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**VEGETATION CLASSIFICATION AND MAPPING IN
SOUTH SUMATRA, INDONESIA, USING SPOT
MULTISPECTRAL DATA**

By

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March 1992**



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ABSTRACT

The problems relating to tropical rain forest exploitation for timber production, cultivation and land settlement schemes are all well known. Conservation of this forest resource in Indonesia demands a knowledge of the extent of such forest. The distribution of tropical rain forest types in Sumatra is not known in detail. This thesis investigates the possibilities of using SPOT multi-spectral imagery as a cheaper and less time consuming way of producing a vegetation map and inventory in comparison with more traditional methods.

The use of SPOT data to investigate vegetation distribution is reviewed, and the use of this data set in Indonesia is discussed. SPOT multi-spectral imagery for the Baturaja district of Sumatra for July 1986, in conjunction with a vegetation classification produced by BAKOSURTANAL, is used as a basis for the production of a vegetation inventory.

Three sample areas within Baturaja district are selected for detailed study in order to provide a range of different vegetational conditions within the general forest environment. Baturaja City provides a complex of urban units, plantation, and secondary forest, Lebak is a mixture of swamp land, plantation, settlement, and cultivation whilst the Subanjeruji extract covers reforestation and secondary forest.

The imagery has been grouped using a standard box classification to produce eight divisions of land cover. These are then compared with a similar eight class grouping using maximum likelihood classification techniques for the Subanjeruji area. A more detailed sixteen class grouping using a maximum likelihood classifier has been conducted on all these study extracts. All classes were subjected to comparison with map land cover information in order to assess their validity. Several areas of confusion were identified, the principal difficulties arising from similarity between tree crops and secondary forest cover, and newly planted tree crops and grassland. The difficulties might be resolved using multi-temporal imagery.

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CHAPTER 1

INTRODUCTION

1.1 Study Background.

Indonesia is a tropical country, It has about 13,677 islands stretching 5,152 km from east to west and 1,770 km from north to south with a total land area of 1,905,443 square kilometres (Gastellu-Etchegorry, 1988b). Indonesia is the fifth most populous country in the world. The distribution of population is not equal over the various islands, at least 63 % of the total population live on Java (Kardono, 1987). Even though Indonesia's government has produced Planned Parenthood and transmigrations programmes, it still has various population problems such as, housing, food, job opportunities (Asmoro, 1978).

Indonesia being a tropical country, has tropical rain forests with many vegetation species: between 20,000 and 30,000 species of trees, shrubs, and grasses , belonging to about 2,500 families (Robequain, 1958). The typical rain forest is usually about 50 - 55 m in height, although certain trees may reach 60 m, and usually contains shrub and herb layers. The tropical forest in Indonesia is the second largest in the world after the Amazon basin in Latin America, and many problems typical of rain forest, for example, deforestation, shifting

cultivation, and timber production, are experienced. The most reliable method of knowing the distribution of vegetation is via a vegetation map as this produces an inventory of the habitat of many vegetation species. Vegetation maps in particular, serve three purposes : a) they are inventories of plant communities existing at a given time and place, and show the areal distribution of vegetation types in the landscape, b) they are tools for analyzing the natural environment and the relations between it and the various phytocenes, c) through interpretation of the information on vegetation maps, it is possible to plan future action with regard to optimal land use and also produce maximum qualitative and quantitative production without damage to the soil and water economy of the landscape (Küchler, 1965).

The use of vegetation maps as a cartographic device and as a scientific tool has evolved slowly over time. Vegetation mapped by traditional methods usually involves field work which is time consuming and expensive, but today satellite remote sensing has provided the means for collecting spectral data over large land areas in support of these renewable and non-renewable resource inventories and to monitor information needs for, geology, hydrology, land use / land cover, vegetation data, etc. By using remote sensing techniques and digital image processing it may be possible to provide a cheaper and less time consuming

method of vegetation inventory and map production compared with more traditional methods.

There are many kinds of satellite remote sensing, for example, Landsat MSS, Thematic Mapper (TM), SEASAT and, SPOT. This study uses SPOT multispectral data with 20 m spatial resolution, recorded on 21st July 1986. The general quality of the SPOT image is very good, being very clear with no cloud cover.

1.2 The Aim of the Study.

The objective of this study is to produce a vegetation map of part of Sumatra by interpretation and analysis of SPOT - 1 multispectral scanner data (1986). This study follows the scheme indicated below:

- 1). Choose a study area and study extracts.
- 2). Interpret vegetation types within the study area using digital image processing.
- 3). Supervised classification methods: box and maximum likelihood classifiers, are used to group the vegetation.
- 4). The results of digital image processing of vegetation types are used to produce a vegetation map.

1.3 Methodology.

The primary technique employed was a supervised, computer assisted interpretation of the image data using a GEMS image processing system for Maximum Likelihood classification, an R-CHIPS (system 3) image processing system for Box classification, and an R-CHIPS (system 4) for maximum likelihood classification. Three sample areas with different conditions have been selected for study: Baturaja City as city and commercial estates, Lebak as wetland, and Subanjeruji as a reforestation and commercial estates area. Each sample area shows different classes dependent on the condition of the area.

Box classification and maximum likelihood classification on the image processing systems permit the recognition of eight land cover / vegetation classes.

1.4 Location of Study.

Baturaja is located between longitude $103^{\circ} 51' 55''$ E and $104^{\circ} 35' 36''$ E, and latitude $3^{\circ} 42' 05''$ S and $4^{\circ} 19' 58''$ S (Statistik dan BAPPEDA, 1986). This area of approximately 3.6 million hectares is divided between three regencies : 0.12% of Ogan Komering Ilir regency, 11.17% of Muara Enim regency and 39.76% of Ogan Komering Ulu regency (BAKOSURTANAL, 1988), figure 1.1.

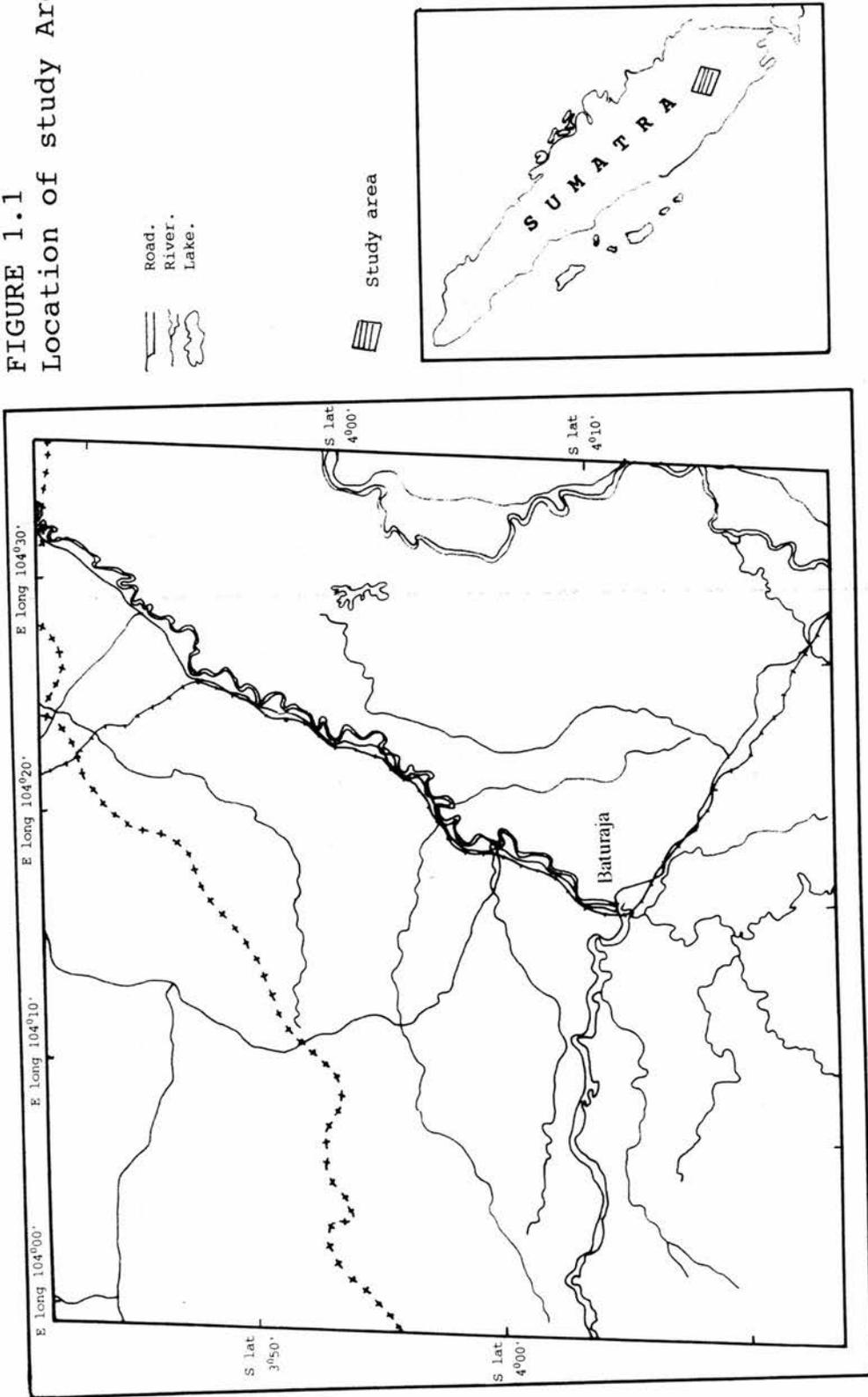
1.4.1 Physical Environment.

The elevation of Baturaja is varied, from approximately 12 m to 1,619 m above sea level, with most of the study area being plains. The lowest area is in east side of the study area and the highest area is in the south west (Bukit Nanti).

There are many different landforms in Baturaja, for example volcanic cones can be found in the top of the Bukit Nanti (1,619 m elevation above sea level), where there is dense vegetation, and little erosion. Also at Bukit Nanti volcanic slopes can be found (500 - 1,000 m elevation above sea level), and volcanic foot slopes on the south west side of Baturaja city. The east side of Ogan Komering is a volcanic plain, and denuded volcanic hills can be found approximately 20 - 30 km north west of Baturaja city. The relief of the anticlinal hills is varied, (approximately 75 - 300 m), these hills lie between Gunungmeraksa and Kepayang. The fluvial plain which is the result of sedimentation processes, can be found at the right and left hand side of Air Ogan and Air Komering (BAKOSURTANAL, 1988), figure 1.2.

The majority of the soils in the study area can be classified into 8 soil groups (FAO/UNESCO 1974), Podzols, Latosols, Fluvisols, Regosols, Andosols, Rendzinas, Lithosols, and Gleysols. In this study area the majority are Podzols, and can be found across most

FIGURE 1.1
Location of study Area.



Scale 1 : 500,000.

of the study area from the plains to hill lands. The Podzols group can be sub-divided into Yellowish brown Podzols, Yellowish Red Podzols, and Reddish Brown Podzols. On the top of the soil profile, the organic matter is very thin (5 - 7.5 cm). The lower horizons are fine textured and usually acid (BAKOSURTANAL, 1988). There are two different Latosols: Reddish Brown Latosols, found around Subanjeruji and Yellowish Red Latosols found on the volcanic middle and foot slopes of Bukit Nanti (south west of Baturaja city) and on the south side of Gunungmeraksa. Rendzinas can be found approximately 25 km west and 15 km south west of Baturaja city, Regosols on the south side of Air Komerling and Brown Dark Andosols at the top of the slope on Bukit Nanti. The Fluvisols consist of Grey Alluvials at Air Komerling and Yellowish Brown Alluvials at Air Ogan (BAKOSURTANAL, 1988), figure 1.3.

The study area has 2 classes of bioclimates : 1). Perhumid Bioclimates with precipitation from 2,500 - 3,000 mm/year, and 2). Hyperhumid Bioclimates with precipitation more than 3,000 mm/year and the number of rainy days varying from 180 to 220 (Fontanel and Chantefort, 1978).

1.4.2 Land Use and Land Cover.

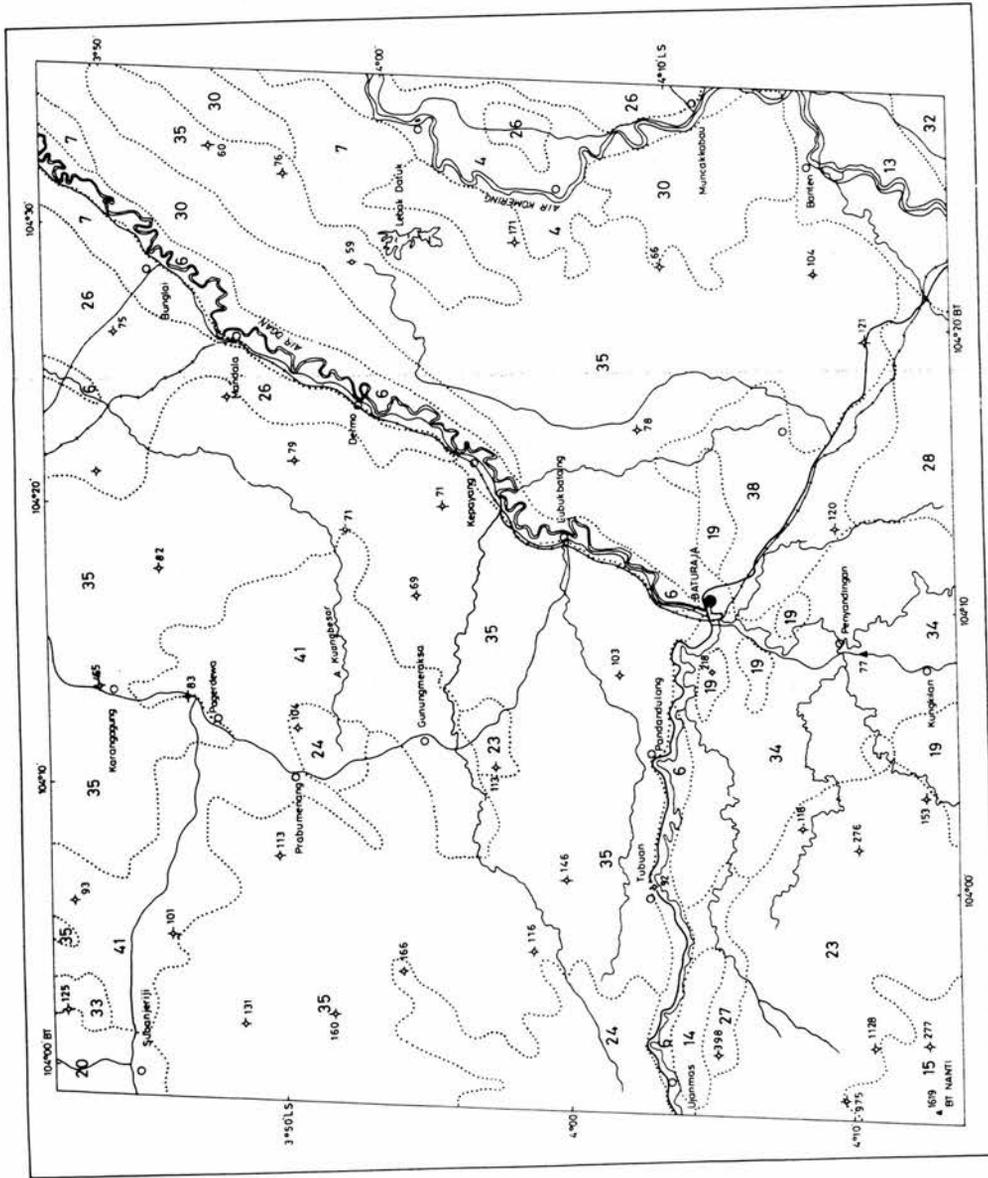
There are many land use/cover types in this study area, such as grass land, dry rice fields, dry fields,

SOILS OF BATURAJA

SCALE 1 : 500,000

Explanation of Soil Map Symbols:

- 4 Grey Alluvials.
 - 6 Yellowish Brown Alluvials.
 - 7 Gleysols.
 - 13 Grey Regosols.
 - 14 Rendzinas.
 - 15 Brown Dark Andosols.
 - 19 Association of Brown Latosols and Litosols.
 - 20 Reddish Brown Latosols.
 - 23 Yellowish Red Latosols.
 - 24 Association of Reddish Brown Latosols and Yellowish Red Latosols.
 - 26,27,28 Yellowish Brown Podzols.
 - 30,32,33,35 Association of Yellowish Brown Podzols and Yellowish Red Podzols.
 - 34,41 Association of Yellowish Red Podzols and Yellowish Brown Podzols.
 - 38 Reddish Brown Podzols.
- District town.
 - Subdistrict town.
 - △/◇ Triangulation station.
 - Road.
 - +—+—+ Railway.
 - ~ River.
 - ⊖ Lake.



Made and published by BAKOSURTANAL...
Cibinong, INDONESIA, 1988.

Figure 1.3

plantations, settlement, dry forest land, mixed crops, wet conditions, bush and shrubs. The dry rice fields are not extensive in the Martapura and Pengandonan subdistricts. Many dry fields can be found in this area, which are representative of permanent and non permanent (shifting) dry field cultivation. The location of permanent dry fields is usually near a settlement or a road, whilst the non permanent dry fields are near primary forest.

1.4.3 Climatic Influences

According to SCHMIDT-FERGUSON classification systems, which consider a dry month as one with a rainfall average of $< 60\text{mm}$ and a humid month with a rainfall average of $> 100\text{mm}$, the general climate of Sumatra displays A, B, and C classes, where A is the most humid and H is the driest (Laumonier, 1981). The rainfall type A has a values of Q (ratio of the number of dry months by the number of humid months per year) 0 - 14.3 and the number of dry months 0 - 1.5 per year. Type B has Q values of 14.3 - 33.3 and between 1.5 to 3.0 dry months; whilst type C has Q values of 33.3 - 60.0 with between 3.0 to 4.5 dry mounths. In particular, the Baturaja study area has two types of bioclimates: a) Over-humid (2,500 - 3,000 mm/year) with the number of rainy days (D) varying from 140 to 170 per year, and Hyperhumid ($> 3,000$ mm/year) when D varies from 180 to 220 per year. During the dry season (May - October) the average

monthly rainfall in Baturaja City is about 115 - 214mm and 264 - 363mm during the rainy season.

1.4.4 Vegetation.

The study area shows a basic difference in vegetation classes between upland and lowland. The upland vegetation types are dominated by Saninten (*Castanopsis* spp.), Mempening (*Quercus* spp.), Kelat (*Eugenia* spp.), Kedondong hutan (*Santiria* spp.), Keruing (*Dipterocarpus* spp.), Meranti (*Shorea* spp.), Pasang (*Lithocarpus* spp.), Mahang (*Macaranga* spp.), Pulai (*Alstonia* spp.), and Kapok (*Ceiba petandra*).

In the lowland vegetation types, the dominant is Puspa (*Schima wallichii*), and displays forest degradation into open land, secondary forest, bush, and savanna through human activity. Shifting cultivation for example consists of cutting down the vegetation, burning it at the end of the dry season, and then sowing or planting in the ashes. The field thus cleared is abandoned after being cultivated for a short time, and is used again after nature has reconstituted the substances which make the soil sufficiently fertile for another crop. But if the area was large and the density of population is still low, the cultivators do not return to the space they had previously burned and cultivated until after a lapse of scores of years.

The appearance of the forest is changed, it becomes a secondary growth, commonly called "bush". Species which had been merely sporadic become dominant, and fast growing, for example Puspa (*Schima wallichii*) which is dominant in the lowlands of the study area as secondary forest. The transition from primary to secondary forest and then to savanna is gradual, the nature of the savanna/forest boundary, and emphasis the human impact on the vegetation characteristics. In the study area distribution of Alang-alang (*Imperata cylindrica*), a transitional species, takes place in the lowland between secondary forest, bush, and shrubs.

Along the Air Ogan river fruit gardens can be found, for example, Durian (*Durio zibethinus*), and Duku (*Lansium domesticum*). A small part to the North East of Baturaja city is wet land (swamp) with a different vegetation cover on it compared with dry land. Here the dominant vegetation types are Gelam (*Melaleuca cajuputi*), Tembusu (*Fagraea fragrans*), Kayu obi (*Pternandra* sp.), and Lombokan (*Ludwigia* sp.).

Near Baturaja city, there are commercial oil palm estates, the plants are relative young (around 5 - 10 years), as in the rubber commercial estates areas. A small part in the South West of Baturaja city has coffee gardens mixed with bush and rubber plantations but the area is dominated by field crops.

1.5 Structure of the Thesis.

This study is presented in five chapters.

Chapter 1 : Introduction, consists of: study back ground, aim of study, methodology , and location of study. Chapter 2 : Literature review, discusses the use of SPOT imagery for land cover, forest, and vegetation mapping.

In chapter 3 the basic principles of remote sensing, radiance characteristics of plants and vegetation, multispectral scanner imagery, digital image processing, and SPOT - 1 resource satellite are described. The GEMS and R - Chips image processing systems used in this study, are also presented in this chapter.

In chapter 4 : the imagery of the study area, ground data acquisition, vegetation classification scheme, and image classification are described. The choice of study extract used to produce the map through box and maximum - likelihood classification of SPOT - 1 is justified. The vegetation map of Baturaja, is presented, and its accuracy assessed.

Chapter 5 considers the potential and problems of vegetation mapping using SPOT - 1 imagery and recommendations are produced for further work in tropical countries.

CHAPTER 2

LITERATURE REVIEW

To date much research has been done using SPOT imagery for studies in hydrology, cartography, geomorphology, etc. This chapter will describe briefly evaluations of SPOT (including simulation) imagery for land - use, forest, and vegetation mapping.

2.1 The Use of SPOT Imagery for Land Use/ Land Cover Mapping.

Betts, *et al.* (1986) studied an evaluation of SPOT simulation imagery for land use mapping and ecological investigation in an Upland areas of Northern Ireland. The SPOT simulation imagery was obtained from overlapping runs flown on 12 May 1984 and 4 July 1984. Analysis was undertaken using a GEMS image processing system and images were assessed as to the potential of SPOT for land use and vegetation mapping, forest and peatland resource development and related ecological implications.

The problem in this area is that the field size is in most cases too small for adequate discrimination. In the best agricultural land fields are often no more than 200 m x 200 m, while in poorer areas fields are

approximately only 50 m x 100 m in size. These size limitations are important in the evaluation of SPOT for land - use and vegetation mapping. Only four types of land - cover were investigated : blanket and raised peat bog vegetation, marginal land, coniferous and deciduous forest and improved grassland. From these types investigations were conducted at two levels : a) Whether each cover could be discriminated consistently from the others and b) As to how much internal detail could be discriminated. This study used density slicing, (with four or five slices), box classification and maximum - likelihood classification.

The results of image analysis were dependent on the date of the SPOT simulation imagery, methods of analysis undertaken, and the use of single or combined bands. For example, on false colour composites it is possible to differentiate between associated bog vegetation, the drier *Calluna* edge, bare peat and recolonized gullies. In the small training areas with little variation in spectral response good delimitation was possible between the calluna edge and marginal land with rushes and poor grass by using maximum likelihood classification, but inside the blanket peat classification was incomplete. In the marginal land density slicing failed to delimit marginal areas, because in some areas they were associated with other cover types. Senescent grasses could be confused with some bare soils by using

false colour composites in May. At the same time a band 3/band 2 ratio was better than the false colour composite for delimiting marginal land. In May, by using all three bands improved grassland could be clearly distinguished. The boundaries can be seen in poorer fields with broader hedges, but at 20 m resolution the content within the boundaries is not evident. In forested land, areas are readily recognized on all bands although, young or poor forest can be confused with calluna. Separation of coniferous and deciduous woodland was generally good by using separate bands in May.

The conclusions of the potential of SPOT in this study were that the increased spatial resolution of SPOT gives considerable advantages over earlier 80 m Landsat MSS resolution for the Northern Ireland environment with its small scale, intricate variations. This suggests that frequent monitoring from the SPOT satellite could give support to forestry work in relatively unapproachable uplands. The various studies of separate bands, false colour composites and ratios show that SPOT can be used to delimit peat areas and to differentiate types of vegetation inside them. SPOT could be used to monitor the rate and location of hill land improvement. Multitemporal SPOT data could provide trends and permit the seasonal growth of such crops to be monitored. Cereals could be separated from grass and from root crops. The use of SPOT data can be envisaged to

distinguish differences within the four cover types, but the division into cover types should not be neglected.

Toulios, et al. (1990) considered "Land-use mapping using visual interpretation of false colour composites based on Landsat Thematic Mapper and SPOT data. They took West Messinia, Greece as their study area; it is located south of $38^{\circ}12'$ N and west of $22^{\circ}00'$ E coordinates and constitutes the south western part of the Peloponnese.

A supervised classification method was applied in this study. According to this, recognition and the classification of each land-use class was based on the comparison of ground truth data, through special test sites, with their appearance on the false colour composites of Landsat TM and SPOT. Sampling took place between 14 and 27 July 1987 because July is considered to be the most appropriate month for detecting and mapping a great number of land uses/covers.

