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LAND USE CLASSIFICATION OF THE BANGKOK, THAILAND  
AREA BY DIGITAL ANALYSIS OF LANDSAT MULTISPECTRAL DATA

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## ABSTRACT

Computer-implemented pattern recognition techniques were used to analyze Landsat-1 multispectral scanner data and produce a land use map of 3,900 km<sup>2</sup> in the Bangkok, Thailand area. Using reformatted digital data obtained by satellite scanner on 6 January 1973, the analyst first selected five training sites covering 17% of the study area and classified each site into 14 spectrally separable cluster classes. Spectral statistics of the 70 cluster classes were examined by the analyst and used as a basis for combining clusters with similar spectral characteristics and reducing the number of spectral classes to 37. The analyst combined her general knowledge of the area and the limited ground observation data available to her and related general land use classes with clusters having different spectral characteristics. A merging of spectral statistics of the 37 classes provided the basis for the final classification of 14 land use classes, consisting of four classes of water, four of vegetation, two urban,



two denuded, and two soil/vegetation complex classes. An examination of the spectral statistics of each of the land use classes in the final classification suggests that a high level of accuracy was obtained in the recognition of the vegetation and water classes. A greater amount of spectral variance was exhibited by the denuded, complex, and urban classes. A more satisfactory set of training and testing samples could have been selected had more complete ground observation data been available. From the results of this study it may be concluded that digital analysis of Landsat multispectral scanner data may be used successfully to produce general land use maps in Thailand at scales up to 1:25,000.

## CHAPTER I - INTRODUCTION

### Statement of the Problem

Thailand is a tropical, primarily agricultural country with a population of approximately 43 million. More than four million Thais live in the rapidly expanding capital city of Bangkok. Four-fifths of the population inhabit the rural areas. An estimated twenty-five percent of the total land area of 514,000 sq km is suitable for cultivation. Another 30% is covered by forests. The predominantly agricultural economy is based on rice, the staple food of the people. Several serious problems related to the development and management of agricultural resources face the country: escalating production costs, insufficient yields of rice and other crops, limited irrigation capabilities, inadequate credit facilities, and limited development of domestic and international markets.

The Thai Government, aware of these difficulties, is defining and implementing policies to improve the situation. Action programs include land development, economic moves to improve domestic prices, expanded agricultural research, credit, foreign exchange and public investment (Mosher, 1965). Recent years have brought major emphasis to land

use planning as an important step in effective agricultural development. The responsibility for land use classification and planning in Thailand was assigned to a newly created Department of Land Development in the Ministry of Agriculture and Cooperatives.

During recent years the Department of Land Development developed a land use classification for Thailand (Omakupt, 1973). The major land use categories for Thailand include urban and built-up, agricultural land, forests, grassland, marshland, and water (Table 1). Recently, the Thai land use classification has been revised and published for use by those governmental agencies concerned with land use planning, land tenure, and land consolidation.

Since 1971 remote sensing techniques have been considered in Thailand to be a useful tool for the identification, mapping and management of natural resources. Soon after the launch of Landsat-1 in July 1972 Thai officials recognized that Landsat imagery would be advantageous for collecting large quantities of data over extensive geographic areas in a very short time. To cover by aerial photography the 34,000 square kilometers of a single Landsat frame would require literally hundreds of conventional aerial photographs. Whereas conventional photography records reflectance in the 0.4 to 0.7 $\mu$ m and infrared photography in the 0.4 to 0.9 $\mu$ m portion of the electromagnetic spectrum, the Landsat scanner records reflectance measurements in the

Table 1. Land use classification system for Thailand  
(Omakupt, 1973).

- I. Urban Area (U)
  - 1. Residential and commercial
  - 2. Home garden
  - 3. Institutional
  - 4. Transportation
  - 5. Industrial
    - 5.1 Mine
    - 5.2 Factories
- II. Agricultural Land (A)
  - 1. Horticultural crop
    - 1.1 Intensive cultivation, truck cropping
    - 1.2 Vineyard
  - 2. Perennial
    - 2.1 Orchard
    - 2.2 Rubber
    - 2.3 Coconut
    - 2.4 Banana
    - 2.5 Kapok
    - 2.6 Sugar palm
    - 2.7 Oil palm
  - 3. Field crop
    - 3.1 Corn
    - 3.2 Sugar cane
    - 3.3 Manioc
    - 3.4 Cotton
    - 3.5 Tobacco
    - 3.6 Pineapple
    - 3.7 Bean, peanut
    - 3.8 Fiber crop
    - 3.9 Caster bean
    - 3.10 Sorghum
    - 3.11 Sesame
    - 3.12 Chili
  - 4. Paddy field
    - 4.1 Broadcast
    - 4.2 Transplanted
- III. Grassland (G)
  - 1. Improved grassland
  - 2. Unimproved grassland
  - 3. Idle land
- IV. Forest (F)
  - 1. Lowland and piedmont forest
    - 1.1 Dense forest
    - 1.2 Cut forest
  - 2. Hill and mountain forest
    - 2.1 Dense forest
    - 2.2 Cut forest
  - 3. Mangrove
    - 3.1 Dense forest
    - 3.2 Cut forest
- V. Marsh and Swamp (M)
- VI. Water (W)
  - 1. Salt pan
  - 2. Shrimp pond
  - 3. Fish pond
  - 4. Water body

0.5 to 1.1 $\mu$ m range. The synoptic view and other advantages provided by Landsat images were recognized by Thai scientists. Although the spatial resolution of the scanners of Landsat-1 and -2 is only 0.45 ha, the relatively low cost of data, the spectral resolution, the repetitive coverage, relatively low distortion, and reliability of Landsat data offer great advantages over alternative systems of data acquisition.

Landsat data are available from the EROS Data Center, Sioux Falls, South Dakota in a variety of formats, including computer compatible tapes (CCT's), black and white negatives and prints at various scales, and color composite prints at various scales. Images are routinely available in the following scales: 1:250,000; 1:500,000; 1:1,000,000; and 1:3,369,000. Since Landsat data are available on magnetic tapes and as images, both visual interpretation methods and computer-implemented pattern recognition techniques may be used in analyzing and interpreting the data.

Since the early 1970's many colleges and universities have offered new courses in the theory and applications of remote sensing technology. Applications areas commonly include agriculture, forestry, soils, geology, hydrology, urban development, land use, and civil engineering. With a thorough understanding of geomorphology, an appreciation of the variations in the landscape, or a knowledge of the natural forces of erosion and weathering, a scientist can

use remote sensing technology effectively to identify and map vegetative cover, soil characteristics and variations in water quality and quantity. Advances in the digital analysis of Landsat scanner data have brought interesting new possibilities for mapping soils. Several investigators have used Landsat data as a tool for surveying soils (Westin and Frazee, 1976; Kirschner et al., 1977; and Kristof et al., 1977).

Rapid growth in population and industrialization during recent decades has resulted in new emphasis on urban planning. Changes in urban development can be recorded on aerial photography or imagery, demonstrated or monitored by machine processing of Landsat data, and finally classified as land use patterns.

Competition for land is seriously depleting forest resources in many areas of the world. Destruction of forests in Thailand is occurring at an alarming rate. Urban development and highway construction remove large areas from wood production each year. Shifting cultivation is also a serious threat to forest resources in many areas of the world. New remote sensing techniques offer an opportunity to map and monitor such areas and to define quantitatively for the first time ever the kind and rate of change which is occurring.

Of perennial concern to all urban centers such as Bangkok, undergoing rapid expansion, is water supply. It is of

great importance to have an adequate supply of quality water. As the competition for available water becomes more critical, the need for inventorying and monitoring water resources becomes more important. Remote sensing technology provides a new approach to the study of water quality and quantity.

### Objectives

The objectives of this investigation were as follows:

1. To identify and map Bangkok and the surrounding area into broad land use categories by digital analysis of Landsat multispectral scanner data;
2. To examine the spectral characteristics of the landscape features of the Bangkok area and to determine the spectral separability of forests, horticultural crops, agricultural crops, soils, urban features, water classes, and other surface features of interest;
3. To evaluate the land use classification and spectral characteristics produced from digital analysis of Landsat data obtained over the Bangkok area.

## CHAPTER II - REVIEW OF LITERATURE

### Remote Sensing

There are several definitions of remote sensing which provide a general understanding of the nature and origin of data. One of the most generalized concepts states that remote sensing is the science of acquiring information about distant objects from measurements made without coming into contact with them.

Hoffer (1971) defined remote sensing as the discipline involved with the gathering of data about the earth's surface or near surface environment through the use of a variety of sensor systems that are usually borne by aircraft or spacecraft, and the processing of these data into information useful for the understanding and managing of man's environment. Another description defines remote sensing as the acquiring of information about a portion of the earth's surface, utilizing instruments operated from a distant location.

Generally, remote sensing offers opportunities to detect, count or measure something that could not otherwise be detected, counted or measured. In most definitions remote sensing involves the instrument systems,



sensors at a distant location, processing of data to information, a man-machine interaction, and application-management. The development of remote sensing technology includes three basic ingredients:

- data collection
- data storage, processing, analysis, and dissemination
- information utilization.

