardens show a relatively lower erosion rate due to the grass and litter cover which effectively protects the soil from raindrop impact.

Natural forest and reforestation area show the lowest erosion rate despite the slopes of those two classes being much steeper than those of the other land use classes.

The massive land conversions towards monoculture plantation during the period of 1970s until early 1980s influence the runoff characteristics in the area. Sinukaban *et al,* 2000, reported that there was an increase of surface runoff and base flow (as the percentage to rainfall) in the Way Besai catchment during those periods. However, it was concluded that soil water retention in the area was maintained due to management improvement and soil conservation measures like crop residue mulch, slit pits, unweeded coffee gardens.

1.5 Scope of the study area

Regarding the research problems in Sumberjaya catchment and the involvement of ICRAF through its project in the area, a subset in the catchment was chosen where the detailed study takes place. This subset becomes the study area of this thesis. The study area also determined the scope of the satellite imageries as the main data source for this thesis.

The study area is located in the northern part of Sumberjaya catchment around the district town of Fajarbulan, which is the downstream part of the catchment. The elevation of most of the study area, is located on 800-900 m asl, while in the northwestern part and south eastern part of the study area the elevation can reach up to 1500 m asl. The physiography is undulating. The slopes range from 0 to >100%. The internal terrains are dissected by river valleys.

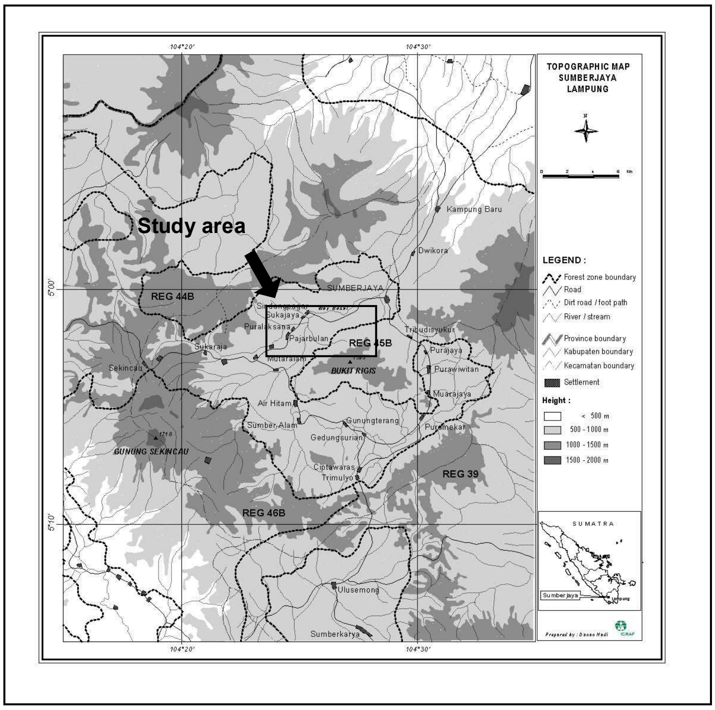


Figure 1.4 The location of the study area within Sumberjaya catchment (courtesy of ICRAF SE Asia)

1.6 Data availability

Satellite Imageries available for this particular study are:

- IKONOS Multispectral , 4 m resolution, acquired on 7 Sept 2000 at 14:57
- IKONOS Panchromatic, 1 m resolution, acquired on 7 Sept 2000 at 14:57

Other data

- Existing Topographic Map, 1:50,000

1.7 General approach of the study

The background mentioned above provides the basis for the author to define the objectives and questions of the study, and from that point , methodology is explored, keeping in mind the data availability and the possibilities of different remote sensing approaches. The following diagram (Figure 1.5) shows the general approach of this study.

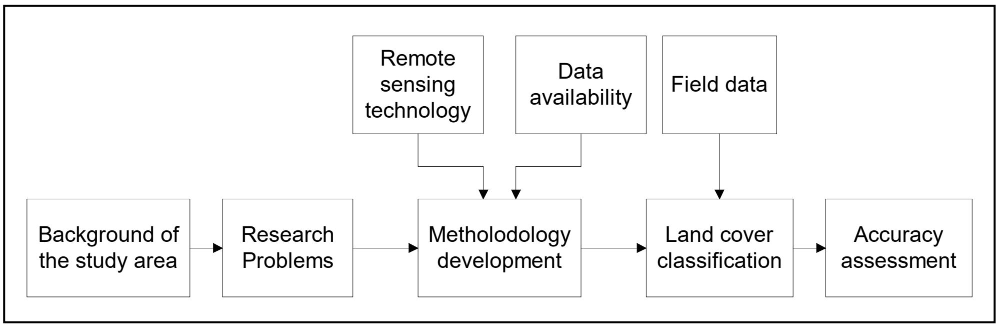


Figure 1.5 General approach of the study

1.8 Structure of the thesis

The thesis consists of six chapters, including Chapter 1 as the introduction. Chapter 2 will go over the theory, concepts of the methods to be applied in this study and some relevant works having been conducted utilizing the approaches. In Chapter 3, the methodology of the study is discussed. Chapter 4 presents the image processing works conducted following the methodlogy. This chapter includes the presentation of the resulting classified images. Chapter 5 bears the main discussion on the results and on the findings over the attempts of applying different methods to improve the accuracy of the classification. In this chapter, the strengths and the weaknesses of the methods will also be discussed. The last chapter, Chapter 6, is the summary and conclusion. This chapter summarizes the works done and discusses what the author considers as the success and the failures in this study. In this chapter possible approaches to be sought for improvements in future work will also be discussed.

2 Remote sensing approaches: a literature review

Remote sensing approach for land cover classification, vegetation classes in particular has been widely utilized. The reflectance of vegetation captured by electromagnetic wavelength within the visible range and infrared bands of optical satellite imageries have been very useful in various vegetation studies. Further discussion in this literature review mostly refers to the use of optical satellite imageries, as this is the type of data source being utilized for this study.

2.1 Spectral and spatial properties of satellite imageries

Satellite imageries are represented in raster format having grid cells as the smallest dimension carrying information. The values of each of the pixels denote the spectral properties of the image. Spatial properties of the image data set refer to both the size of the pixels as a representation of ground measurement, and the variability of spectral values in the neighboring pixels.

In the next two sections in this chapter the author will try to present the theory and concepts as well as works having been attempted in related to the approaches that will be explored in this thesis, based on each of the property mentioned above. These two approaches are:

- Pixel-based approach (spectral-based approach)
- Spatial-based approach

2.2 Pixel-based approach

Prior to pixel-based classification various image enhancements are commonly conducted to increase the interpretability of the image. Several of those enhancement techniques relevant to this work are discussed below.

2.2.1 PC transformation

Multispectral images often contain correlated DN values in its layers. To compress the data and extract the maximum spectral information, Principal Component (PC) transformation is conducted. This approach creates a set of orthogonal axes based on the covariance matrix in the scatter diagram of the image data set. The number of orthogonal axes depends on the number of input bands.

For easy visualization, PC transformation of two bands can be seen in Figure 2.1, and this figure shows the simplified description of transformation to PC1 and PC2. A new axis is created as transect of the data cloud and the points in the scatter diagram are given new coordinates. The coordinates of the points in the scatter diagram are basically the values of the pixels, therefore with the transformation the pixels obtain new values. Depending on the *n*-

dimensionality (number of bands in the image), there will be *n* output of PC bands. However the first few PCs, PC1 and PC2, are the ones giving the biggest variance, while the rest are more as leftovers of the variation. The direction of the axis of PC1 is called the *first eigen vector* while the length is called the *first eigen value*.

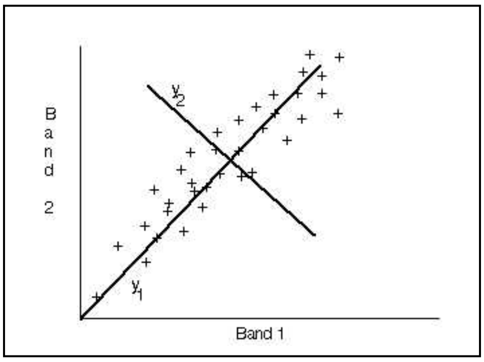


Figure 2.1 PC transformation of two bands, y1 is the new axis of PC1, y2 is of PC2

2.2.2 IHS transformation

RGB to IHS transformation basically is a manipulation of what usually is perceived as colors in the combination of Red-Green-Blue into another color scheme of Intensity-Hue–Saturation. It separates the spatial (I) and spectral (H,S) information from a standard RGB image (Pohl & van Genderen, 1998).The three channels in the transformed image are as follows and graphically described in Figure 2.2. (ERDAS Field guide, 1995):

- Intensity is the brightness of the color in the image, varying from 0 (black) to 1 (white), in gray level
- Hue is the representative of colors as they gradually change in a 'color wheel'. Since it is circular, the value ranges from 0 at the red midpoint going around through different colors to the red midpoint at 360.
- Saturation is the purity of the color relative to gray. In the color wheel it is the distance from the center of the wheel to the edge. The value is the radial distance and it varies from 0 to 1.

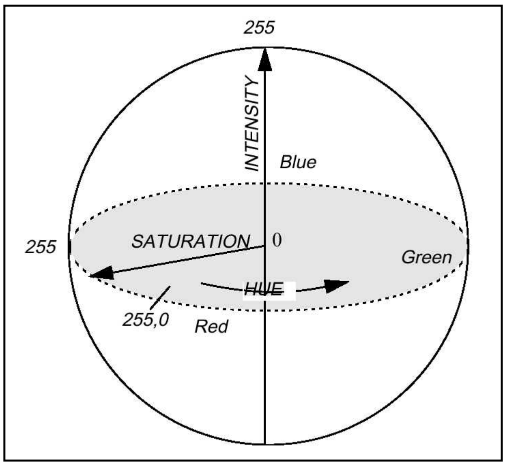


Figure 2.2 IHS transformation (taken from ERDAS Field Guide)

2.2.3 NDVI

In measuring the vegetation condition, several vegetation indices have been developed. These indices mainly utilize the ratio of NIR band to the visible bands, because of the strong reflectance of chlorophyl and mesophyll in green leaves at NIR band (Kuterema, 1998). Vegetated areas will yield high values for vegetation index because of their relatively high NIR reflectance and low visible reflectance (Lillesand and Kiefer,1998). One of the indices is NDVI (Normalized Difference Vegetation Index) which is represented by the ratio transformation of Red and NIR bands as shown below:

$$NDVI=(NIR-R)/(NIR+R)$$

The values range from –1 to 1. This index is commonly used as a measure of the "greenness" of the vegetation areas, and therefore an area with high NDVI denotes an area with high vegetation cover.

Canopy cover is usually derived from the ratio between red and NIR bands, as presented by various vegetation indices (*e.g.* NDVI). However, there are conditions where canopy reflectance reaches saturation level, *e.g.* during growing season or where canopy closure completely covers the ground. Another index which measures the canopy closure on the ground is LAI , which is a ratio between leaf area per unit area on the ground. Saturation level is reached at the LAI value of 5 for visible bands and 3 at NIR band (Guyot, 1990). For the highly dense canopy cover and where vegetation is composed of multi levels (complex system), the use of vegetation indices such as NDVI must be done carefully.

The reflectance of the canopy mainly depends on the combined reflectance of the leaves and the soil underneath. During the growth of the plants, the contribution of the soil's reflectance decreases, replaced by the leaves' reflectance (Guyot, 1990). And since the reflectance of bare soil is high in visible bands, and that of the leaves is high in NIR band, therefore during the growth of the plant the reflectance in the visible band decreases while in the NIR band it increases. As suggested by Lillesand and Kiefer, rock and baresoils have similar reflectance in visible and NIR bands, and result in the values near zero in vegetation indices.

2.2.4 Resolution enhancement

Image interpretability can be improved by various techniques utilizing various sources of remotely sensed data . Image fusion or image merging, which principally is a combination of two or more different images to form a new image by using a certain algorithm (Pohl and van Genderen, 1998), is a common technique for that purpose. Image fusion can be conducted at different levels of processing, pixel level, feature level and decision level, as described in detail in Pohl and van Genderen, 1998. Pixel level fusion, which will be further applied in this study, refers to merging of the physical parameters of the image. At this level, high accuracy of geometric positions of the fused raster data is highly required, and they should be resampled to a common pixel spacing and map projection (Pohl and van Genderen, 1998).

As from the objective's point of view, image fusion can be applied to increase the spatial resolution. One common approach is to fuse panchromatic image with lower resolution multispectral image. The techniques in fusing images to enhance spatial resolution is commonly done by replacing the I component with panchromatic image in IHS transformation technique.

Chavez, 1991, in Pohl & van Genderen, 1998, stated that replacing the intensity –sum of the bands- by higher resolution value and reversing the IHS transformation leads to composite bands.

As a result, it increases the variability of brightness within the multispectral image. Later on, in texture analysis section in this chapter, this variability of brightness will be discussed further.

2.3 Spatial-based approach

2.3.1 Textural analysis

Texture

In vegetation classification case, it is clear that some elements of certain vegetation cover types are likely to be similar. For example, a plot of wood consisting of high trees and shrubs, will be similar to a plot of multistrata coffee garden which consists also of shrub-like coffee trees with high shade trees in between. This phenomenon in the field will always result in spectral overlap in the scatter diagram.