The interpretation of satellite data was realized by use of the following three steps : First, all test sites were visually located on the false-colour composite, with the help of air photos, topographic maps, and photographs of the test sites. The sites were located on the images of both Landsat TM and SPOT. Identification problems occurred because of the dominance of mixed pixels in the area. The classification of the whole

surface area was done on the basis of spectral, geomorphological, geological, geometric, and geographical data. Second, the identification of annual irrigated crops was based on the angular context of their spatial characteristics and their geographical distribution. Forest land identification was based only on altitude (using topographic maps). Sandy beaches were very easily distinguished. It was impossible to identify meadows, because alfalfa is irrigated and it is easily confused with annual irrigated crops. Grasslands were confused with olive groves, especially in the dry season. Third, the last step resulted a land-use map of Messinia, at a scale 1 : 50,000.

The conclusions of this study were that the methodology employed led to the compilation of a land-use map in which the most extensive mapping unit is that of the land use complex. The mapping accuracy is quite satisfactory, in spite of the great variability of the test sites in the land use classes. The acquisition of more - detailed land use maps at the scale of 1 : 50,000 is very difficult, even with the use of TM and SPOT imagery in areas similar to the study area landscape, due to the adverse effect of land fragmentation and mixed and complex land uses. However, compiling this kind of land-use map, based on more general land-use classes in combination with a good knowledge of the area, is rather easy and quite accurate.

Negative factors and conditions that have affected the map accuracy of the land use classes in Messinia may be noted. These are : 1) in this study area one can find nearly all land use/cover types, from uncultivated land to the perennial vegetation, of enclosed land and woods, 2) The wide spread cultivation of olives and vines. The main land - use classes are the olive groves and the vine yards; their presence everywhere makes it difficult to define pure land - use classes, 3) the mixed character of multiple land use, 4) the differing degrees of agricultural development, 5) the different management of the same crop, 6) the very complex topography of the area.

The most important factors that reduced the mapping accuracy were : 1) the lack of multitemporal spectral data. The use of Landsat TM and SPOT data is necessary on at least two different dates in a year: one in spring (March - April) and another in Summer (August) if land covers are to be distinguished with any success, 2) the spectral bands which were used and their correlation, owing to the high correlation between band 2 and 3 of TM and between band 1 and 2 of SPOT. Band 7 of TM is also considered necessary in that it can be used to separate geomorphological features and can improve the boundaries of the mapping units.

2.2 The use of the SPOT imagery for forest mapping.

De Gloria, (1984) researched "The interpretation of forest resources in California on simulated SPOT imagery". This study used simulated SPOT data on 25 June 1983, for an area located in Plumas County, California. The forest land covers approximately 570,000 hectares. Yellow pine forest and red fir forest are the major forest cover types. They occur between 600 m - 1,800 m elevation above sea level for the yellow pine forest and between 1,800 m - 2,800 m elevation above sea level for the red fir forest.

In this study area the soils are derived from geologic materials composed of metamorphic and igneous rocks. The soils are formed on serpentine, peridotite, granite, and andestic parent materials. Each soil parent material displayed different forest conditions. For example, on serpentine and peridotite parent material were low density forests which were the least productive. Granitic parent material was more productive, and andestic parent materials were the most productive.

The field data collected in August 1982 used an aircraft mounted sensor for developing an understanding of vegetation and soil conditions. Interpretation methods used manual interpretation techniques from high resolution multispectral SPOT by combining the 3 -

bands. The image was interpreted by using the image characteristics of tone, texture, pattern, and association. Four major forest cover conditions could be distinguished :

- a. mature stands having large sawlog size timber, low crown closure percentage, and sparse shrub understory (non commercial).
- b. young forest stands having small sawlog size timber, low crown closure percentage, and dense shrub understory.
- c. mature forest stands, with medium sawlog size timber, medium crown closure percentage, and sparse shrub understory.
- d. mature forest stands, showing large sawlog size timber, high crown closure percentage, and variable shrub and shade - tolerant tree understory.

From a comparison of the simulated SPOT hard copy and Zeiss aerial photography significant results were obtained :

1. by using the SPOT hard copy, densities and size classes can be distinguished.
2. by using the SPOT imagery when the association between distinct vegetation patterns and landforms can be identified, major soil associations and sites suitable for reforestation can be distinguished.

3. Both are important for updating transportation networks on existing maps or for generating new maps.

The simulated SPOT data quality is excellent in representation of forest vegetation features when compared to standard infrared photo products. Both the stereoscopic and off - nadir imaging capability of SPOT should enhance the assessment of forest resources.

The conclusions of this study was that renewable resource assessment in forested environments can be satisfied by the use of SPOT image in film format. For the global mapping and monitoring of forest resources and land management practices. SPOT data is seen by De Gloria as a valuable addition to the suite of earth observation systems currently in operation or at the planning stage.

Buchheim, (1985) has studied "Forest cover type mapping and spruce budworm defoliation detection using simulated SPOT imagery". The location of this study was in the Chequamegon National forest in Northwest Wisconsin, an area 5 km by 12 km. This area contained, 1) Upland: with a forest type dominated by sugar maple, yellow birch, white pine, northern red oak, red maple, white birch, balsam fir, aspen, and red pines plantations. 2) Lowland: the dominant types here were black spruce, tamarak, white cedar, and balsam fir. This study used SPOT simulation (panchromatic and multispectral)

acquired on 18th June 1983, 1 : 42,000 scale colour infra red photography, photographic prints of the panchromatic and multispectral digital data, black and white negatives for each band of the digital data and the USGS 1 : 24,000 scale topographic maps as a base for plotting the photo and scanner coverage.

Analysis techniques of this study used manual and computer - assisted image interpretation. The computer assisted interpretation of image data was accomplished using image processing software and manual interpretations were done using the original photographic prints and SPOT (panchromatic and multispectral) data. Classification was carried out according to the Anderson et al - USGS classification system (Anderson et al., 1976)

Manual interpretation of the panchromatic print detail to level II of the Anderson system was easily obtained. The multispectral image product allowed species delineation to level III over most of the scene. The training set delineation was more involved than had been the case with data of coarser spatial and radiometric resolution (i.e, Landsat MSS data) by using the greater spectral diversity and complexity of the simulated SPOT imagery. The high degree of local variability made it difficult to delineate an adequate number of pixels, with sufficient similarity and appropriate distributional properties, capable of accurately

characterizing a spectral class. By using airborne imagery within this high degree of overall variability, it became difficult to be certain that all spectral variants within a given information class had been adequately characterized. The results of the maximum likelihood classifiers were followed by re - training in areas that had not previously been visually identified as spectrally distinct and for classes that had not been adequately characterized.

The conclusions of this study from the limited experience gained, with the SPOT simulation data suggests that in comparison to Landsat MSS data, SPOT satellite data will most likely afford a substantial increase in the accuracy and specificity of forest cover type mapping under the spectrally and spatially complex conditions found.

2.3 The Use of SPOT Imagery for Vegetation Mapping.

Stow, et al (1989) have reported on "Mapping Arctic tundra vegetation types using digital SPOT/HRV - XS data". The area of their study is in the Arctic Foothill Province of Alaska. The aim of this research was to use standard computer assisted image classification techniques to assess how appropriate SPOT/HRV digital multispectral (XS) data are for mapping vegetation types

of the Arctic Foothill Province (AFP) of Alaska. The SPOT/HRV imagery was acquired on 7th and 22nd June 1987, with the clearer 22nd June 1987 image being used in this study. The study was selected to correspond to a 22 km² area, and included in the test area is the Imnaviat Creek drainage basin (a sub - basin of the Kuparuk River Watershed). Six cover types of vegetation classification within the study area at this level of generalization, were recognised including four tundra vegetation types : 1) water and aquatic types, 2) wet sedge, moss tundra, 3) water track and riparian tundra, 4) moist tussock tundra, 5) dry heath tundra, 6) barren and partially vegetated areas. Supervised and unsupervised classification methods using a maximum likelihood decisions rule were tested. All three SPOT/HRV multispectral bands were input to each classification.

The results of this study was deemed to be generally unsatisfactory for many of the procedures tested using SPOT/HRV multispectral - based classification of the 22nd June image, particularly when an unsupervised classification approach was taken. Estimating the percentage of total area coverage by each category using SPOT/HRV - XS data produced an encouraging result. The conclusions from map analysis showed that even SPOT/HRV - XS with its 20 m spatial resolution may not be fine enough to resolve many arctic tundra vegetation parcels. The 10 m spatial resolution of the SPOT/HRV in

panchromatic mode would appear to resolve spatially most of the vegetation parcels of this landscape. However, analysis of multispectral signatures in the XS bands suggest that the spectral sensitivity of the panchromatic mode is inappropriate for discriminating the vegetation types that are commonly found as small parcels.

Tommervik (1986) made a "Comparison of SPOT - simulation and Landsat 5 TM imagery in vegetation mapping". The study area was based on Habafjell - Skarubben, in central Tromso, Northern Norway. Two Landsat TM images were used in this study: Landsat 5 TM (197/11), for 3rd June 1984 and Landsat TM (197/11), for 2nd October 1984. SPOT simulation (30th June 1982), IR imagery (30th June 1982), and BW imagery (July 1975) were also used.

The conclusions of this study were that Landsat 5 TM and SPOT/HRV will increase the level and accuracy of digital classifications, giving an overall accuracy of 90% or more, but unfortunately the scenes were taken too early in the spring time or taken too late in the autumn. Comparison between the Landsat 5 TM - sensor and the simulated SPOT/HRV - sensor has shown that the two sensor systems have almost the same ability to detect and map vegetation cover types within the area, due to the higher radiometric resolution for the TM - sensor compared to the simulated HRV - sensor. Classification of the SPOT simulated imagery showed that for vegetation

units within small areas, texture and patterns were better detected, due to the higher spatial resolution for the HRV - sensor compared to the TM - sensor.

2.4 Application of SPOT data in Indonesia.

Many studies using remote sensing systems (Landsat, Radar, etc) have been undertaken in Indonesia, for research into hydrology, land - use/cover, forestry, urban etc. But few studies exist using SPOT data, and especially few can be found for vegetation inventory and/or mapping. Applications of SPOT data use in Indonesia will be discussed briefly as follows:

Gastellu-Etchegorry (1988b) studied land cover / use mapping in Wonosari, Yogyakarta ($7^{\circ} 40' - 8^{\circ} 00' S$; $110^{\circ} 3' - 110^{\circ} 5' E$) and Wonogiri, Surakarta ($7^{\circ} 50' - 8^{\circ} 00' S$; $110^{\circ} 48' - 110^{\circ} 58' E$), Indonesia. The study in Wonosari used SPOT multispectral data k/j = 293/366, acquired on 28th September 1986 and infrared false colour aerial photographs, at 1 : 30,000 scale, for 1981 to check the mapping obtained from SPOT. In Wonogiri SPOT data acquired in 1986 were used, k/j = 293/366 and aerial photographs (NIR 1 : 30,000) in 1981 was used.

The summary statement of this study suggests many SPOT band combinations and ratios were tested. Acreage percentages of all classes are given. Six land cover/use classes were characterized in Wonosari: water, rain fed

rice fields, irrigated rice fields, dry fields, settlements and mixed gardens, and forest/plantation. Five land cover/use classes were characterized in Wonogiri: lake, rice fields, dry fields, settlement and forest. The land cover/use map obtained from SPOT is a simplification of the SPOT spectral classification. The spectral information of SPOT data established it as being very useful for deriving detailed thematic information. This capability is undoubtedly very useful for many applications. The mini/micro - computer technology and the human capability for extracting spatial information when combined suggest these methodologies have undoubtedly a very promising future in Indonesia. Multidate SPOT data should be useful for forecasting crops yields. Mapping with SPOT data has established it to be time saving, cost effective and much more convenient. This is entirely appropriate for the Indonesian landscape, where the small size of holdings and the dynamic nature of land use are problematic in efforts to develop the capacity to classify and monitor these systems.

Gastellu-Etchegorry (1990a), has made "An assessment of SPOT XS and Landsat MSS data for digital classification of near - urban land cover". The study was undertaken around Yogyakarta, central Java, Indonesia. Two types of level 1B SPOT data were available : SPOT multispectral digital data acquired by SPOT - 1 on 1st August 1986 and

a 1 : 50,000 black and white print of SPOT panchromatic data acquired on 10th July 1987. Landsat MSS digital data from a scene (path 122, and row 65) acquired by Landsat - 4 on 9th April 1983 were also studied.

Other data sources were land cover maps derived from aerial photographs of 1967 (1 : 50,000 black and white panchromatic), and 1981 (1 : 30,000, colour infrared). This study was carried out with IBM - compatible micro computers, and used Box and Maximum Likelihood classification on SPOT data.

In Indonesia, a common limitation for accurate land cover classification is due to the heterogeneity of local land use/cover. The analysis of SPOT bands and colour composites provided immediate recognition of landscapes of interest (for example, city and built-up areas, villages and mixed gardens, grass and cultivated areas). This recognition of land cover was undoubtedly less obvious with Landsat data. The vegetation can be discriminated with SPOT data within cultivated areas. The almost immediate visual discrimination of most land cover types of interest, combined with a good knowledge of the area, led to an easy and quick sampling, which provided a determination of the spectral signatures of all SPOT XS and Landsat MSS spectral classes. Some general trends were noted :

- a. Bare lands and built-up areas share similar SPOT spectral signatures: radiometry of bands XS1 and XS2

has produced nearly identical values and there is a small increase in the digital number with XS3.

- b. Cultivated areas and grass display a small decrease from band XS1 to band XS2 and a strong increase from band XS2 to XS3.
- c. Settlement and mixed garden areas display a decrease from band XS1 to XS2 and a very strong increase from band XS2 to XS3.

The SPOT derived map was compared with maps derived from 1 : 50,000 SPOT P images and aerial photographs from 1965, 1981, and 1987. These maps were achieved without any stereo plotting. Information from field checking combined with the maps derived from the aerial photographs of 1987 was used to test the validity of the maps derived from Landsat MSS and SPOT XS and P data. Several important points were stressed at this point :

1. The average accuracy of the maps derived from the spectral classification of SPOT XS data is about 81%, whereas normally the average accuracy of the SPOT derived acreages is better than 95%.
2. The cartographic accuracy of the maps derived from SPOT XS and P is far better.
3. Global urban/agricultural mapping is much faster and more convenient if SPOT data are used, either as the main source of data, or when combined with other sources.

4. Visual extraction of spatial information from SPOT images is necessary when a detailed urban/agricultural map of heterogeneous environments is required.
5. SPOT P 1 : 50,000 photographic prints are particularly valuable for providing straight delineation of settlement and cultivated areas
6. Only the borders of the city of Yogyakarta are well outlined with the Landsat MSS derived maps. The delineation of small settlement areas is very inaccurate using MSS and many cultivated areas which corresponded to mixed pixels were unclassified.

Some very important changes occurred in the study area surrounding Yogyakarta between 1965 and 1987. For example, settlement areas increased a great deal. The most important acreage increase occurred for the city of Yogyakarta which nearly doubled in size and the acreage of agricultural lands decreased accordingly, due to the increasing population pressures.

The conclusions of this study were:

Mapping with SPOT XS and P proved to be much faster and more convenient, leading to better cartographic documents than the visual interpretation (without stereo-plotting) of 1 : 30,000 near-infrared (NIR) aerial photographs. This result is especially important for a country like Indonesia where many maps are very old.

Results derived from aerial photographs and SPOT images appeared to be consistent.

Finally, for routine delineations of agricultural /suburban interfaces, it was shown that SPOT XS and P data can come close to taking the place of 1 : 100,000 and 1 : 50,000 aerial NIR photography, respectively. This is especially the case when one considers the added advantages of being able to analyse digitally the data for special problems and applications, including the quantification of certain components of an urban/suburban/agricultural area, determining the area occupied by each such component and developing numerical discriminations to support and strengthen the visual interpretations.

CHAPTER 3

REMOTE SENSING SYSTEM AND SPOT 1 DATA

3.1 Basic Principles of Remote Sensing.

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by device that is not in contact with the object, area, or phenomenon under investigation (Lillesand and Kiefer, 1987). In the interpretation of information for the environmental sciences of geography, agriculture, forestry, geology, and meteorology, it usually refers to the use of electromagnetic radiation sensors to record images of the environment (Curran, 1985). The interpretation of remotely sensed images of the environment depends on how radiation interacts with the earth's surface. It also depends on a knowledge of radiation and remote sensing systems. Interpretation of any remotely sensed image can be assisted by using computer - based image processing techniques.

3.1.1 Electromagnetic Radiation.

In remote sensing, information transfer from an object to a sensor is accomplished by electromagnetic radiation (Barrett and Curtis, 1982). It has four components,

First, a source of electromagnetic radiation: either natural , e.g, the sun's reflected light or the earth's emitted heat or man-made like microwave radar. Secondly, interaction of electromagnetic radiation with the earth's surface. Thirdly, electromagnetic energy passing through the atmosphere is distorted by reflection, scattering, and absorption. Fourthly, electromagnetic radiation, modified by earth and atmosphere, is recorded by a sensor (radiometer or camera) either on an aircraft or satellite or held in the hand. The link between the components of the remote sensing system is electromagnetic energy (Curran, 1985) (Figure. 3.1)

The most familiar type of electromagnetic radiation is visible light, which forms only a very small portion of the full electromagnetic spectrum. Ultraviolet rays, x rays, radio waves, and heat are other familiar forms. These energy patterns are inherently similar and radiate in accordance with basic wave theory. The theory explains electromagnetic energy as travelling in a harmonic, sinusoidal fashion at the velocity of light. There are three measurement used to describe electromagnetic waves : First, wave length (λ) in micrometers (μm), which is the distance from one wave peak to the next. Secondly, frequency (m) in Hertz (Hz) which is the number of peaks passing a fixed point in space per unit time. Thirdly, velocity (c) in ms which

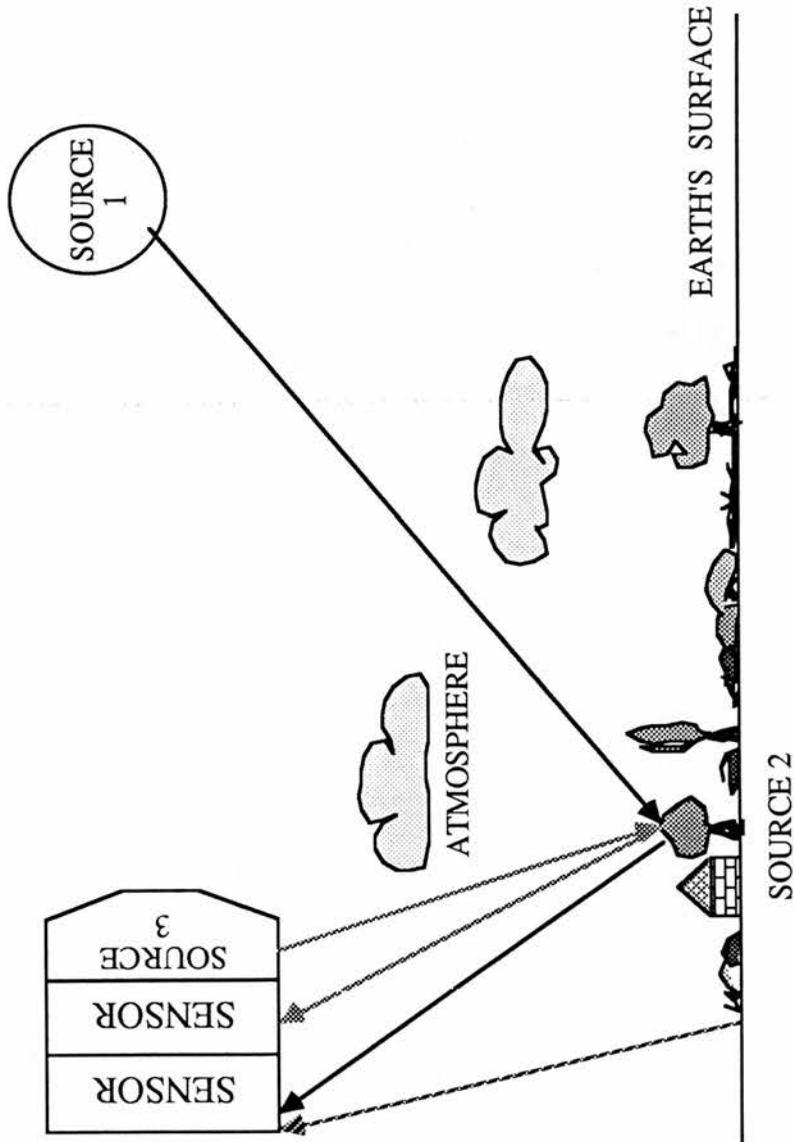


Figure 3.1 A Remote Sensing System
(Adapted from Curran, 1985).

within a given medium is constant at the speed of light (3×10^8 m/sec). The visible spectrum constitutes a very small portion of the total electro - magnetic spectrum, it has obvious significance in remote sensing. The limits of the visible spectrum are defined by the sensitivity of the human eye and extends only from about $0.4 \mu\text{m}$ to approximately $0.7 \mu\text{m}$. Visible light is subdivided into three segments, the three additive primaries, defined in the approximate range of blue $0.4 - 0.5 \mu\text{m}$, green $0.5 - 0.6 \mu\text{m}$, and red $0.6 - 0.7 \mu\text{m}$ (Campbell, 1987; Lillesand and Kiefer, 1987) (Figure. 3.2).

3.1.2 Interaction with Earth Surface.

When electromagnetic energy is incident on any given earth surface feature it is either reflected, absorbed, and/or transmitted. No energy is lost in this process. The interrelationship between these three energy interactions may be described as follows:

$$EI(\lambda) = ER(\lambda) + EA(\lambda) + ET(\lambda)$$

where $EI(\lambda)$ is the incident energy, ER (reflected energy), EA (absorbed energy) and ET (transmitted energy) (Lillesand and Kiefer, 1987). This is illustrated in Figure. 3.3.

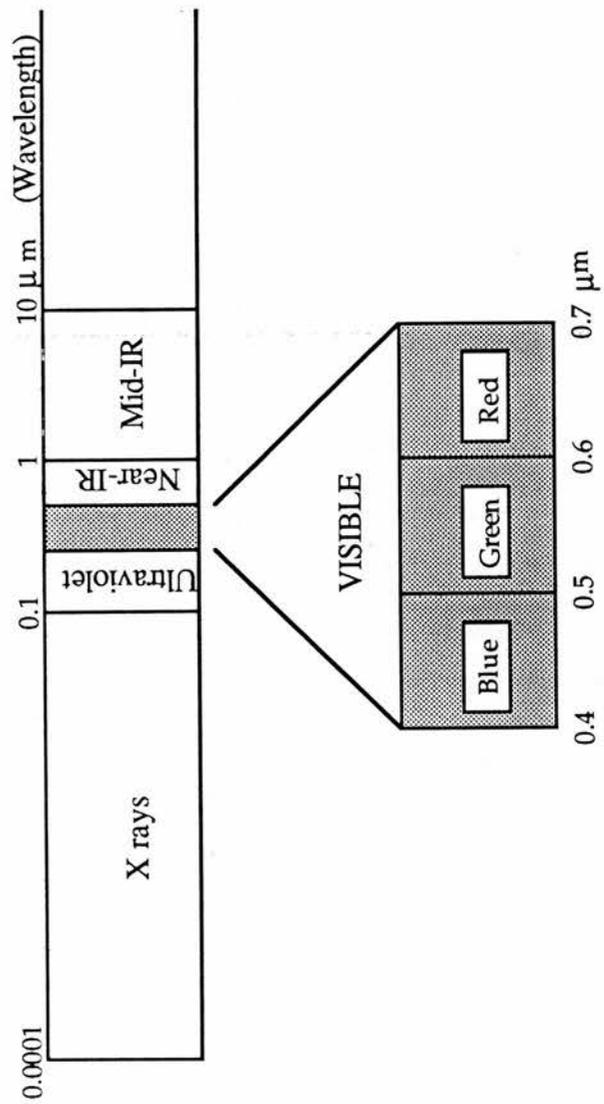


Figure 3.2 The Electromagnetic Spectrum.
 (Adapted from Lillesand and Kiefer, 1987).