#### Utilization of Landsat Data

Since the launch of Landsat-1 in July 1972 dramatic advances have been made in remote sensing technology. Scientists of many disciplines and nations have participated in developing the capabilities to analyze and interpret multispectral data acquired by satellite scanner systems (Hoffer, 1975). As in other areas of scientific inquiry, the capability to collect or acquire data by remote sensors far exceeded the capability to analyze and interpret data. This being the case, great emphasis has been directed during the past several years toward the development of computer-implemented pattern recognition techniques for the analysis of large quantities of multispectral data. Many recent advances have also been made in visual interpretation methods, especially with many image enhancement techniques.

These new analysis and interpretation techniques have been used in many applications in agriculture and natural resources. Pownall (1950) was an early user of aerial

photography to classify and map the Madison, Wisconsin area into different land use categories on the basis of tone, texture, pattern, distribution, and associative characteristics.

Vegas (1972) used small-scale photography to classify land use patterns in rural areas and Alexander (1973) classified land use change in urban areas. Allan and Alemayehu (1975) used rural land use parameters as interpreted from 1:20,000 scale aerial photography to estimate the population of a 200 sq km area in Wolamo, Ethiopia. Use of machine-processing techniques for analysis and interpretation of rural areas was attempted by Wilson and Peterson (1973) and Joyce (1974). The same techniques were used by Ellefsen, Swain, and Wray (1973) to classify urban areas.

With the development of computer-implemented pattern recognition techniques, the applicability of remote sensing to land use inventory was significantly increased. Todd and Baumgardner (1973) analyzed multispectral scanner data obtained over Marion County, Indiana at an altitude of 915 kilometers to evaluate the utility of satellite data for urban land use classification. Odenyo and Pettry (1977) used Landsat-1 data for mapping of land use patterns in Virginia. Baumgardner, Todd, and Mausel (1976) used digital analysis of aircraft scanner data obtained at an altitude of 600 m to identify and map different urban land use categories in Marion County, Indiana.

Many soil scientists have used multispectral data to delineate soils by the differences in surface spectral characteristics. Organic matter is one of the important soil variables which affect reflectance. Numerous research results have been reported on the relationships between various soil properties and the reflectance properties of different soils and geologic materials. Baumgardner et al. (1970) studied the correlation between multispectral reflectance and organic matter content of surface soils. Kristof, Baumgardner, and Johannsen (1973) found digital analysis of multispectral data may be effectively used to delineate and map surface soils areas containing different levels of soil organic matter. Anuta et al. (1971) reported the identification and separation of two soils, loamy soil and clayey soil, in the area of El Centro in the Imperial Valley, California. For their analysis they used digitized multispectral photography obtained on one of the Apollo satellite passes over southern California. Kristof and Baumgardner (1975) found that with increasing crop canopy the soil multispectral reflectance changed and spectral separability of soils became increasingly difficult.

Much attention has been given to the identification and mapping of cultivated crops by digital analysis of multispectral data (Bauer, 1975; Bauer et al., 1977; Stockton et al., 1975; and MacDonald et al., 1975). Successful identification of crop species by spectral measurements is

greatly dependent upon stage of growth, condition of the crop, amount of vegetative cover, and spectral contrast between cropped and surrounding fields or features.

The 1971 Corn Blight Watch Experiment (MacDonald et al., 1972) used three independent methods to assess the spread and severity of the Southern Corn Leaf Blight (*Helminthosporium maydis*) over the U.S. Corn Belt. These methods included (1) detailed field observations of selected sample sites periodically throughout the corn growing season, (2) photointerpretation of color infrared photography obtained every two weeks at an altitude of 18,000 meters along each of thirty north-south flightlines 160 km long, and (3) digital analysis of multispectral scanner (13 bands) data obtained at an altitude of 1000 m over thirty test areas in western Indiana.

Perhaps the most ambitious experiment yet undertaken with Landsat MSS data is the Large Area Crop Inventory Experiment (LACIE). The U. S. Department of Agriculture, National Aeronautics and Space Administration and National Oceanic and Atmospheric Administration have cooperated in evaluating the use of Landsat data, meteorological observations, and field measurements to identify and measure areas of wheat in the Great Plains states and to predict yield (MacDonald et al., 1975).

In their use of Landsat data Siegal et al. (1977) found that MSS band ratios 4/5 and 6/7 remained constant

with increasing amounts of vegetation. Edwards et al. (1973) found that a separation of diseased from non-diseased trees could be done with a high degree of accuracy by digital analysis of multispectral data.

Digital analysis of multispectral data has been used to investigate other fields of natural resources, such as basic forest cover mapping (Coggeshall and Hoffer, 1973). Spectral differences between clear and turbid water have been examined. Turbid river water gave a higher reflectance than clear water in the red (0.6-0.7  $\mu\text{m}$ ) and near infrared (0.7-0.9  $\mu\text{m}$ ) portions of the spectrum (Bartolucci et al., 1977). Similar investigations have indicated that the spectral response in Landsat MSS band 5 was linearly related to levels of turbidity caused by suspended solids (Weisblatt et al., 1973).

Huson (1970), with the use of medium scale photography, delineated twelve major land use categories in the Crati Valley, Italy. Morley (1974) reported the use of remote sensing techniques in Canada to measure river velocity, water level, precipitation, ice thickness, ice movement, water quality, air and water temperature, and to map forest fire burns, large reservoirs, and land use patterns. Similar investigations have been conducted by governmental officials in Thailand in an attempt to map land use patterns, vegetative covers, and forest (Angsuwatana et al., 1974).

An important contribution has been made by Anderson et al. (1976) in their examination and documentation of land use and land cover categories which may be identified and mapped by remote sensing techniques.

#### Multispectral Scanner System

Landsat-1 was launched by the National Aeronautics and Space Administration (NASA) of the United States on 23 July 1972. At an altitude of 920 km the satellite is in sun-synchronous polar orbit and encircles the earth every 103 minutes. The orbital and instrumental design is such that the Landsat-1 multispectral scanner (MSS) obtains data over land areas at mid-morning local time. It has the capability of scanning the entire surface of the earth every 18 days. That is, there is repeat scanner coverage of the same scene every 18 days (NASA, 1972).

The Landsat multispectral scanner (MSS) measures reflected energy from the earth's surface in four discrete wavelength bands as follows:

<u>Band</u>	<u>Wavelength</u>
4	0.5-0.6 $\mu\text{m}$
5	0.6-0.7 $\mu\text{m}$
6	0.7-0.8 $\mu\text{m}$
7	0.8-1.1 $\mu\text{m}$

An examination of the electromagnetic spectrum shows bands 4 and 5 to be in the visible and bands 6 and 7 in the near infrared portions of the spectrum (Figure 1). MSS data are

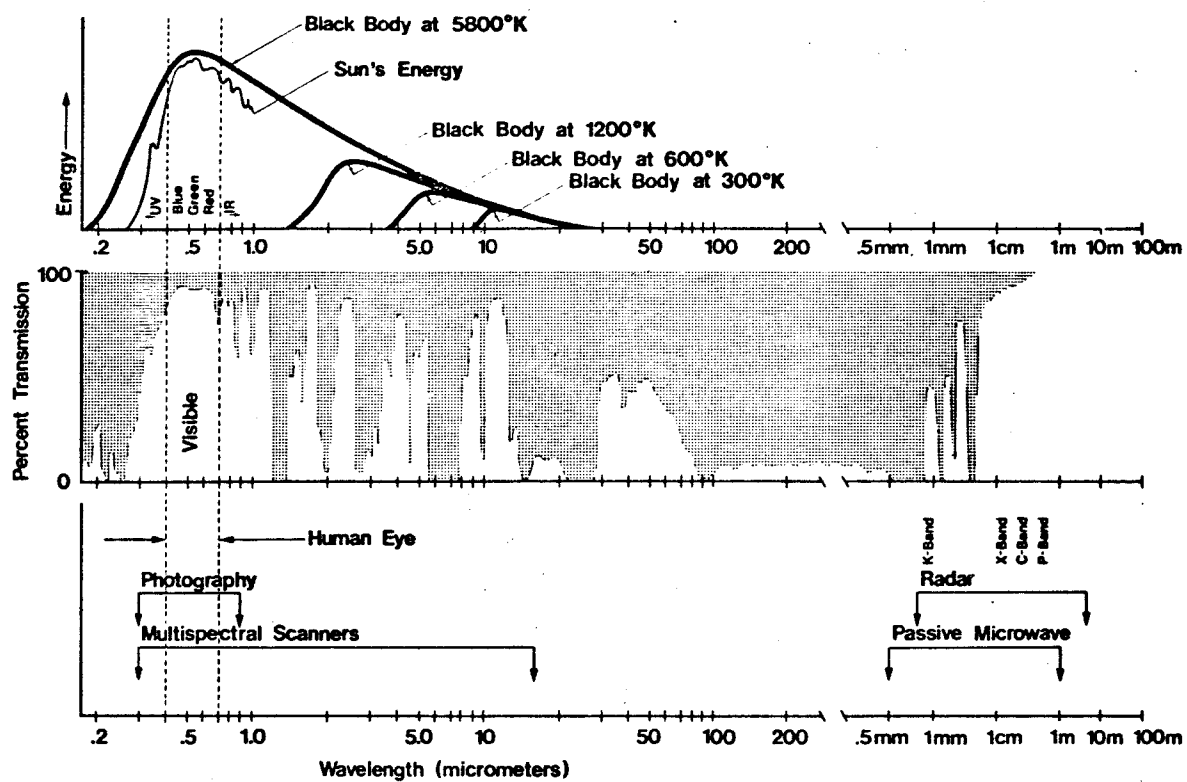


Figure 1. The electromagnetic spectrum.

telemetered to receiving stations where the data are recorded on magnetic tape in digital form.