Visually, high resolution satellite imageries provide more details because of the effects of spatial features caught by human eyes aside from the spectral information produced by the pixels. The spatial features in an image are recognized by human vision as different levels of brightness. As in the example given above, the tree and the shrub (or coffee trees) will give effect of brightness to the human eyes due to the frequency of the trees or shrubs and their spatial distribution. The property of these spatial features is known as textures which on the image representation is a function of the spatial variation of the digital number (Barberoglu *et al*, 2000). Lira and Frulla, 1998, define texture as an organized spatial phenomenon of pixels values, and therefore a texture object is a specific organization of pixels. The existence of textures brings up the importance of textural analysis in the classification of high spatial resolution imageries. (Wang and He, 1990, in Dikshit, 1996).

Different algorithms have been developed to extract information from textures. To run the analysis over the spatial distribution of textured objects, their statistical properties are used as the descriptors. At this point, texture can be described as set of statistics derived from a large ensemble of local picture properties (gray level values) (Dikshit, 1996).

Several 1st order measures have commonly developed for texture analysis like average grey level difference and mean euclidean distance. Average gray level difference is based on absolute differences between pairs of gray levels or average gray levels (Serrano, 1992). From the previous work by Dikshit, first order algorithms have shown to give higher accuracy than higher-order ones in texture analysis (Dikshit, 1996). In addition, Irons and Petersen, also showed that higher order algorithms (third and fourth orders) didn't prove to be significantly useful for land cover categories. (Irons and Petersen, 1981)

Dimensionality aspect

Since textural analysis can be done in each band, it will increase the dimensionality of the scatter diagram of the spectral values . This will cause extra processing time as well as huge space for data storage. To get rid of this problem, texture analysis is done with only selected images. Dikshit, 1996, used only the first principal component of Landsat TM bands 5,7, and 9, since it accounts for 70 % of the total variation in the data set, while Cross *et al*, 1988, used the first principal component of an airborne multispectral scanner and band 1 of simulated SPOT.

2.3.2 Segmentation

The term segmentation here is used to describe an approach where an image is divided into homogeneous areas (of texture, color, etc). The purpose of image segmentation is to subdivide an image into regions that are homogeneous according to certain criteria, in a way that these regions correspond to relevant objects in the terrain (Gorte, 1998). In the case of textured image, the segmentation and labeling of the object in one of a category of class textures is basically an implication of texture object recognition (Lira and Frulla, 1998).

In a different procedure but holding similar principle, Barberoglu *et al*, 2000, described this approach, in which he integrated vector data (field boundaries) and raster images using GIS, as 'per-field approach'. Averaging process (majority calculation) is incorporated mainly for the purpose of reducing the within-field variability and labeling the spatial unit based on extra attribute aside from the radiance values, like texture (Barberoglu *et al*, 2000), before supervised classification routines follow.

2.4 Integration of pixel-based approach and spatial-based approach

Segmentation process is an unsupervised approach. It only splits and merges the regions in an image as different objects based on a certain algorithm applied in the process. The characterization of the objects involves knowledge of the ground truth which is required in the classification routines. As suggested by Gorte, 1998, segmentation is followed by a supervised classification step, in which each segment is compared with class characteristics that are derived from training data. Regarding the two approaches, pixel-based approach and spatial-based approach discussed in the previous two sections, two types of integration are commonly applied and they will be discussed below.

The first type of integration is when spatial-based approach precedes the pixel-based approach. In this approach segmentation is done to the image and the process of classification follows. Image is already divided into homogeneous regions when the training samples are defined in the fields and supervised classification follows. As noted by Gorte, 1998, in this type of integration, a balance during the region merging and splitting has to be ensured, because once regions are merged into one segment, subsequent classification will not split them. While in terms of region splitting, the risk is lower, as long as the resulting segments are classified into one class.

The second approach is, when a classified image , which is the product of pixel-based approach, becomes the input of segmentation. In this approach the split and merge technique is applied to the thematic values of the different classes resulted from the classification result. This approach is considered having the disadvantage of carrying errors and uncertainties from one stage to another, *i.e.* mixed pixels at field boundaries will become segments which do not have meaning (Gorte, 1998)

3 Methodology of the study

3.1 Land cover classes in the context of the study

As previously mentioned, the dominant vegetation cover in the study area is coffee gardens. Despite this important land cover in the area, other types of cover are also found in various extent of areas, like ricefields which occupy the river valleys, secondary growth of woody shrubs, herbs and grassland. Altogether these patches create a configuration of landscapes which play important role in maintaining the soil and water conservation in the area.

Specifically speaking, to further relate to soil and water conservation purposes, the whole configuration of vegetation elements are expected to have the filter function in maintaining water , both runoff and base flow, and sediment flow. However, in this thesis, detailed classification will be made for coffee gardens, while other land covers are classified only based on the type of vegetation, without further elaboration.

3.1.1 Coffee gardens

Coffee bushes found in the study area are of two species *Coffea robusta* and *Coffea Arabica*, with dominance of *Coffea robusta*. The height of the trees normally does not exceed 4 m high. With pruning and topping done by farmers, the trees are kept lower than 2 m height (Budidarsono *et al*, 2000). The planting distance between trees is 1-2 meters. Referring to the previous discussion on coffee typology, there are two criteria on which the coffee classes will be based. The two criteria are as follows:

1. Vegetation structure complexity
2. Canopy cover

3.1.1.1 Vegetation structure complexity

The two classes under this category are:

1. Monoculture coffee

In Monoculture coffee system, only coffee bushes are planted, without shade trees. Included in this system is also newly planted coffee areas, where shade trees are not yet planted . In the study area, this coffee system is mainly restricted to the newly planted coffee plots. For better description of this type, refer to Figures 3.1, 3.2 and Plate 10 (b).

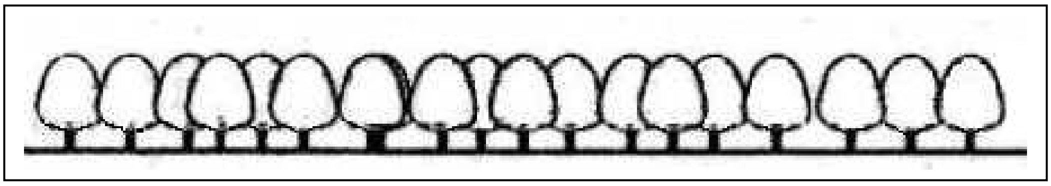


Figure 3.1 Monoculture coffee (adapted from Moguel, 1999)

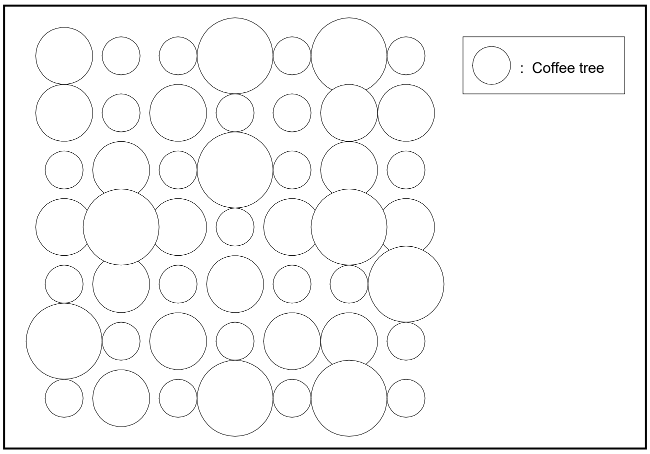


Figure 3.2 Tree pattern of monoculture coffee

2 Multistrata coffee garden:

Multistrata coffee garden refers to a coffee garden where shade trees are planted in between coffee bushes. The planting distance of coffee bushes is similar to that of monoculture, between 1 to 2 m, while the shade trees are planted with more varied planting distances, as it is also based on the tree species. The common shade trees in the study area are *Gliricidae* and *Erythryna*. At some gardens Cinnamon and Banana are found as shade trees.

The extent of canopy cover as well as the diversity of shade trees are varied and can fall into two extremes: one is where the shade trees are sparsely planted, with low canopy cover and only one type of species, the other extreme refers to a complex agroecosystem where the canopy cover reaches saturation level, and the diversity of shade tree species is high. Visual description of this type can be found in Figures 3.3, 3.4, 3.5, 3.6, and Plate 10 (a).

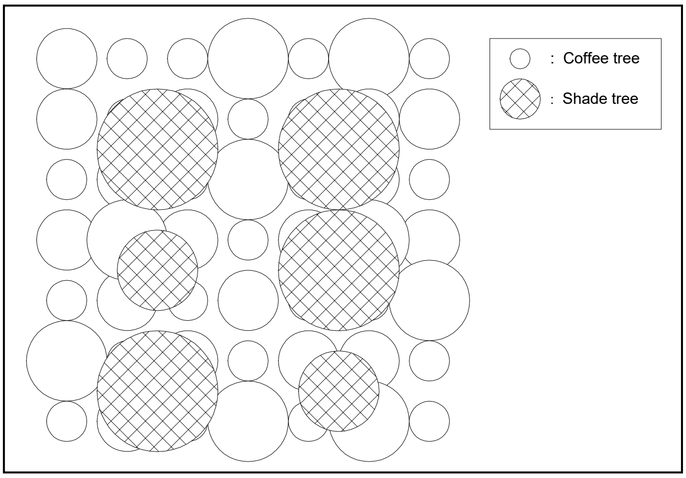


Figure 3.3 Tree pattern of multistrata coffee garden

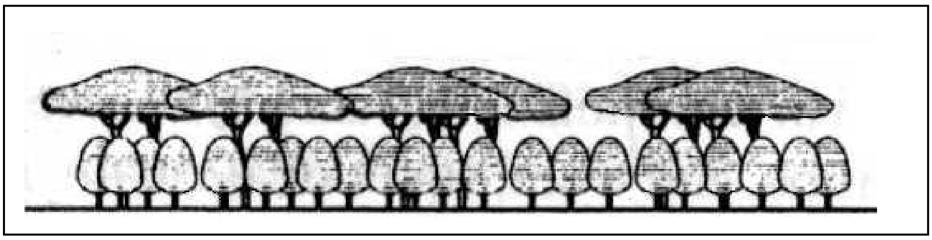


Figure 3.4 Multistrata coffee garden with single species of shade trees (adapted from Moguel,1999)

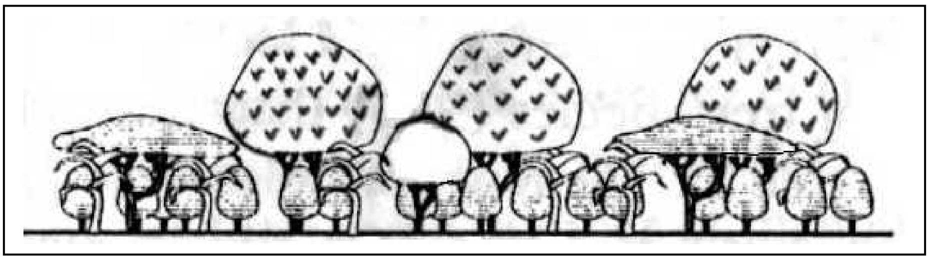


Figure 3.5 Multistrata coffee garden with higher diversity in shade trees (adapted from Moguel, 1999)

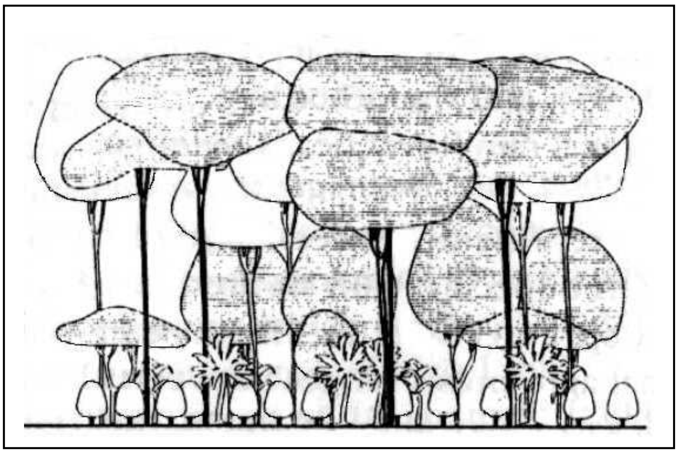


Figure 3.6 Multistrata coffee garden in complex agroecosystem (adapted from Moguel, 1999**)**

3.1.1.2 Canopy cover

The differentiation in coffee canopy cover refers to the combined canopy cover of coffee bushes and shade tree cover for the multistrata type, and the canopy cover of coffee bushes alone for the monoculture coffee garden. In this study, aside from canopy cover estimates during field observation, field measurement was also conducted to obtain the canopy cover. However, due to insufficient samples of measurement, only the estimate using visual observation is used. One way to eliminate subjectivity in this approach is by having replicates in data collection done by more than one observer.

The classification based on canopy cover is as follows:

- High : > 50
- Medium : 25-50 %
- Low : <25 %
- Sparse : ≤ 5 % (referring to newly planted coffee plot)

In general, it is expected that multistrata coffee gardens will have total canopy covers from high to low, while the mono culture type will have medium to very sparse covers. It is very rare to find sparse multistrata coffee gardens, *i.e.* gardens with only one or two shade trees. On the other hand, monoculture coffee garden is unlikely to be in high canopy cover because the absence of shade trees impedes the growth of the leaves into dense canopy, or because the coffee bushes are still young that the canopy cover is still low.