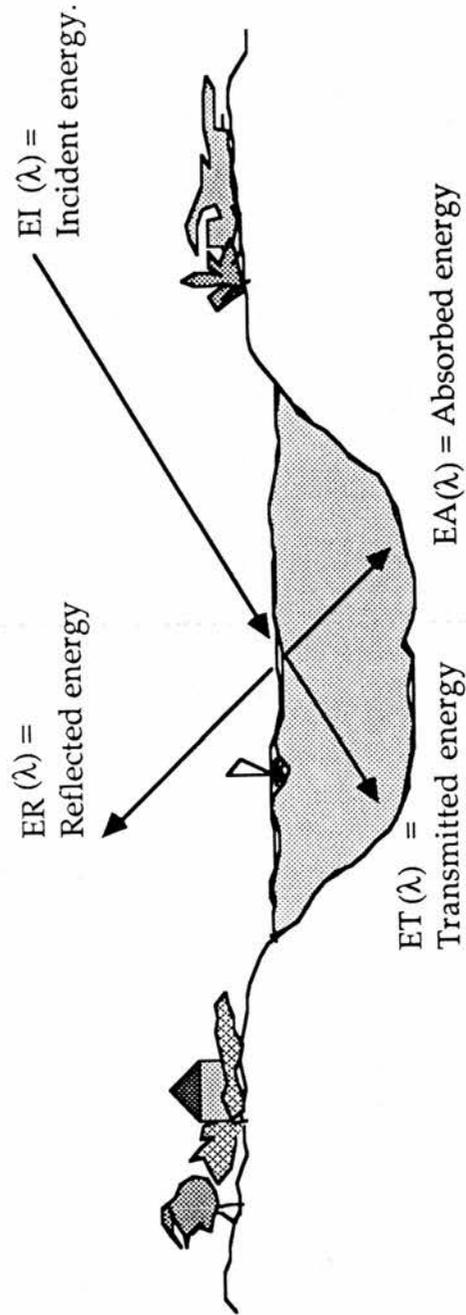


Figure 3.3 Interaction Between Electromagnetic Energy and an Earth Surface Feature.
(Adapted from Lillesand and Kiefer, 1987).

Two points regarding this relationship should be noted.

1) The proportion of energy absorbed, reflected, and transmitted will vary, depending on conditions and material type. 2) the wavelength dependency means that, even within a given feature type, the proportion of the reflected, absorbed, and transmitted energy will vary at different wavelengths. For example, the visible part of electromagnetic radiation ($0.45 - 0.67 \mu\text{m}$) has long been used in vegetation studies. A leaf is built of layers of structural fibrous organic matter, within which are pigmented, water - filled cells and air spaces. Each of the three features - pigmentation, physiological structure and water content have an effect on the reflection, absorbance, and transmittance properties of a green leaf (Curran, 1985). Chlorophyll, for example, strongly absorbs energy in the wavelength band centred at about $0.45 \mu\text{m}$ and $0.67 \mu\text{m}$. An important feature of the visible and near infrared radiation is the relationship between reflectance and green vegetation. The association of strong positive correlation in near infrared and strong negative correlation in visible red can be used for consideration of vegetation amounts (Olsson, 1986). Bands 1, 2, and 3 of SPOT image cover these parts of the spectrum, and the association of visible and near infrared bands may be expected to give new possibilities for assessing vegetation conditions.

3.2 Radiance Characteristics Of Plants And Vegetation.

For monitoring plant areas and/or specific vegetation patterns depends on the spectral properties of individual leaves and plants. The hemispherical reflectance of an individual leaf or leaves cannot itself completely explain the remotely sensed bidirectional reflectance of a vegetation canopy. This is because most vegetation canopies are mixtures of different elements, including leaves, and other components of the canopy (flowers, fruit, stalks, trunks), characteristics of soil back ground, shadow, solar angle and sensor elevation (Colwell, 1974 ; Curran, 1980; Campbell, 1987). The hemispherical reflectance of light in the chlorophyll absorption bands, in the visible spectral region (0.4 - 0.7 μm) of the electromagnetic spectrum, is causally and negatively related to the amount of chlorophyll within the leaves (Curran, 1983). Higher plants contain four primary pigments which absorb in visible wavelengths of electromagnetic radiation: chlorophyll a, chlorophyll b, carotene, and xanthophyll. The most important pigments, chlorophyll a and b, absorb portions of blue and red light. Chlorophyll a absorbs at a wavelength of 0.43 μm and 0.66 μm and chlorophyll b at wavelength 0.45 μm and 0.65 μm (Curran, 1985), Figure no. 3.4.

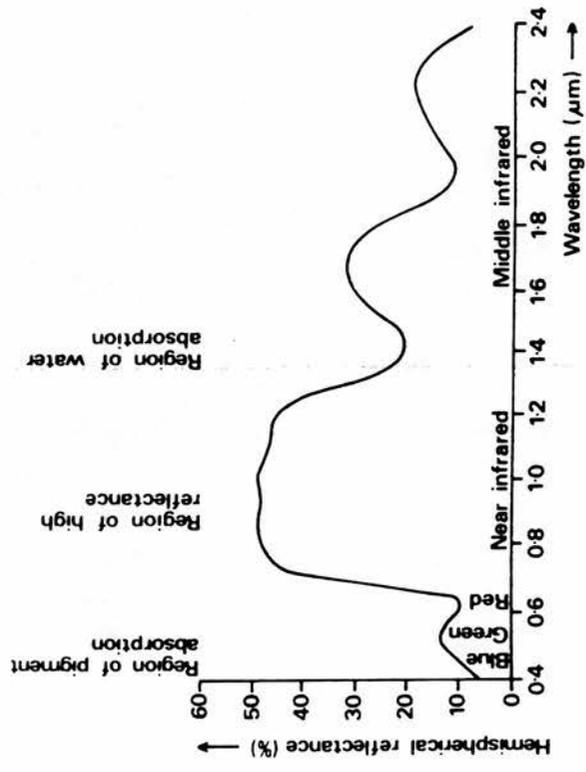


Figure 3.4 The Hemispherical Reflectance of Leaf (Adapted from Curran, 1985).

Soil background may be quite important in affecting canopy reflectance, especially at low values of percent vegetation cover, because it is a complex mixture having various chemical and physical properties, including iron oxide, organic matter, moisture, texture, and surface roughness, which determine the amplitude of reflectance (Colwell, 1974; Bauer, 1985). The reflectance in the near infrared spectral region (0.7 - 0.8 μm) was greater from a forest canopy with a grass background, and the red (0.6 - 0.7 μm) reflectance of a forest canopy which had a grass background was less than that of a forest canopy with equivalent percent cover and a rock rubble background (Colwell, 1974). The relationship between reflectance and vegetation amount will be weak in a particular waveband if the reflectance of the soil is similar to the reflectance of vegetation in that waveband. This shown in Figure : 3.5, which shows the Bidirectional Reflectance of simulated vegetation canopies on a light soil and on a dark soil in the green, red, and infrared wave bands. On dark soil with a low infrared reflectance, the relationship between infrared reflectance and vegetation amount is more than on a light coloured soil with strong infrared reflectance (Curran, 1980).

Another way in which the reflectance patterns of vegetation could be influenced is by shadowing (Colwell, 1974). Vinogradov (1969) in Colwell (1974) found a

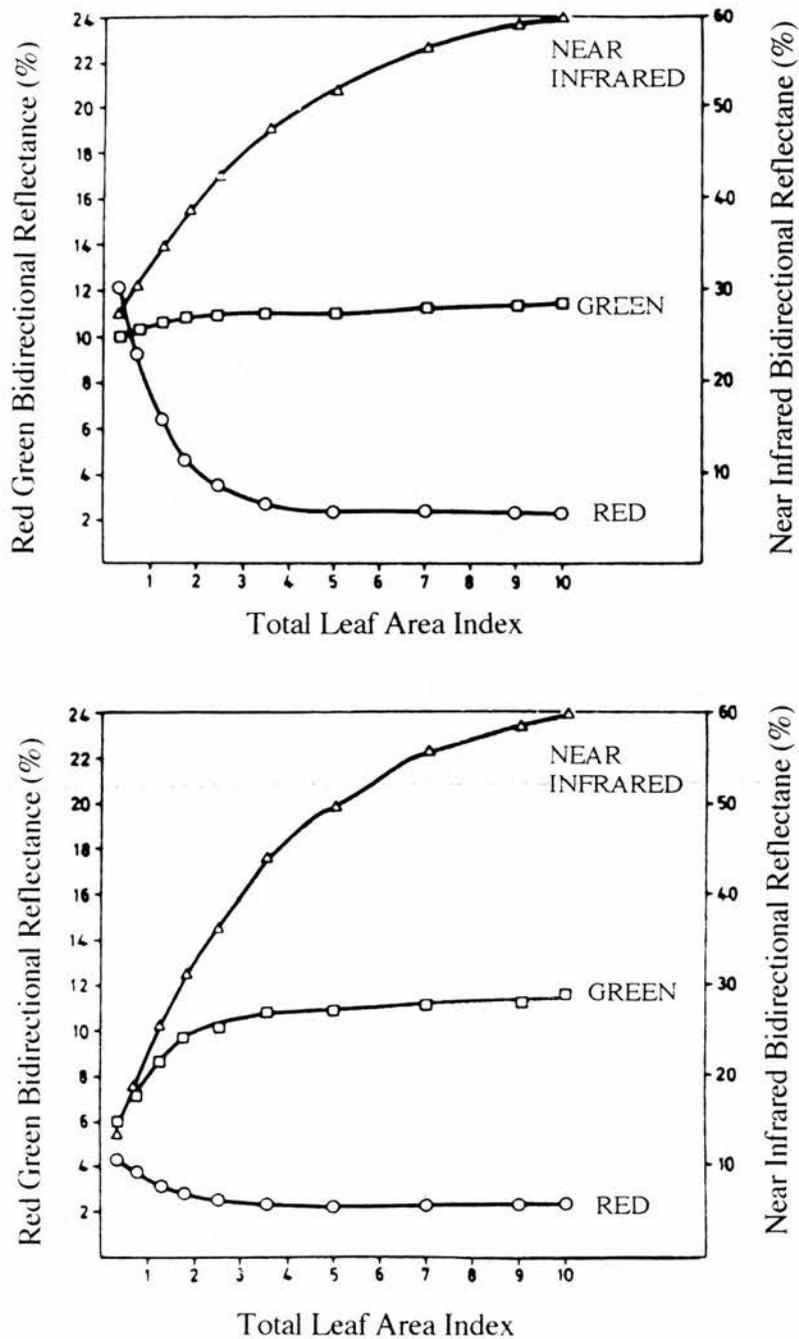


Figure 3.5 The Bidirectional Reflectance of Simulated Vegetation Canopies on a Light Soil (top graph) and a Dark Soil (bottom graph) in Green, Red, and Infrared Wavebands (Adapted from Colwell, 1974).

negative correlation between reflectance and percent vegetation cover for grass in the visible spectral region, which he attributes to an increasing amount of shadowing by the canopy as the percent vegetation cover increases. Near - IR reflectance of coniferous forest canopies were also found to decrease by Roller (1973). Colwell (1974) using experimental field results, showed that by smoothing out a grass canopy with several strokes of the hand, canopy shadows decrease while the amount of red reflectance increased to a value over 50%.

3.3 Multispectral Scanner Imagery.

Multispectral scanner systems are designed to sense energy in a number of narrow spectral bands simultaneously. There are three advantages of a multispectral scanner system. 1) They have a very high radiometric resolution in narrow and simultaneously recorded wave bands. 2) Bands may range from ultraviolet wavelengths through the visible, near IR, mid IR, and thermal IR. 3) These data can be stored in digital form for correction and quantitative analysis (Curran, 1985).

The various satellite sensors/platforms above the earth's surface are carrying multispectral scanners. Radiation from the earth's surface across a wide range of wave bands in the electromagnetic spectrum has been

measured simultaneously by these instruments. The first satellite in the SPOT program, SPOT - 1, was launched on February 21st, 1986; carrying two HRV (high resolution visible) sensors. This is illustrated in Figure. 3.6. The HRV sensors operate in two modes, 1) The Panchromatic mode. This sensor records across a broad spectral band from 0.51 - 0.73 μm . 2) The Multispectral configuration. Here the HRV instrument senses three spectral regions, band 1: 0.50 - 0.59 μm (green), band 2: 0.61 - 0.68 μm (red, chlorophyll absorption), and band 3: 0.79 - 0.89 μm (near infrared, atmospheric penetration) (Campbell, 1987). Every image may be thought of as consisting of tiny equal areas or picture elements or pixel. Each pixel has a brightness number or gray scale value, with 0 for black and 255 for white (Sabins, 1977).

The HRV instruments can have their angle of inspection of the earth's surface tilted up to 27 degrees either side of vertical to allow oblique off nadir viewing. The acquisition of imagery at different angles during successive passes gives rise to relief displacement. This displacement in turn allows measurement of the parallax differences and three dimensional stereoscopic viewing. This instrument consists of a static solid state array of detectors (Charge Coupled Device) operating in the visible and near infrared part of the spectrum (Fontanel, 1985). It is normally oriented

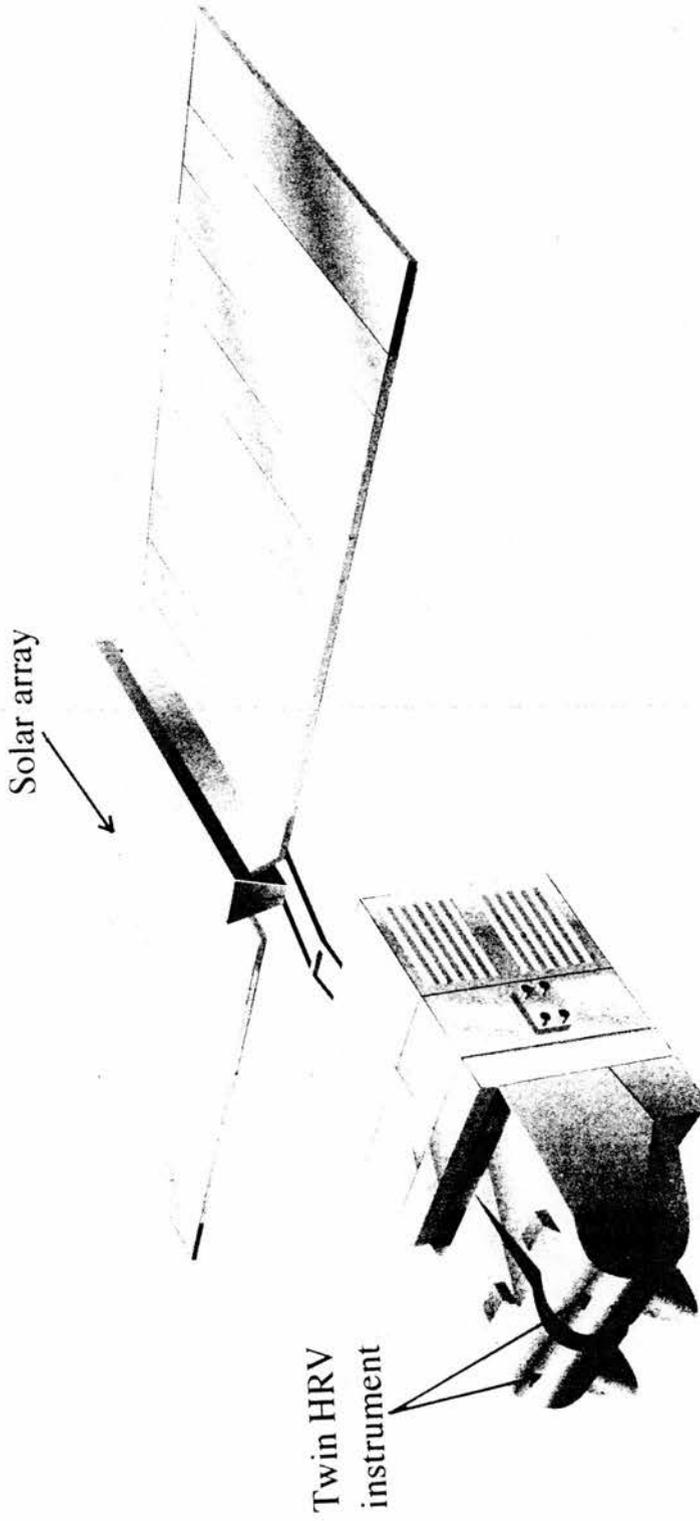


Figure 3.6 General View of SPOT - 1
(Adapted from CNES, 1989)

perpendicular to the direction of sensor motion. Image data in one dimension can be obtained by instantaneous sampling of the response of the detectors along the array (Lillesand and Kiefer, 1987).

3.3.1 SPOT - 1 Onboard Sensors.

The main body of the SPOT - 1 system is approximately 2 x 2 x 3.5 m, it weighs approximately 1750 kg, and the solar panels have a length of approximately 9 m (Brachet, 1983). The HRV sensors are the first earth resource satellite system to include a linear array sensor and employ push - broom scanning techniques (Figure 3.7), imaging a complete line of the ground scene in the cross - track direction in one look without any mechanical scanning (Campbell, 1987). With this system, each line of the image is electronically scanned by a linear array of detectors in the instrument focal plane, and successive lines of the image are produced as a result of the satellite's movement along its orbit (Chevrel, 1981).

This system offers two major advantages :

- a) The "exposure" time for each ground point imaged is automatically maximized, and
- b) The principle of the instrument ensures excellent photogrammetric quality along the linescan axis (Chevrel, 1981).

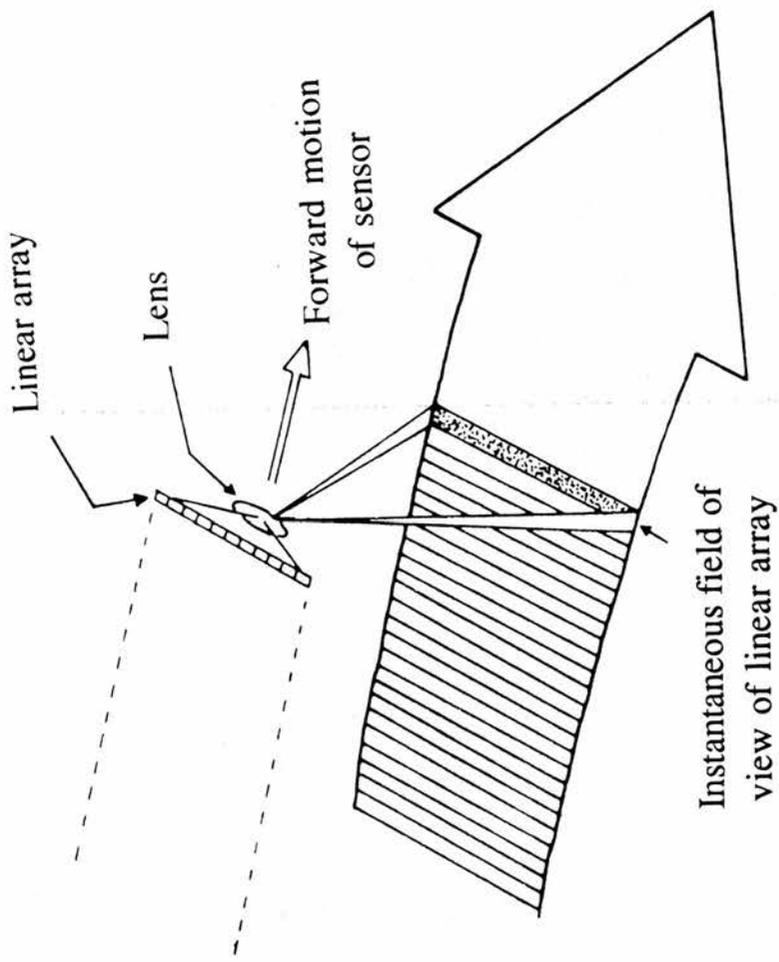


Figure 3.7 Pushbroom Scanning
(Adapted from Campbell, 1987).

The specification of the HRV instrument included the following requirement:

- a. High radiometric resolution to discriminate very low variation of radiation in each of the four spectral bands.
- b. High spatial resolution.
- c. High structural stability to minimize effects which would result in image distortion.
- d. The off - nadir viewing mechanism will have an absolute pointing accuracy (no ground calibration) of 4×10^{-4} radians for any position with range between $- 27^{\circ}$ and $+ 27^{\circ}$.
- e. A capability for simultaneous operation in the panchromatic and multispectral modes for periods in the order of 12 minutes (Courtois, 1986).

The HRV sensor can be operated in one of two modes. In the panchromatic mode for vertical (nadir) viewing of 6,000 x 6,000 pixels, the spatial resolution is 10 x 10 m. In the multispectral mode for vertical (nadir) viewing of 3,000 x 3,000 pixels, the spatial resolution is about 20 x 20 m.

The first element in the optical system is cross - track viewing, for example, for mirror pointing angles between 0° and the maximum value of 27° from the vertical in 45 steps of 0.6 each. The instrument can observe any area within a 950 km wide strip centred on the satellite

track. The swath width of individual images range between 60 and 80 km, depending upon viewing angles (Figure 3.8 and 3.9) (Brachet, 1984; Campbell, 1987). When the two instruments are operated with the mirror pointing angles near 0° the result is termed a "bi - scene". Such SPOT bi - scenes cover the two 60 km swaths with an overlap of 3 km giving a total image swath of 117 km (Campbell, 1987; Lillesand and Kiefer, 1987) This is illustrated in Figure. 3.10

3.3.2 SPOT - 1 Orbit and Coverage.

SPOT - 1 is placed in a sun - synchronous orbit at about 834 km, above the earth with a 10.30 a.m equatorial crossing time, and an inclination of 98.7° (Campbell, 1987; Lillesand and Kiefer, 1987). The pointable optics of the system enable off - nadir viewing during satellite passes separated alternatively by 1 and 4 (and occasionally 5) days, depending on the latitude of the area being viewed. At the equator, the same area can be targeted 7 times during the 26 days of an orbital cycle (Day D and Days D +5, +10, +11, +15, +16, and +21), a total of 98 times in one year with an average revisit of 3.7 days (Figure 3.11). At latitude 45° , the same area can be targeted 11 times in a cycle (Day D and Days D +1, +5, +6, +10, +11, +16, +20, +21, and +25) (Figure 3.12). This gives 157 visits in one year, with average revisit time of 2.4 days, a maximum time lapse of 4 days

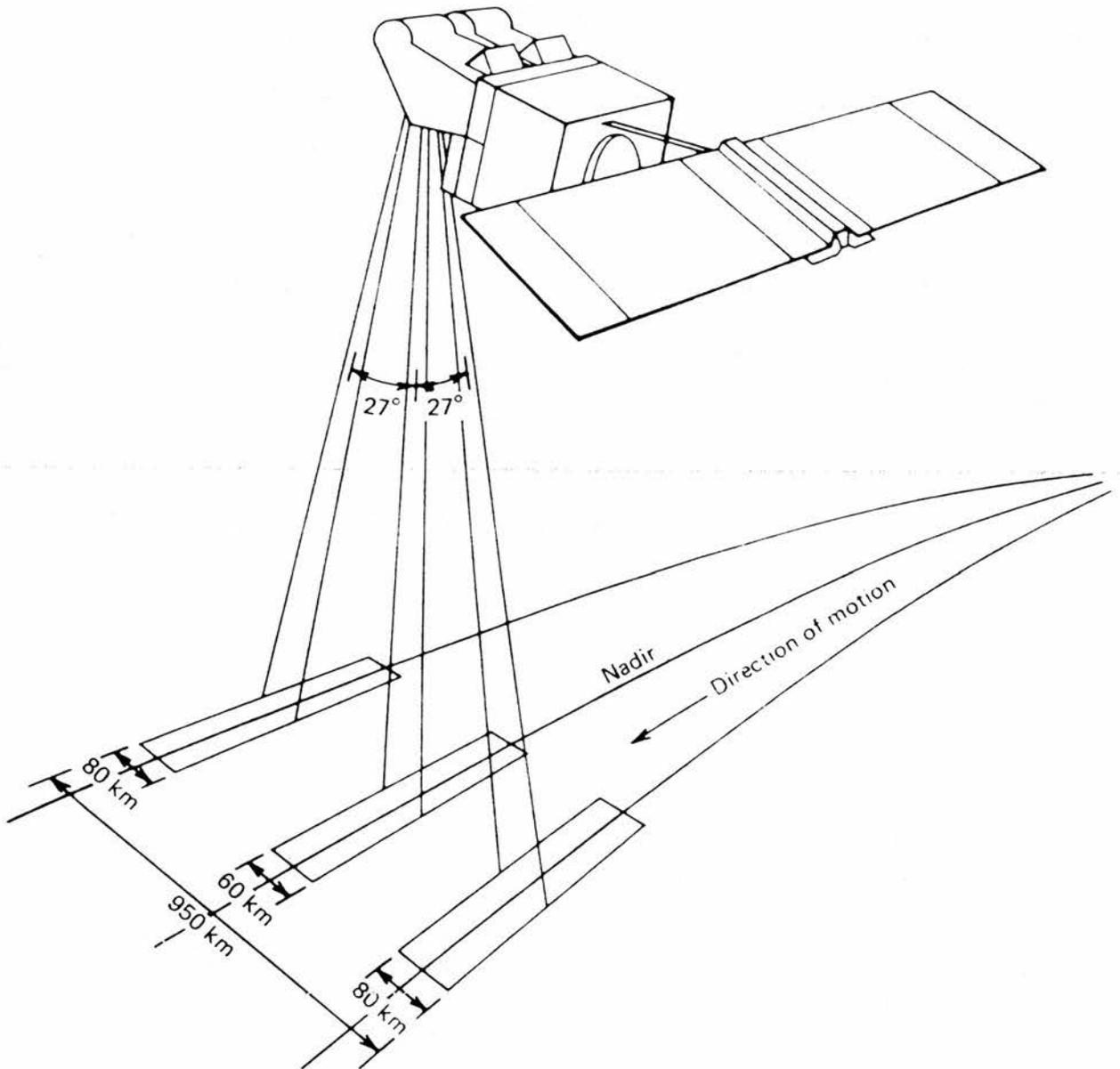


Figure 3.8 SPOT - 1 Off Nadir Viewing Range
(Adapted from Campbell, 1987).