In each orbit data are scanned along a north-south continuous swath 185 kilometers wide. Images and computer compatible tape products are made available to Landsat data users.

The computer compatible tapes containing Landsat MSS data may be reformatted for analysis on a particular hardware system. Each data point is given a specific address in a coordinate system of lines and columns. This makes it possible to give an accurate location of any data point or group of data points (Hoffer, 1972). After appropriate reformatting, the data may be geometrically corrected and precision registered so that the four bands of data may be combined or overlaid and produce images or maps of cartographic quality.

#### Pattern Recognition Analysis

Pattern recognition techniques as applied at the Laboratory for Applications of Remote Sensing (LARS) is basically the examination of spectral statistics by the computer and the classification or clustering of areas into separate categories having similar spectral characteristics. Remote sensing data may originate in image or numerical format. The analyst can use images, numerical data or both in the analysis. The software for the actual analysis sequence may be divided into four sections: (1) statistical



analysis, (2) feature selection, (3) classification, and (4) results display. In the past the main approaches for classification were based on various supervised techniques which require reference spectral reflectance of known features from training areas on the ground (Fu et al., 1969). Supervised classification requires that a set of training samples of known features or classes be selected in the multispectral data and that the addresses and identification of these training samples be input into the computer. In other words, the computer has been given a spectral definition of each of the features or classes to be identified (Su, 1972). Variations in field measurements and difficulty in exact locations of training samples in the multispectral data may require new ground observations and re-training of the computer (Henderson et al., 1975).

In a second approach to spectral classification no training samples are selected. Instead, spectral data representing the scene under study are classified on the basis of spectral separability only. This method, also called "clustering," uses an algorithm which examines the spectral statistics of the data points in the scene and classifies the scene into subsets or clusters which are spectrally similar (Patrick and Hancock, 1966). Basically, this method makes use of statistics (the overall mean, covariance, and correlation) when the distribution is non-Gaussian. The number of clusters requested is arbitrary

and depends largely on the knowledge of the spectral characteristics of the data set. Usually, a rule-of-thumb is to request twice the number of expected information classes, except in an area of rugged terrain (Lindenlaub, 1973). After cluster classes are requested, the computer then assigns the individual data points to various spectral classes and prints out a cluster map. Each spectral class is identified using map and aerial photography as reference data.

The next approach, a hybrid of the supervised and non-supervised or cluster method, is called "modified clustering." In this method small training areas containing several cover types are designated. Each area is clustered separately and then all spectral cluster classes are combined by means of natural grouping. Then the spectral classes are correlated with the desired informational classes. After the statistical parameters have been determined, the maximum likelihood algorithm is utilized to classify the entire data set (Fleming et al., 1975).

In this study, a modified clustering approach was followed in the analysis of Landsat-1 data (Figure 2).

#### Statistical Analysis

The first step in the analysis is to select training areas for which the computer derives data samples and necessary statistical parameters for the classification algorithm. The data were displayed on the digital image display to

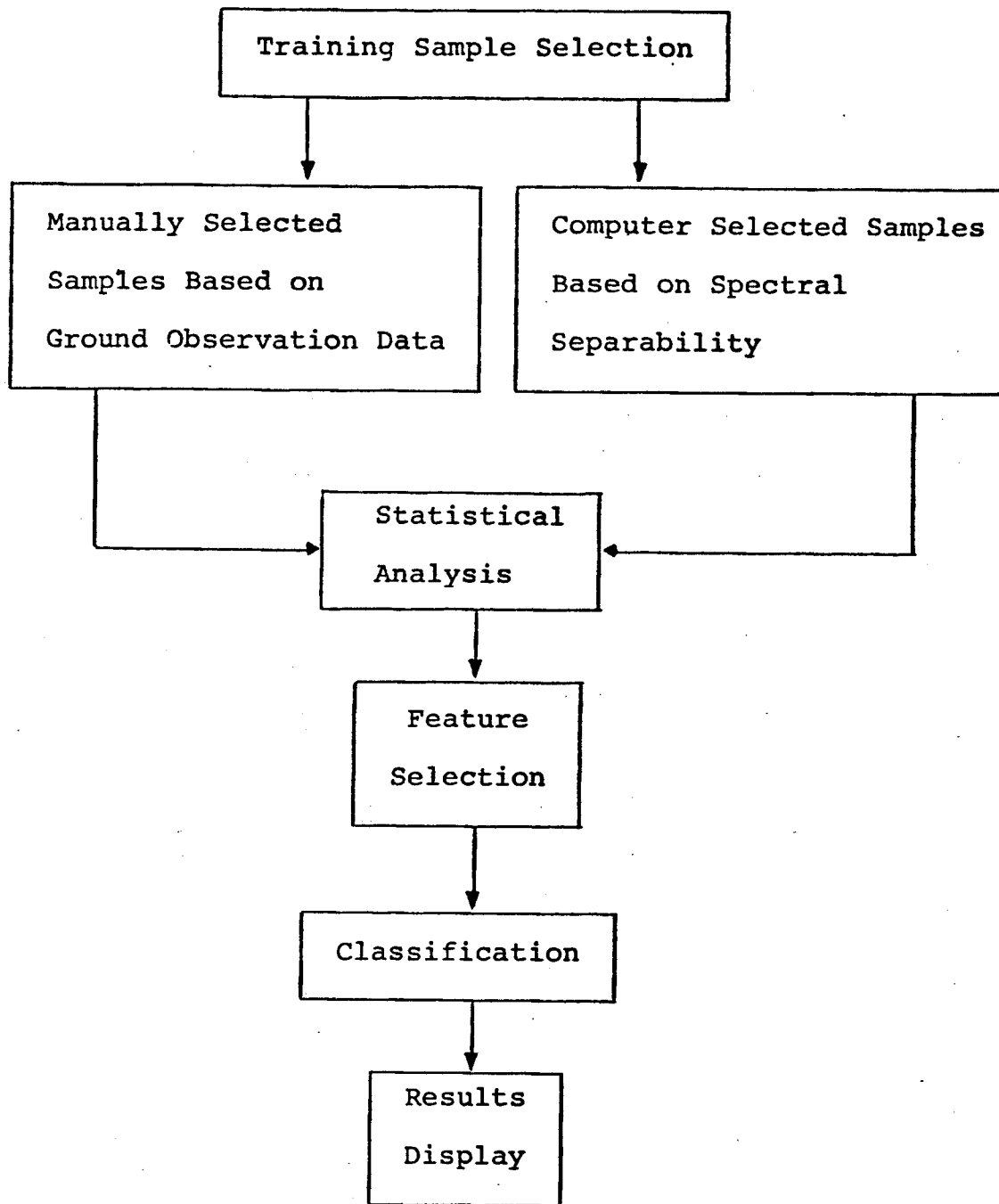


Figure 2. General analysis sequence used in this study.

locate the coordinates for geometric correction. Once the coordinates were known, a request was made for a gray scale printout to use for selection of training areas. In the gray scale printout an alphanumeric character is assigned to represent each gray level so that the relative density of the character corresponds to the relative density of gray level. These characters are printed out producing a gray scale image of data with numerical line and column designations. The analyst then can simply specify line and column coordinates for each training sample chosen. Before proceeding further, the analyst examines the data, the overall scene as well as the ground observations in order to determine which ground cover features will be designated information classes. The objective in selecting training samples is to obtain statistically valid samples which will be representative of each of the desired information classes. Training samples are selected so that each information class is contained in at least one of the areas of training sample selection or, if possible, in more than one of the training areas. The area of training sample selection should be appropriately distributed over the scene being classified. Usually, representative training data for all information classes are selected from four to eight training areas (Cary and Lindenlaub, 1975).

After training areas have been selected, they are submitted to a cluster function. This program automatically

clusters the similarly spectral data points to a number of cluster classes requested by the analyst. Consequently, a statistics processor provides a set of statistical parameters for each cluster class. These parameters are primarily based on an assumed Gaussian distribution including the mean, standard deviation, covariance, divergence (a statistical measure of separability of classes), histograms, correlation matrix, and coincident spectral plots. Histograms of individual fields or classes contribute an idea of the distribution of the data points in various MSS bands to the analyst (Hoffer, 1972). Coincident spectral plots give the amplitude of the spectral responses of those various classes in each individual wavelength. The mean spectral response with plus or minus standard deviations is an indication of statistical quality of data and of the spectral separability of the ground cover classes in the various wavelength bands.

To assure obtaining correct classification, the ratio function may also be requested. The computer calculates the ratio of spectral mean response between the sum of reflectance values of two bands in the visible wavelength range (0.5-0.6  $\mu\text{m}$  and 0.6-0.7  $\mu\text{m}$ ) and of two bands in the near infrared wavelength range (0.7-0.8  $\mu\text{m}$  and 0.8-1.1  $\mu\text{m}$ ) for each class. Then the ratio, magnitude (total relative reflectance), and spectral mean response of each class are tabulated in order by ranking from the highest response to the lowest one. Classification by using spectral mean

values and ratio is based on the typical reflectance properties of three basic cover types: bare soil, green vegetation, and water (Figure 3). The analyst can request a punch deck, the other form of statistical output containing a statistical definition of the ground cover classes in the training deck. This statistics deck will be used for further analysis.