3.1.2 Weeding in coffee gardens

Another management aspect which is of relevance to the environmental impacts of coffee gardens is the weeding activities. There are two types of coffee gardens which fall under this category:

- Clean weeded coffee garden
- Unweeded coffee garden

In general, not many coffee gardens fall under the category of unweeded coffee gardens, since weeding is considered important for the growth of coffee bushes, and farmers do the weeding periodically. Unweeded coffee gardens are only found in the areas where the accessibility is very poor and considering the high labor cost, the gardens are left unweeded. In this work, weeding is not considered as a criterion in coffee garden categorization due to several reasons:

- Limited training samples for the permanently unweeded type.
- The limitation of data acquisition by remote sensing to capture this aspect for the gardens with high canopy cover (>75%)
- The need for temporal data is high since weeding is done periodically once in a few months.

3.1.3 Non coffee classes

The non coffee classes defined in this study area are:

1. **Ricefield**

   Rice fields in the study area are mostly irrigated ones and they occupy the river valleys. As ricefield is mostly only for subsistence purposes, they are found only in relatively small patches of less than 0.5 ha of ownership per farmer. The identification of ricefield in this study is based on whether it is still green and inundated or it's already yellow and the soil is dry. Therefore two classes of ricefields will be identified (R1 and R2).

2. **Woody shrubs**

   Woody shrubs in the study areas are mostly in small patches as they are mostly leftovers from the reforested areas which are re-opened for coffee planting. Therefore the species in this class is mainly *Calliandra*, which is the species introduced in reforestation program.

3. **Herbs and grass**

   As is the case of woody shrubs, herbs and grass also occupy small patches. These landcovers are mainly the lands left for fallow period . Herbs and grass can also be found in the valleys in the abandoned ricefield areas.

4. **Cleared land**

   This land cover type or bare land is found where lands are just reopened by the farmers to start cultivating their coffee garden. Therefore spatially it is expected that cleared lands will be found in relatively large areas in the foothill of Bukit Rigis, since recent land opening is mostly found in the foothills, where farmers move closer to the forest areas. This landcover type also groups bareland, villages and roads.

5. **Water**

   Two types of waterbody are found in the study area, namely ponds and streams. However they will be considered as one class in the classification.

6. **Forest**

   The only forested area in the study area is found in Bukit Rigis area, at the southeastern part of the image. Boundary identification will be done based on visual interpretation and the output will be masked out from the rest of the processing.

7. **Urban**

   The only urban area is Fajarbulan sub-district town located in the southwest of the image, As with the case of forest, this area is also masked out prior to classification process.

The expected land cover classification for the study area and its detailed description is as follows:

	Coffee		Remarks	
1	C1	Coffee	Multistrata	>50 %
2	C2	Coffee	Multistrata	25-50%
3	C3	Coffee	Multistrata	<25%
4	C4	Coffee	Monoculture	25-50 %
5	C5	Coffee	Monoculture	< 25%
6	C6	Coffee	Monoculture	Newly-planted field
	Non-coffee		Remarks	
7	R1	Ricefield	Green	Inundated
8	R2	Ricefield	Yellow	Dry
9	S	Shrubs	Woody	
10	H	Herbs & grass	Non-woody	
11	B	Cleared land/bareland		
12	W1	Waterbody		
13	F	Forest		
14	U	Urban area		

Since urban areas and the Bukit Rigis forested area are masked out prior to image processing, 12 classes are left to be further identified.

3.2 Image transformation prior to classification

The whole framework of the image processing procedures leading to classification of land cover classes is presented in Figure 3.7, and each of the methods are discussed in this section.

Several image transformations will be conducted prior to classification . These techniques transform pixel values based on statistical algorithms (PCA) , color transformation (RGB-IHS-RGB), indices (NDVI), resolution enhancement, and neighborhood analysis (textural analysis and segmentation). These techniques can be categorized into two :

- Pixel-based approach (PCA, IHS transformation, NDVI and resolution enhancement)
- Spatial-based approach (textural analysis and segmentation)

3.2.1 Pixel-based approach

The techniques which fall under this approach are:

- PCA
- IHS Transformation
- NDVI
- Spatial resolution enhancement

Detailed explanation on the theories of these techniques can be found in section 2.2. The application of the techniques above in this study is described below.

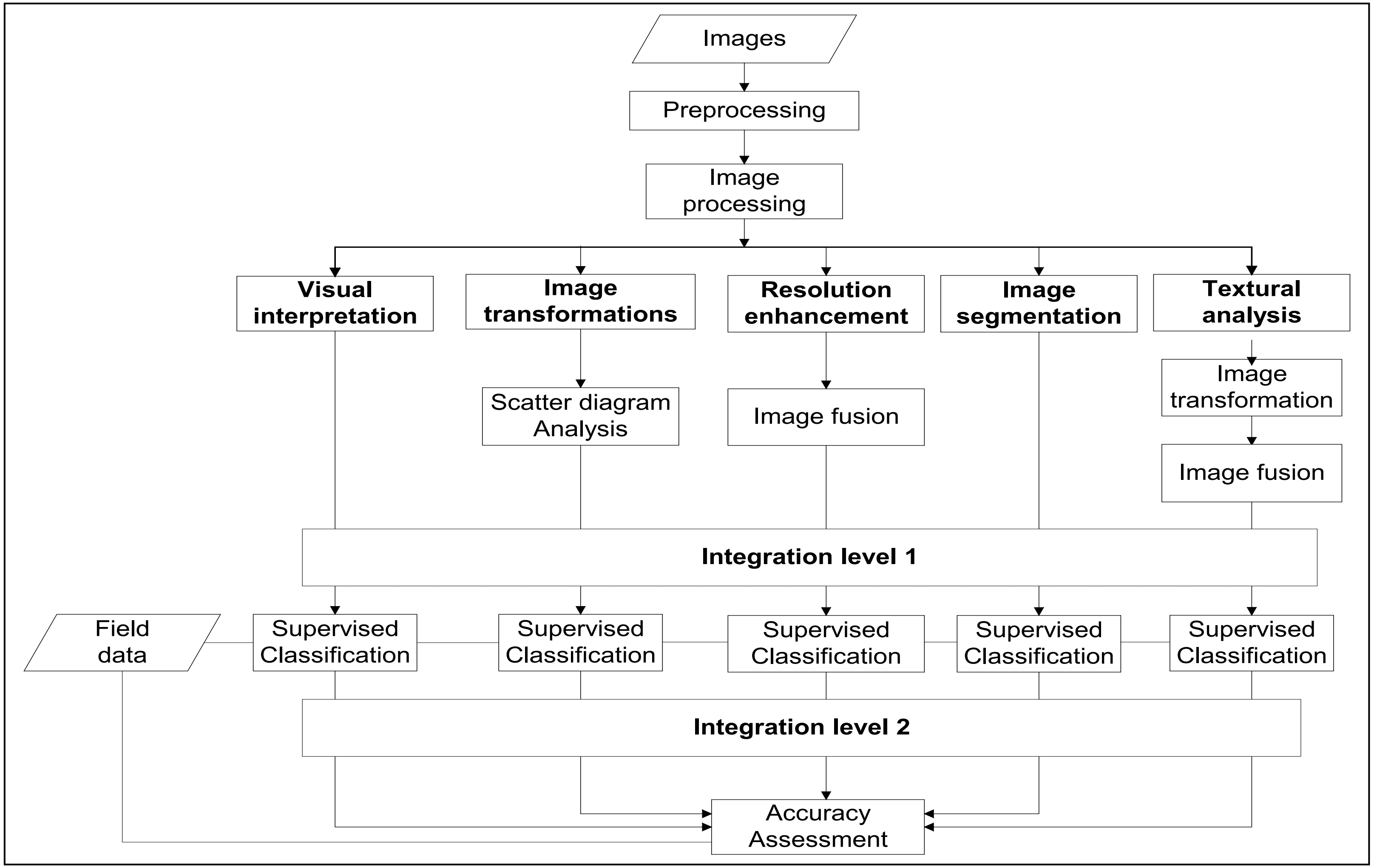


Figure 3.7 Overall framework of the approaches

3.2.1.1 PCA

PCA is conducted for two different purposes. First, it will be used as input for supervised classification. Lillesand and Kiefer, 1998, suggested that if used in an image classification process, principal components data are normally treated in the classification algorithm simply as if they were original data (Lillesand and Kiefer, 1998). Therefore, after PCA is conducted, the three layers (PC1, PC2 and PC3) will be combined as a color composite image and be inputted for supervised classification routines.

The second purpose of conducting PCA is for further combination with the other transformed images. Comparison will be conducted between each PC with NDVI in the scatter diagram to see which images show the least correlated image.

3.2.1.2 IHS transformation

The purpose of conducting IHS transformation is twofold. First, the intensity layer will be used to assess the values of panchromatic band as intensity image. Second, the resolution enhancement is done under the scheme of IHS to RGB transformation, by replacing the Intensity layer with the panchromatic image. Although this technique has the purpose of enhancing the spatial resolution, since it's purely using the spectral value and not considering the neighboring pixels, it is still considered as pixel-based approach.

3.2.1.3 NDVI

The purpose of incorporating classification of NDVI image is because spectral mixtures are anticipated for the classes having middle to low canopy cover, and for both types of the vegetation structure complexity aspect for coffee classes (multistrata and monoculture). Using NDVI image, it is expected that within those classes spectral seperability will be improved. NDVI image to be produced in this study will also become the input of supervised classification routines.

3.2.1.4 Resolution enhancement

This method bears the concepts of image fusion because it will incorporate the fusion technique of two images with different spatial resolutions. The enhancement will be done to the IKONOS multispectral to produce the color composite image of 1 m resolution.

Image-to-image registration will be the first stage and image resampling will follow. Ideally, the lower resolution image should be registered to the higher resolution one. But considering the fact that the IKONOS multispectral was geometrically corrected, while the panchromatic one was not, the inverse process will be applied. To ensure the spatial precision of the fused image to be within one pixel of panchromatic image, the RMS error of the transformation should be lower than 0.25 x pixel of the multispectral image.

Resolution enhancement will be done within the IHS transformation. The panchromatic image will replace the intensity layer during the reverse transformation of IHS image back to RGB image. Later the resulting three-layer image will be combined as false color composite, and the term 'enhanced FCC bands' will be used.

3.2.2 Spatial-based approach

The two methods being applied under this approach are:

- Textural analysis
- Segmentation

The categorization of these two techniques under spatial-based approach is because the transformation of the properties of any pixel within the image considers the values of the neighboring pixels. In many scientific papers and literatures, segmentation is referred to as "object-based classification" (see Gorte, 1998) yet, since what is meant by classification in this study is the "labeling" procedure into the land cover classes following supervised approach, segmentation is not considered as a classification method, instead it assists the supervised classification by defining homogeneous regions prior or after the classification process.

3.2.2.1 Textural analysis

Texture in image is the variability of the values of neighboring pixels and it is characterized by a non-uniform spatial distribution of image intensities (Simon J.C, as cited by Serrano, 1992). These non uniform intensities are measured by a moving window in which the center pixels get the values of the statistical algorithm applied in the process. The result of this process is a texture image whose values will be high in the area where the variability of pixels is high, and low in the area of low variability.

Having a resolution of 1 m, panchromatic band produces better variability of pixel intensity values. Tree canopy sizes vary between 2 to 10 pixels considering the average canopy size does not exceed 10 meters diameter. It is expected that differences in canopy features due to the different coffee types (multistrata and monoculture) will emerge significantly through texture values processed from panchromatic image. Therefore for this purpose textural analysis will be applied to the panchromatic image .

The result of this process will be a texture image which will become the input of a transformation . The values of the pixels in the texture image denote intensity values that take into account the spatial context. The original 3 bands are used for a transformation into IHS channels to produce three layers: Intensity, Hue and Saturation values. The next process is the fusion of texture image with the other channels, by the replacement of Intensity (I) layer with the texture image when transforming back the IHS to RGB. This method at the same time implies a resolution enhancement because the texture image is obtained from the panchromatic band.

Texture algorithms

Two of the mostly used texture measures are of the first order algorithm (Mean Euclidian Distance (MEUC)), and the second order (variance). In this study variance will be used as the parameter in textural measures. Let $I(i, j, \lambda)$ represents a gray level of band λ found at row i column j. The transformation creates another channel, k, where the value $I(i, j, k)$ is the variation of gray levels in and around pixel i, j of the original image. This new image is what is called as texture image. The variance values follow the algorithm below:

$$\text{Var} = \sum (x_{ij} - MNL)^2 \Big/ n-1$$

$$\text{MNL} = \sum x_{ij} \Big/ n \qquad \text{where } x_{ij} = \text{gray level vector norm length of pixel } (i, j)$$

$$n = \text{number of pixels in a window}$$

A window size of 7 x 7 is used for the purpose of capturing the texture value denoting the tree canopy cover.

3.2.2.2 Segmentation

The high resolution images of 4 m and 1 m used in this study presents high variability in neighboring values which result in textured features. Texture brings important aspect of the image for the differentiation of vegetation types, strata and canopy covers relevant to the purpose of the study. For textured regions, a step to decompose the regions into more homogeneous areas, whose values represent the information of the textures will be examined in this section.