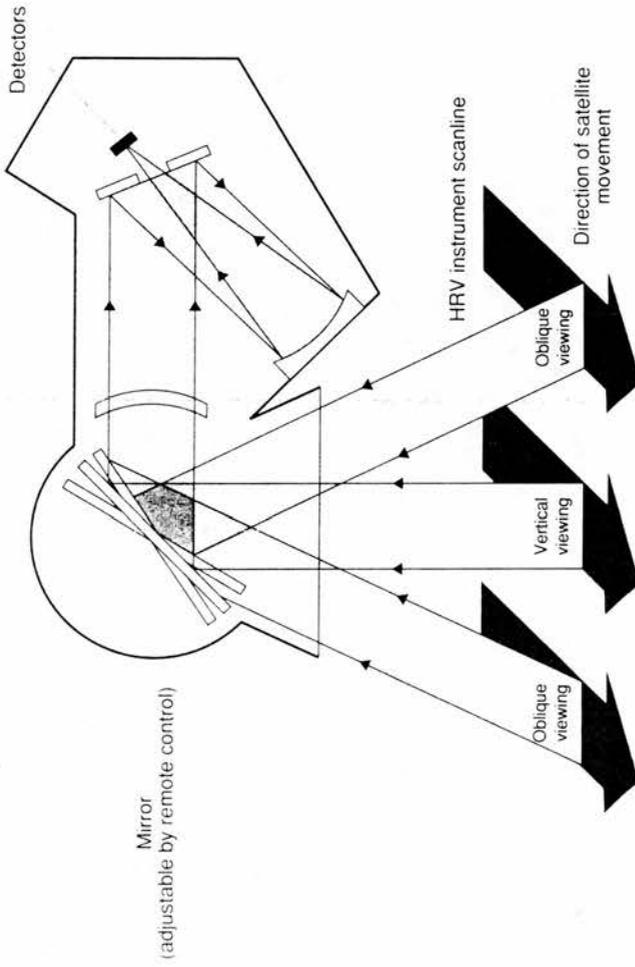


Figure 3.9 HRV Instrument
(Adapted From CNES, 1989).

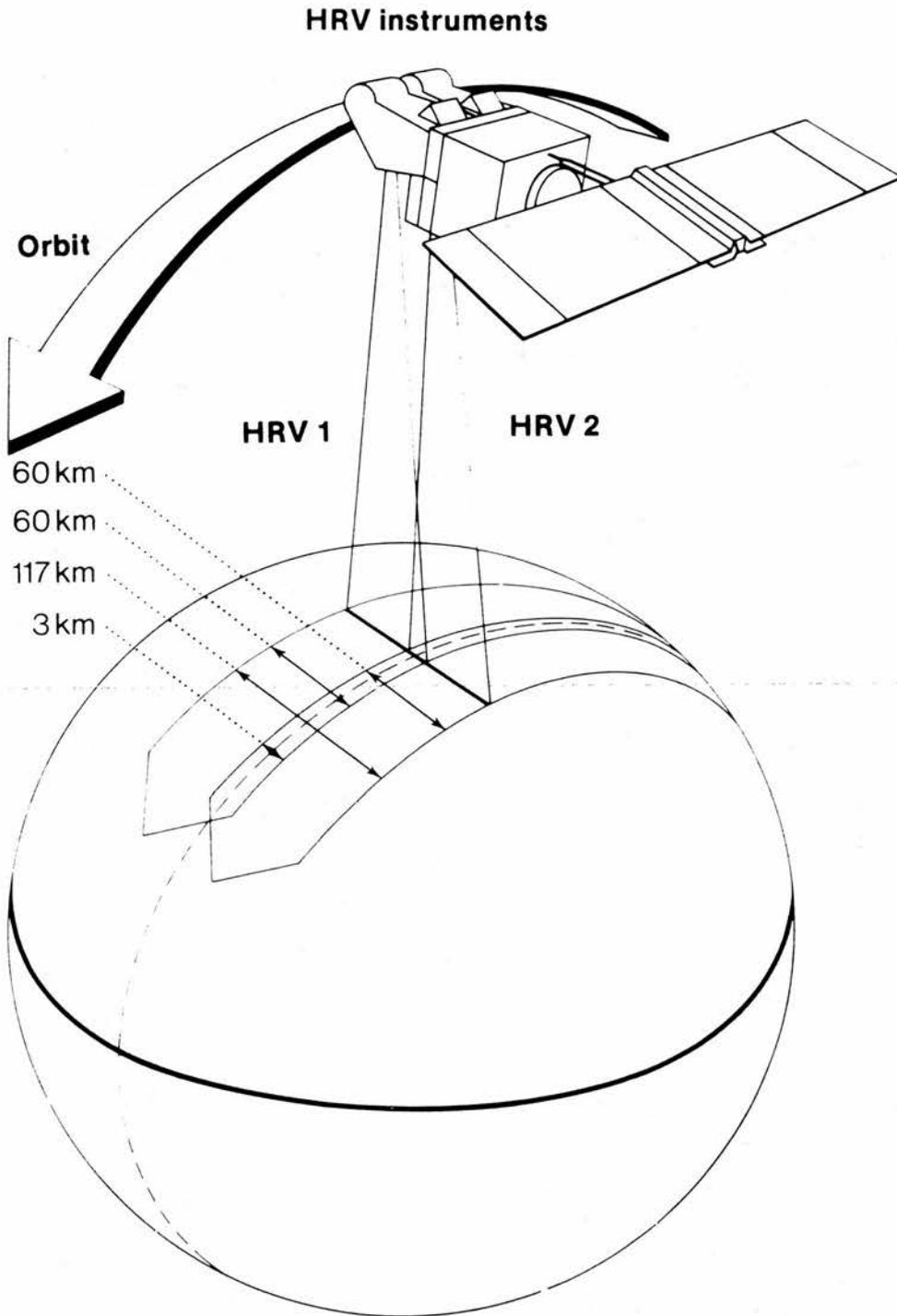


Figure 3.10 Geometry of SPOT - 1 Imagery
Nadir Viewing
(Adapted from CNES, 1989).

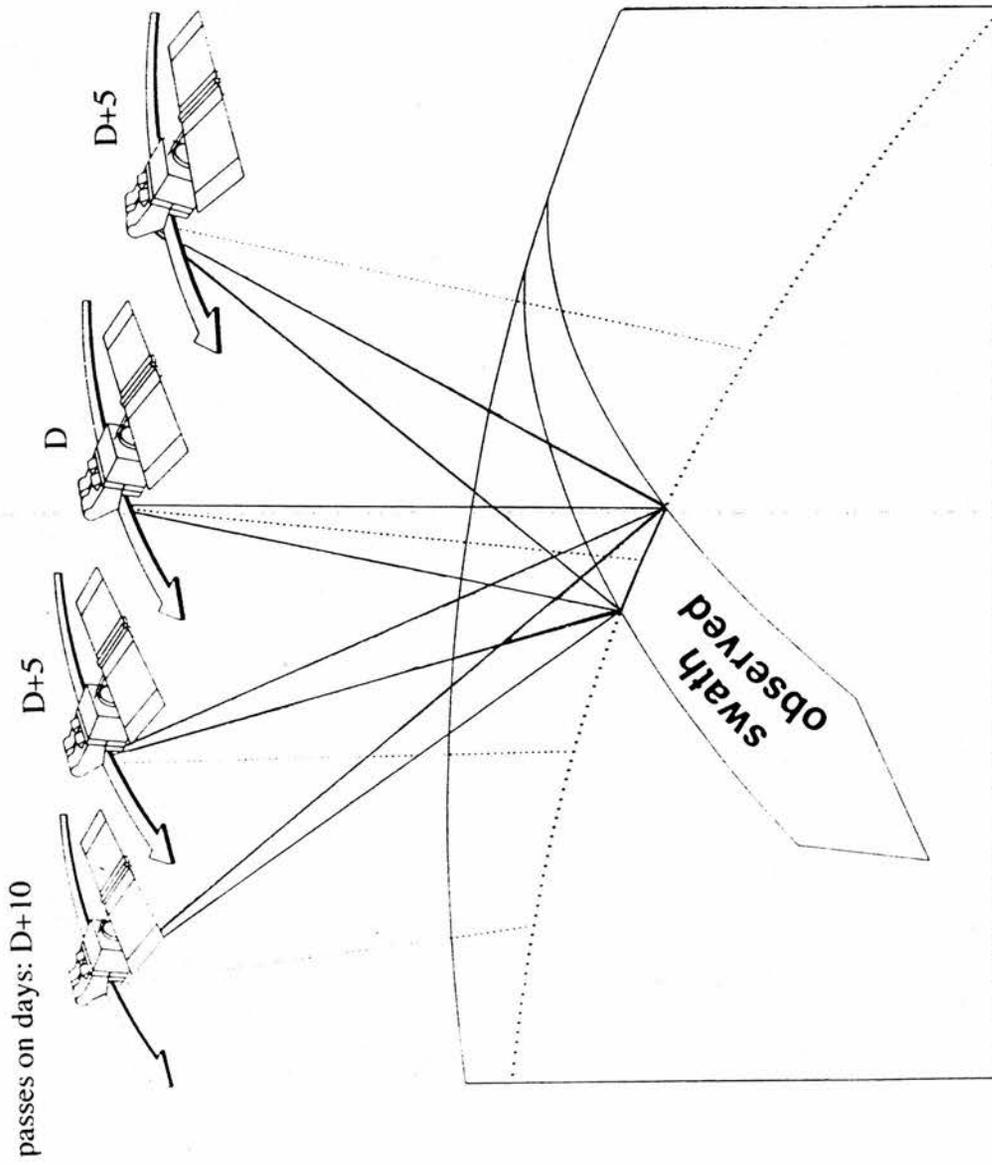


Figure 3.11 SPOT - 1 Revisit Pattern (latitude 0° and 45°)
(Adapted from CNES, 1989).

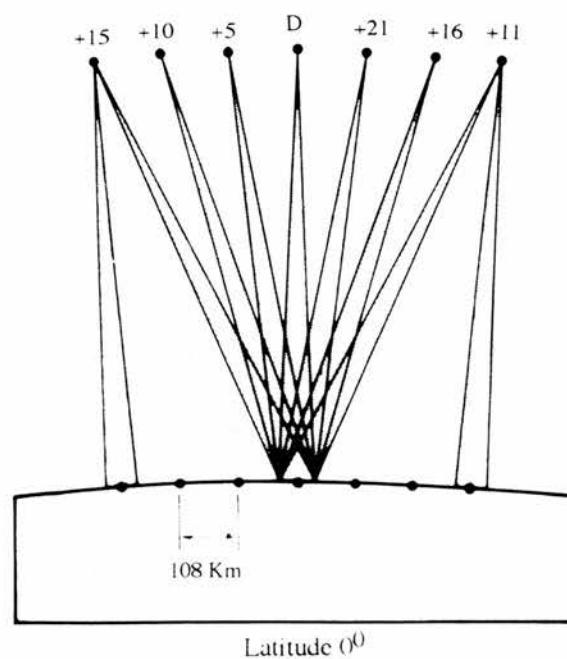
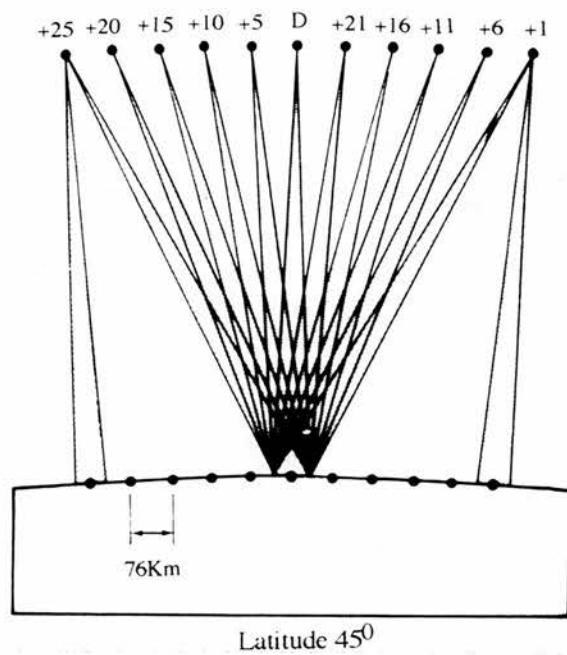


Figure 3.12 SPOT - 1 Revisit Pattern
(latitude 0° and 45°)
(Adapted from Lillesand, 1987).

and a minimum time lapse of 1 day (Brachet, 1983; Lillesand and Kiefer, 1987).

3.4 Digital Image Processing.

Digital image processing is an extremely broad subject and it often involves procedures which can be mathematically complex (Lillesand and Kiefer, 1987). Processing of digital remotely - sensed images is normally done by computer (Mather, 1987). Applications of digital image processing are common in various sciences, for example physics, biology, geography, and geomorphology. In the mid - 1970s, geographers were among the first scientists to recognize the potential of digital methods for investigating patterns of land use.

Image processing is important in the realm of remote sensing, to improve the interpretation of an image. The area of the ground represented by a multispectral SPOT pixel over a 60 km swath requires an array of 3,000 detectors per spectral band, sampled every 3 milliseconds, while a panchromatic pixel over the same swath width requires 6,000 detectors per line, to be sampled every 1.5 milliseconds, thus producing a formidable amount of data which can only be successfully analysed by electronic image processors.

3.4.1 GEMS Image Processing.

Digital systems for processing images, for examples, Landsat, SPOT, and other images, have been developed by a number of universities, government facilities, and commercial organizations. One of these is GEMS, made by Computer Aided Design Centre, United Kingdom (Curran, 1985). GEMS has been used for this current research at the University of St. Andrews.

GEMS is an image processing instrument and GEMSTONE is the software system that controls GEMS (Bagot, 1986). This combination of GEMS and GEMSTONE can cope with a variety of image interpretation tasks. GEMSTONE provides easy control of GEMS by means of a menu system. Rather than typing computer commands at a terminal, the user points at commands on the monitor screen. It is easy to move a cursor around the image and select commands.

Commands are arranged within individual boxes on GEMSTONE's menu pages. A main menu page provides access to individual menu pages. Each page is associated with choose an image, density slice, contrast stretching etc. The menu pages are divided up into primary and secondary commands. Primary commands are used to select a processing operation, and the secondary commands will determine how image data should be treated in that operation.

GEMS is designed to display images where the range of digital numbers are from 0 to 255, 127 corresponds to mid - grey (Bagot, 1986 and Jewell, 1986).

3.4.2 R-CHIPS Image Processing.

The software system known as R-CHIPS has been designed to make image processing both affordable, and user friendly. It combines an excellent graphics display with a menu system via a series of programs.

R-CHIPS has two user interfaces to communicate with the system, the first interface is menu driven and structured and the second is a command line interface.

A list of program options are displayed by the computer as a menu. The R-CHIPS menu interface is structured, so that program options with similar functions are grouped together into thematic menus which are accessed from a main menu. The whole of the R-CHIPS system is usually run from menus which are interconnected to form a menu network.

R-CHIPS uses 512 pixels by 512 lines and the graphic card, is split into four boards: red, green, blue and overlay. These boards are used by R-CHIPS both individually and concurrently

3.5 Image Acquisition and Catalogue/Index.

For general purposes, the grid reference system (GRS) for SPOT divides the earth into five zones:

- the intermediate zone extends from 51.5° N to 51.5° S (in latitude).
- the North and South zones extends from 51.5° to 71.7° North or South, respectively.
- the North and South Polar zones, for latitudes beyond 71.7° North and South, respectively (Figure 3.13).

The grid reference system is used to identify the geographic location of SPOT images (CNES and SPOT images, 1988).

The grid is made up of nodes located at the intersection of columns (k) and rows (j). Each image is identified by a column number k and a row number j (Figure 3.14). K columns are derived directly from SPOT reference tracks. Each track number N corresponds to two k columns :

- $K = 2N-1$ (odd number) associated with HRV 1 and located to the west of track N .
- $K = 2N$ (even number) associated with HRV 1 and located to the east of track N .

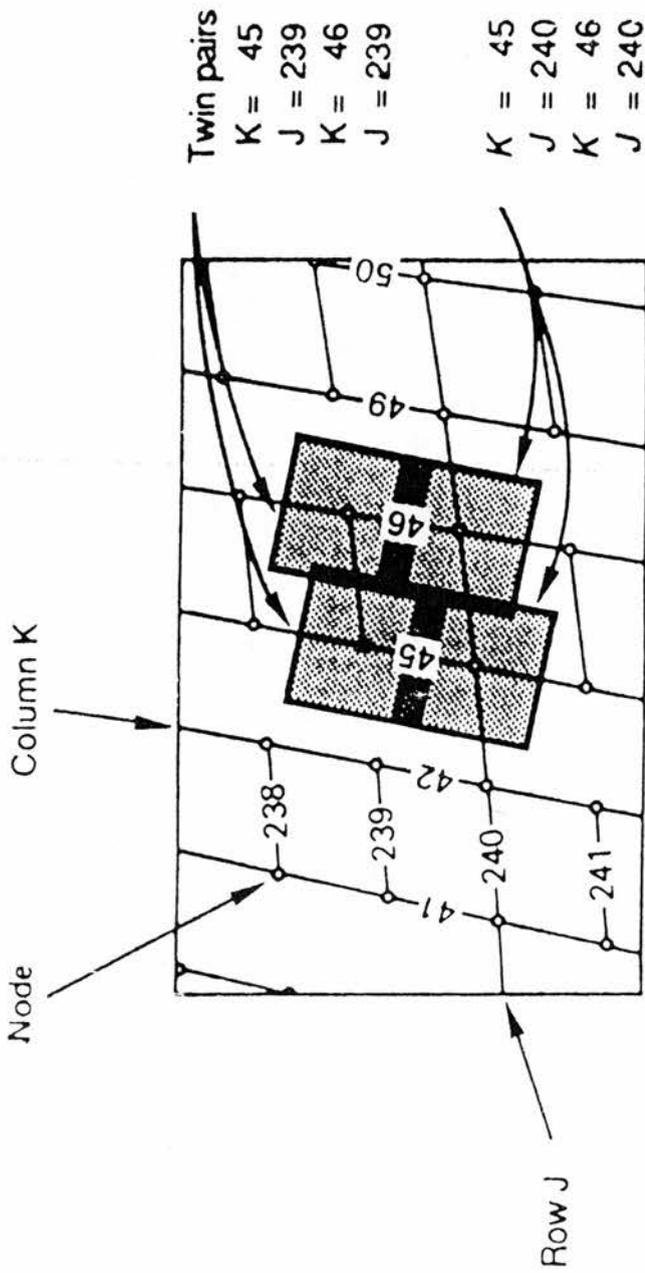


Figure 3.13 Description of a Part of the GRS (Two Pairs of Scenes Acquired in Twin-Viewing configuration) (Adapted from CNES and SPOT Image, 1988).

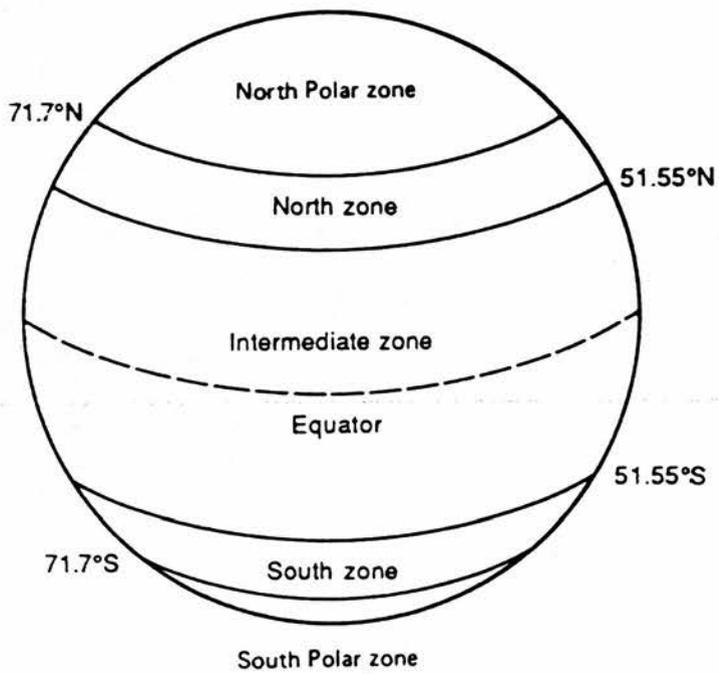


Figure 3.14 Division of the Earth into GRS Zones
(Adapted from CNES and SPOT Image, 1988).

The distance between $K = 2N-1$ and $K = 2N$ is constant at about 58 km and is a direct result of the twin-vertical configuration. J rows correspond to latitude lines (for example, all GRS nodes at the same latitude share the same J designator).

In the GRS the columns are numbered from 1 to 738 to east, and the rows numbered from 246 to 455 from North to South, resulting in 154,242 nodes in the intermediate zone.

CHAPTER 4

VEGETATION MAPPING OF BATURAJA

4.1 The Imagery of The Study Area.

The SPOT imagery for this study uses multispectral mode. It was taken on July 21st, 1986, k/j = 278/358 on computer compatible tape (CCT) and covers Baturaja town, South Sumatera Province, with corner parameters of:

corner	latitude	longitude
c1	S003 ⁰ 41'38"	E103 ⁰ 57'05"
c2	S003 ⁰ 47'32"	E104 ⁰ 33'40"
c3	S004 ⁰ 13'36"	E103 ⁰ 49'49"
c4	S004 ⁰ 19'20"	E104 ⁰ 26'26"

The imagery was from obtained by BAKOSURTANAL who have a joint agreement with the Swedish Space Corporation. The level of SPOT imagery is 1B, that means this level includes the radiometric corrections mentioned above and geometric corrections associated with systematic distortions introduced by the system (earth rotation, viewing angle, panoramic effect, stripping effect). Absolute location accuracy is 800 m (rms error) for vertical viewing, while internal distortion is less than 10^{-3} (Gastellu-Etchegorry, 1988b).

4.2 Ground Data Acquisition.

To support SPOT imagery interpretation ground data are needed especially in training areas. There are two kinds of ground data to support this study : a vegetation map and topographical maps. The vegetation map is at a scale 1 : 250,000 compiled from SPOT imagery (black and white) at a scale of 1 : 100,000 under taken on 21st July 1986 and field checks. This map is very useful for guidance in the location of training area boundaries and indicating various vegetation types. The topographical map has a scale of 1 : 50,000.

4.3 Vegetation Classification Scheme.

Plant communities have so many characteristic features that it is not possible to use them all in devising a classification of vegetation. Details for vegetation classification, such as physiognomy, and floristic criteria, makes it imperative that the vegetation be studied in the field, thoroughly and without bias. The various classification systems for vegetation emphasize different features. The best-known systems are (Küchler, 1967) :

- 1). Physiognomic systems
- 2). Ecological systems
- 3). Physiognomic-ecological systems

- 4). Areal-geographical-ecological systems
- 5). Dynamic-floristic systems
- 6). Physiognomic-floristic systems

In tropical regions like Indonesia, the number of important species in a given area may be so large as to make it impossible for the mapper to convey an adequate idea of vegetation.

Remote sensing can be useful for monitoring areas planted to specific crops, thus contributing to accurate production forecasts. Remote sensing has been important in mapping forests, including studies of timber volume and site quality, and may provide the only practical means of mapping and monitoring changes in major ecological regions. In this study, using SPOT imagery, it is impossible to produce a classification of vegetation based on Kùchler's scheme. Therefore several alternative avenues in vegetation classification can be considered, for example, separating the vegetated from nonvegetated regions or forested from open lands.

The choice of a suitable classification scheme is the most important factor in determining the success of vegetation mapping. For this study the vegetation classification scheme has been adapted from the BAKOSURTANAL and SEAMEO - BIOTROP vegetation classification. This classification is given below:

BAKOSURTANAL and SEAMEO-BIOTROP
Vegetation Classification

A. Natural Vegetation.

A.1 Vegetation formation sub-montane natural forest of Bukit Barisan (high elevation 1,000 - 1,800 m above sea level).

1. Primary tropical ombrophilous sub-montane forest
Dominant : Saninten (*Castanopsis* spp.),
Mempening (*Quercus* spp.), Kelat
(*Eugenia* spp.), and Kedondong Hutan
(*Santiria* spp.).