### Feature Selection

The feature selection may require a considerable effort when a large number of wavelength bands are available. In research with aircraft scanners having 12 to 24 bands, it has been found that the best combination of four or five MSS bands will give classification accuracies only slightly less than the use of all bands. For Landsat MSS imagery which contains only four bands, the analyst generally uses all four bands. The feature selection program calculates the separability between all possible pairwise combinations of all classes contained in the punch deck for all four bands. The whole idea of feature selection is to assist the analyst to select the best combination of spectral bands.

### Classification

This phase of the analysis sequence involves the classification of unknown data points. A "perpoint" classifier is most commonly used. This classifies data points

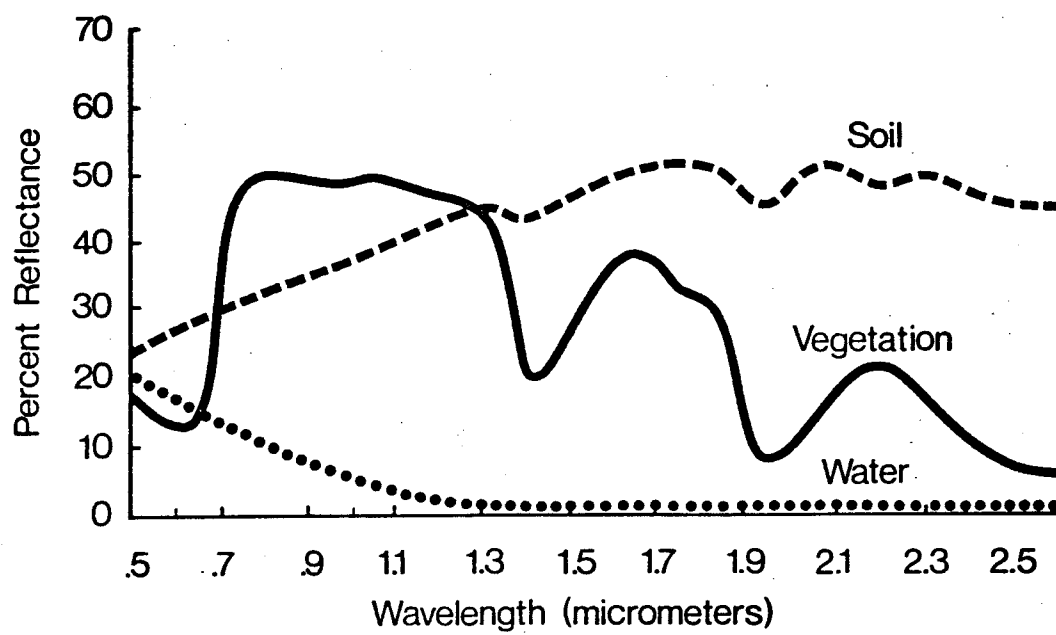


Figure 3. Typical reflectance curves for soil, green vegetation and water.

individually and requires the statistics deck, the selected combination of bands, and the coordinates of the areas which the analyst wishes to classify. Based on the maximum likelihood algorithm, the unknown data points are assigned to one of the statistically defined classes after desired feature selection. The results are then recorded on magnetic tape or disk for later display (Hoffer, 1972).

Another classification algorithm is called "per field" or "per sample" classifier, which, instead of classifying data points individually, classifies entire fields of data points as individual decisions (Anuta et al., 1971). Field coordinates designating samples of known cover type to be classified are required to be input into the computer in addition to the statistics deck and selected channel combination. Each field will be classified into one of the cover type classes which have been designated to the computer. The product is a table which presents quantitative results of the classification. Unlike the perpoint classifier, the classification results may not be displayed in a maplike image.

#### Results Display

The classification which is stored on magnetic tape or disk is now ready to be displayed qualitatively as a maplike image. Qualitative or maplike displays of classification results may be obtained in one or more forms. First, it may be obtained from an alphanumeric line printer which



provides a product similar to that described earlier. For this maplike display the analyst can assign various symbols or characters to represent various classes. A second form of the classification is a color-coded classification which may be obtained by several methods one of which may be from the digital image display. By this method the analyst specifies colors to represent the various classes and the machine determines the gray levels for each of the three images which are displayed one at a time (Coggeshall and Hoffer, 1973). The photographic accessory unit on the display allows the analyst to obtain a color image by using multiple exposures of the three gray scales, each through different filters (blue, green, and red). The result is a color composite of the classification results.

If the analyst considers the first classification results to be incorrectly classified, he may go through a process of refinement of training fields or classes by examining the statistics. The sequence is repeated in order to produce a better classification.

## CHAPTER III - MATERIALS AND PROCEDURE

### Introduction

The procedure described in this chapter is the modified clustering approach following the analysis sequence described in the Review of Literature. The study area consists of about 3,900 square kilometers located on the vast central plain of Thailand. This includes six important provinces (Changwats), Nontha Buri, Prathum Thani, Samut Song Khram, Samut Sakon, Samut Prakarn, and Bangkok, the capital city. The Chao Phraya River flows through six changwats from the northern part of the country to the Gulf of Siam, south of Changwat Samut Prakarn. Soils found in this area are alluvial with characteristic black or deep gray surface color and brown mottling in the subsurface. The splotches or mottles are an indication of a high water table and very poor drainage. These soils are high in organic matter content and low in pH. Rice is the major crop. Other vegetation includes perennial and truck crops.

### Multispectral Scanner Data

Digital data for Landsat-1 scene number 116703070, obtained on 6 January 1973, were reformatted in preparation for analysis. The scene was examined on a digital image

display, and coordinates designated for the specific sub-scene area to be analyzed and classified. The display received the digital image directly from the IBM 360/67 computer, stored the data in the video buffer and displayed the image in a raster scanning mode on the high resolution television screen. The analyst, using a light pen and the appropriate program functions at the display key board, can edit and modify the image. The coordinates, lines 1 through 650 and columns 1 through 1118, were selected and this sub-unit of the Landsat scene was geometrically corrected.

#### Training Site Selection

The corrected data were then used to produce an alphanumeric image of the study area. In this process the pictureprint function of the LARSYS software designates a set of alphanumeric symbols to represent different levels of spectral reflectance of each of the data points in the scene. An alphanumeric gray scale image was produced for each of the four bands of MSS data. These gray scale images were used in the selection of five training sites within the study area. Care was exercised to assure that training sites provided adequate representation of urban features, dominant vegetation types, soils, and differences in surface water. Previous studies have indicated that MSS bands 4 and 5 (visible) provide good contrast for some soils and urban features and bands 6 and 7 may be particularly useful in identifying certain differences in vegetation

and water. Gray scale images, displayed in alphanumeric format at a scale of 1:25,000, served as the first basic consideration for selecting areas of known cover types for training.

Each site was comprised of several cover types some of which were known to the analyst. The first training site included the central city of Bangkok and the residential area through which the Chao Phraya River passes. This site was considered desirable for studying metropolitan features. The second training site was selected to the northwest of Bangkok in a horticultural area which includes a portion of an old channel (oxbow). This area was characterized by a rather uniform spectral response and an extensive, uniform tone and pattern of green vegetation. Paddy fields almost cover the entire area of the third training site. The patterns of the irrigation systems, the irrigated fields and non-irrigated fields provide the major characteristics of the scene in the central plain of Thailand. The good quality of soils, available water, and good management account for this dominant land use in the central plain. In Samut Songkhram Province, southwest of Bangkok, some woodland and marshland along with irrigated rice fields make up the landscape. The unusually high reflectance in MSS band 6 prompted the selection of this remarkably dense woodland pattern as a training site. Woodland and marshland were scarcely observable in the Landsat

image in the area around Bangkok except in the extension to the south near the Gulf of Siam. For the study of the spectral characteristics and separability of shrimp ponds, salt pans, and water bodies, an area along the Chao Phraya River and a portion of the delta were chosen. Along the coast there are many salt pans and bodies of surface water with different spectral properties. A total of five training sites consisting of 121,000 data points (pixels) were designated as a basis for identifying seven known major land use classes. Analysis results of these five training sites, consisting of less than 17% of the total study area, were used to classify the entire study area.

#### Statistical Analysis

The basic analysis procedure has been described in the Review of Literature. In this study all data points for each of five training sites were clustered into fourteen distinct cluster classes by the cluster processing function using all four bands of MSS data. Punch statistics were required in accordance with the parameters, means, standard deviation, covariance and correlation matrix. In the next step each cluster class of each training site was intensively considered and associated with information classes, or areas known to the analyst. To carry out this step of analysis, all available reference data were used so that the cluster classes could be reliably identified. The reference data available for Bangkok included two base maps

(scale 1:250,000) or ND 47-11 and ND 47-12 sheets, four land use maps (scale 1:250,000), the report of land capability for upland crops and soil suitability for paddy (wetland rice), and the report on the analysis of the water quality of the Chao Phraya River. In addition to some of the reference maps, the ratios of the spectral reflectance between two visible wavelength bands and two near infrared wavelength bands were tabulated in order by cluster class, magnitude (mean total relative reflectance), and ratio. Combining knowledge of this area and the spectral characteristics of the spectrally separable classes, the analyst related general cluster classes to informational classes (Table 2).