A segmentation process incorporates a set of procedures in splitting and merging the region based on what is defined as 'different regions' (to be split) or the 'same region' (to be merged). An algorithm is used for images with high speckles such as SAR data. Segmentation follows a "cartoon model" which is a decomposition of an image into a collection of regions on each of which the intensity is constant (Cook *et al*, 1994). The reason of applying this algorithm to the optical image in this study is because of the textured areas present in this image which need to be split or to be merged so that regions with homogeneous values area obtained. The mean values of the region is applied in the cartoon of the segments.

The textured-region merging algorithm that will be used in this work is called Merge Using Moments (MUM)(Cook *et al*, 1994). The flow diagram of this procedure is presented in Figure3.8

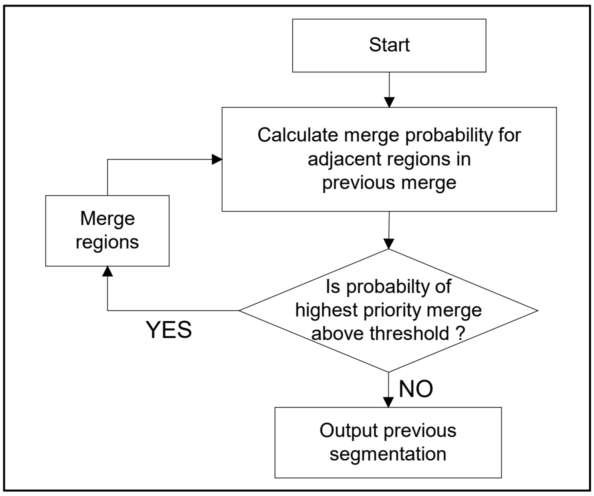


Figure 3.8 Flow diagram of segmentation process using MUM algorithm (adapted from Oliver, 1998**)**

Segmentation algorithm

The principle behind the algorithm of MUM is that at the initial stage, each pixel is a region, which is followed by a merging calculation of the 'similar' adjacent regions. For two adjacent regions, it calculates the likelihood (probability) of whether they belong to the same actual region by assessing the statistical properties. The two similar regions are tagged and those tagged regions are in the end merged. If two regions are significantly different, they are left as they are (no merging is conducted).

In determining whether two regions are significantly different, the log probability of merging and splitting are calculated using the following algorithms (Cook *et al*, 1994).

The a priori means (μ) of the intensity (I) with N as the number of pixels in a region:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_{i} = \bar{I}$$

The log likelihood of splitting two regions (A and B) is given below:

$$\lambda_{split} = L\left(-N_A \log(\bar{I}_A) - N_B \log(\bar{I}_B) - N_A - N_B\right)$$

The log likelihood for merging two regions are as follows:

$$\lambda_{merge} = L\left(-(N_A + N_B)\log\left(\bar{I}_A + \bar{I}_B \big/ 2\right) - N_A - N_B\right)$$

The log likelihood of the difference, $\lambda_D = \lambda_{split} - \lambda_{merge}$ is as follows:

$$\lambda_D = L\left(-N_A \log(\bar{I}_A) - N_B \log(\bar{I}_B) + (N_A + N_B)\log\left(\bar{I}_A + \bar{I}_B/2\right)\right)$$

Where L is the order parameter, N is number of pixels A and B are the regions to be processed.

L represents the level of textures present in the image which implies the quality of the image. High value of L means that the image has less noise and the less severe the treatment in considering the high variability of values as noise, and the result will be rougher features. On the other hand low L will result in smoother features, because the smoothing treatment is more severe. Therefore, in processing optical image, higher L 's are considered, in contrast to SAR data.

A larger λ_D means a higher probability in splitting the regions, and lower probability of the regions to be merged into one region. Visually this will result in an image with more segments which means higher variability of values.

In executing the segmentation procedures, to determine whether two regions are to be merged or to be split, a 'merge threshold' should be set (P). Two adjacent regions will be merged if the probability that they are samples from the same distribution is larger than this threshold. Smaller values of the threshold will result in larger regions, which means less segments in the image.

3.3 Classification methods

There are two approaches in producing the classified images in this study , namely:

1. Pixel-based classification
2. Integration of spatial-based processing with pixel-based classification

3.3.1 Pixel-based classification

The objective of classification is to automatically categorize all pixels in an image into land cover classes or themes (Lillesand and Kiefer, 1998). Classification is considered as a supervised one if the pixel categorization is guided by training areas that are used to generate numerical descriptors of spectral attributes for each feature type. Based on the descriptors produced, two classifier tools that will be used in this work are discussed below:

- Minimum-distance-to-means classifier
- Maximum likelihood classifier

Minimum-distance-to-means classifier

This classifier will classify a pixel in an image based on the closest euclidian distance of its value to the mean value of a class . Using a scatter diagram of two bands, as is shown in Figure 3.9, an unknown pixel "?" will be classified as "ricefield" for its distance to the mean value of "ricefield" signature is the closest compared to the other classes. This classifier is simple and requires only a minimum calculation procedure, and therefore it is computationally efficient. However, it has a limitation because it is insensitive to different degrees of variance in the spectral response data (Lillesand and Kiefer, 1998). Therefore for data set which shows high variability in spectral responses, this classifier will produce poor result.

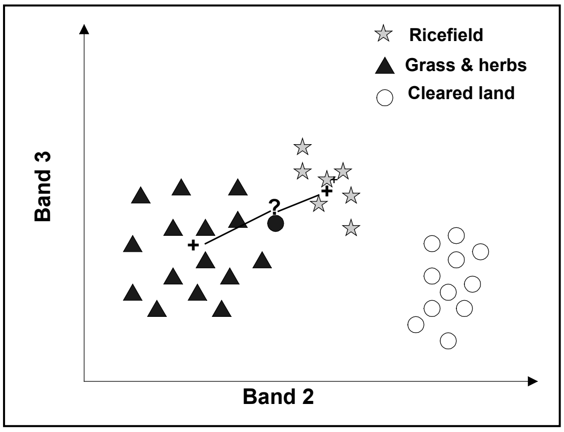


Figure 3.9 Clusters of signatures' spectral responses in scatter diagram of band 2 and 3.

Maximum likelihood classifier

Maximum likelihood classifier computes the variance and covariance of the spectral response of the signatures. This classifier assumes a normal distribution and the spectral response pattern is described by the mean vector and the covariance matrix. With these parameters, a probability of an unknown pixel to be a member of a certain class is calculated. The assignment of a class to that unknown pixel is based on the highest probability value obtained by that pixel. Referring to Figure 3.9 as an example, the pixel "?" may be assigned to class "grass and herbs" instead of to "ricefield" because it has higher probability to be a member of "grass and herbs" than to be a member of "ricefield" .

3.3.2 Integration of spatial-based approach with pixel-based classification

Referring to the discussion in section 2.4 on the two approaches in integrating pixel-based and spatial-based approaches, the integration that will be further discussed below basically falls under three categories:

1. Spatial-based method preceding pixel-based classification
2. Pixel-based classification preceding the spatial-based processing (segmentation in this regards)
3. Combination of both methods using cross classification and majority rule

In this study the first method and the third method will be emphasized while the second method -- pixel-based classification preceding spatial-based approach--- will be considered as a brief comparison. This is based on the consideration that the values extracted from the textured features, using segmentation or textural analysis, represent the immediate transformed values of the pixels, and therefore these processes must be applied directly to the original bands before other procedures take place.

The different methods are shown in the diagram below (Figure 3.10), and four classified images are expected as the outcome of the integration approach.

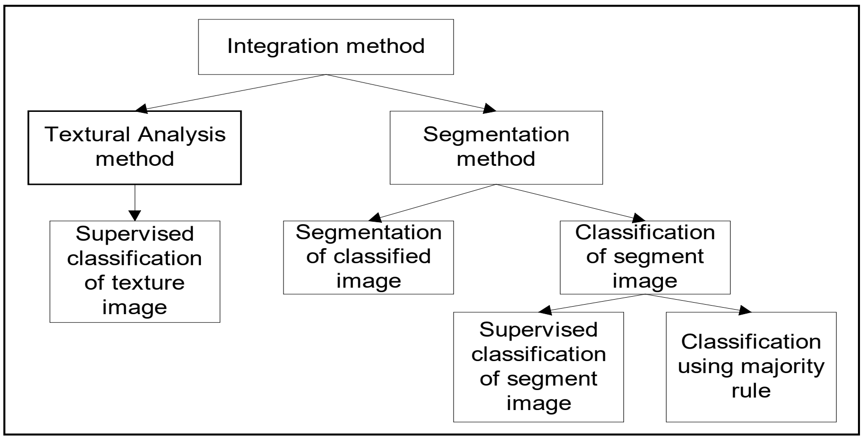


Figure 3.10 Different methods in the integration of pixel-based and spatial-based approach

Under the textural analysis domain, the supervised classification routines using maximum likelihood classifier will be conducted as the decision rule. Under segmentation domain there are two main methods which are of the inverse direction, one is the segmentation of classified image and the second one is the classification of segmentation image, both utilizing the classified image resulting from pixel-based classification. The second method, classification of segment image, is divided into two methods, namely:

1. Supervised classification of the segment image (referring to category 1 previously mentioned in this section)
2. Classification of segment image using majority rule (referring to category 3 previously mentioned in this section)

The first one refers to the supervised classification for the mean values of the segmented image. The procedure being applied is similar to the ordinary classification where training samples are taken and later guided by decision rule of the classifier to classify the rest of the segments.

The second method (classification using majority rule) is principally the pure combination of spatial and spectral properties of the image. The resulting segment image provides the geometry of the homogeneous areas which are assumed to have single values representing the objects on the terrain. The labels defined for the land cover classes come from the majority function applied to the classes resulted from pixel-based classification which fall under the geometries of the segments. The diagram below (Figure 3.11) describes this method .

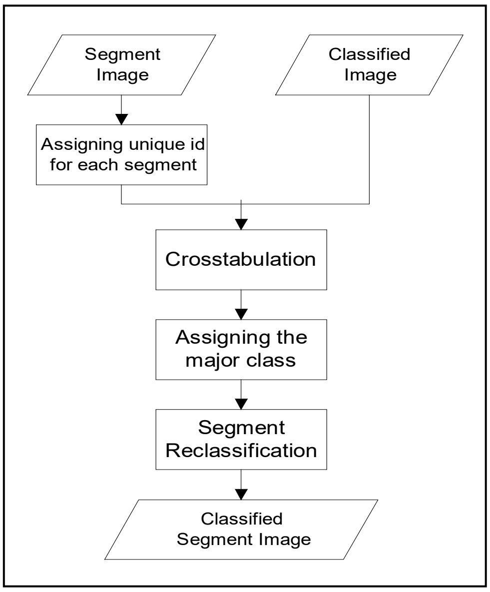


Figure 3.11 The flow diagram of classification using majority rule

3.4 Accuracy assessment

For each classified image produced, accuracy assessment is conducted using an error matrix. An error matrix compares, on a category-by-category basis, the relationship between known reference data (groundtruth) and the corresponding results of an automated classification (Lillesand and Kiefer, 1998). The matrix lists the classes taken from the groundtruth samples (as columns) and those from the classification process (as rows). The correctly classified pixels will occupy the major diagonal of the matrix while figures at the other pixels denote the errors. These errors can be grouped and then categorized as error of omission (exclusion) and error of commission (inclusion). The accuracy obtained from this matrix are of three kinds:

1. Overall accuracy: total number of correctly classified pixels (sum of the figures along the major diagonal) divided by total number of reference pixels
2. Producer's accuracy results from dividing the number of correctly classified pixels in each category by the number of ground truth pixels in each category.
3. User's accuracy, is the result of dividing the number of correctly classified pixels of each category by the number of pixels classified (by classifier) in each category. This is the figure which indicates the probability that a pixel classified into a given category actually represents that category on the ground (Lillesand and Kiefer,1998)

The implication of the accuracy result has to be considered carefully, because it only judges the accuracy of the classified image in the areas where the ground truth pixels are taken. In another way of saying, it only assesses how well the classification works in the ground truth areas. This assessment indicates little about how the classifier performs elsewhere in the scene (Lillesand and Kiefer, 1998)

4 Data processing and analysis

4.1 Image preprocessing

4.1.1 Image data set

IKONOS images used in this study are the multispectral bands (IKONOS MS) and the panchromatic band (IKONOS Pan). IKONOS MS is available in bands 1,2,3, and 4 with the wavelength of 0.45 - 0.52 μm (band 1), 0.51 - 0.60 μm (band 2), 0.63 - 0.70 μm (band 3) and 0.76 - 0.85 μm (band 4), while the IKONOS Pan band covers a range of 0.45 - 0.90 μm. The spatial resolution of IKONOS MS is 4 m, and for the panchromatic band is 1 m. Both data sets are already radiometrically corrected. The MS data is already corrected geometrically with Bicubic resampling method, and projected to the UTM coordinate system zone 48 S, while the panchromatic data set is still geometrically uncorrected.

The coverage of IKONOS imageries in this study is approximately 9.5 km x 4 km, with the approximate position between 5.05° S, 104.383° E and 5.05° S, 104.467° E.

From 4 bands of a multispectral data set, the combination of bands 4,3 and 2 (NIR, Red and Green) in RGB channels is chosen as in accordance to the suitability of combination for vegetation study, as shown in Figure 4.1. (adapted from Lillesand and Kiefer, 1998). This combination produces the false color composite (FCC) image of the IKONOS MS.