A.2. Vegetation formation natural forest East of Bukit Barisan (high elevation 300 - 1,000 m above sea level).

1. Primary tropical ombrophilous forest
(high elevation 300 - 1,000 m above sea level)
Dominant: Keruing (*Dipterocarpus* spp.),
Meranti (*Shorea* spp.), and Pasang
(*Lithocarpus* spp.).
2. Secondary forest (height > 5 m)
Dominant: Mahang (*Macaranga gigantea*), Pulai
(*Alstonia* spp.), and Kapok (*Ceiba*
Petandra).

A.3. Lowland vegetation formation, east part (high elevation below 300m above sea level).

A.3.1. Palembang- Jambi lowland.

A.3.1.1. Dry land :

1. Secondary forest (height > 5m)

Dominant: Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), and Kelat (*Eugenia* spp.).

2. Secondary forest (height > 5m)

Dominant : Puspa (*Schima wallichii*).

3. Shrub (height < 5m)

Dominant : Puspa (*Schima wallichii*).

4. Bush and shrub

Dominant: Simpur (*Dillenia* sp.), Puspa (*Schima wallichii*), and Harendong (*Melastoma* spp.).

5. Mosaic of bush, shrub, and mix crop.

6. Alang-alang (*Imperata cylindrica*).

A.3.1.2 Wet land :

1. Secondary swamp forest (height > 5m)

Dominant: Gelam (*Melaleuca cajuputi*), Tembusu (*Fagraea fragrans*), and Kayu obi (*Pternandra* sp.).

2. Bush and shrub swamp

Dominant : Lombokan (*Ludwigia* sp.).

3. Wet or flooded grassland

Dominant : Umbot-umbot (*Cyperus* sp.).

A.3.2. Sekampung and Lampung Timur lowland.

1. Secondary forest

Dominant: Puspa (*Schima wallichii*), semi-deciduous montane forest.

B. Man made communities.

1. Rubber (*Hevea braziliensis*) commercial estates.
2. Oil palm (*Elaeis guineensis*) commercial estates.
3. Damar matakucing (*Shorea javanica*) orchards mixed with coffee, and old secondary forest.
4. Rubber (*Hevea braziliensis*) mixed with secondary forest (height > 5 m) consist of : Mahang (*Macaranga gigantea*), Balik angin (*Homalanthus populneus*), Terentang (*Camptosperma* sp.), and Simpur (*Dillenia* sp.).
5. Acacia (*Acacia mangium*) nurseries.
6. Fruit orchards consist of : Durian (*Durio zibethinus*), Duku (*Lansium domesticum*).
7. Coffee orchards mixed with mainly field crops, rubber, and bush.
8. Pinus (*Pinus merkusii*) reforestation with isulator plants: acacia (*Acacia Auriculiformis*), and Mahoni (*Swietania macrophylla*).
9. Ekaliptus (*Eucalyptus* sp.) reforestation with isulator plants : Acacia (*Acacia*

Auriculiformis), and Mahoni (*Swietenia macrophylla*).

10. Secondary crop and tree crops mixed with young bush.
11. Reforestation.
12. Wetland rice.
13. Settlements.
14. Towns.

This classification was based on manual interpretation of SPOT panchromatic photographs at a scale of 1 : 100,000. BAKOSURTANAL and SEAMEO-BIOTROP have used this classification to produced a vegetation map at a scale of 1 : 250,000 (see page 69a).

4.4 Image Classification.

Satellite remote sensing produces very large quantities of digital data. A SPOT HRV multispectral scene covering a ground area of 60 Km x 60 Km contains 27 megabytes of data. A strip 60 Km wide uses 3,000 pixels per line, at a spatial resolution of about 20 m x 20 m. Usually each pixel is treated as an individual unit composed of values in several spectral bands. It is possible to assemble groups of similar pixels into classes by comparing pixels with one another and with pixels of known identity.

From the 1 : 250,000 scale vegetation map it was possible to gain a general impression of the vegetation of the area. At this scale, however much of the variety to be found within the broader classification units is lost and it was necessary to attempt to establish test areas showing as much of the variety as possible. Visual inspection of the map suggested a number of possibilities as to where this variety might best be found, and it was decided to select three areas for detailed investigation. These are

- a) Baturaja City which shows a mixture of urban land, oil palm commercial estates and rubber small holdings
- b) Lebak which shows a swamp vegetation, rainfed rice field, and rubber commercial estates.
- c) Subanjeruji which shows *accasia Mangium* nurseries, Alang-alang, and mixed reforestation.

Two further considerations also determined the choice of sample areas. The effectiveness of the spatial resolution of SPOT imagery was to be tested using known small patches of different vegetation within the larger community groupings, and secondly it was necessary to attempt to identify the spectral response of these smaller vegetation groupings.

Image classification has formed a significant part of the fields of remote sensing, image analysis and pattern recognition. The analyst must select from these alternatives the classifier that will best accomplish a specific task. But for all situations it is not possible to state that a given classifier is best, because the circumstances for each study vary so greatly and so do the characteristics of each image (Campbell, 1987). One of the most widely used methods of information extraction is multispectral classification. The process of multispectral classification may be performed using either of two methods : supervised or unsupervised (Jensen, 1986).

In supervised classification, the location and identity of some of the pixel types are known (pixels already assigned to information classes) a priori through a combination of analysis of aerial photography, maps, field work, and personal experience. Samples of known identity are those pixels located within training areas. Each training area has multivariate statistical parameters, such as means, standard deviations, covariance matrices, etc (Jensen, 1986).

The result of supervised classification accuracy depends upon the selection of suitable training areas with a careful choice of wavebands. For example, in a small but representative training area, determination of the

relationships between DNs (digital numbers) and object type in the chosen wavebands, can lead to the extrapolation of these relationships to the whole image data and the display and accuracy assessment of the resultant images (Curran, 1985), as illustrated in Figure 4.1.

Unsupervised classification is the definition, identification, labelling, and mapping of these natural classes (Campbell, 1987). In other words unsupervised classification requires only a minimal amount of initial input from the analyst as these methods do not utilize training areas as the basis for classification. The classifier involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on natural groupings. The basic reason is that values within a given cover type should be close together in the measurement space, whereas data in different classes should be comparatively well separated.

The advantages of unsupervised classification are: a) No detailed prior knowledge is required, but a knowledge of the region is required to interpret the meaning of the result produced by the classification process, b) No detailed decisions are required, c) The classes defined by unsupervised classification are often much more uniform in respect of composition than are those generated by supervised classification, d) Unique areas

are identified as distinct units. The disadvantages of unsupervised classification are : a) The analyst has very limited or no control over the menu of classes and their specific identities, b) Spectral properties of specific information classes will change over time, c) This method only identifies spectrally homogeneous classes within the data (Campbell, 1987).

4.4.1 The Training Class.

Supervised classification methods are based upon prior knowledge of the number of spectral classes, and details of the statistical attributes of these classes, which are represented as unknown pixels on an image. The use of a supervised classification method will be affected by the classification characteristics of the classes that are to be estimated from the training sample pixels. There are two factors which will affect the accuracy of a supervised classification analysis : a) the representativeness of the estimates produced for the number and statistical nature of the spectral classes present in the image data and b) the degree of departure from the assumptions upon which the classification technique is based (Mather, 1987).

Two factors affect the validity of statistical estimates: the sizes and the representativeness of the samples. Sample size is related to the number of

variables whose statistical properties are to be estimated, and the number of these statistical properties. Training samples are normally located by map interpretation, field work or from air photographs, and their positions on the image found by carrying out a geometric correction or by visual inspection of the area to be classified.

4.4.2 Density Slicing.

This is an interactive technique to group an image into a number of discrete intervals through a histogram of the continuous digital numbers. In this classification, the digital numbers from 0 - 255, in the original single band image, will be divided automatically into slices interactively specified by the operator and assigning into a specific colour. For example, a red colour is assigned to a certain range of brightness values, such as 0 - 15 DN, another is assigned to values of 16 - 22 DN and so on. Therefore, each terrain cover type is associated with a distinct density, from darkest to brightest. This technique is generally an effective way of highlighting the different (but homogeneous) areas within a single band image. However, the range of classes which are defined will vary depending on the user or the band of an image.

4.4.3 Box (Parallelepiped) Classifier.

Box classification is the simplest form of multispectral analysis and the most popular classifier for remote sensing applications (Curran, 1985 ; Harris, 1987). Four or more bands may be used and this method can operate in one of two ways : qualitatively and quantitatively. Qualitatively, classes can be identified from a combination of brightness in thermal infrared and visible waveband. In a quantitative box classifier, a range of values can be plotted on each axis for any one cover type. The range defined by the highest and lowest digital number values in each band appears as a rectangular area in a two-channel scatter diagram. The ranges of digital numbers are plotted on the two axes, shown in Figure 4.2.

In the box classifier two extreme cases may be considered. First, pixels of unknown types may be found as the point representing a particular pixel does not lie inside any of the regions defined by the boxes. In the second case the point lies inside just one of the boxes, and the corresponding pixel is therefore labelled as a member of the class represented by the box. The decision becomes more complicated because the possibility exists that a point may lie inside two or more overlapping boxes.

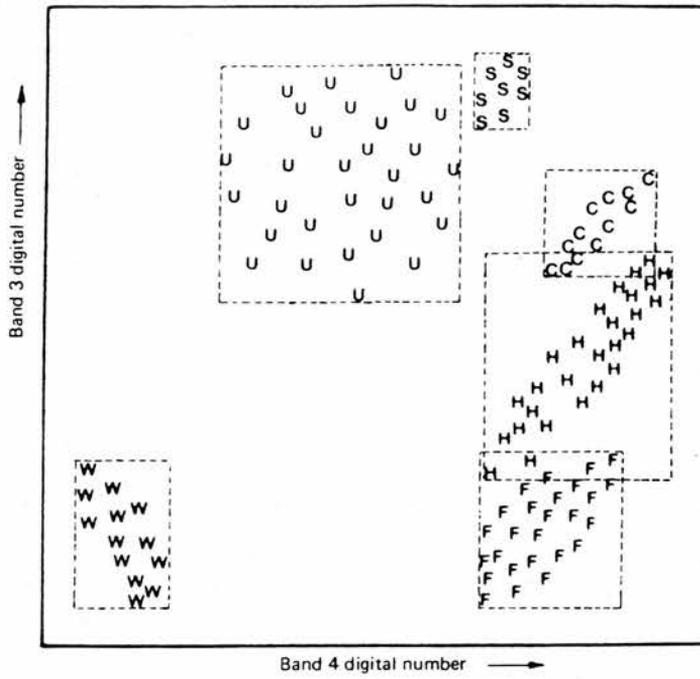


Figure 4.2 Box Classification Strategy.
(Adapted from Curran, 1985).

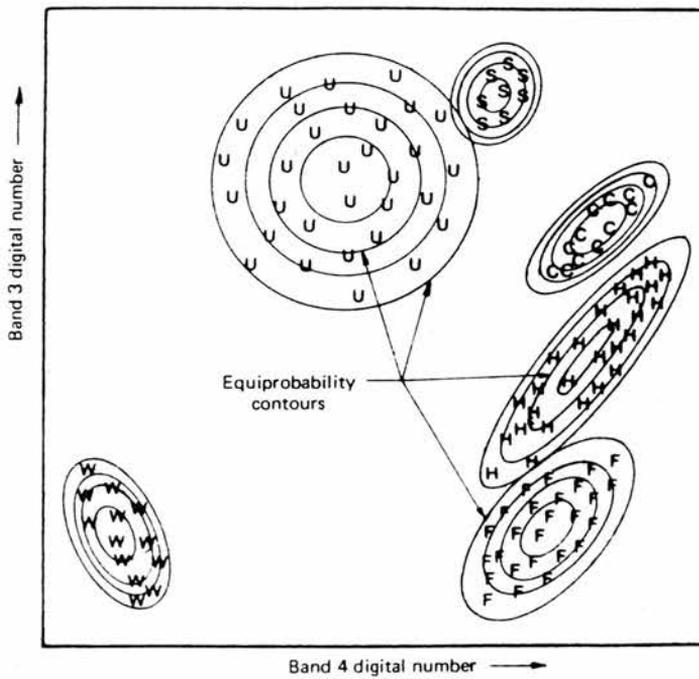


Figure 4.3 Maximum Likelihood Classification Strategy.
(Adapted from Curran, 1985).

4.4.4 Maximum Likelihood Classifier.

This method is usually the most accurate classifier. It operates by calculating the mean vector, variance and correlation for each land cover class in the training areas (Curran, 1985). The assumption is made that the training data for each class are normally distributed. With this information, the distribution of the category response pattern can be completely described by the mean vector and the covariance matrix. The probability of all points in the feature space are plotted, so that each point has a probability of belonging to each of the classes identified. In the scatter diagram, the maximum likelihood classifier delineates ellipsoidal "equiprobability contours", shown in Figure 4.3.

In maximum likelihood classification it is possible to interactively weight each class to improve the accuracy of this method for particular applications (Curran, 1985). Such manipulation is justified in two situations, a) If the training area is not representative of the proportion of the classes in the total scene, b) When all of the pixels in a given class must be classified as belonging to that class.

4.5 Vegetation Mapping in Baturaja.

To make an inventory of vegetation communities in the humid tropics produces many problems. In Sumatra,

economic and demographic pressures are the most common causes of rapid, large scale modifications to existing ecosystems. These alterations may occur before the area has been mapped in detailed. As areas can be difficult to reach, traditional methods of producing vegetation maps and inventories are slow. By using remote sensing techniques and given the availability of satellite data such as SPOT, it may be expected that such problems will be partially solved.

The choice of study extract and the result of two different classification techniques will be discussed in the following sections.

4.5.1 Choice of Study Extracts.

A tropical country like Indonesia has many different types or categories of vegetation, so problems will arise during image classification processing particularly in spectral pattern recognition. Even though SPOT - 1 multispectral scanner has 20 m ground resolution, it is still not sufficient to provide "detailed" information on vegetation types. Uncertainties of spectral resolution exist when attempting to classify a full image scene, so it is necessary to work at full resolution on the image via a series of study extracts.

In this investigation three extracts were defined, namely Baturaja City, Lebak, and Subanjeruji. The reasons for choosing these extracts are: a) many different types of vegetation exist in the extracts selected, b) from these extracts the problems of radiance characteristics of plants and vegetation, and other structures such as soil background, reflectance and shadow may be illustrated.

**4.5.2 Box classification of SPOT image (1986) of three study extracts:
Baturaja City, Lebak, and Subanjeruji.**

The processing of digital remotely - sensed images is normally done by computer. Data from remotely - sensed images are so voluminous that they would be impossible to use if they had to be typed in at a visual display terminal (VDT) by a human operator. These data are transmitted to earth from a satellite in digital form and stored on magnetic tape. The Computer Compatible Tape or CCT is the tape which is converted at the ground receiving station to a form suitable for use in image processing systems.

The image display subsystem is used in storing and manipulating digital images and converting into analogue form for display on a colour monitor. There are three signals combining at each pixel position on the screen

of a colour monitor: these signals correspond to the red, green, and blue components of the picture.

A knowledge of the training area is very important. Usually this is obtained by assembling maps, aerial photographs or input derived from field work, which will then be used as samples for classification purposes. There are seven key characteristics which are important in training area selection (Campbell, 1987): a) the number of pixels selected for each training area class must be at least 100 pixels, b) the size of the training area must be large enough to provide accurate estimates of the properties of each training area class. Therefore, they must be enough to form reliable estimates of the spectral characteristic of each class. However, individual training classes should not be too big, to avoid undesirable variation, c) square or rectangular areas are the easiest training area shapes to define and to minimize the number of vertices that must be specified, d) the location of training areas are important, each category should be represented by several training areas positioned throughout the image and must be positioned in locations that accurately and conveniently transfer from maps or aerial photographs to the digital image, e) the minimal number of training areas in each information category should be about five to ten, to ensure that the spectral properties of each categories are represented, f) the training area should

be placed in an accurate location with respect to distinctive features or land cover. And they should be distributed throughout the image to provide a representation of diversity within the scene, g) uniformity or homogeneity are the most important properties of a good training area. Data within each training area should show a unimodal frequency distribution for each spectral land to be used.

4.5.2.1 Box Classification of Baturaja City.

In the study extract of Baturaja City, eight different cover types exist, namely: 1) Rubber (*Hevea* spp.) small holdings, 2) oil palm commercial estates 1 (open land and grass / unvegetated), 3) oil palm commercial estates 2 (vegetated), 4) secondary forest Puspa (*Schima wallichii*), 5) bush Puspa (*Schima wallichii*), 6) bush and shrubs Puspa (*Schima wallichii*), 7) Alang-alang (*Imperata cylindrica*), and 8) Urban areas (see Plate 4.1). The classification result of vegetation is shown in table 4.1 and 4.2, and the final result of digital image processing shown in Plate 4.2. Bush : Puspa (*Schima wallichii*) is dominant in this study extract (about 25.34 %). A sample photo of bush dominant Puspa (*Schima wallichii*) is shown on Plate 4.3a and bush and shrubs dominant Puspa (*Schima wallichii*) on Plate 4.3b.

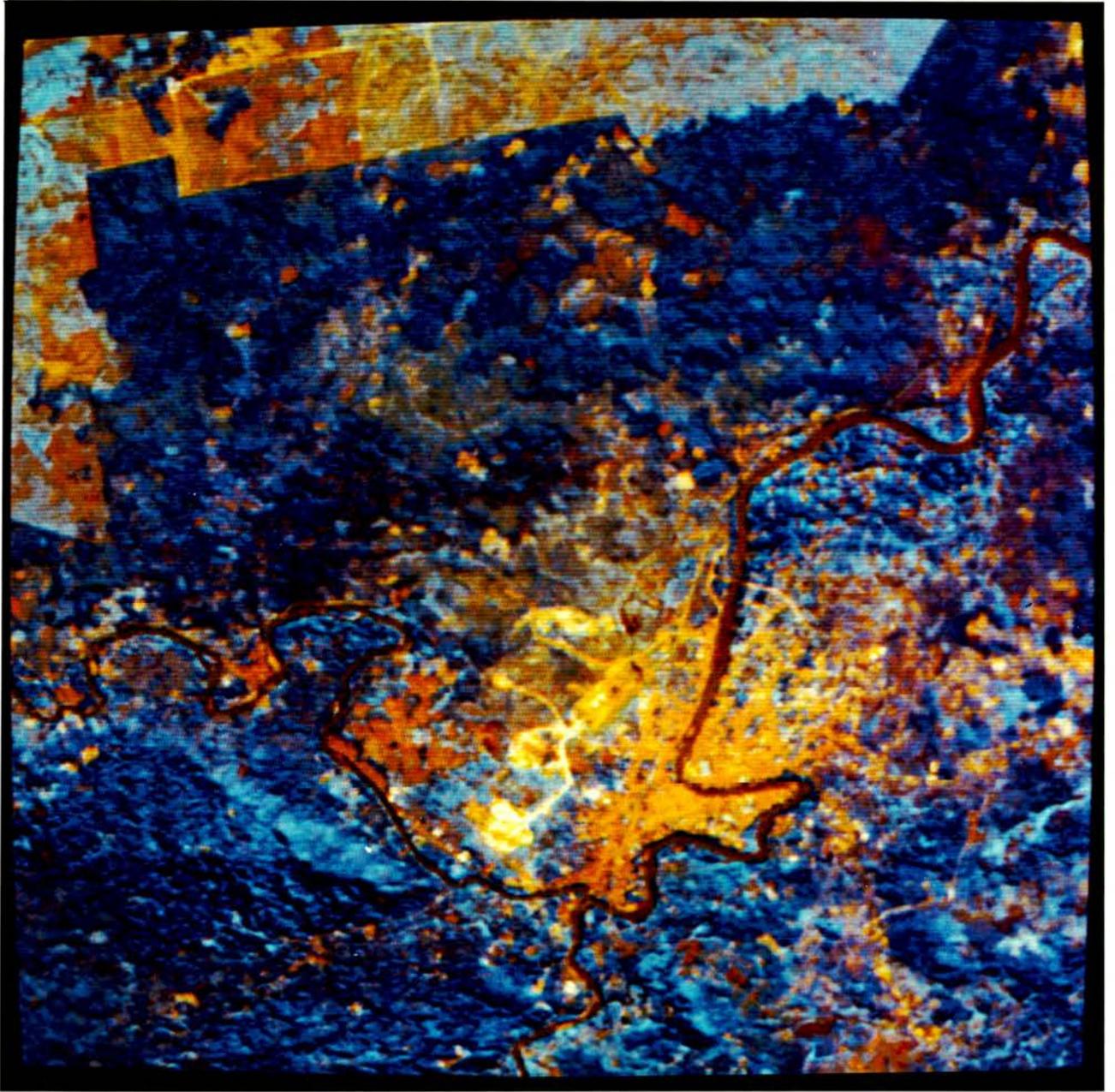


Plate 4.1 SPOT multispectral band XS 1, XS 2, and XS 3 of image 1986, Baturaja City study extract (normally distributed / Gaussian).



Class	Colour	Number of pixels	% of image
1	Black	19338	7.38
2	Red	6682	2.55
3	Green	23417	8.93
4	D.Blue	26967	10.29
5	Pink	66423	25.34
6	L.Blue	35527	13.55
7	Yellow	37103	14.15
8	White	19066	7.27
Unclassified		27621	10.54

Table 4.1 Percentage image classification results of Baturaja city using Box Classification.

- Black = Rubber small holdings.
 Red = Oil palm commercial estates (unvegetated).
 Green = Oil palm commercial estates (vegetated).
 D. blue = Secondary forest Puspa (*schima wallichii*).
 Pink = Bush Puspa (*schima wallichii*).
 L. blue = Bush & shrubs Puspa (*schima wallichii*).
 Yellow = Alang-alang (*Imperata cylindrica*).
 White = City.

		Class Number & Colour							
		1 black	2 red	3 green	4 d. blue	5 pink	6 l. blue	7 yellow	8 white
Band XS 1	Mean	18	34	24	18	20	22	29	65
	Maximum	21	40	28	21	24	26	35	118
	Minimum	15	28	21	17	19	21	23	37
	No. Pixels	512	335	421	526	460	196	230	376
	Std. dev	1.32	2.24	1.34	0.96	1.07	1.24	2.52	15.97
Band XS 2	Mean	35	45	41	34	37	39	43	73
	Maximum	40	52	44	38	40	41	50	129
	Minimum	31	39	39	32	35	35	39	50
	No. Pixels	512	335	421	526	460	196	230	376
	Sdt. dev	1.51	1.96	1.45	1.68	1.04	1.21	2.37	16.88
Band XS 3	Mean	86	51	93	77	77	74	69	69
	Maximum	106	67	111	91	87	86	82	115
	Minimum	69	41	77	69	70	64	55	45
	No. Pixels	512	335	421	526	460	196	230	376
	Std.dev	7.15	6.28	6.17	3.97	3.35	3.32	4.65	12.76

Table 4.2 Classification results of Baturaja City by using Box Classification.