At this point in the analysis sequence, training sites had been clustered and the cluster classes had been associated with information classes. In order to lead to a better representation of the cover types the spectrally similar clusters were combined. This reduced the number of cluster classes. The separability function was used at the threshold of 1000 and 1200 (Phillips, 1973) to determine which clusters could be combined. Cluster classes were then reduced to 9, 7, 8, 6, and 7 classes for training sites 1, 2, 3, 4, and 5, respectively (Table 3). For further refinement all classes of the five training sites which had similar spectral characteristics were merged. By this step the analyst was able to identify cover types in

Table 2. An example of association of cluster classes and information classes.

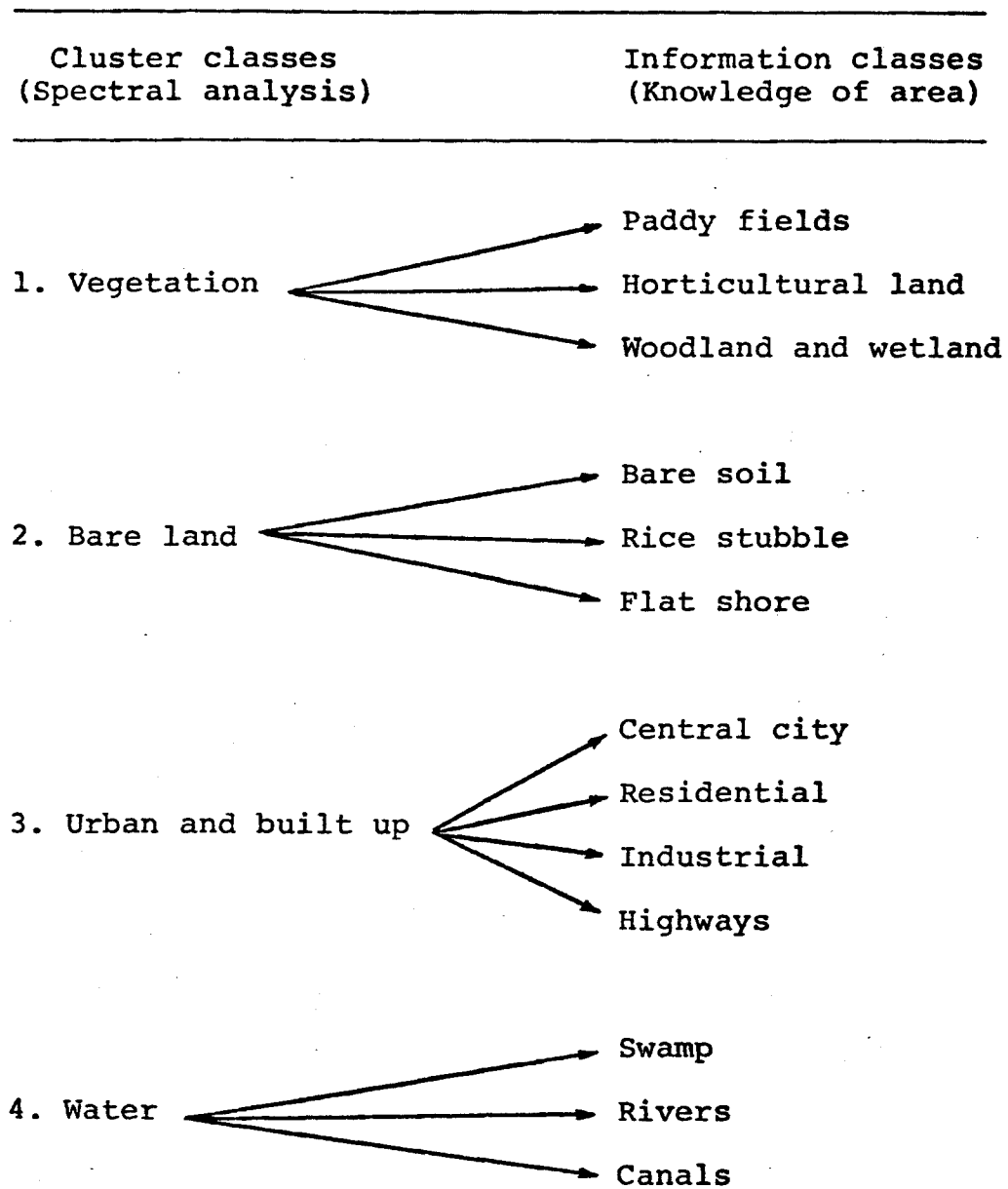


Table 3. Summary of spectral statistics for original cluster classes (14 classes for each of 5 training sites) and combined cluster classes.

	Cluster Classes (70)				Combined Cluster Classes (37)			
	Sym	Mag.*	Ratio**	Desc***	Sym	Mag.*	Ratio**	Desc***
Site 1	.	121.0	0.73	Veg2	C	121.0	0.73	Veg2
	B	90.1	0.80	Veg 3a	I	97.9	0.84	Veg3
	J	111.5	0.90	Veg 3b				
	S	104.3	1.05	Veg4	\$	104.3	1.05	Veg4
	R	83.8	1.22	Cmplx1a	*	98.3	1.17	Cmplx1
	/	124.9	1.16	Cmplx1b				
	G	95.3	1.16	Cmplx1c				
	3	107.9	1.32	Cmplx2a	+	100.4	1.38	Cmplx2
	8	94.1	1.45	Cmplx2b				
		151.1	1.53	Denud1		151.1	1.53	Denud1
	Y	100.6	1.70	Urban1a	/	94.5	1.74	Urban1
	Q	86.7	1.79	Urban1b				
	L	118.4	1.61	Urban2	=	118.4	1.61	Urban2
	M	72.3	3.24	Water	0	72.3	3.24	Water2

\* Sum of relative reflectance for all four MSS bands.

\*\*Ratio between visible (Bands 4 and 5) and infrared (Bands 6 and 7) reflectance.

\*\*\*Description



Table 3. (Continued)

Cluster Classes (70)				Combined Cluster Classes (37)				
Sym	Mag.*	Ratio**	Desc	Sym	Mag.*	Ratio**	Desc	
Site 2	Y	93.6	0.63	Veg1a	J	91.4	0.65	Veg1
	8	89.8	0.67	Veg1b				
	G	88.3	0.74	Veg2a	C	91.8	0.75	Veg2
	3	99.4	0.75	Veg2b				
	S	93.6	0.77	Veg2c				
	B	88.4	0.88	Veg3a	I	95.6	0.91	Veg3
	J	104.2	0.93	Veg3b				
	L	95.6	0.92	Veg3c				
	/	97.6	1.09	Veg4a	\$	93.6	1.10	Veg4
	R	86.8	1.11	Veg4b				
	.	115.6	1.13	Cmplx1a	*	109.2	1.17	Cmplx1
	.	105.0	1.19	Cmplx1b				
	M	74.1	3.38	Water2	0	74.1	3.38	Water2
Q	86.2	1.53	Water4	X	86.2	1.53	Water4	
Site 3	.	120.1	0.67	Veg1	J	120.1	0.67	Veg1
	8	99.0	0.77	Veg2a	C	103.9	0.73	Veg2
	S	108.5	0.70	Veg2b				
	L	116.1	0.83	Veg3a	I	106.4	0.87	Veg3
	3	105.3	0.85	Veg3b				
	B	91.8	0.89	Veg3c				
	/	125.1	0.97	Veg3d				
	Y	109.5	1.03	Veg4	\$	109.5	1.03	Veg4
	R	73.7	1.13	Cmplx1a	*	81.4	1.15	Cmplx1
	G	88.3	1.17	Cmplx1b				
	J	130.3	1.25	Cmplx2a	+	118.7	1.32	Cmplx2
	Q	109.4	1.39	Cmplx2b				

Table 3. (Continued)

Cluster Classes (70)				Combined Cluster Classes (37)			
Sym	Mag.*	Ratio**	Desc	Sym	Mag.*	Ratio**	Desc
<b>Site 3</b>							
(Cont.)	157.3	1.34	Denud2		157.3	1.34	Denud2
M	75.7	2.05	Water3	M	75.7	2.05	Water3
<b>Site 4</b>							
S	105.3	0.58	Veg1a	} J	98.8	0.63	Veg1
3	98.6	0.63	Veg1b				
Y	92.8	0.68	Veg1c				
L	98.1	0.82	Veg3a	} I	91.4	0.83	Veg3
G	87.0	0.83	Veg3b				
J	110.5	1.03	Veg4a	} \$	92.9	1.05	Veg4
8	90.4	1.04	Veg4b				
Q	80.8	1.06	Veg4c				
/	98.9	1.08	Veg4d				
	119.6	1.22	Cmplx1	*	119.6	1.22	Cmplx1
.	106.7	1.30	Cmplx2a	} +	96.7	1.32	Cmplx2
B	94.9	1.33	Cmplx2b				
R	84.7	1.37	Cmplx2c				
M	68.0	1.53	Water4	X	68.0	1.53	Water4