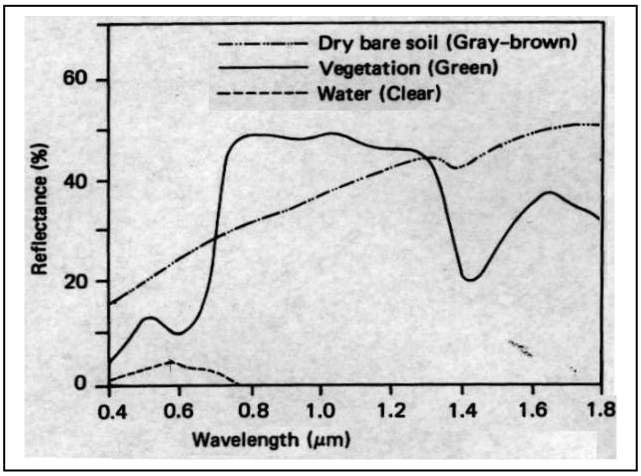


Figure 4.1 Reflectance of different land covers in the different electromagnetic wavelength (adapted from Lillesand and Kiefer, 1998)

4.1.2 Geometric correction

IKONOS MS used in this work has been radiometrically and geometrically corrected, while the original panchromatic band is still geometrically uncorrected, therefore in order to be able to do further pixel-based integration both image should be co-registered. Twenty-four ground control points were collected to rectify IKONOS Pan to IKONOS MS following first order transformation with the RMS error of 0.198 pixel or 0.792 m (See Appendix 1.) This error is considered sufficiently low for the purpose of conducting pixel-based fusion, because it falls below the size of panchromatic image (1 m). Subsequently, IKONOS Pan was resampled using Nearest Neighborhood convolution.

4.2 Image processing

This section refers to all the processing conducted prior to the classification procedures.

4.2.1 Image transformation

Three PC transformations were carried out using the original bands (2,3 and 4) resulting in three new images, PC1, PC2 and PC3. Transformation to IHS was also done, and from the three images of PCA and the Intensity of IHS image , it was found out that PC1 shows similar distribution of the intensity value of the IHS image. Comparison was also done between the I layer of IHS to IKONOS Pan image which then shows the fitness of the panchromatic image as intensity image.

The statistics of the three images, transformed into 8-bit data, are as follows (see Figure 4.2):

Statistic parameters	I of IHS	PC1	Pan
Min	1	7	1
Max	255	255	255
Mean	111.658	114.069	110.85
Median	110	112	105
Std. dev.	24.927	32.725	34.271

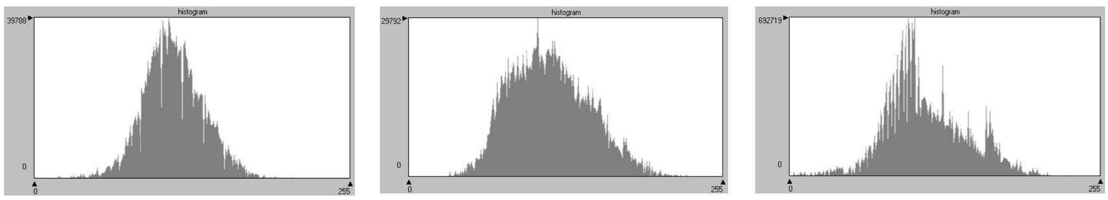


Figure 4.2 Histograms of intensity layer from IHS, PC1 and panchromatic band (left to right)

Another transformation of the original bands is by image ratioing, generating NDVI layer. Comparison was done between the PC images to the NDVI image. By analyzing the scatter diagram of spectral values of two layers at a time, the least correlation was found between PC1 and NDVI (Figure 4.3(c).). These layers were put in a stack for a purpose of supervised classification.

4.2.2 Spatial resolution enhancement

An RGB to IHS transformation was carried out to the original bands. Since the purpose of this approach is to increase the spatial resolution of the original bands, the I channel was then replaced by the panchromatic image (resolution 1 m). As the next step, the three channels were transformed back to RGB channels and a false color composite combination is obtained with 1 m resolution(a term 'enhanced FCC image' is used). To compare the detailed features of the enhanced FCC image compared to the original FCC image, see **Plate 1(a)** and **(b).** Visually the textured areas as well as the color are more pronounced and this would help the visual interpretation.

4.2.3 Textural analysis

Textural analysis applying variance parameter was conducted to the panchromatic band and the window size of 7x7 was used. The resulting texture image shows that high variance exists in the regions with high intensity variability, as compared to the original panchromatic image. Very high values exist in the boundaries where intensities vary extremely in neighboring pixels, like river edge, road edge, and field boundaries of different land cover types. For comparison of original panchromatic band and texture image see **Plate 2(a)** and **(b)**.

Subsequently, this texture image replaced the intensity channel in the layer stack of IHS layers. And as the next stage a transformation back to RGB channels was conducted. The result was placed as FCC bands (bands 3,2,1 in RGB channels). Visually it looks similar to the original FCC, yet the effect of pixel variability is seen from the bright to dark effect in the image. Dense vegetated areas with high variance appear in bright red and the vegetated areas with low variance appear in reddish black . Feature boundaries appear in bright bluish-white linear shapes.

4.2.4 Image segmentation

Image segmentation applied to the original bands is the only segmentation conducted in this study. An attempt to apply the segmentation procedure to the enhanced bands (resolution 1 m) failed due to the technical problems of extremely long segmentation processing, and considering time constraint, this approach was not proceeded.

As explained in the methodology, the split-and-merge approach using Merge Using Moments (MUM) algorithm is used in segmenting the original bands. Two parameters had to be set for the segmentation, the order of parameter (L) and the merge threshold (P) (see section 3.2.2.2). Since the effect of changing L is equivalent to the changes in P (Cook *et al* , 1994), P is set to a fixed value (10^{-10}). The attempts to see which values of parameters would give the "ideal" segmentation is done only by changing the values of L. The values put on trials are 100, 50 and 20, and the one considered to give the best result is L=50. The results of L=100, L=50 and L=20 are shown in **Plate 1(c),(d),(e)**.

The segment image has three layers which are combined in RGB stack as FCC image. As compared to the original FCC image, the segment image shows smooth surface in the textured areas and the mean values of the merged regions become the values of the output segments.

4.3 Image classification

4.3.1 Training sample collection

Collection of training samples was the initial step of the process. The sample collection was done based on several methods:

- Training data collected during field work
- Visual interpretation both on FCC image, panchromatic and the enhanced FCC image.
- Spectral signature of the class clusters in the scatter diagram

For 12 classes determined beforehand (see section 4.1), 2414 pixels of training samples in 52 training patches were collected and for each class the number of training pixels is shown in the table below:

Class	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Pixels	105	467	473	126	67	282	260	125	127	141	119	122	2414

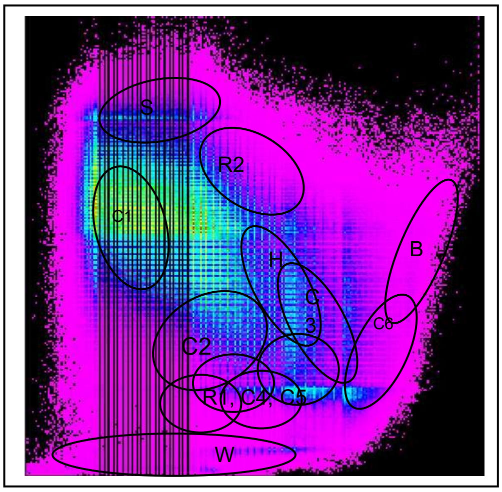
4.3.2 Pixel-based classification

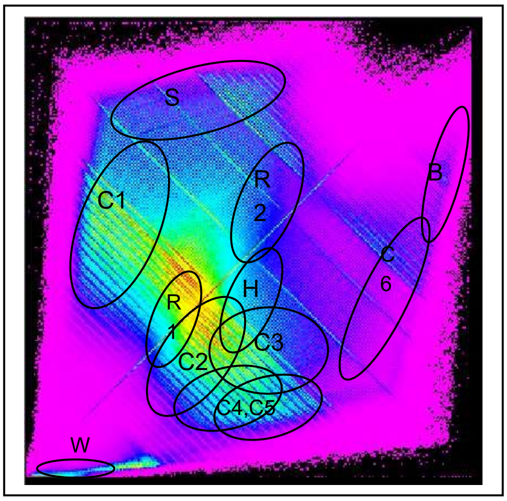
4.3.2.1 Supervised classification

Supervised Classification of the original bands

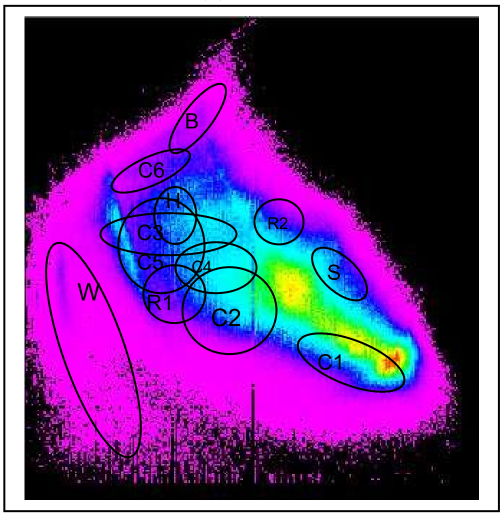
When plotted as scatter diagram of red and NIR bands, using ellipse vector delineation and the standard deviation set to 1, general pattern of the vector positions of the training samples for each land cover is as shown in Figure 4.3 (a). The seperability of C1, S, C2, R2, C6, B and W in various degrees is better than C3, C4, C5,R1 and H. Coffee gardens with medium to low cover are spectrally mixed with one another and with grass and herbs.

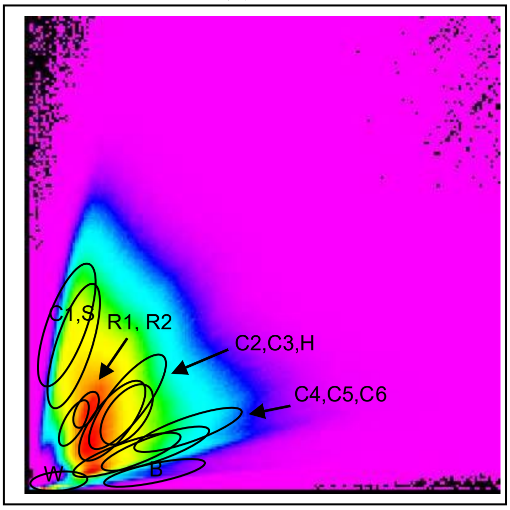
Using the training samples mentioned above, the Maximum Likelihood (ML) classifier is guided to classify the IKONOS original bands. All training patches are set to equal probability (1) and without any rejected pixels (pixels remain unclassified). The equal probability is set to all classes by the author because there is no a priori knowledge to set particular probability values for particular classes. Therefore, the classification applied is fully automated. The result of the classification of the original bands is shown in **Plate (3).**



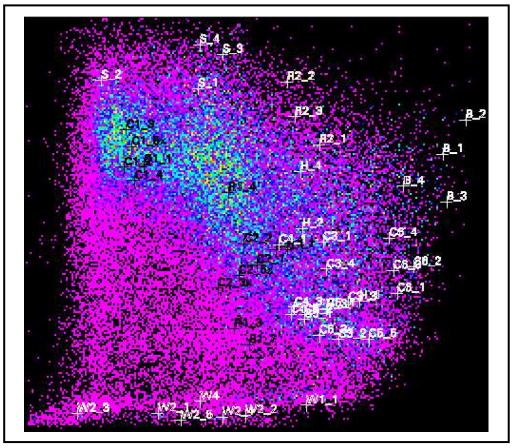


(a) (b)





(c) (d)



(e)

Figure 4.3 Scatter diagram and the training sample signatures of (a) bands 2 and 3 of the original bands. (b) bands 2 and 3 of the enhanced bands. (c) NDVI and PC1 images. (d) bands 2 and 3 of texture image. (e) bands 2 and 3 of the FCC segment image

Supervised Classification to the enhanced FCC bands (1 m resolution)

The same training sample patches are used to guide the classifier. The scatter diagram of the enhanced bands (see section 4.2.2), of Red and NIR band, is shown in Figure 4.3 (b). The signatures of the 12 classes are shown in ellipse vector delineation, with the standard deviation of 1. Several classes are mixed spectrally , *i.e.*: C2, C3, C4, C5, R1 and H, comparable with the case of signatures in the original bands (See Figure 4.3 (a)). The same procedure and parameters are set to the ML classifier, and the result is shown in **Plate (4)**

4.3.2.2 Classification of transformed images

For the transformed images, classification was done with PC1-PC2-PC3 images and to the NDVI-PC1 image. The same training samples were applied to guide the classification of PC images and NDVI-PC1 image, and ML classifier was applied as the decision rule, with the probability set to 1 (see section 4.3.2.1). The results of the classifications are shown in **Plate (5)** and **Plate (6)**

4.3.3 Integration of pixel-based and spatial-based approaches

4.3.3.1 Supervised classification of texture image

When plotted in the scatter diagram of band 2 against band 3 (Figure 4.3(d)) , it is observed that the signatures of all classes are located relatively in low values in the scatter diagram . C1 and S form a cluster with low value in band 2 and a big range of values in band 3. The other clusters are mixtures of classes , although there is a gradual shift in the vector positions of those clusters, towards bigger values of band 2 and lower values of band 3.