Note: See table 4.1

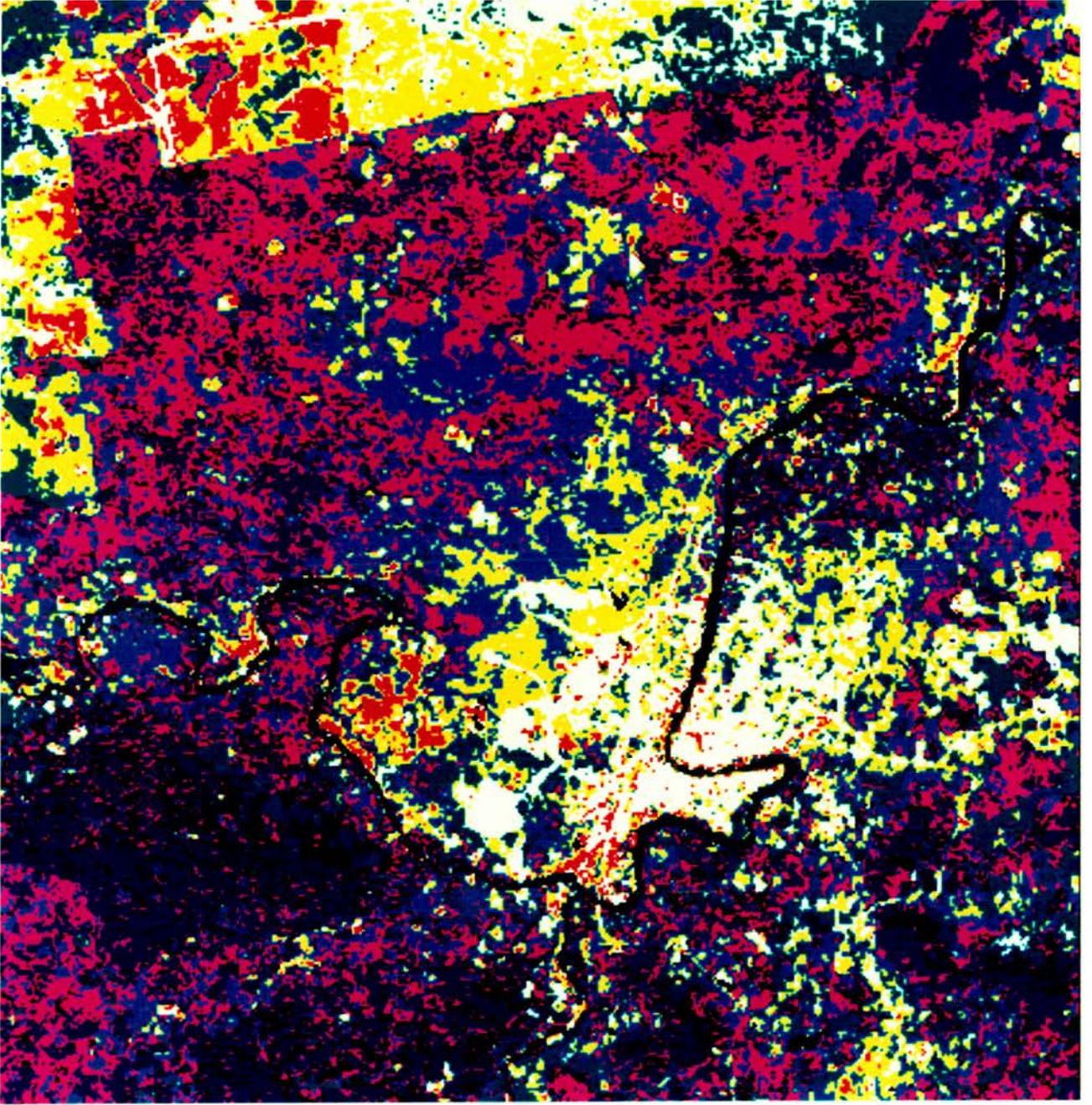


Plate 4.2 Classified image of Baturaja City study extract 1986, using box classification.





Plate 4.3.a Bush dominant Puspa (*Schima wallichii*) found over most of the Baturaja area.



Plate 4.3.b Bush and shrubs dominant Puspa (*Schima wallichii*), in Baturaja City study extract area.

There are two different types of land cover for oil palm commercial estates. First; this area was established for oil palm commercial estates, but when SPOT - 1 imaged this area unvegetated land parcels remained, the second area of the oil palm commercial estates shows relative young plants, about 5 - 10 years old and planted about 3 metres apart with some grass or unvegetated land. It is shown on Plates 4.4a and 4.4b.

The oil palm commercial estates 1 (unvegetated) and town and/or road have similar reflectance values, and the result of classification for the oil palm commercial estates (unvegetated) also includes town and/or road. The result of digital image processing shows that a part of town and/or road is the same as the oil palm commercial estates 1 (unvegetated) with red colour, as shown on Plate 4.2. In this study extract the percentage of the oil palm commercial estates (vegetated) is higher than the oil palm commercial estate (unvegetated). There is 8.93 % of the oil palm commercial estate (vegetated) while the oil palm commercial estate (unvegetated) is only 2.55%, (Table 4.1).

The reflectance value of rubber (*Hevea* spp.) small holdings, bush, and bush & shrubs types were similar, because the height, type, and the density of vegetation was similar. The Rubber (*Hevea* spp.) small holdings mix in with secondary forest (height > 5m), it contains :



Plate 4.4.a Commercial oil palm estates with young plants found near Baturaja City.



Plate 4.4.b Commercial oil palm estates mixed with grasses found near Baturaja City.

Mahang (*Macaranga gigantea*), Balik angin (*Homalanthus populneus*), Terentang (*Camptosperma* sp.), and Simpur (*Dillenia* sp.). Bush was dominated by Puspa (*Schima wallichii*) (height > 5m) and mixed with Mahang (*Macaranga gigantea*), Simpur (*Dillenia* sp.), Harendong (*Melastoma* sp.), and Damar mata kucing (*Shorea javanica*). Bush and shrubs types show co-dominant Simpur (*Dillenia* sp.), Puspa (*Schima wallichii*), and Harendong (*Melastoma* sp.). This type is a degradation from bush with similar vegetation but containing more young plants. The areas covered by Rubber (*Hevea* sp.) small holdings (magenta), Bush (yellow), and Bush & shrubs (cyan) are shown on Plate 4.2.

4.5.2.2 Box classification of Lebak Study Extract.

Lebak is a small part of the SPOT image of Baturaja, located north east of Baturaja city. The majority of this this study extract is swamp, and is shown on Plate 4.5. Eight different types of land cover appear in the image classification of this study extract namely : 1) swamp bush & shrubs Lombokan (*Ludwigia*), 2) rainfed rice fields, 3) rubber commercial (*Hevea braziliensis*) estates, 4) secondary forest Puspa (*Schima wallichii*), 5) bush Puspa (*Schima wallichii*), 6) bush & shrubs Simpur (*Dillenia* sp.), Puspa (*Schima wallichii*), and Harendong (*Melastoma* spp.), 7) secondary swamp forest:

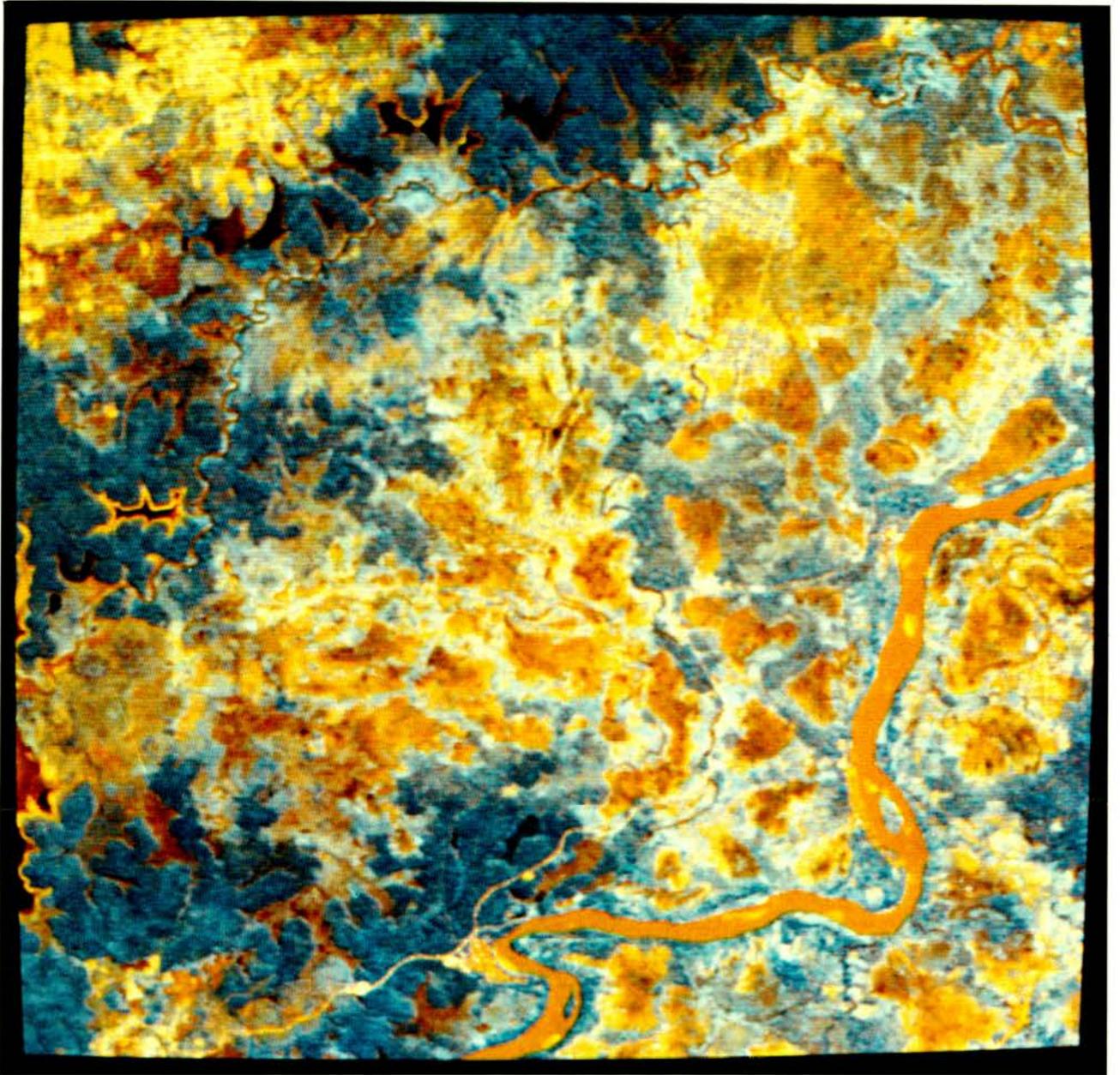


Plate 4.5 SPOT multispectral band XS 1, XS 2, and XS 3 of image 1986, Lebak study extract (normally distributed / Gaussian).



Harendong (*Melaleuca cajuputi*), Tembusu (*Fagraea fragrans*), and Kayu obi (*Pternandra* spp.), 8) water bodies,

The problems in this study extract are similar to those of Baturaja city. In the area of rubber (*Hevea braziliensis*) commercial estates have both young plants and land surfaces covered either by grass or remaining unvegetated, as seen in the sample photo shown on Plate 4.7. This has a reflectance characteristic similar to rainfed rice fields outwith the planting season and open land. Digital image classification results in a small part of rainfed rice fields and open land being included in rubber (*Hevea braziliensis*) commercial estates, as shown in Plate 4.6.

The percentage of rainfed rice field in this study extract is 21.49 % (red colour), it is shown on Table 4.3. The reflectance of open land and rainfed rice field outwith the planting season are similar, and cannot be distinguished. The unclassified area is 13.63 %, and consists of river, lake, and a small part of swamp bush and shrubs. The river and lake cannot be accommodated in the water bodies class because of their different reflectance values. The result of classification of the Lebak study extract is shown on Table 4.3 and 4.4. The second dominant in this study extract is swamp bush and shrubs Lombokan (*Ludwigia*) and a sample photo is shown on Plate 4.8. A sample photo of a rainfed rice field is

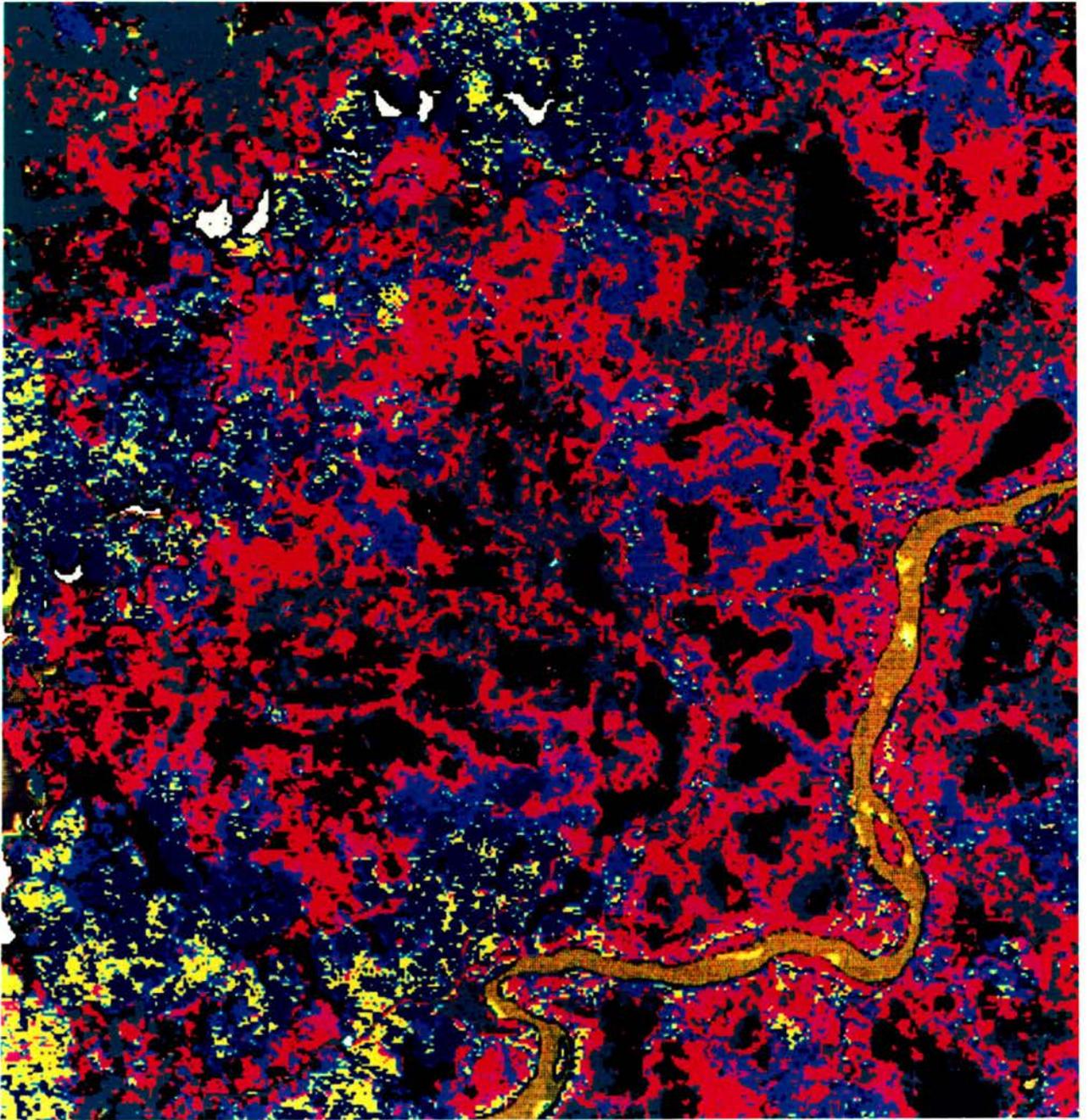


Plate 4.6 Classified image of Lebak study extract 1986, using box classification.



Class	Colour	Number of pixels	% of image
1	Black	53917	20.57
2	Red	56325	21.49
3	Green	28575	10.90
4	D.Blue	24253	9.25
5	Pink	16315	6.22
6	L.Blue	35456	13.53
7	Yellow	10880	4.15
8	White	686	0.26
Unclassified		35737	13.63

Table 4.3 Percentage image classification results of Lebak using Box Classification.

- Black = Swamp bush & shrubs dominant Lombokan (*Ludwigia*).
- Red = Rainfed rice field.
- Green = Rubber commercial estates (unvegetated).
- D. blue = Secondary forest Puspa (*Schima wallichii*).
- Pink = Bush Puspa (*Schima wallichii*).
- L. blue = Bush & shrubs Simpura (*Dillenia* sp.), Puspa (*Schima wallichii*), Harendong (*Melastoma* spp.).
- Yellow = Secondary swamp forest Gelam (*Melaleuca cajuputi*), Kayu obi (*Pternandra* spp.), Tembusu (*Fagraea fragrans*).
- White = Water bodies (swamp/lake).

	Class Number & Colour							
	1 black	2 red	3 green	4 d. blue	5 pink	6 l. blue	7 yellow	8 white
Band XS 1	Mean Maximum Minimum No. Pixels Std. dev	25 31 21 183 1.49	48 70 33 349 7.09	18 21 17 694 1.15	21 24 18 282 1.05	21 24 19 346 0.94	19 22 18 195 0.84	18 22 15 286 1.91
Band XS 2	Mean Maximum Minimum No. Pixels Std. dev	41 46 38 183 1.72	55 87 45 349 5.58	34 36 32 694 0.78	37 41 35 282 1.20	36 40 34 346 1.22	34 37 32 195 1.14	30 34 28 286 1.78
Band XS 3	Mean Maximum Minimum No. Pixels Std.dev	87 104 46 183 7.70	73 90 55 349 6.74	73 82 64 694 3.10	86 115 69 282 10.09	77 91 59 346 5.31	77 90 67 195 4.66	17 30 15 286 2.82

Table 4.4 Classification result of Lebak by using Box Classification.
Note: See table 4.3



Plate 4.7 Commercial rubber estates mixed with shrubs and grasses, in Lebak study extract area.



Plate 4.8 Swamp bush and shrubs dominant Lombokan (*Ludwigia*), in Lebak study extract area.

shown on Plate 4.9a. Another type of rice cover is the dry rice field, but it only occupies a small area in the Baturaja study extract and cannot be classified (Plate 4.9b). About 13.53 % of the Lebak study area has been classified as bush and shrubs (dominants Simpung (*Dillenia* sp.), Puspa (*Schima wallichii*), and Harendong (*Melastoma* spp.)). These are shown in Plates 4.10a and 4.10b.

4.5.2.3. Box Classification of Subanjeruji Study Extract.

The Subanjeruji study extract is a reforestation area, the location of Subanjeruji being north west of Baturaja City. There are eight different land cover types namely: 1) reforestation *Pinus merkusii*, 2) *Acacia mangium* nurseries, 3) reforestation area (unvegetated or open land), 4) secondary forest Puspa (*Schima wallichii*), 5) bush Puspa (*Schima wallichii*), 6) reforestation (grasses), 7) Alang-alang (*Imperata cylindrica*), 8) secondary forest Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), and Kelat (*Eugenia* spp.). This image is shown on Plate 4.11.

The result of classification of the Subanjeruji study extract is shown on Tables 4.5 and 4.6. In this study extract Alang-alang (*Imperata cylindrica*) is dominant at



Plate 4.9.a Rainfed rice field at the planting season, in Lebak study extract area.



Plate 4.9.b Dry rice field.



Plate 4.10.a Bush and shrubs dominant Simpur (*Dillenia* sp.), Puspa (*Schima wallichii*), and Harendong (*Melastoma* spp.), in Lebak study extract area.



Plate 4.10.b Bush and shrubs dominant Simpur (*Dillenia* sp.), Puspa (*Schima wallichii*), and Harendong (*Melastoma* spp.), in Lebak study extract area.

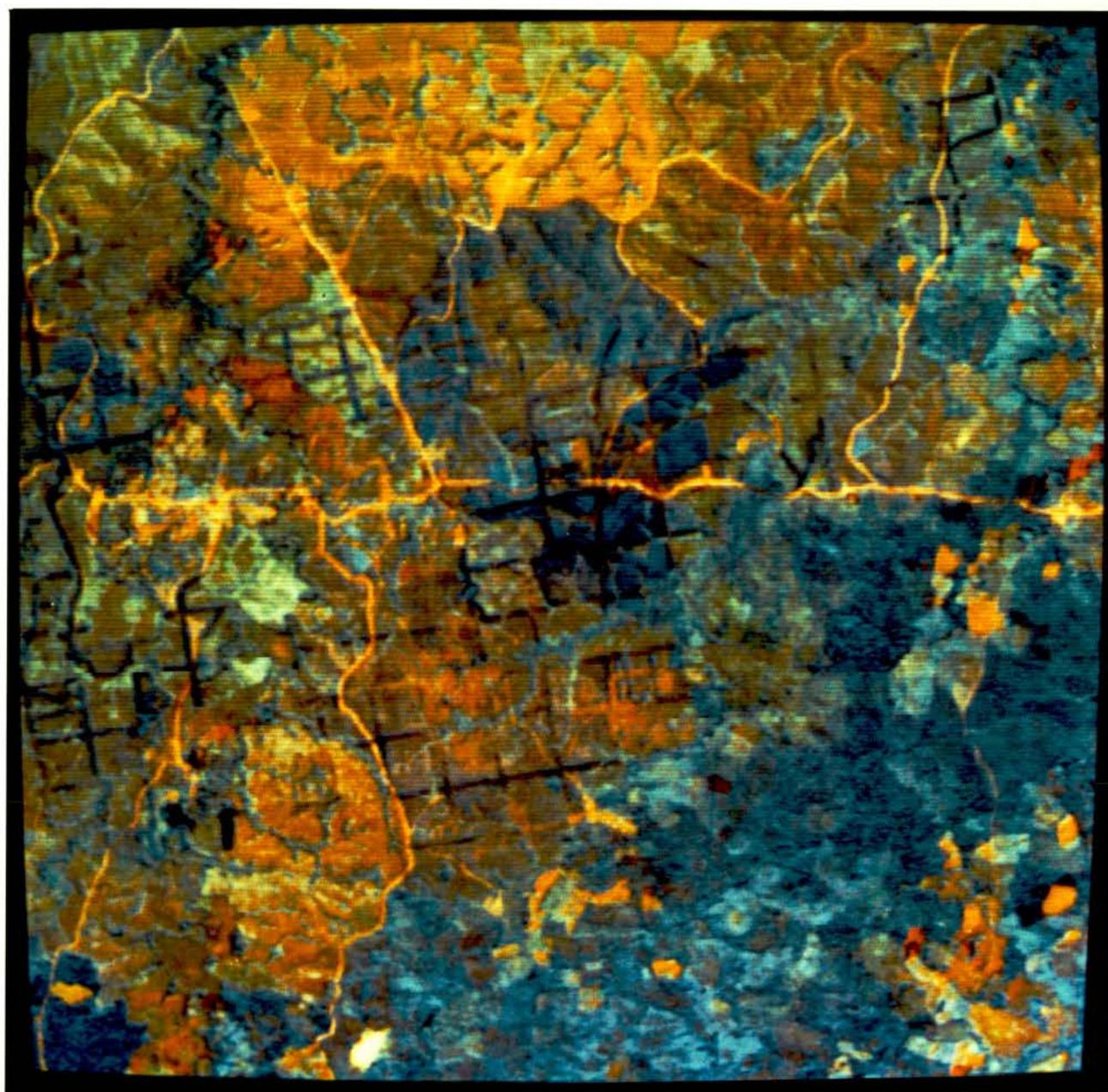


Plate 4.11 SPOT multispectral band XS 1, XS 2, and XS 3 of image 1986, Subanjeruji study extract (normally distributed / Gaussian).



Class	Colour	Number of pixels	% of image
1	Black	24596	9.38
2	Red	32496	12.40
3	Green	9439	3.60
4	D.Blue	19382	7.39
5	Pink	31431	11.99
6	L.Blue	11896	4.54
7	Yellow	90575	34.55
8	White	1648	0.63
Unclassified		40081	15.52

Table 4.5 Percentage image classification results of Subanjeruji using Box Classification.

- Black = Reforestation Pinus (*Pinus merkusii*).
 Red = *Acacia mangium* nurseries and sedges.
 Green = Reforestation (unvegetated).
 D. blue = Secondary forest Puspa (*Schima wallichii*).
 Pink = Bush Puspa (*Schima wallichii*).
 L. blue = Reforestation (grasses).
 Yellow = Alang-alang (*Imperata cylindrica*).
 White = Secondary forest Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), Kelat (*Eugenia* spp.).

		Class Number & Colour							
		1 black	2 red	3 green	4 d. blue	5 pink	6 l. blue	7 yellow	8 white
Band XS 1	Mean	26	20	41	19	20	27	26	18
	Maximum	30	22	51	21	22	32	29	20
	Minimum	24	19	34	18	19	23	24	17
	No. Pixels	232	128	230	320	323	329	455	299
	Std. dev	1.34	0.74	2.35	0.60	0.75	1.75	1.13	0.64
Band XS 2	Mean	45	35	53	35	37	41	41	34
	Maximum	49	37	64	37	39	44	44	36
	Minimum	41	35	48	33	35	38	39	33
	No. Pixels	232	128	230	320	323	329	455	299
	Std. dev	1.43	0.96	2.69	0.78	0.74	1.25	0.84	1.00
Band XS 3	Mean	90	84	68	78	91	57	72	77
	Maximum	103	88	76	87	106	72	80	88
	Minimum	76	78	63	67	82	43	66	69
	No. Pixels	232	128	230	320	323	329	455	299
	Std.dev	5.30	2.10	2.41	3.48	4.13	6.34	2.55	3.22

Table 4.6 Classification results of Subanjeruji by using Box Classification.
Note: See table 4.5

about 34.55 %. The result of the box classification is shown on Plate 4.12 and the sample photo on Plate 4.13. The unclassified area is 15.52 % which contains a road, and a small part of the reforestation area. The problem in this study extract is found in *Acacia mangium* (nurseries or insulator) and bush Puspa (*Schima wallichii*). The characteristics of these vegetation groups are similar: they have similar height, shape and density of leaves, therefore the reflectance value is the same on band XS 1, XS 2, but can be separated on the IR.

4.5.3. Maximum Likelihood Classification of SPOT 1 Image (1986) of Three Study Extract : Baturaja City, Lebak, and Subanjeruji.

The maximum likelihood classification has been done using GEMS in this study. The main different between maximum likelihood and box classification is that maximum likelihood will work on up to sixteen classes simultaneously. This therefore might be considered to be a more accurate classifier. The result of the maximum likelihood classification of three study extracts are now considered in turn.