Table 3. (Continued)

Cluster Classes (70)				Combined Cluster Classes (37)			
Sym	Mag.*	Ratio**	Desc	Sym	Mag.*	Ratio**	Desc
Site 5	115.9	0.61	Veg1a				
/	93.0	0.64	Veg1b	J	100.7	0.64	Veg1
.	103.6	0.66	Veg1c				
L	88.0	0.78	Veg2a				
J	96.8	0.78	Veg2b	C	92.4	0.78	Veg2
3	90.5	1.01	Veg3a				
S	106.9	0.95	Veg3b	I	95.1	0.99	Veg3
8	83.3	1.26	Cmplx2a				
Y	134.0	1.34	Cmplx2b	+	92.2	1.30	Cmplx2
G	103.9	1.38	Cmplx2c				
M	57.9	4.43	Water1a				
Q	66.0	4.32	Water1b	W	62.2	4.37	Water1
R	78.7	2.37	Water3				
B	80.5	1.72	Water4	M	78.7	2.37	Water3
				X	80.5	1.72	Water4

order to get the training classes. Making use of the separability function again, the analyst grouped together the cluster classes from the same cover type whose inter-class statistical distances were less than the chosen threshold (1600). A group of cluster classes of the same cover type would have a smaller variance than would a group of the other cluster classes. When cluster classes from the same cover type had a pairwise statistical distance greater than the chosen threshold, the conclusion would be that the cluster classes were spectrally distinct subclasses of that cover type (Phillips, 1973).

After the procedure was repeated for further refinement, the last step in the process was the classification of the multispectral data for the entire study area. The classifypoints processing function classified multispectral data one point at a time into classes defined by the training statistics. The decision rule implemented in LARSYS was based on a maximum likelihood classification rule. Each data point to be classified was compared to all of the training classes, and was assigned to the most likely class. The classification results which were produced was stored on a results tape. In order to assess and evaluate classification results, another LARSYS processing function was employed. The printresults processing function provided an alphanumeric printout of all classes with each class represented by a different symbol. The analyst arbitrarily

assigned those symbols to the classes. Another black and white classification product was produced on an electronic printer/plotter where each class was represented not by letters or numbers but by a textural symbol. For example, woodlands may be represented by a symbol in the form of a tree; rice may be represented by a "grass-like" symbol.

The digital image display was also used to present the classification results for evaluation. Classified areas were displayed; a color was assigned to each class; and a color coded classification was produced by multiple exposures of the image through a set of filters onto color film. The color coded classification was obtained in the form of 35 mm transparencies. Another color coded classification (scale 1:50,000) of the study area was produced electronically by Mead Technology, Dayton, Ohio.

#### CHAPTER IV - RESULTS AND DISCUSSION

A false color image of the study area was produced on the digital image display by sequential projection of the image in MSS bands 4, 5 and 7 and multiple exposure of color film to these images through a series of color filters (Figure 4). This color composite provides the analyst with an excellent synoptic view of the entire study area and the range of spectrally separable features or variables in the scene.

After the coordinates for the five training sites were located (Figure 5) and the desired number of clusters determined, the analysis sequence outlined in the preceding chapter was followed (Figure 6). The LARSYS processor implemented an iterative, Euclidean distance clustering algorithm. A punch statistics deck was refined to the point that it produced cluster classification results which were judged by the analyst to be acceptable.

Approximately 17 percent of the study area was included in the five training sites, consisting of a total of 121,000 data points. This is a larger proportion than is normally used for training the classifier algorithm. A more common training fraction ranges from 1 to 10 percent.



Figure 4. False color image of Bangkok, Thailand study area, produced from Landsat MSS bands 4, 5 and 7.

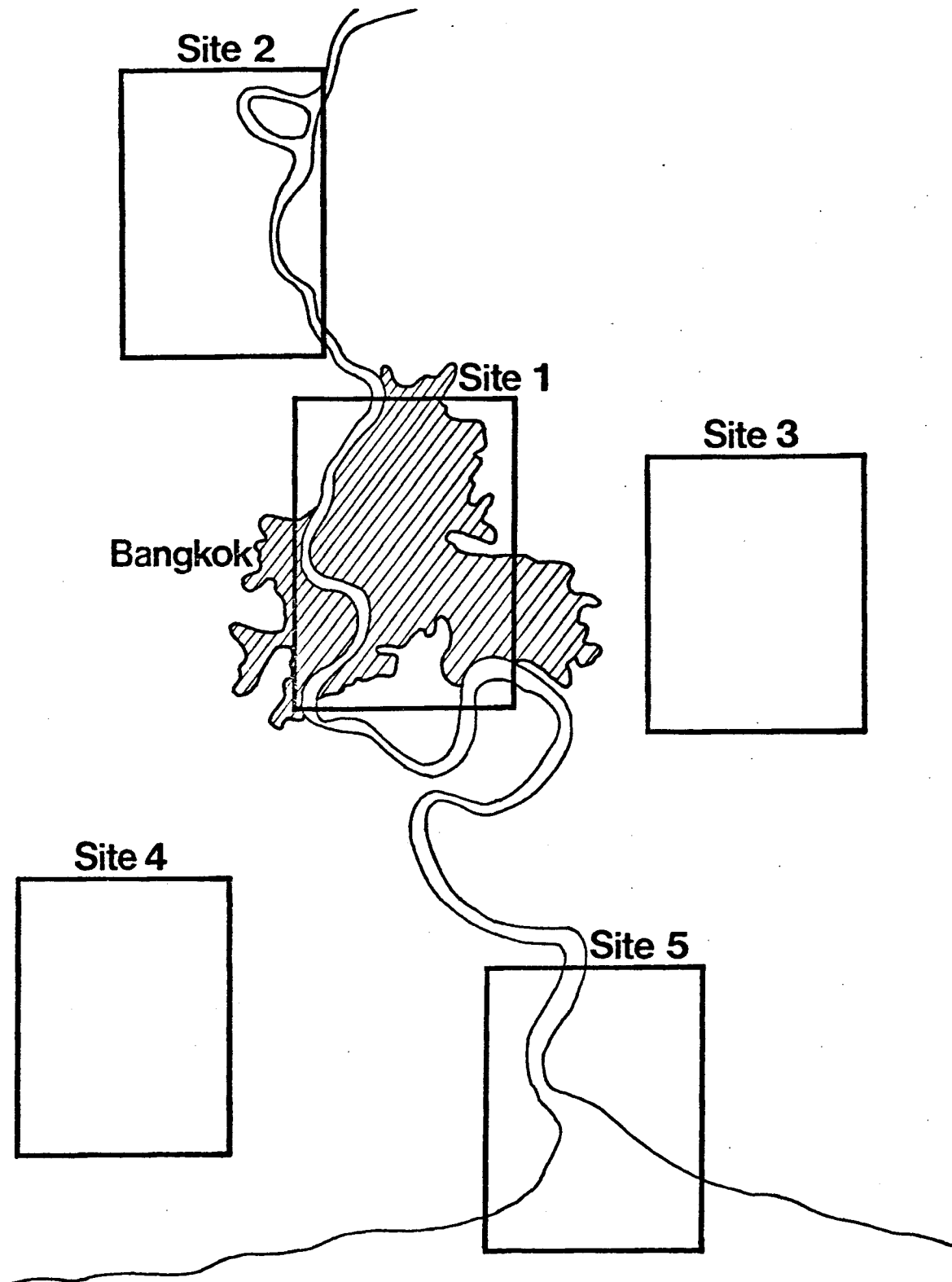


Figure 5. Outline of study area and location of five training sites.