Following is the classification procedure using the same training samples used in the previous approaches, and using ML classifier. The result is shown in **Plate (7)**

4.3.3.2 Segmentation of pixel-based classified image

Despite the anticipated weakness of this method (see section 2.4), it is still tested in this study to see whether it would improve the accuracy of the classification. This method was tested to the classified image of the original bands**.** As for the parameters setting in the segmentation process, the merge threshold (P) was set to 10^{-10}, and L is established by trial and error.

4.3.3.3 Supervised classification of segment image

The values of the segments in the segment image are the mean values of the originally-merged regions. These values give lower density of values in the scatter diagram of band 2 against band 3 of the segment image (Figure 4.3 (e)), although the distribution is similar to that of the original bands. The same training samples were used, and when plotted in the scatter diagram, the variability of the values in each training patch become smaller while most of them become single values, compared to a range of values in the original bands.

Both maximum likelihood (ML) classifier and minimum-distance-to-means (MD) classifier were applied. Assessed visually, the result of ML classification shows overestimation for C1, C2 and C6, while the other classes do not appear in the result. The classified image using MD shows better result because all the classes are represented in the classified image. Therefore for further discussion and accuracy tests, only the latter will be included. The classified image is shown in **Plate (8)**.

4.3.3.4 Classification of segment image using majority rule

The segment image is integrated with the pixel-based classified image, following the graph in section 3.3.2 (see Figure 3.11) . The color-coded segment image is basically made of three original segmented bands placed in RGB channels. Since the classification basically needs the geometry of the segment, PC transformation was conducted and the geometry of PC1 layer was used for the segment classification. Afterwards, unique ID was given to each segment, and crosstabulation was conducted between the segment image and the classified image. At the end of the process statistical parameters of maximum value, minimum value, means and the major class, were generated. For this purpose, the major class is used as the new attribute of the segments, and recoding the segments based on the corresponding attribute values was done as the last stage.

This method of classifying the segment image is based on the pixel-based supervised classification. To avoid excessive processing, only the classified image(s) with good accuracy results was incorporated in this method, which is the classified image of the original bands in this respect. In addition to that, for the purpose of brief comparison, the classified image of enhanced bands (1 m resolution) was also tested. The classified image is shown in **Plate (9)**

4.4 Accuracy assessment

Accuracy assessment for the resulted classified images was conducted by taking groundtruth pixels in each class on the image as the training samples. 471 pixels were collected, and the distribution of pixels for each class is shown in the table below:

Class	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
pixels	83	34	32	35	34	27	35	31	44	39	37	40	471

It should be taken into consideration in the discussion of the result of accuracy assessment that spatial distribution pattern of the groundtruth training samples is more as clusters than as random points. This is due to the time constraints, that groundtruth samples were taken at the same period as the training samples for classification were collected, following the same areas of field visit. The clustered pattern of the groundtruth samples taken in the study area is shown in Figure 4.4

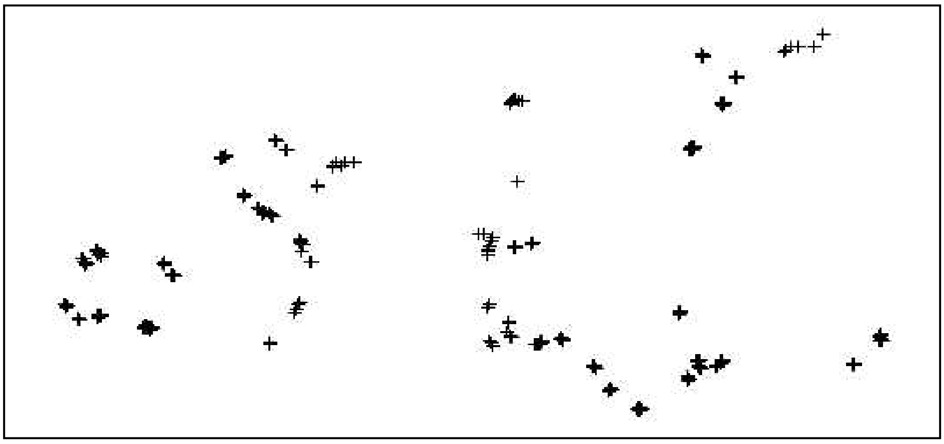


Figure 4.4 The clustered distribution of the groundtruth pixels.

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5 Discussion on results

In this chapter, the results of the application of different methods will be discussed. Not all the products attempted in those methods produce satisfactory results, assessed from the classification accuracy test. Therefore, not all them will be put into elaborate discussion below. However, considering the two approaches pursued, the discussion below will include all the outcomes, despite the low accuracy of classification achieved, in a way that all the methods are represented.

5.1 Classification of original bands

The supervised classification conducted with the three original bands is shown in **Plate (3)**. This product is considered as the standard product of supervised classification in this study. From visual assessment, the classified image gives reasonable results, in terms of landscape configuration based on field observation. Many dense coffee gardens are found in the northwestern part of the study area, while in the southeastern part approaching Bukit Rigis area, coffee gardens are less dense. In the foothills many patches of newly planted coffee are found. Ricefields occupy most of the river valleys, which are well observed in the classified image and patches of herbs and grass are often associated with abandoned. What looks unreasonable visually is the presence of ricefields (R1 and R2) in the Bukit Rigis foothill areas. This is considered as misclassification and is caused by the spectral mixtures of the signatures of R1 and R2 with grass and herbs (H).

The overall accuracy of this classification is 74.52 %, as shown in the table below (for detailed error matrix, see Appendix 2.) High accuracy (>70%) is shown by C1, C2, C4, R1, R2, S, B and W, which are spectrally separable (see scatter diagram, Figure 4.3.(a)), while the low accuracy is shown by classes C3 and C5, which is also shown by their spectrally-mixed signatures.

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Fccov	**94.2%**	**86.7%**	**47.4%**	**70.0%**	**27.6%**	**68.8%**	**79.6%**	**85.7%**	**52.5%**	**92.9%**	**100%**	**100%**	**74.5%**

5.2 Effect of spatial resolution enhancement

The fusion technique within the IHS-RGB transformation was applied to enhance the spatial resolution of the IKONOS MS. And the result is considered as the enhanced IKONOS MS. When the three bands of 321 are put in RGB channels, the result shows a similar visual appearance to that of the original bands. However, the resulting enhanced FCC bands produce better visualization for the image interpretation prior to the classification process, since both the textures and the colors become more pronounced.

After the classification procedures applied for both images (original bands and enhanced bands), the result shows that for the enhanced bands, due to the higher spatial resolution, the boundaries of several covers show a more natural shape compared to the block shapes in the classified image original bands. However, the high spatial resolution also brings disadvantage; small land cover patches produce noise in the classified image. The classified image is shown in **Plate (4)**

In comparing the accuracy assessment of the classified image of original bands (Fccov) with that of enhanced bands (Fccov1m), refer to the table below. The detailed error matrix can be seen in Appendix 3:

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Fccov	94.2%	86.7%	47.4%	70.0%	27.6%	68.8%	79.6%	85.7%	52.5%	92.9%	100%	100%	74.5%
Fccov1m	**97.5%**	**87.5%**	**67.7%**	**60.6%**	**23.5%**	**55.8%**	**79.1%**	**83.3%**	**34.8%**	**79.0%**	**94.7%**	**100%**	**70.7%**

Compared to the accuracy of the classification of the original bands, the overall accuracy decreases by 3.8 %. By land cover class, significant increase in accuracy only takes place in the C3, while large decrease in accuracy takes place in C4,C6, H. C6 is mainly mixed with B, and H is mixed with R2. They are indeed spectrally close to each other and considering the higher spatial variability in higher resolution image the chance for misclassification is higher. For S, despite the decrease, the accuracy is still considerably high (79 %). This result shows that in this study the resolution enhancement does not increase the overall accuracy, on the contrary, it even decreases accuracy of many classes.

The increase in classification accuracy of coffee type C3 is worth noting, though. From the scatter diagram, a shift of C3 signature cluster away from C4, C5, and C6 is observed (see Figure 4.3(b)). This gives higher accuracy in classifying this coffee type. C3 is multistrata coffee of low cover, while C4 and C5 are monoculture coffee, the better separability introduced by the resolution enhancement results from the higher variability of pixels of multistrata fields observed in the image, while in monoculture fields the variability is lower.

5.3 Effect of spectral transformation

5.3.1 PCA

The rationale of classification using PC layers (PC1, PC2 and PC3) is mainly due to the values of the PC images which are not correlated to each other. The classified image resulting from supervised classification of PC layers (Pccov) shows a reasonably good overall accuracy (73.9 %), slightly lower than that based on the original bands. The classified image is shown in **Plate (5)** The detailed accuracy result is shown in the table below.

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Fccov	94.2%	86.7%	47.4%	70.0%	27.6%	68.8%	79.6%	85.7%	52.5%	92.9%	100%	100%	74.5%
Pccov	**94.2%**	**86.2%**	**46.3%**	**70.0%**	**23.3%**	**71.9%**	**79.6%**	**75.0%**	**51.7%**	**92.9%**	**100%**	**100%**	**73.9%**

Compared to classified image of original bands (Fccov), there are no significant differences in terms of increase and decrease of accuracy. It shows that the classification of three principal components of a three-band image, produces no difference because the transformation does not give any significant changes to the compression of the data sets.

5.3.2 NDVI

The objective of incorporating NDVI is to observe whether the detailed coffee classes pursued in this study can be well differentiated. In the scatter diagram of the least correlated transformed images, namely NDVI and PC1, the spectral signatures of the training samples are plotted (see Figure 4.3 (c)). It is seen that classes that are spectrally separable, namely C1, C2, S, C6, B and W are spectrally separable in this diagram. Signatures of C3, C4, C5 are still mixed, along with H and C2. However, it can be observed that C2 and C4, which have the similar canopy cover range (25-50%) show higher values at NDVI (x axis) compared to C3 and C5 (canopy cover < 25%). The differences in the vegetation structure complexity can not be discriminated in this manner; C2 (multistrata) and C4 (monoculture) have similar NDVI values. The classified image of NDVI is shown in **Plate (6)**.

The accuracy result of classified image based on NDVI-PC1 image is shown in the table below (for detailed error matrix, see Appendix 5) Overall accuracy of the classified image is considered very low. Only classes with spectrally separable signatures give good accuracy result, while coffee classes with medium to low cover show low accuracy results. The misclassification occurs in the classes : C3 mixed with C5 and R2, C5 with C4, C6 and H, R2 with H and S, and H with C3, C5, and R2. In regards to the canopy cover, all of them belong to middle to low cover, and it shows that the values obtained from NDVI are not able to differentiate them. In this respect, only three levels of tree canopy cover can be differentiated : high density vegetation (C1 and S), middle to low cover (C2, C4, C3, C5, R1, R2, H) and very low cover (C6). The NDVI is useful for differentiation of vegetated and non-vegetated areas (cleared land and waterbody). Therefore the purpose of increasing the accuracy of classifying detailed coffee classes in this study by supervised classification of NDVI-PC1 image is considered unsuccessful.

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Ndcov	**96.4%**	**85.7%**	**34.9%**	**63.6%**	**11.1%**	**64.7%**	**50.0%**	**37.5%**	**37.8%**	**92.3%**	**100%**	**100%**	**65.2%**

Regarding the failure in the classification of NDVI image, the author considers that different approaches should be applied in utilizing NDVI image. One approach is applying only the canopy cover attribute, regardless the vegetation structure complexity factor. Combining with other approaches to finally determine the coffee classes, including the vegetation structure complexity factor can be applied afterwards. Another approach that requires knowledge of deterministic model of NDVI values in relation to canopy cover in the field is by clustering the NDVI image, followed by classification of canopy cover.

Intensity values are obtained in PC1 image and from the scatter diagram between PC1 and NDVI it can be observed that, regarding coffee classes, there is an increase in intensity along with the decrease of canopy cover and vegetation structure complexity. The increase in intensity of coffee classes starts from C1 (lowest intensity), C2, C4 and C5 (having similar intensity), C3 and C6 (highest intensity). Having in mind a systematic changes of canopy cover in NDVI values, a combined method utilizing PC1 image (intensity) and NDVI can be useful in determining coffee classes taking into account both the canopy cover and the vegetation structure complexity. This may be explored in future studies.

5.4 Effect of integration with texture image

The texture image in this study is based on the variance parameter measured in the 7x7 window throughout the image. From the scatter diagram, it is observed that the signatures of all classes only occupy the lower values of both bands (bands 2 and 3). The high values, approximately above 115 (of 8-bit data values) , are mostly occupied by the feature boundaries, which are observed in the image by linear features in extremely bright pixels. The frequency of low variance values is very high. The high density of the signature clusters in the area where variance is low, causes spectral mixtures, and this creates the low accuracy due to misclassification.

The classified image is shown in **Plate (7)** . Visually, water (W) overclassifies some classes, *i.e.* non-vegetated areas (B) and ricefield (R1). The mixed classification between R2 and H occurs in many areas.