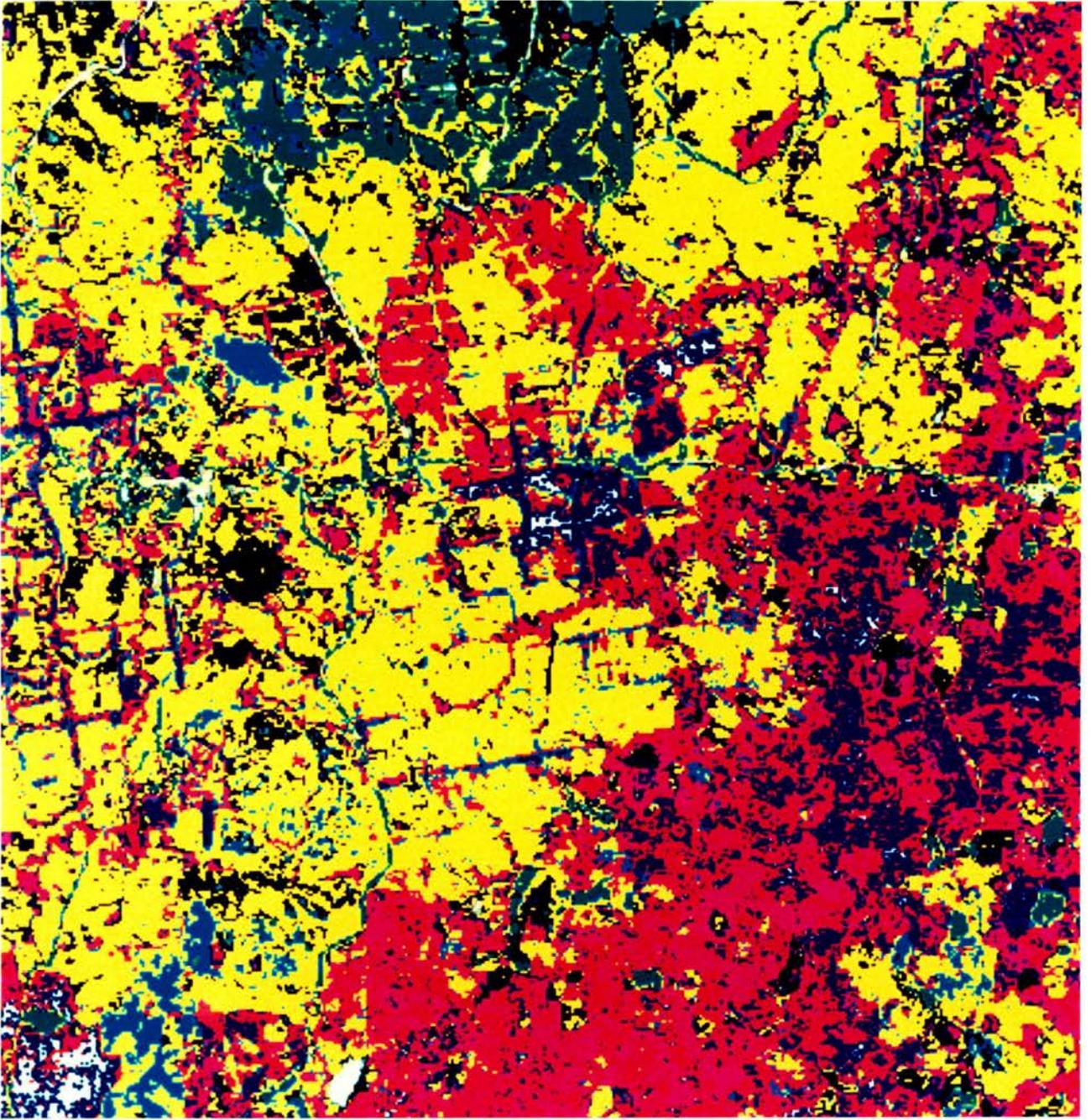


Plate 4.12 Classified image of Subanjeruji study extract 1986, using box classification.





Plate 4.13 Alang-alang (*Imperata cylindrica*), in Baturaja City and Subanjeruji study extract area.

4.5.3.1 Maximum Likelihood Classification of Baturaja City Study Extract.

The study area of Baturaja city for maximum likelihood classification is the same as the study area of Baturaja city for the box classification shown on Plate 4.1. There are sixteen class types namely : 1) rubber small holdings 1, 2) rubber small holdings 2, 3) water bodies 1, 4) water bodies 2, 5) oil palm commercial estates 1, 6) oil palm commercial estates 2, 7) oil palm commercial estates 3, 8) secondary forest Puspa (*Schima wallichii*) 1, 9) secondary forest Puspa (*Schima wallichii*) 2, 10) bush Puspa (*Schima wallichii*), 11) bush and shrubs Puspa (*Schima wallichii*) 1, 12) bush and shrubs Puspa (*Schima wallichii*) 2, 13) road 1, 14) town, 15) road 2, 16) Alang-alang (*Imperata cylindrica*).

There are three training classes in commercial oil palm estates. The first area has been prepared for oil palm commercial estate, but is still unvegetated. The second, area is dominated by grasses, and the third area has young oil palm trees as dominants. The rubber small holding training class has two sub-classes, first is rubber small holdings influenced by shadow on the image and the second is rubber small holdings.

The dominant land cover in this classification is secondary forest Puspa (*Schima wallichii*) at 20.52 %. Unclassified area is 17.20 % consist of openland,

grasses and/or Alang-alang (*Imperata cylindrica*), and water bodies. Alang-alang in this instance is not included in class 16 owing to the intimate admixture of land cover within some pixels. The result of the classification of Baturaja city using maximum likelihood is shown on Tables 4.7 and 4.8. The image classification result is also shown on Plate 4.14. as a classified image.

4.5.3.2. Maximum Likelihood Classification of Lebak Study Extract.

In the Lebak study area, there are sixteen training classes namely: 1) swamp bush and shrubs Lombokan (*Ludwigia*) 1, 2) swamp bush and shrubs Lombokan (*Ludwigia*) 2, 3) water bodies 1, 4) water bodies 2, 5) rainfed rice field 1, 6) rainfed rice field 2, 7) rainfed rice field 3, 8) secondary forest Puspa (*Schima wallichii*), 9) bush and shrubs Puspa (*Schima wallichii*) 1, 10) bush and shrubs Puspa (*Schima wallichii*) 2, 11) bush Puspa (*Schima wallichii*), 12) rubber commercial estates 1, 13) rubber commercial estates 2, 14) water bodies 3, 15) swamp bush and shrubs Lombokan (*Ludwigia*) 3, 16) secondary swamp forest Gelam (*Melaleuca cajuputi*), Kayu obi (*Pternandra* spp.), Tembusu (*Fagraea fragrans*).

No	Training Class	Colour	Total Pixels	% Class
1.	Rubber small holding 1	Red	7309	3.08
2.	Rubber small holding 2	Green	8289	3.49
3.	Water bodies 1	Blue	1828	0.77
4.	Water bodies 2	Yellow	816	0.34
5.	Oil palm comm. estates 1	Magenta	1343	0.57
6.	Oil palm comm. estates 2	Cyan	14209	5.98
7.	Oil palm comm. estates 3	Grey	10916	4.60
8.	Secondary forest 1	Gold	44017	18.53
9.	Secondary forest 2	Orange	4724	1.99
10.	Bush	Purple	31192	13.13
11.	Bush & shrubs 1	Dark Red	34821	14.66
12.	Bush & shrubs 2	Dark Green	3741	1.58
13.	Road 1	Dark Blue	12223	5.15
14.	Town	192/255/0	2894	1.22
15.	Road 2	255/0/192	3036	1.28
16.	Alang-alang	0/255/192	15303	6.44
Unclassified			40839	17.20

Table 4.7 Percentage image classification Baturaja city using Maximum Likelihood Classifier.

No.	Training Class	Band XS 1		Band XS 2		Band XS 3	
		M	SD	M	SD	M	SD
1.	Rubber small holding plant. 1	69.2	6.5	33.2	1.1	16.7	0.5
2.	Rubber small holding plant. 2	96.7	5.8	37.2	1.4	19.7	0.5
3.	Water bodies 1	26.6	7.3	38.0	1.6	23.9	0.9
4.	Water bodies 2	23.2	5.7	40.3	0.8	24.1	0.5
5.	Oil palm comm. estates 1	51.4	6.3	42.5	2.0	31.0	0.9
6.	Oil palm comm. estates 2	74.8	3.8	44.9	2.7	30.6	0.8
7.	Oil palm comm. estates 3	97.7	5.8	42.1	1.9	24.4	0.8
8.	Secondary forest 1	79.6	3.7	35.6	0.9	18.9	0.5
9.	Secondary forest 2	76.8	4.5	33.4	0.7	18.0	0.2
10.	Bush	73.8	2.9	35.7	1.3	21.0	0.5
11.	Bush & shrubs 1	73.0	4.2	40.8	1.8	23.9	0.6
12.	Bush & shrubs 2	69.8	2.8	41.8	1.9	25.3	0.5
13.	Road 1	64.8	7.2	50.5	5.3	37.4	1.9
14.	Town	60.9	6.7	55.2	5.3	48.4	2.2
15.	Road 2	89.5	19.7	79.1	7.0	68.0	4.5
16.	Alang-alang	58.4	6.8	47.7	3.6	32.1	1.0

Table 4.8 Classification results of Baturaja City by using Maximum Likelihood Classifier.

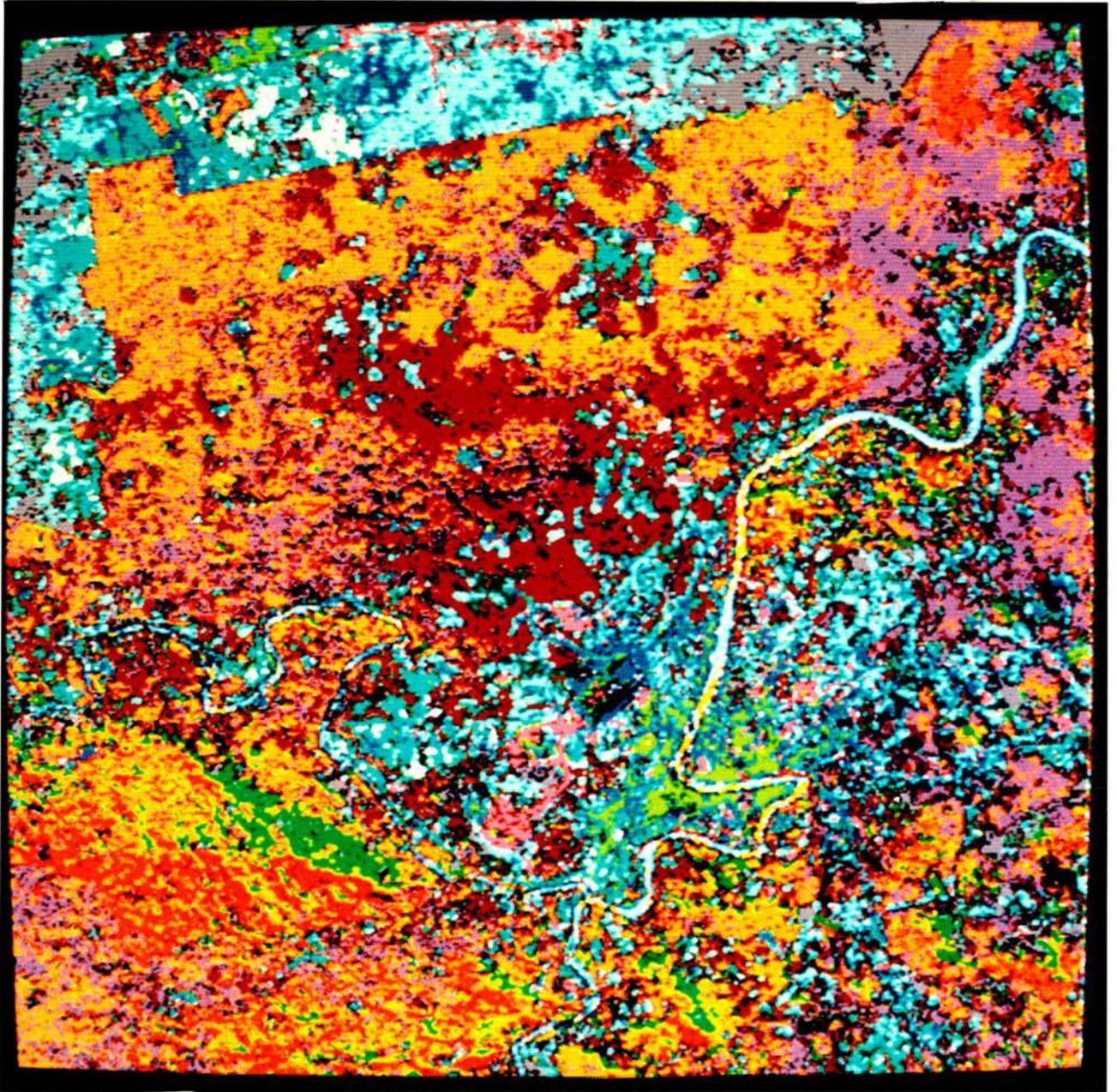


Plate 4.14 Classified image of Baturaja City study extract 1986, using maximum likelihood classification.



The dominant type in the image classification using maximum - likelihood is swamp bush and shrubs Lombokan (*Ludwigia*) at 19.28%. Three training classes of swamp bush and shrubs Lombokan (*Ludwigia*). The first training area shows dense vegetation. In the second class the vegetation is not as dense and the area is wet, third is the area with much less vegetation. Unclassified parts of the image amount to 18.82 % and consist of rainfed rice field mixed with settlement. The classification results of Lebak using maximum likelihood are shown on Table 4.9 and 4.10. The image classification is shown on Plate 4.15.

4.5.3.3 Maximum Likelihood Classification of Subanjeruji Study Extract.

Subanjeruji is a reforestation area, and the types of vegetation for reforestation include: *Pinus merkusii*, and *Acacia mangium*. Sixteen training classes exist, namely: 1) *Acacia*, 2) reforestation *Pinus merkusii* 1, 3) reforestation *Pinus merkusii* 2, 4) reforestation *Pinus merkusii* 3, 5) Alang-alang (*Imperata cylindrica*) 1, 6) Alang-alang (*Imperata cylindrica*) 2, 7) Alang-alang (*Imperata cylindrica*) 3, 8) reforestation (unvegetated) 1, 9) secondary forest dominant Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), Kelat (*Eugenia*

No	Training Class	Colour	Total Pixels	% Class
1.	Swamp bush & shrubs 1	Red	1235	0.52
2.	Swamp bush & shrubs 2	Green	2842	1.20
3.	Water bodies 1	Blue	2925	1.23
4.	Water bodies 2	Yellow	4307	1.81
5.	Rainfed rice field 1	Magenta	5294	2.23
6.	Rainfed rice field 2	Cyan	14490	6.10
7.	Rainfed rice field 3	Grey	12209	5.14
8.	Secondary forest	Gold	23863	10.05
9.	Bush & shrubs 1	Orange	7628	3.21
10.	Bush & shrubs 2	Purple	23937	10.08
11.	Bush	Dark Red	37630	15.84
12.	Rubber comm. estates 1	Dark Green	343	0.14
13.	Rubber comm. estates 2	Dark Blue	9360	3.94
14.	Water bodies 3	192/255/0	240	0.10
15.	Swamp bush & shrubs 3	255/0/192	41708	17.56
16.	Secondary swamp forest	0/255/192	478	2.01
Unclassified			44708	18.82

Table 4.9 Percentage image classification Lebak area using Maximum Likelihood Classifier.

No.	Training Class	Band XS 1		Band XS 2		Band XS 3	
		M	SD	M	SD	M	SD
1.	Swamp bush & shrubs 1	24.2	10.4	31.9	2.1	19.8	0.6
2.	Swamp bush & shrubs 2	50.9	5.1	35.2	1.0	22.9	0.6
3.	Water bodies 1	19.3	1.2	43.1	0.7	32.4	0.5
4.	Water bodies 2	42.3	17.1	55.4	7.5	45.5	2.3
5.	Rainfed rice fields 1	52.0	3.6	41.3	1.7	30.4	0.5
6.	Rainfed rice fields 2	63.5	5.9	48.8	4.1	39.6	1.1
7.	Rainfed rice fields 3	50.5	4.9	39.4	2.4	27.4	0.7
8.	Secondary forest	72.6	2.9	33.7	0.8	18.7	0.5
9.	Bush & shrubs 1	97.0	5.7	40.3	2.9	22.9	0.6
10.	Bush & shrubs 2	84.6	4.6	38.6	1.9	22.3	0.6
11.	Bush	79.5	6.0	37.6	1.4	21.6	0.6
12.	Rubber commercial estates 1	61.7	5.9	57.4	2.3	50.8	1.2
13.	Rubber commercial estates 2	75.1	7.9	55.1	4.1	47.4	2.0
14.	Water bodies 3	18.4	2.6	29.7	1.0	17.2	0.6
15.	Swamp bush & shrubs 3	67.1	5.5	37.9	2.1	23.9	0.7
16.	Secondary swamp forest	45.1	6.0	37.5	2.5	26.9	0.8

Table 4.10 Classification results of Lebak using Maximum Likelihood Classification.

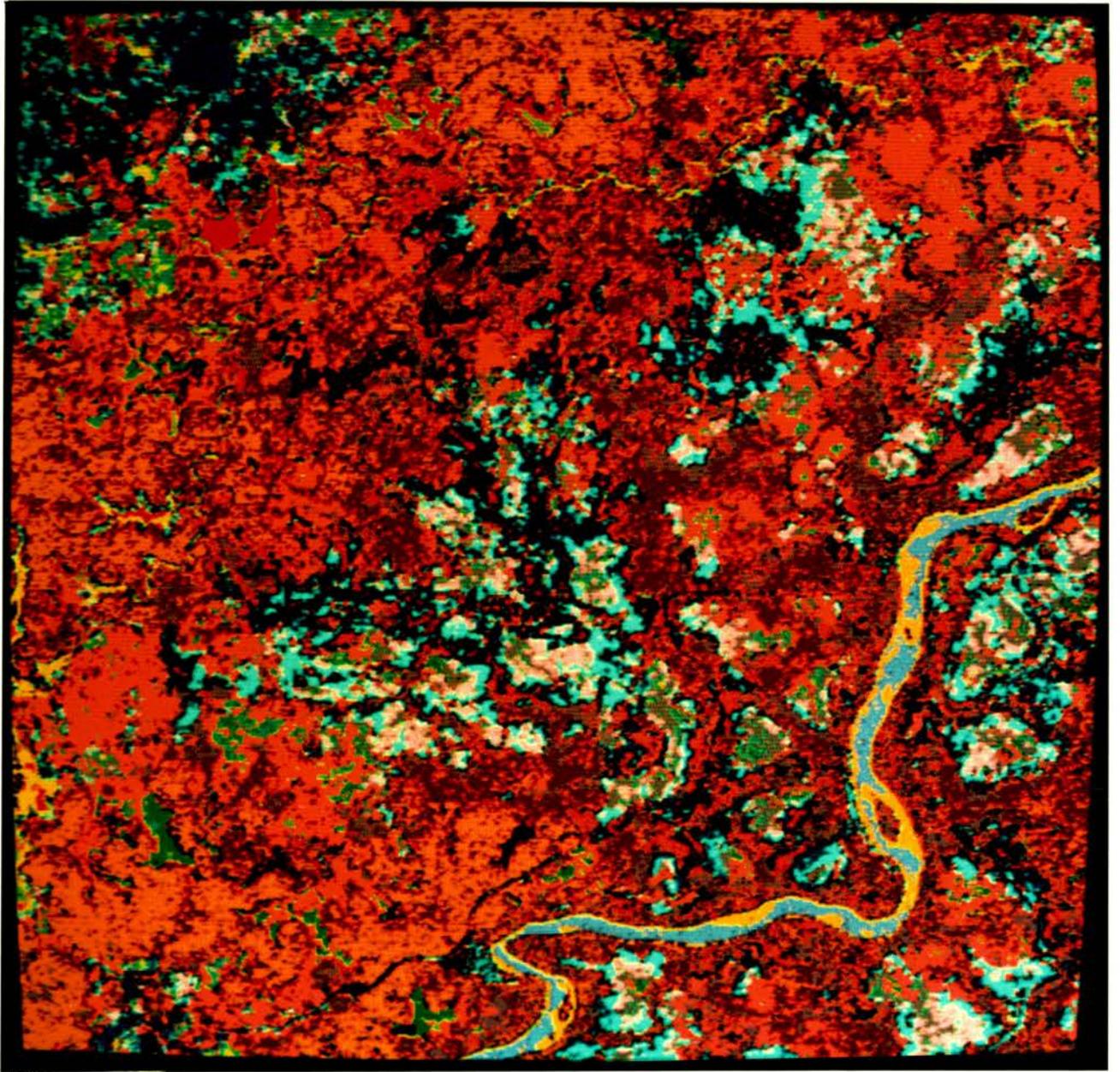


Plate 4.15 Classified image of Lebak study extract 1986, using maximum likelihood classification.



spp.) 1, 10) secondary forest dominant Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), Kelat (*Eugenia* spp.) 2, 11) bush dominant Puspa (*Schima wallichii*), 12) road and open land 13) reforestation *Pinus merkusii* 4, 14) reforestation (unvegetated) 2, 15) *Acacia mangium* nurseries, 16) Alang-alang (*Imperata cylindrica*) 4.

Four training classes exist for *Pinus merkusii*, first is the area prepared for *Pinus merkusii* reforestation but still unvegetated, second is the reforestation area with young plants dominated by grasses, third is the reforestation area dominated by young plants, fourth is the reforestation area dominated by Alang-alang (*Imperata cylindrica*). The percentage of reforestation for pinus in this area is 15.73 %. The classification result of Alang-alang (*Imperata cylindrica*) is 12.44 %, from four training classes for this type, a) Alang-alang mixed with grasses and vegetation after cutting, b) Alang-alang mixed with shrubs, c) Alang-alang pure, d) Alang-alang and grasses. The percentage for the road class is 37.14%, as it is mixed with open land. The largest class is of open land and road, which have similar reflectance characteristics, with both reflectances being dominated by bare soil. The result of image classification is shown on Plate 4.16, and classification statistics of Subanjeruji using maximum likelihood shown on Table 4.11 and 4.12.

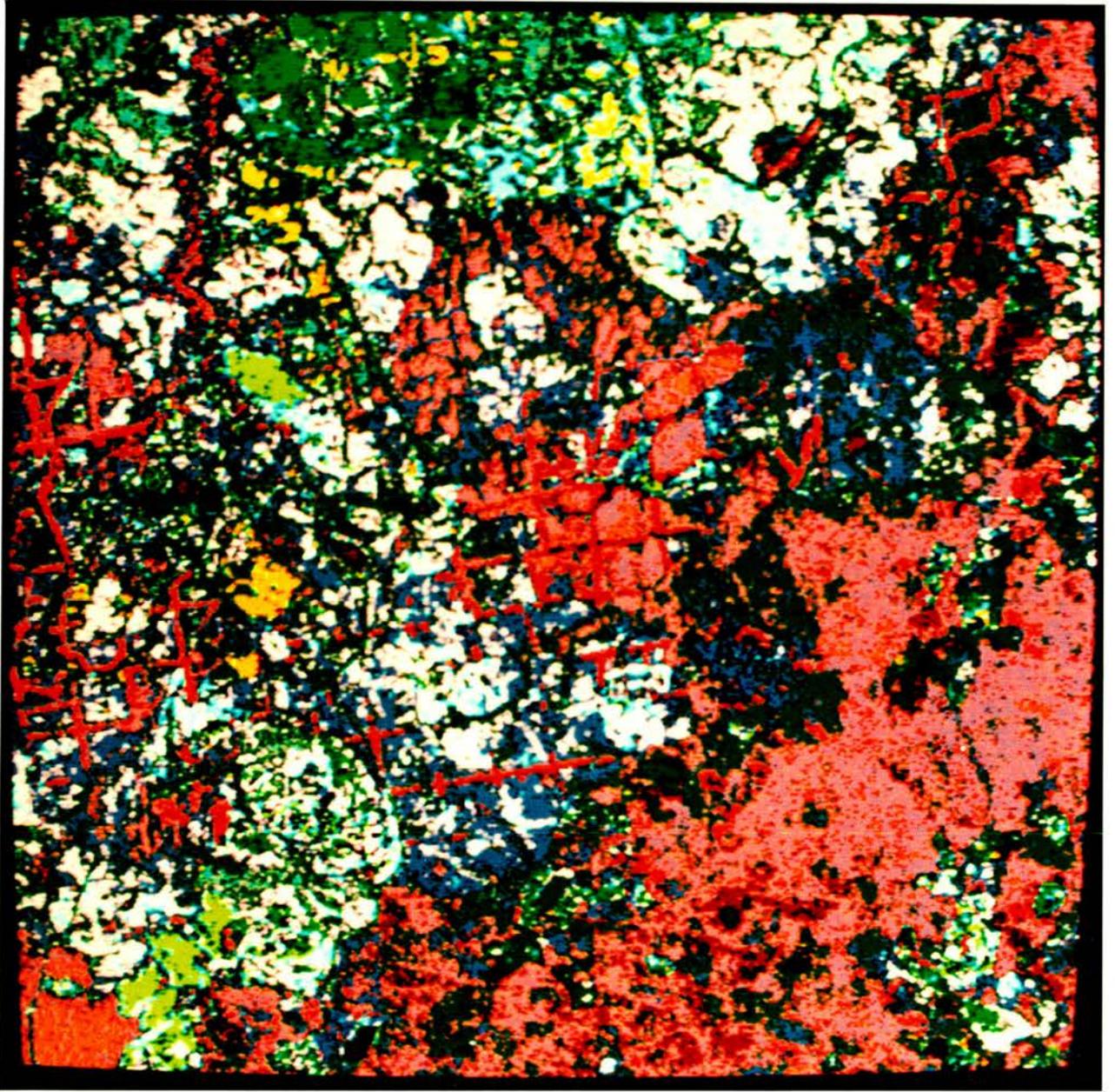


Plate 4.16 Classified image of Subanjeruji study extract 1986, using maximum likelihood classification.