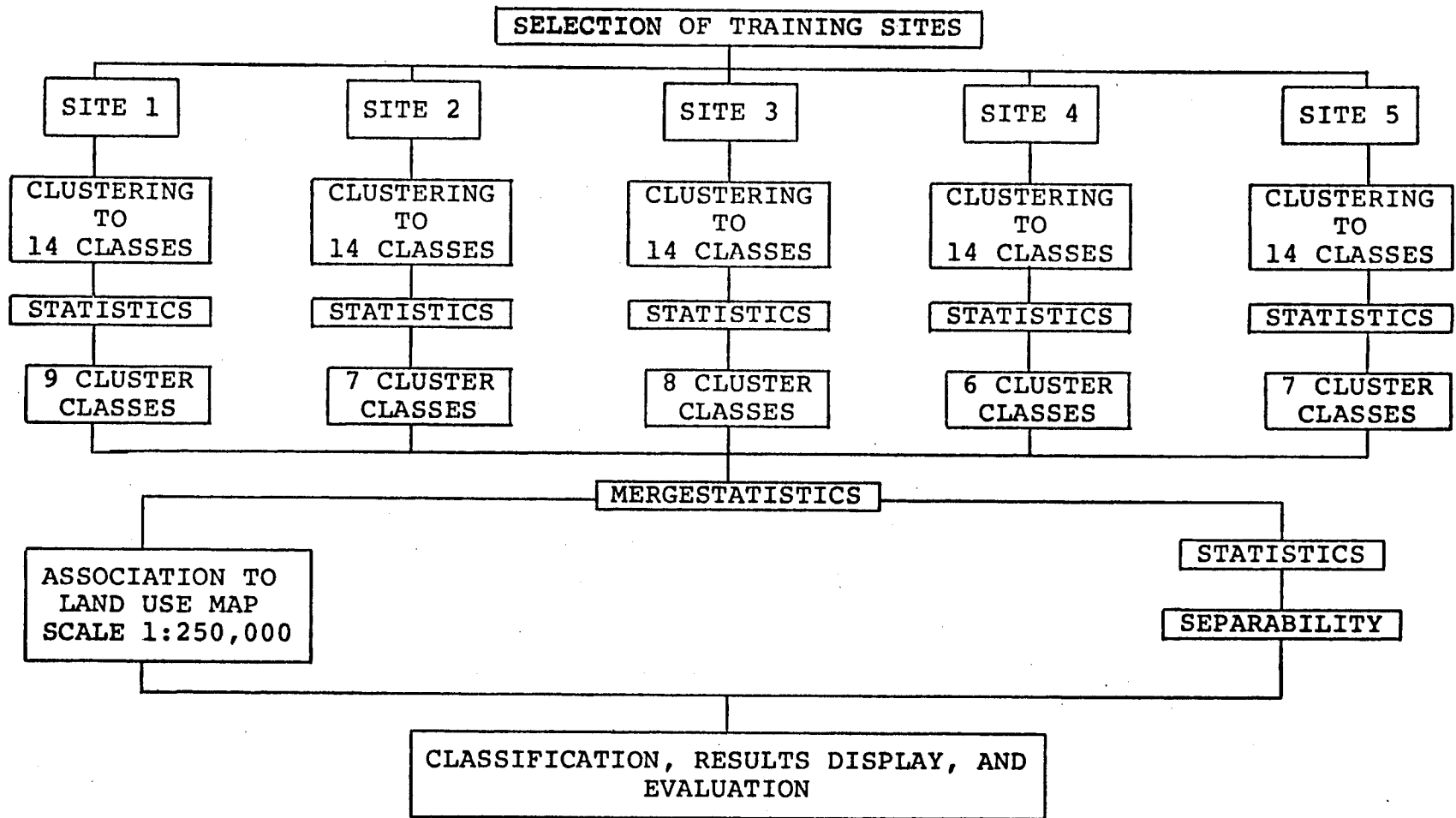


Figure 6. Digital analysis and interpretation sequence used in a land use classification of the Bangkok, Thailand area.

The study area included 726,700 data points, approximately one-tenth of a Landsat frame of 34,000 km<sup>2</sup>.

### Interpretation of Cluster Results

Data from each of the five training sites were classified into 14 cluster classes, twice the number of expected functional or informational classes (Figures 7, 8, 9, 10, 11). Although the spectral patterns for each of the training sites are complex, each cluster map is distinctive. The cluster map for the Bangkok reveals an intricate network of urban features having spectrally separable characteristics (Figure 7). It is interesting to note in this figure that the horticultural area to the northwest of Bangkok shows up in this cluster map as a homogeneous, uniform cluster, represented by the symbol "B." Incidentally, this cluster map was inadvertently printed with only every second line, giving it a 1:25,000 horizontal scale and 1:50,000 vertical scale.

A representative spectral pattern of training site 2, the horticultural area, is also complex (Figure 8). This is an excellent example of the spectral separability into many different clusters of an area which at first glance might appear to be quite homogeneous and uniform. Before the final land use classification is produced, many of these spectrally separable clusters will be combined into fewer classes. It should also be noted that the greater the number of spectrally separable classes the more precise





and complete the ground observation data must be in order to relate spectral class to informational class.

Training site 3 was located in the important rice production area of the Central Plain. From the complex patterns of the 14 class cluster map (Figure 9), it is difficult to discern the dominant features of irrigated rice, canals, harvested rice, and non-irrigated fields. It will require a combining of spectrally similar classes before the pattern of the dominant features will begin to appear.

The area along the coast to the southwest of Bangkok, test site 4, contains a complex pattern of rather large homogeneous features and many small, irregularly shaped features--mangrove swamps, marshland, salt pans, shrimp ponds, paddy fields, and canals (Figure 10). The same difficulty with the interpretation of fourteen cluster classes exists in this training site as in the others. The spectral separability has been extended beyond the limits of the analyst to explain the differences between classes on the basis of ground observation data. A combining of clusters with similar spectral characteristics will improve the probability of relating the spectral classes to informational classes.

The final example of the initial cluster results is for test site 5 along the Chao Phraya River near the Gulf of Siam (Figure 11). The water in the river appears as two



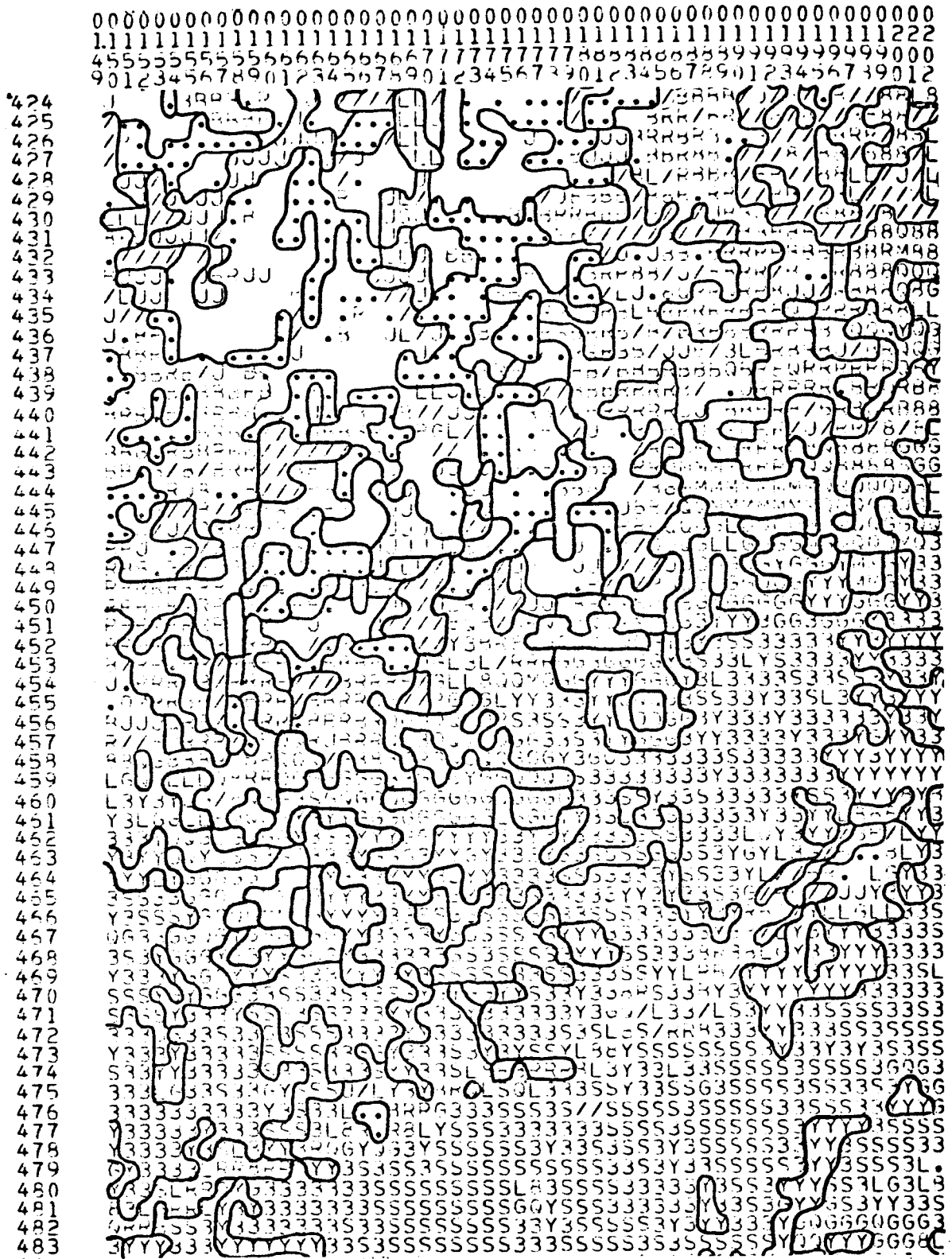


Figure 10. Fourteen cluster classes of a portion of training site 4, complex area of marshes, shrimp ponds, salt pans, canals, lakes along the coast southwest of Bangkok (scale 1:25,000).





distinct clusters, "M" and "Q." The remaining twelve clusters give intricate patterns representing forests, agricultural lands, swamps, and urban features.

#### Interpretation of Spectral Statistics

The results from the cluster processor included a measure of cluster separability for each pair of clusters. The interpretation of the separability measure based on both the means and covariances of the clusters was the most crucial step in the analysis procedure. The analyst subjectively decided how clusters should be combined into subclasses and how many clusters could be contained in each group of clusters which represented each cover type. The cluster separability interpretation algorithm indicated which clusters were spectrally similar and could be combined into subclasses having unimodal, approximately Gaussian distribution.

Those cluster classes having relatively low visible reflectance and very high infrared reflectance were classified as vegetation. There is an alternative processor that can help the analyst to make such decisions. Theoretically, the green vegetation will give a visible/IR reflectance ratio value of less than 1.0. It should be noted that in this investigation the classes judged to be green vegetation had spectral ratios ranging from 0.58 to 1.11 (Table 3). Within this ratio range four classes of vegetation were separated spectrally. From Table 4 it may

be observed that all four classes of vegetation were identified only in the horticultural area (training site 2) and the paddy area (training site 3).