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Varcov	**81.9%**	**83.3%**	**55.3%**	**46.7%**	**10.8%**	**55.2%**	**37.3%**	**65.2%**	**22.0%**	**76.0%**	**67.9%**	**92.9%**	**58.2%**

From the error matrix (see Appendix 6.), it is seen that mixed classification occurs in most the middle-low canopy cover classes (C3, C4, C5, C6, R1, R2, H). Good accuracy only exists in the two extreme classes of very low variance (B and W) and very high variance (C1, C2).

The low overall accuracy is attributed to the low accuracy in most of the classes. The replacement of intensity layer with texture information (using variance parameter in this study), causes the loss of original information (spectral reflectance), which eventually affects the classification of the pixels.

5.5 Effect of integration with segmentation approach

Under this part of integration only the ‘classification of segment image’ will be discussed, while ‘segmentation of classified image’ will not be discussed , considering the low accuracy (overall accuracy = 66%) achieved, as well as considering the anticipated weaknesses of this type of integration mentioned in the literature review (section 2.4). There are two sub sections within this integration:

- Supervised classification of segment image
- Integration using majority rule

5.5.1 Supervised classification of segment image

The segment image gives lower density of spectral values, for each segment bears only the mean values of the merged regions. This can be seen in the scatter diagram of bands 2 and 3 of the image (see Figure 4.3(e)). This also results in lower variability in the training patches for the supervised classification, while most of them become single-value patches. Both ML classifier and MD classifier were applied. The result of ML classifier shows overclassification of classes C1, C2, C6, while C3, C4, C5 and R2 do not appear in the image. The single value patches in the signatures of those classes produce no statistical parameters required by the ML classifier to classify the pixels, and therefore signatures which have ranges of values over-classify the other classes.

Minimum-distance-to-means classifier only considers the shortest euclidian distance between the arbitrary pixel and the signature pixels, and this classifier works well in the case of classifying segment image, because it suits the condition of the lack of other parameters. The classified image used for further discussions and integration is the result of MD classifier and it is shown in **Plate (8)**.

When comparing the classified segment images with the pixel-based classified images visually, the small patches of certain classes clearly become larger patches. This presents as an advantage for the coffee classes, because it reduces the minor variabilities unnecessary within the fields. However, for the classes which are likely to exist in small patches like shrubs and herbs, this results in overestimation of the patch areas or, on the other hand, elimination of the patches. The overestimation of R1 also exists, because spectrally the signature occurs in a wide range of values in the scatter diagram, and therefore overinclusion to this class is likely to occur.

The accuracy assessment result of this classified image is shown below, and the error matrix is presented in Appendix 7.

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Fccov	94.2%	86.7%	47.4%	70.0%	27.6%	68.8%	79.6%	85.7%	52.5%	92.9%	100%	100.%	74.5%
Segcov	**95.3%**	**65.9%**	**65.7%**	**100%**	**42.4%**	**73.9%**	**70.7%**	**22.2%**	**41.0%**	**100 %**	**96.9%**	**100%**	**72.8%**

Although the overall accuracy decreases by 1.7 % from the accuracy of the classification of the original bands (Fccov), several coffee classes that are spectrally mixed in the original FCC bands and are difficult to differentiate using the NDVI approach, namely C3, C4, C5 and C6, can be more accurately classified by this method. The segmentation that preceded the classification produced representative values for the textured areas. Because of the lower variability in neighboring pixels chances for misclassification due to noise pixels are reduced. Nevertheless, 100 % accuracy in C4 should be considered carefully. This coffee type does not exist in large areas in the study area and reliable samples are rarely found . This led to a condition that only small samples could be taken for both the training areas as well as for groundtruth pixels, and spatially they are not independent from each other because they are located in the close vicinity.

5.5.2 Integration using majority rule

The discussion of this method refers to the integration with the classified image of original bands, considering that within pixel-based approach this classified image produced the best overall accuracy. In addition to that, an attempt to try this integration to the classified image of 1 m resolution (enhanced FCC bands) was pursued, yet it didn't result in improved accuracy (overall accuracy = 69.9 %). No elaborate discussion will be done to this result.

As mentioned in section 4.3.3.4, this method utilizes the PC transformation of the segment image in order to obtain one layer out of the three layers of segment image arranged in RGB channels. PC1 is considered the compressed layer regarding the values in the three layers, and geometrically it also represents the best intersection of the three layers.

Compared to the classified segment image, visually it is observed that the overestimation of grass and herbs (H) that commonly exist in small patches in the field is reduced. And over-classification of R1 (see the discussion of section 5.5.1) is also reduced.

From the accuracy assessment result, in overall, the accuracy increases only by 0.64 % compared to the classified image of original FCC bands (Fccov), and by 2.34 % compared to the classified segment image (Segcov). The accuracy of each class (also in comparison with classified image of original FCC and with the classified segment image) is shown in the table below. The detailed error matrix is presented in Appendix 8:

	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
Fccov	94.2%	86.7%	47.4%	70.0%	27.6%	68.8%	79.6%	85.7%	52.5%	92.9%	100%	100%	74.5%
Segcov	95.3%	65.9%	65.7%	100%	42.4%	73.9%	70.7%	22.2%	41.0%	100%	96.9%	100%	72.8%
Segpcfcov	**88.0%**	**68.0%**	**58.2%**	**100.%**	**60.9%**	**51.4%**	**100.%**	**66.7%**	**53.3%**	**94.1%**	**100.%**	**100.%**	**75.2%**

The increase occurs in classes of C4, C5, R1, H. Yet, 100 % accuracy for class C4 should be considered carefully, as it was discussed in section 5.5.1. Despite the decreases of accuracy for some classes, the values are still high (>80 %) , *e.g.* C1 and S, and in some other classes variations of increase and decrease in accuracy take place among the three compared classified images.

As compared with the supervised classification conducted to the segment image, this method reduces the possibility of error in the pixel inclusion due to the averaging effect to the pixel values. And as compared to the pixel-based classified image, the incorporation of the geometry of the segments as homogeneous objects, reduces the noise in the areas where high variability of pixels occurs.

6 Summary and conclusion

6.1 Summary

Attempts to achieve detailed classification of coffee gardens in Sumberjaya, Lampung, Indonesia were explored by utilizing the availability of high resolution satellite imageries and by applying various remote sensing methods and techniques.

Two remote sensing approaches were attempted in this work in searching for the best method for the classification of multistrata vegetation with emphasis to detailed classification of coffee gardens. The two approaches are : pixel-based approach and spatial-based approach.

The methods to enhance image interpretability prior to classification are:

- Image transformation using PCA
- Image ratioing using NDVI
- Spatial resolution enhancement using image fusion technique
- Integration with texture image generated from the panchromatic band
- Segmentation of the original bands

The classification procedures listed below have been applied. The rationale for the application of these procedures is discussed and the results are evaluated.

- Supervised classification of the original bands
- Supervised classification of the spatially-enhanced bands
- Supervised classification of the PC 123 layers
- Supervised classification of the NDVI-PC1 layers
- Supervised classification of the texture image
- Supervised classification of the segment image
- Classification of segment image applying class majority of pixel-based classified image

The graph below shows the overall accuracy of the resulting classified images:

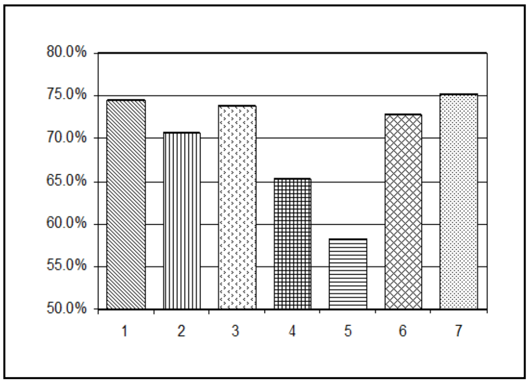

Figure 6.1 Accuracy assessment results of (1) classification of original bands, (2) classification of enhanced bands,(3) classification of PC123, (4) classification of NDVI-PC1, (5) classification of texture image, (6) classification of segment image, (7) classification of segment image using majority rule.

6.2 Conclusion

6.2.1 Conclusion of the results

By assessing the outcomes of image transformations and the results of the classification, it is concluded that:

1. The transformation with Principal Component Analysis (PCA) does not produce significant data compression because of the low dimensionality of the original bands (3 bands). Therefore, classification of PC123 layers produced the same level of accuracy as that of the original bands.
2. The least correlation is shown by NDVI and PC1 images. The purpose of utilizing NDVI to improve the classification of vegetation without full canopy cover in this work is not achieved. However, the differentiation of the two extremes of vegetation, dense canopy cover of multistrata type in the one side and low canopy cover of monoculture type at the other side, proved to be successful.
3. The lower accuracy in the classification of the enhanced FCC layers is attributed to the following factors:
   - The higher spatial resolution provides more detailed information. However some classes such as multistrata type pertain to a varied response. In the classification this leads to misclassification because of a wide spread of the training set.
   - The groundtruth pixels were originally defined on the 4 m resolution image. Later they were applied to the spatially enhanced image (1 m resolution). The transfer of the sample coordinates created bias.
4. The creation of texture image by fusion of variance image during the inverse transformation of HIS to RGB does not improve the accuracy result. The strength of the integration, *i.e.* the inclusion of the variability values of the adjacent pixels, is achieved at the expense of losing information of the original spectral response. This loss of information contributes to the low accuracy of the classification.
5. Segmentation has the advantage of averaging variability of values based on the objects on the terrain. Yet the "correct" assignment of splitting and merging regions is beyond the control of the user, and the result may introduce errors.
6. Although the supervised classification of the segment image in this work does not improve the overall accuracy, for some classes, the accuracy improves significantly. This improvement is attributed to the homogeneity of the regions which results in less chances of misclassification due to the "noise" pixels.
7. The result of classifying the segment image using the class majority of pixel-based classified image gives an improved overall accuracy. This method is considered as the optimization of both approaches pursued in this work. The supervised classification is based on the original spectral responses and the assignment of the class boundaries is obtained from the segmentation. Assuming a reliable segmentation process, labeling the segment by assigning the major class within those boundaries gives the best result.

6.2.2 Overall conclusion

In referring to the research questions raised in this work, the overall conclusions are:

1. Classifying multistrata vegetation with the emphasis of detailed coffee classes incorporating canopy cover and vegetation structure complexity, gives satisfactory results to the two extreme classes, dense canopy cover of multistrata type on the one side and low canopy cover of monoculture type on the other side. Classifying the middle classes gives unsatisfactory results. Overall accuracy obtained is between 58.2 % to 75.2 %.
2. The best method judged from the accuracy result is the integration of pixel-based supervised classification and segmentation technique by applying majority rule.

6.3 Recommendation

Regarding the unsatisfactory results and the weaknesses of the methods observed by the author in this work, several points of evaluation as well as recommendations for improvements in further studies will be noted in this section.

1. The NDVI data is not sensitive to the vegetation structure complexity factor (multistrata or monoculture) of the coffee classes. If only classes are based on canopy cover alone, the result can be much better. The integration of NDVI with PC1 in order to include vegetation structure complexity factor should be explored with other methods to improve the result.
2. Regarding the unsuccessful integration with texture image, improvements can be done by:
   - maintaining the spectral information so there is no loss of information.
   - having tests with different window sizes
3. Regarding the overall accuracy of all the results in this work several points are evaluated:
   - overall accuracy can still be improved by having more groundtruth samples that are independent from the training samples and are distributed randomly .
   - The possibility of inaccurate observation in estimating the canopy cover is also noted. To give a better estimate, more field measurements are required.
4. Segmentation to the spatially enhanced bands was not pursued in this work. In treating the high variability of neighboring pixels in this image, segmentation process might result in a better object-based classified image to be processed further with supervised approach or integration with other methods.
5. It might be attractive to apply a merge technique to the classes with the highest accuracy resulted from different methods into one classified image. However, the optimum decision rule should be carefully sought to minimize the risk of misclassification.