No	Training Class	Colour	Total Pixels	% Class
1.	Acacia	Red	8374	3.53
2.	Reforestation Pinus 1	Green	5607	2.36
3.	Reforestation Pinus 2	Blue	1568	0.66
4.	Reforestation Pinus 3	Yellow	1285	0.54
5.	Alang-alang 1	Magenta	20736	8.73
6.	Alang-alang 2	Cyan	6932	2.92
7.	Alang-alang 3	Grey	2493	1.05
8.	Reforestation *) 1	Gold	939	0.4
9.	Secondary forest **)	Orange	2951	1.24
10.	Secondary forest ***)	Purple	20922	8.81
11.	Bush	Dark Red	5069	2.13
12.	Road and open land	Dark Green	88219	37.14
13.	Reforestation Pinus 4	Dark Blue	28914	12.17
14.	Reforestation *) 2	192/255/0	3283	1.38
15.	Acacia nurseries	255/0/192	14534	6.12
16.	Alang-alang 4	0/255/192	1746	0.74
Unclassified			23928	10.07

Table 4.11 Percentage image classification Subanjeruji area using Maximum Likelihood Classification.

- *) = Reforestation unvegetated.
 **) = Secondary forest dominant Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), Kelat (*Eugenia* spp.).
 ***) = Secondary forest dominant Puspa (*Schima wallichii*).

No.	Training Class	Band XS 1		Band XS 2		Band XS 3	
		M	SD	M	SD	M	SD
1.	Acacia	72.6	2.8	35.9	0.6	20.5	0.5
2.	Reforestation Pinus 1	67.9	4.1	46.8	1.9	33.0	0.6
3.	Reforestation Pinus 2	71.8	7.4	63.7	4.7	51.3	1.2
4.	Reforestation Pinus 3	68.3	1.7	53.2	1.4	42.2	1.2
5.	Alang-alang 1	73.8	2.7	41.1	1.0	26.2	0.5
6.	Alang-alang 2	70.5	2.1	40.5	1.0	26.0	0.6
7.	Alang-alang 3	82.7	3.3	44.7	1.8	29.1	0.6
8.	Reforestation *) 1	94.7	3.9	46.0	1.5	26.7	0.6
9.	Secondary forest **)	76.6	3.1	34.4	0.6	18.1	0.5
10.	Secondary forest ***)	80.4	3.3	35.7	0.7	19.3	0.6
11.	Bush	94.0	2.4	36.8	0.7	20.2	0.5
12.	Road and open land	79.6	9.5	50.6	3.5	38.2	2.0
13.	Reforestation Pinus 4	76.3	2.5	38.5	0.9	23.4	0.5
14.	Reforestation *) 2	54.8	6.0	41.5	1.6	27.8	0.7
15.	Acacia nurseries	84.4	2.4	35.7	0.7	19.7	0.5
16.	Alang-alang 4	84.7	3.0	44.8	1.7	28.7	0.7

Table 4. 12 Classification results of Subanjeruji area using Maximum Likelihood Classifier.

*) = Reforestation unvegetated.

) = Secondary forest dominant Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), Kelat (*Eugenia* spp.).*) = Secondary forest dominant Puspa (*Schima wallichii*).

A maximum likelihood classification has been written for the most recent version (version 4) of the R-CHIPS system (January 1992). The training areas selected for the box classification may also be used for the purpose of running a maximum likelihood classification, utilizing the same eight classes. The result of the maximum likelihood classification (Plate 4.17) can thus be compared with the box classification, it is not possible to do this directly with the GEMS 16 classes version. Only 9.49 % of this area was unclassified, compared with the box classification which is 15.52 % . The largest difference has occurred in the Alang-alang, and Acacia nurseries which is smaller than the box classification result. The area of Alang-alang was reduced mainly to reforestation (grasses). Alteration also occurred in the Acacia nurseries areas which changed to secondary forest Puspa (*Schima wallichii*). The result of six other classes showed greater values than the box classification. The largest changes occur in the reforestation (grasses), bush Puspa (*Schima wallichii*), and reforestation Pinus (Table 4.13). However, difficulties in comparison of both classification system results occurred mainly as a result of hard copy processing.

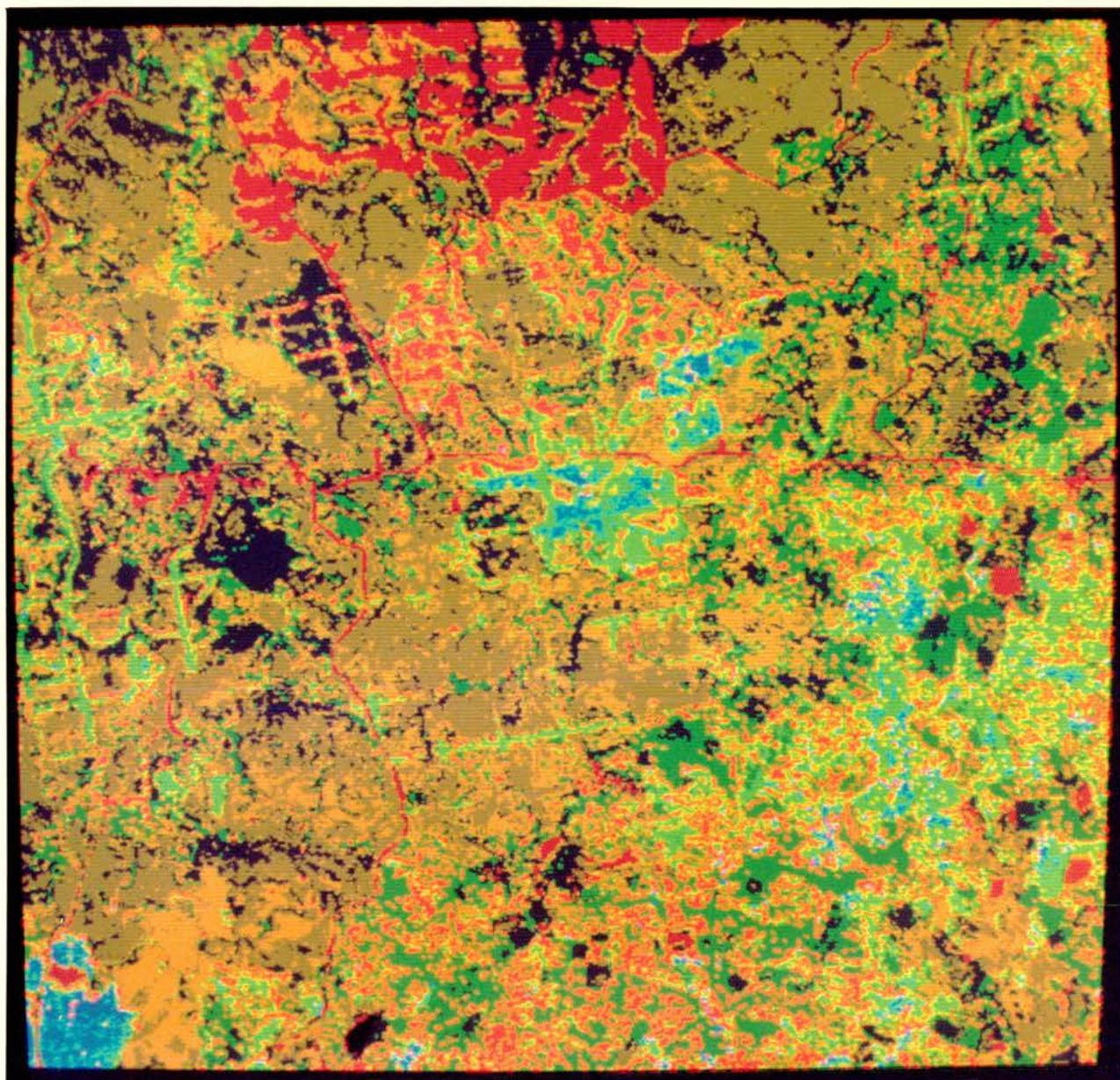


Plate 4.17 Classified image of Subanjeruji study extract 1986, using maximum likelihood classification (R-CHIPS version 4).



Class	Colour	Number of pixels	% of image
1	Black	36897	14.08
2	Red	22514	8.59
3	Dark Red	11122	4.24
4	Green	27400	10.45
5	Dark Green	50990	19.45
6	Brown	31535	12.03
7	Dark Brown	53858	20.55
8	Blue	2962	1.13
Unclassified		24866	9.49

Table 4.13 Percentage image classification results of Subanjeruji using Maximum Likelihood Classification R-CHIPS system 4.

Black	= Reforestation Pinus (<i>Pinus merkusii</i>).
Red	= <i>Acacia mangium</i> nurseries and sedges.
Dark Red	= Reforestation (unvegetated).
Green	= Secondary forest Puspa (<i>Schima wallichii</i>).
Dark Green	= Bush Puspa (<i>Schima wallichii</i>).
Brown	= Reforestation (grasses).
Dark Brown	= Alang-alang (<i>Imperata cylindrica</i>).
White	= Secondary forest Meranti (<i>Shorea</i> spp.), Kempas (<i>Koompassia malaccensis</i>), Jelutung (<i>Dyera costulata</i>), Terap (<i>Artocarpus</i> spp.), Kelat (<i>Eugenia</i> spp.).

4.6 Accuracy Assessment

One of the important criteria used in selecting a remote sensing system is the accuracy of the information produced. Every method of image classification using manual interpretations produces problems, usually caused by excessive generalization, errors in registration, misidentification of parcels, and variations in detail of an interpretation. The errors of image classification using machine analysis come from sensor resolution, complex interactions between the spatial structures of the landscape, preprocessing algorithms, and classification procedures. Many methods can be used to test the accuracy of digital classification, such as, measurement of map accuracy, the error matrix, etc.

In this study, some assessment accuracy of the box and maximum likelihood classification results was obtained by comparing some test sites of the image classification result with available map information. In particular it was suggested that accuracy analysis of image classification be obtained in quantitative terms but there are many additional problems in quantitative analyses of accuracy. For example : the map information source was produced at the relatively small scale of 1 : 250,000, by manual interpretation of SPOT panchromatic imagery at a scale of 1 : 100,000 ($k/j = 278/358$ on 21st July 1986) and field work.

In the Baturaja City study extract, one land cover type cannot be classified. It is the fruit orchards (dominants Durian (*Durio zibethinus*) and Duku (*Lansium domesticum*)). The problem of this cover type is that it is similar to bush dominated by Puspa (*Schima wallichii*) and/or bush and shrubs (dominant Puspa (*Schima wallichii*)). This type can be found along the Air Ogan river, usually mixed with settlement, and tree crops. Secondary forest (dominant by Puspa (*Schima wallichii*)) shown on the map appeared as bush dominated Puspa on the classified image. Whilst both the land covers show *Schima wallichii* domination, the difference in maturity of the two systems has not been recognized in classification procedures for the SPOT imagery. The other problem comes from the result of the classification of rubber small holdings found south west of Baturaja City where they are mixed with secondary forest, bush and shrubs dominated by Puspa (*Schima wallichii*). As discussed above, one error of manual interpretation will arise from generalization, at a small scale. Machine interpretation of the SPOT image, showed oil palm commercial estates in three sub-classes identified as a) open land, b) grasses or c) young oil palm, but from the map information they appear only as commercial oil palm estates.

The result of the image classification in Lebak study area is similar to that in Baturaja City study extract.

The boundaries of swamp bush and shrubs (dominant: Lombokan (*Ludwigia*)) and secondary forest (dominant: Puspa (*Schima wallichii*)) on the classified image are similar to those on the map. But the image classification result for the rainfed rice field areas is greater than that shown on the map, as it includes commercial rubber estates with grass cover or grass areas. This problem occurs because when the SPOT - 1 imaged this area it was the dry season, not the planting season, so ground conditions in the rainfed rice area were the same as those in the grass area. In the Lebak study extract, young rubber plants mixed with either unvegetated ground or grasses can be identified as a separate grouping in the image classification. It is difficult to separate bush from bush and shrubs and secondary forest all of which are dominated by Puspa (*Schima wallichii*). There is also confusion in the image between those Puspa dominated classes and rainfed rice fields.

The Subanjeruji study extract area also has problems of confused classification the other study extracts. For example, areas which should be reforested with *Pinus merkusii* are identified in the image classification as Alang-alang (*Imperata cylindrica*), which dominates the area. In identification of *Acacia mangium* nurseries and sedge there is little confusion with bush, or bush and shrubs dominated by Puspa (*Schima wallichii*). A part of

these types include the *Acacia mangium* and sedge area, but some of the *Acacia* sedge was identified as secondary forest (dominant *Puspa (Schima wallichii)*). As shown in on Figure 4.4 the shaded areas are classified on the map as reforestation. Classification of the image, however, shared the area as a class dominated by *Alang-alang* and grasses. In the south west corner of the map and image, secondary forest is found with co-dominants *Meranti (Shorea spp.)*, *Kempas (Koompassia malaccensis)*, *Jelutung (Dyera costulata)* intermixed with secondary forest dominated by *Puspa (Schima wallichii)* according to the box classification. Map information classifies this as secondary forest only, whilst the maximum likelihood classifier on R-CHIPS indicates secondary forest co-dominated by *Meranti*, *Kempas* and *Jelutung*.

The maximum likelihood classification method is usually the more accurate classifier, because by this method 16 sample classes can be chosen giving more detail than the box classification. In comparing box and maximum likelihood classification in the three study extracts, the result is not very different. Thus the nature of the image processing software used (i.e. GEMS compared with R-CHIPS) can influence classification results. Other problems have been found using the R-CHIPS box classification. For example, in the Baturaja City study extract *Alang-alang (Imperata cylindrica)* was unclassified, because of confusion with grasses. In the

Scale 1 : 85,000

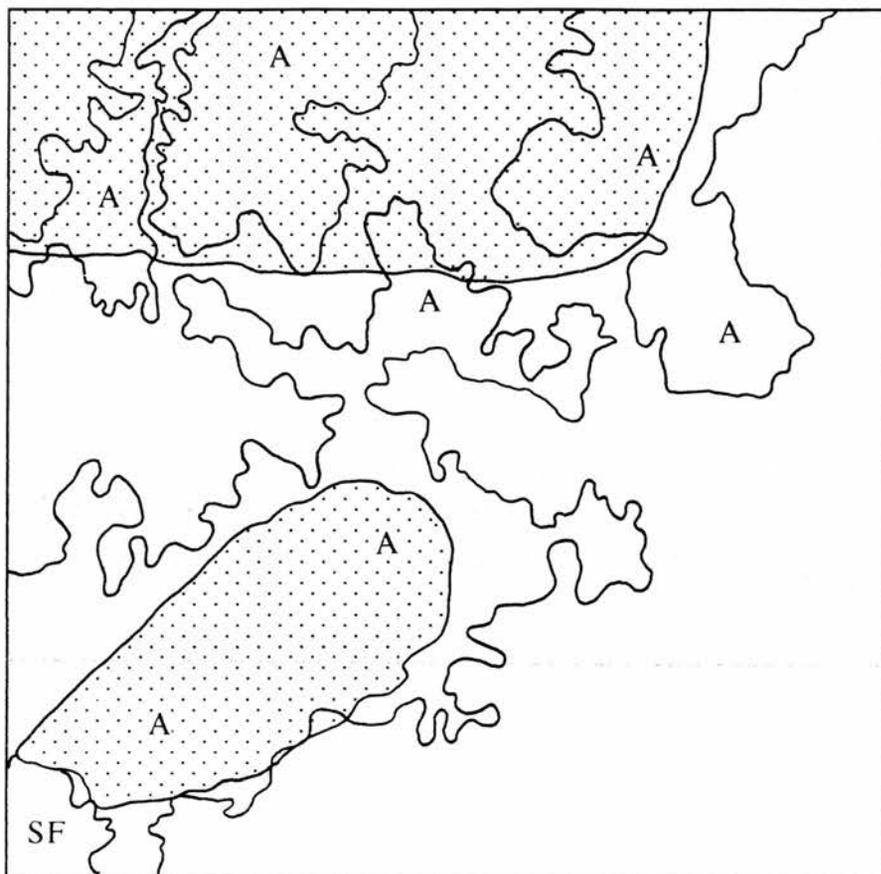


Figure 4.4 Sketch Map of Subanjeruji Study Extract.

Map Symbols :



: Reforestation Areas.

A : Alang-alang and grasses.

SF : Secondary Forest Meranti, Kempas, Jelutung, Terap, and Kelat.

Lebak study extract the same problem occurred with rainfed rice being unclassified because it is mixed with settlement and open land. The problem in the Subanjeruji study extract was that bush and secondary forest (dominant Puspa (*Schima wallichii*)) cannot be identified because it has already been classified in *Acacia mangium* nurseries.

The most recent version (version 4) of R-CHIPS with the 8 class maximum likelihood program, was installed in January 1992 which precluded a full comparison of the classification. To compare the accuracy between box classification and maximum likelihood classification it is necessary to use the same training areas for both classification systems. However, only the Subanjeruji study area has been used in the research as a sample comparison, as it was described in section 4.5.3.3.

CHAPTER 5

CONCLUSION

Remote sensing has proved to be a useful technique for land cover / vegetation mapping for inventory purposes where a quantitative and or qualitative approach is needed. However, digital image processing techniques are necessary for an optimum exploitation of SPOT spectral information.

The problems and potential of using SPOT imagery to interpret vegetation / land cover will be discussed in the following section, and suggestions made for further work and refinements.

5.1 Potential and Problem of Vegetation Mapping Using SPOT - 1 Data.

The purpose of this study is to produce a vegetation map of Baturaja area using SPOT 1 data of $k/j = 278/358$, acquired on 21st July 1986. Supervised box and maximum likelihood classifications were used to produced digital image classification maps.

To reduce misclassification risk and to work at a full resolution, it is necessary to define study extracts within Baturaja study area. Three different study

extracts have been chosen, namely Baturaja City, Lebak, and Subanjeruji.

SPOT data was selected in this study, because of its high spatial and spectral resolution. Spectral resolution information of SPOT data proved to be very useful for deriving detailed land cover and / or vegetation information. SPOT in this study is at level 1B, which includes radiometric and geometric correction. Even though the SPOT - 1 image has high spatial and spectral resolution, this study found some problems, especially for vegetation mapping in tropical countries, such as Indonesia, because of complexes of vegetation species. It is impossible to identify every single vegetation species by remote sensing. To solve this problem it becomes necessary to generalize, for example choose the dominant of the vegetation species in that area.

Some vegetation groups have similar characteristics, such as, vegetation height, canopies, and leaves. This will bias the relationship between energy absorbed, reflected, and transmitted, and the result is the image classification will be confused, for example between bush dominant Puspa (*Schima wallichii*) and *Acacia mangium*, fruits orchard are unidentified, because of similarity with secondary forest (dominant Puspa (*Schima wallichii*)). To solve this problem it is

necessary to run field checks and have a good quality map information source.

Using box and maximum likelihood classification some problems will arise. Box classification, is simpler than maximum likelihood classification. Only 8 training classes can be used to identify an image, but box classification has advantages in that this classification technique was much faster, and more efficient than the maximum likelihood classification. In maximum likelihood more detailed training classes can be chosen. The advantages of this method are more detail, and the error is reduced. Even though only 8 classes have been chosen, the result is much better than the box classification. The maximum likelihood classifier is still the best image classification technique in remote sensing, but it is more time consuming, and more expensive.

5.2 Recommendation for further work.

The composition of land cover / vegetation is constantly changing, either by natural or man made means. Satellite data can provide a less time - consuming and cheaper method of land cover / vegetation inventory and map - production compared with traditional methods.

Radiometric correction, image smoothing, geometric correction, principal component analysis etc, are the

most common preprocessing operations to improve the image quality before classification is carried out. A high quality of map information, photographs, and other ground data will be useful to locate the training area data.

In vegetation mapping, at least two seasonal resolutions of an image are necessary, because of seasonal influences on the life of vegetation. For example, in land use and vegetation mapping studies, the rain season is the planting season in rainfed rice fields and the reflectance values will be different from the dry season.

For vegetation mapping in a tropical country with complex vegetation species groupings, to identify the groupings on an image will be difficult using box classification. Supervised maximum likelihood classification is recommended to identify land cover or vegetation, even if it will take a longer time in computer processing.

Cloud and haze free imagery is necessary to obtain the best results from classification. High spatial resolution is recommended to classify land cover or vegetation. Here SPOT multispectral imagery has a spatial resolution of 20 x 20 m, and it is therefore better than Landsat MSS or Landsat TM with their lower spatial resolutions.

It was suggested by Collin's and MacSiurtain (1991) that the maximum use of the 10 x 10 m resolution of SPOT imagery could be obtained by resampling two of the 20 m resolution XS bands to the 10 m panchromatic band. The colour composites of P (panchromatic), XS 3 (near infrared), and XS 1 (green) bands, assigned to the red, green and blue guns, has been proved to be a useful combination. Using this high resolution composite image and Interactive Visual Interpretation, an efficient identification of mixed broadleaves and coniferous forest stands have been achieved in Ireland, and high level accuracy have been recorded. The technique may be worth investigating in a tropical forest environment for detailed vegetation studies, but the resolution is probably too fine for more generalized investigations.

To date, forest in Sumatra is still being depleted. This deforestation is often catastrophic for the environment with land degradation, soil erosion, loss of rare vegetation species, etc. Therefore, the need of better forest management is increasingly important. However, conventional mapping, in terms of detailed field study and using the latest panchromatic aerial photographs acquired in 1974 at a scale of 1 : 100,000 (Rais, 1986), will not keep pace with rapid deforestation. As was stated by Gastellu-Etchegorry (1988b) SPOT is undoubtedly a very good alternative source to aerial photographs at a scale of 1 : 100,000 and 1 : 50,000,

particularly for vegetation mapping. The advantages of Landsat data comes with the larger pixel size (30 x 30 m TM, 79 x 79 m MSS) and larger scene size which enables a more rapid coverage of a large area, such as Sumatra, to be achieved with a substantial reduction in computer processing. The larger number of bands on Landsat TM might also produce a better correspondence between spectral classes and land cover classes.

As computerized image processing systems are now readily available, SPOT data is at the moment still the best remote sensing data, having better spatial resolution than other satellite data, it also provides stereo vision and a high frequency of repeat data acquisition. These advantages of SPOT will support the use of remote sensing data, particularly for planning purposes in Indonesia.

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spp.) 1, 10) secondary forest dominant Meranti (*Shorea* spp.), Kempas (*Koompassia malaccensis*), Jelutung (*Dyera costulata*), Terap (*Artocarpus* spp.), Kelat (*Eugenia* spp.) 2, 11) bush dominant Puspa (*Schima wallichii*), 12) road and open land 13) reforestation *Pinus merkusii* 4, 14) reforestation (unvegetated) 2, 15) *Acacia mangium* nurseries, 16) Alang-alang (*Imperata cylindrica*) 4.

Four training classes exist for *Pinus merkusii*, first is the area prepared for *Pinus merkusii* reforestation but still unvegetated, second is the reforestation area with young plants dominated by grasses, third is the reforestation area dominated by young plants, fourth is the reforestation area dominated by Alang-alang (*Imperata cylindrica*). The percentage of reforestation for pinus in this area is 15.73 %. The classification result of Alang-alang (*Imperata cylindrica*) is 12.44 %, from four training classes for this type, a) Alang-alang mixed with grasses and vegetation after cutting, b) Alang-alang mixed with shrubs, c) Alang-alang pure, d) Alang-alang and grasses. The percentage for the road class is 37.14%, as it is mixed with open land. The largest class is of open land and road, which have similar reflectance characteristics, with both reflectances being dominated by bare soil. The result of image classification is shown on Plate 4.16, and classification statistics of Subanjeruji using maximum likelihood shown on Table 4.11 and 4.12.