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Appendix 1. Ground Control Points for IKONOS Pan Geometric Correction

Point ID	X Input	Y Input	X Ref.	Y Ref.	X Residual	Y Residual	RMS Error
GCP #5	63.5605	3870.9375	431671.4748	9445634.9406	-0.086668	-0.012796	0.087608
GCP #2	204.9939	213.9906	431809.7765	9441982.5234	0.003374	-0.015202	0.015572
GCP #3	1058.0004	480.0242	432663.3622	9442248.5846	0.113626	-0.230591	0.257067
GCP #4	1587.8613	856.9803	433193.7519	9442625.6762	0.162106	0.011300	0.162499
GCP #7	2610.0750	1905.0791	434216.7004	9443673.2639	-0.315376	0.094911	0.329348
GCP #8	2874.3871	2469.1242	434481.7538	9444236.5655	-0.148639	-0.139638	0.203942
GCP #9	2818.8325	561.0124	434424.5968	9442330.8724	-0.035020	0.000097	0.035021
GCP #10	2318.0924	3377.9120	433926.3647	9445144.2128	0.097712	0.191910	0.215353
GCP #11	4504.1320	2711.9124	436112.3889	9444480.5351	0.081678	0.256088	0.268798
GCP #12	4203.9871	1245.0826	435810.8533	9443015.1122	0.080334	0.081622	0.114524
GCP #13	5174.0088	3813.8768	436783.4810	9445581.4152	0.132554	0.064831	0.147559
GCP #15	5972.8810	2826.9240	437581.7119	9444596.2836	0.153856	0.158656	0.221006
GCP #16	5745.0399	1323.9081	437352.3368	9443094.9603	0.021715	0.178221	0.179539
GCP #17	6987.8672	2476.0000	438596.3401	9444246.1249	-0.166926	-0.175146	0.241952
GCP #18	8028.1859	1440.6652	439636.1419	9443212.9562	-0.043961	0.044825	0.062784
GCP #20	9002.1596	2799.3114	440611.6994	9444570.6313	0.063794	0.076821	0.099855
GCP #1	140.8362	894.0039	431746.2482	9442661.5374	0.044047	-0.146845	0.153309
GCP #6	72.6920	2340.0401	431679.2812	9444105.9062	-0.049400	-0.013856	0.051306
GCP #21	7270.9888	3822.3025	438881.0103	9445590.8284	0.104471	-0.328253	0.344477
GCP #22	9015.8332	3313.0212	440625.7571	9445083.5837	-0.013646	-0.066248	0.067638
GCP #24	7835.0286	2742.0577	439444.0025	9444512.4057	-0.133471	-0.190884	0.232919
GCP #25	5048.3146	1601.2060	436655.5813	9443371.4416	-0.066159	0.160177	0.173302

Control Point Error, X = 0.1178
Control Point Error, Y = 0.1488
Total RMS Error = 0.1898

Appendix 2. Error matrix of classification to original bands

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename: fccov

ERROR MATRIX

Classified	Reference Data											
Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
C1	81	0	0	0	0	0	0	0	0	5	0	0	86
C2	0	26	0	4	0	0	0	0	0	0	0	0	30
C3	0	1	27	1	22	2	0	3	0	0	1	0	57
C4	0	7	2	21	0	0	0	0	0	0	0	0	30
C5	0	0	3	9	8	3	0	0	6	0	0	0	29
C6	0	0	0	0	0	22	0	0	0	0	10	0	32
R1	0	0	0	0	0	0	35	0	7	0	0	2	44
R2	0	0	0	0	0	0	0	12	0	0	2	0	14
H	0	0	0	0	4	0	0	16	31	8	0	0	59
S	2	0	0	0	0	0	0	0	0	26	0	0	28
B	0	0	0	0	0	0	0	0	0	0	24	0	24
W	0	0	0	0	0	0	0	0	0	0	0	38	38
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	86	81	97.6%	94.2%
C2	34	30	26	76.5%	86.7%
C3	32	57	27	84.4%	47.4%
C4	35	30	21	60.0%	70.0%
C5	34	29	8	23.5%	27.6%
C6	27	32	22	81.5%	68.8%
R1	35	44	35	100.0%	79.6%
R2	31	14	12	38.7%	85.7%
H	44	59	31	70.5%	52.5%
S	39	28	26	66.7%	92.9%
B	37	24	24	64.9%	100.0%
W	40	38	38	95.0%	100.0%
Total	471	471	351		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy = 74.52%

Overall Kappa Statistics = 0.7187

Appendix 3. Error matrix of classification of enhanced bands (1 m resolution)
CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename: fcov1m

ERROR MATRIX

Classified	Reference Data											
Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
C1	79	0	0	0	0	0	0	0	0	2	0	0	81
C2	1	28	0	2	0	0	0	0	0	1	0	0	32
C3	0	0	21	0	9	0	0	0	1	0	0	0	31
C4	0	6	2	20	5	0	0	0	0	0	0	0	33
C5	0	0	8	13	12	2	1	0	15	0	0	0	51
C6	0	0	0	0	0	24	0	0	0	0	19	0	43
R1	0	0	0	0	0	0	34	0	8	1	0	0	43
R2	0	0	0	0	0	0	0	15	3	0	0	0	18
H	0	0	1	0	8	0	0	16	16	5	0	0	46
S	3	0	0	0	0	0	0	0	1	30	0	4	38
B	0	0	0	0	0	1	0	0	0	0	18	0	19
W	0	0	0	0	0	0	0	0	0	0	0	36	36
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	81	79	95.18%	97.53%
C2	34	32	28	82.35%	87.50%
C3	32	31	21	65.63%	67.74%
C4	35	33	20	57.14%	60.61%
C5	34	51	12	35.29%	23.53%
C6	27	43	24	88.89%	55.81%
R1	35	43	34	97.14%	79.07%
R2	31	18	15	48.39%	83.33%
H	44	46	16	36.36%	34.78%
S	39	38	30	76.92%	78.95%
B	37	19	18	48.65%	94.74%
W	40	36	36	90.00%	100.00%
Total	471	471	333		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy =
70.70%
Overall Kappa Statistics = 0.6771

Appendix 4. Error matrix of classification of PC123 layers

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename: pccov

ERROR MATRIX

Classified Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
	Reference Data												
C1	81	0	0	0	0	0	0	0	0	5	0	0	86
C2	0	25	0	4	0	0	0	0	0	0	0	0	29
C3	0	1	25	1	23	1	0	3	0	0	0	0	54
C4	0	8	1	21	0	0	0	0	0	0	0	0	30
C5	0	0	5	9	7	3	0	0	6	0	0	0	30
C6	0	0	0	0	0	23	0	0	0	0	9	0	32
R1	0	0	0	0	0	0	35	0	7	0	0	2	44
R2	0	0	0	0	0	0	0	12	0	0	4	0	16
H	0	0	1	0	4	0	0	16	31	8	0	0	60
S	2	0	0	0	0	0	0	0	0	26	0	0	28
B	0	0	0	0	0	0	0	0	0	0	24	0	24
W	0	0	0	0	0	0	0	0	0	0	0	38	38
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	86	81	97.59%	94.19%
C2	34	29	25	73.53%	86.21%
C3	32	54	25	78.13%	46.30%
C4	35	30	21	60.00%	70.00%
C5	34	30	7	20.59%	23.33%
C6	27	32	23	85.19%	71.88%
R1	35	44	35	100.00%	79.55%
R2	31	16	12	38.71%	75.00%
H	44	60	31	70.45%	51.67%
S	39	28	26	66.67%	92.86%
B	37	24	24	64.86%	100.00%
W	40	38	38	95.00%	100.00%
Total	471	471	348		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy = 73.89%

Overall Kappa Statistics = 0.7116

Appendix 5. Error matrix of classification of NDVI-PC1 image

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename:ndcov

ERROR MATRIX

Classified	Reference Data											
Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
C1	80	0	0	0	0	0	0	0	0	3	0	0	83
C2	0	18	0	2	0	0	1	0	0	0	0	0	21
C3	0	0	23	0	24	1	0	10	8	0	0	0	66
C4	0	7	0	14	1	0	0	0	0	0	0	0	22
C5	0	1	0	6	2	4	0	0	5	0	0	0	18
C6	0	0	1	0	0	22	0	0	0	0	11	0	34
R1	1	8	0	12	2	0	34	0	10	1	0	0	68
R2	0	0	0	0	0	0	0	12	7	11	2	0	32
H	0	0	8	1	5	0	0	9	14	0	0	0	37
S	2	0	0	0	0	0	0	0	0	24	0	0	26
B	0	0	0	0	0	0	0	0	0	0	24	0	24
W	0	0	0	0	0	0	0	0	0	0	0	40	40
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	83	80	96.39%	96.39%
C2	34	21	18	52.94%	85.71%
C3	32	66	23	71.88%	34.85%
C4	35	22	14	40.00%	63.64%
C5	34	18	2	5.88%	11.11%
C6	27	34	22	81.48%	64.71%
R1	35	68	34	97.14%	50.00%
R2	31	32	12	38.71%	37.50%
H	44	37	14	31.82%	37.84%
S	39	26	24	61.54%	92.31%
B	37	24	24	64.86%	100.00%
W	40	40	40	100.00%	100.00%
Total	471	471	307		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy =
65.18%
Overall Kappa Statistics = 0.6163

Appendix 6. Error matrix of classification of "texture image"

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename: varcov

ERROR MATRIX

Classified	Reference Data											
Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
C1	77	0	0	0	0	0	2	0	0	15	0	0	94
C2	0	20	0	2	0	0	0	0	0	2	0	0	24
C3	0	4	21	0	11	0	0	0	0	0	2	0	38
C4	0	8	3	14	5	0	0	0	0	0	0	0	30
C5	0	1	8	16	4	3	0	0	4	0	1	0	37
C6	0	0	0	0	2	16	0	0	6	0	5	0	29
R1	0	1	0	0	2	1	19	8	17	1	2	0	51
R2	0	0	0	0	0	0	3	15	5	0	0	0	23
H	0	0	0	3	8	2	9	7	11	2	8	0	50
S	6	0	0	0	0	0	0	0	0	19	0	0	25
B	0	0	0	0	2	5	0	0	1	0	19	1	28
W	0	0	0	0	0	0	2	1	0	0	0	39	42
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	94	77	92.77%	81.91%
C2	34	24	20	58.82%	83.33%
C3	32	38	21	65.62%	55.26%
C4	35	30	14	40.00%	46.67%
C5	34	37	4	11.76%	10.81%
C6	27	29	16	59.26%	55.17%
R1	35	51	19	54.29%	37.25%
R2	31	23	15	48.39%	65.22%
H	44	50	11	25.00%	22.00%
S	39	25	19	48.72%	76.00%
B	37	28	19	51.35%	67.86%
W	40	42	39	97.50%	92.86%
Total	471	471	274		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy = 58.17%

Overall Kappa Statistics = 0.5373

Appendix 7. Error matrix of classification of segment image

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename: segcov

ERROR MATRIX

Classified	Reference Data											
Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
C1	81	0	0	0	0	0	0	0	0	4	0	0	85
C2	0	27	0	8	0	0	6	0	0	0	0	0	41
C3	0	0	23	0	12	0	0	0	0	0	0	0	35
C4	0	0	0	23	0	0	0	0	0	0	0	0	23
C5	0	0	7	2	14	8	0	0	0	0	2	0	33
C6	0	0	2	0	0	17	0	0	0	0	4	0	23
R1	2	7	0	0	2	0	29	0	0	1	0	0	41
R2	0	0	0	2	0	0	0	4	12	0	0	0	18
H	0	0	0	0	6	1	0	27	32	12	0	0	78
S	0	0	0	0	0	0	0	0	0	22	0	0	22
B	0	0	0	0	0	1	0	0	0	0	31	0	32
W	0	0	0	0	0	0	0	0	0	0	0	40	40
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	85	81	97.59%	95.29%
C2	34	41	27	79.41%	65.85%
C3	32	35	23	71.88%	65.71%
C4	35	23	23	65.71%	100.00%
C5	34	33	14	41.18%	42.42%
C6	27	23	17	62.96%	73.91%
R1	35	41	29	82.86%	70.73%
R2	31	18	4	12.90%	22.22%
H	44	78	32	72.73%	41.03%
S	39	22	22	56.41%	100.00%
B	37	32	31	83.78%	96.88%
W	40	40	40	100.00%	100.00%
Total	471	471	343		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy =
72.82%
Overall Kappa Statistics = 0.6995

Appendix 8. Error matrix of classification of segment image using majority rule
CLASSIFICATION ACCURACY ASSESSMENT REPORT

Filename: segpcfcov

ERROR MATRIX

Classified	Reference Data											
Data	C1	C2	C3	C4	C5	C6	R1	R2	H	S	B	W	Total
C1	81	0	0	0	0	0	0	0	0	11	0	0	92
C2	1	34	0	12	2	0	0	0	0	0	0	1	50
C3	0	0	32	4	18	1	0	0	0	0	0	0	55
C4	0	0	0	19	0	0	0	0	0	0	0	0	19
C5	0	0	0	0	14	7	0	0	0	0	2	0	23
C6	0	0	0	0	0	19	0	0	0	0	18	0	37
R1	0	0	0	0	0	0	35	0	0	0	0	0	35
R2	0	0	0	0	0	0	0	8	4	0	0	0	12
H	0	0	0	0	0	0	0	23	40	12	0	0	75
S	1	0	0	0	0	0	0	0	0	16	0	0	17
B	0	0	0	0	0	0	0	0	0	0	17	0	17
W	0	0	0	0	0	0	0	0	0	0	0	39	39
Total	83	34	32	35	34	27	35	31	44	39	37	40	471

ACCURACY TOTALS

Class Code	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
C1	83	92	81	97.59%	88.04%
C2	34	50	34	100.00%	68.00%
C3	32	55	32	100.00%	58.18%
C4	35	19	19	54.29%	100.00%
C5	34	23	14	41.18%	60.87%
C6	27	37	19	70.37%	51.35%
R1	35	35	35	100.00%	100.00%
R2	31	12	8	25.81%	66.67%
H	44	75	40	90.91%	53.33%
S	39	17	16	41.03%	94.12%
B	37	17	17	45.95%	100.00%
W	40	39	39	97.50%	100.00%
Totals	471	471	354		

C1 : Coffee multistrata, canopy >50 %
C2 : Coffee multistrata, canopy 25-50 %
C3 : Coffee multistrata, canopy < 25 %
C4 : Coffee monoculture, canopy 25-50 %
C5 : Coffee monoculture, canopy <25%
C6 : Newly planted coffee
R1 : Ricefields, green, inundated
R2 : Ricefields, dry
H : Herbs and grass
S : Shrubs, woody
B : Cleared land, non vegetated area
W : Waterbody

Overall Classification Accuracy =
75.16%
Overall Kappa Statistics = 0.7252