Complex classes are thought to be bare soil and soil covered with crop residue, perhaps rice stubble. A careful study was made of the ratio and magnitude of these classes (Table 4). Complex 1 is thought to have more high reflective rice stubble than Complex 2 which seems to have the spectral characteristics of exposed dark surface soil.

Four water subclasses were identified and mapped by spectral analysis. The major differences in these four classes of water seem to be related to the turbidity or content of suspended solids in the water. All four water subclasses have medium reflectance in the visible bands of the spectrum while the increasing level of turbidity causes a dramatic increase in very low reflectance which clear water gives in the 0.8-1.1  $\mu\text{m}$  band (Table A-2, Appendix).

The statistics presented under the combined cluster classes (Table 4) give the spectral characteristics for two urban classes. Total mean relative reflectance for Urban 1 is similar to that of several subclasses of green vegetation. However, the V/IR ratio is considerably higher than the ratio for any of the vegetation classes. Features having spectral characteristics similar to those of the two urban classes were identified only in training site 1 (Table 4).

Table 4. Summary of spectral statistics for combined cluster classes (from 70 to 37) and final training set (14 classes) for classification of Bangkok, Thailand study area.

Training Site	Combined Cluster Classes				Final Training Set			
	Sym	Mag*	Ratio**	Description	Sym	Mag*	Ratio**	Description
1		151.1	1.53	Denuded 1		151.1	1.53	Denuded 1
3	"	157.3	1.34	Denuded 2	"	157.3	1.34	Denuded 2
1	C	121.0	0.73	Veg 2				
2	J	91.4	0.65	Veg 1	T	92.6	0.69	Hort/Trees
2	C	91.8	0.75	Veg 2				
3	J	120.1	0.67	Veg 1				
3	C	103.9	0.73	Veg 2	R	100.8	0.74	Rice 1
5	J	100.7	0.64	Veg 1				
5	C	92.4	0.78	Veg 2				
1	I	97.9	0.84	Veg 3				
1	\$	104.3	1.05	Veg 4				
2	I	95.6	0.91	Veg 3				
2	\$	93.6	1.10	Veg 4				
3	I	106.4	0.87	Veg 3	J	99.3	0.96	Rice 2
3	\$	109.5	1.03	Veg 4				
4	I	91.4	0.83	Veg 3				
4	\$	92.9	1.05	Veg 4				
5	I	95.1	0.99	Veg 3				
4	J	98.8	0.63	Veg 1	F	98.8	0.63	Woodland/ Wetland

Table 4. (Continued)

Training Site	Combined Cluster Classes				Final Training Set			
	Sym	Mag*	Ratio**	Description	Sym	Mag*	Ratio**	Description
1	*	98.8	1.17	Complex 1				
2	*	109.2	1.17	Complex 1	*	98.8	1.11	Complex 1
3	*	81.4	1.15	Complex 1				
4	*	119.6	1.22	Complex 1				
1	+	100.4	1.38	Complex 2				
3	+	118.4	1.32	Complex 2	+	99.7	1.35	Complex 2
4	+	96.7	1.32	Complex 2				
5	+	92.2	1.30	Complex 2				
1	/	94.5	1.74	Urban 1	/	94.5	1.74	Urban 1
1	=	118.4	1.61	Urban 2	=	118.4	1.61	Urban 2
5	W	62.2	4.37	Water 1	W	62.2	4.37	Water 1
1	0	72.3	3.24	Water 2	0	74.8	3.28	Water 2
2	0	74.1	3.24	Water 2				
3	M	75.7	2.05	Water 3	M	77.9	2.28	Water 3
5	M	78.7	2.37	Water 3				
2	X	86.2	1.53	Water 4				
4	X	68.0	1.53	Water 4	X	79.9	1.64	Water 4
5	X	80.5	1.72	Water 4				

\* Sum of relative reflectance for all four MSS bands.

\*\*Ratio between visible (Bands 4 and 5) and infrared (Bands 6 and 7) reflectance.

Two of the original cluster classes had rather unique spectral properties (Table 4). Through the entire sequence of combining of clusters and merging of statistics these two classes remained unchanged. They have the highest mean total relative reflectance with values of 151 and 157 and medium ratio values of 1.53 and 1.34, respectively. These classes, named Denuded 1 and Denuded 2, are obviously different spectrally from the water classes, vegetation classes and Complex 1 and Complex 2. The extremely high total reflectance suggests barren, open areas of dry, light colored soil and/or areas covered with highly reflective gravel, sand or concrete. These classes were identified in training areas 1 and 3 only. More precise and complete ground observation data are required to describe these two distinct spectral classes.

Another useful tool for interpreting multispectral characteristics of land use classes is the coincident spectral plot of spectral classes for each Landsat MSS band (Figures 12, 13, 14, 15, 16). The plots for each of the nine combined cluster classes of training site 1 are presented in Figure 11. The letter "A," representing Denuded 1, is located at the point of the mean relative reflectance for each MSS band. The asterisks (\*) on each side of the mean reflectance value represent the variance of one standard deviation from the mean. An examination of the coincident spectral plot for training site 1 reveals that

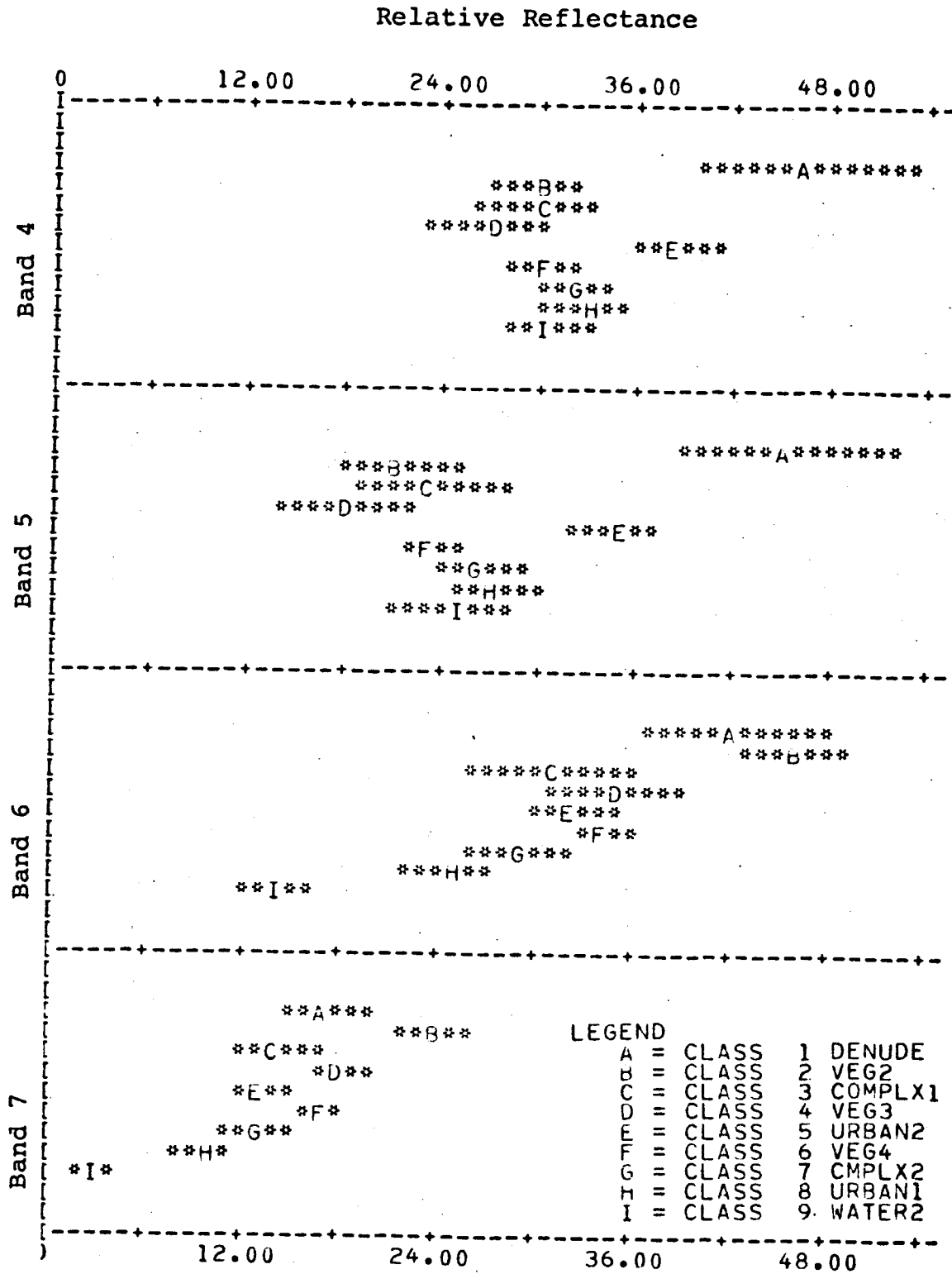


Figure 12. Coincident spectral plot of 9 combined cluster classes for training site 1.

## Relative Reflectance

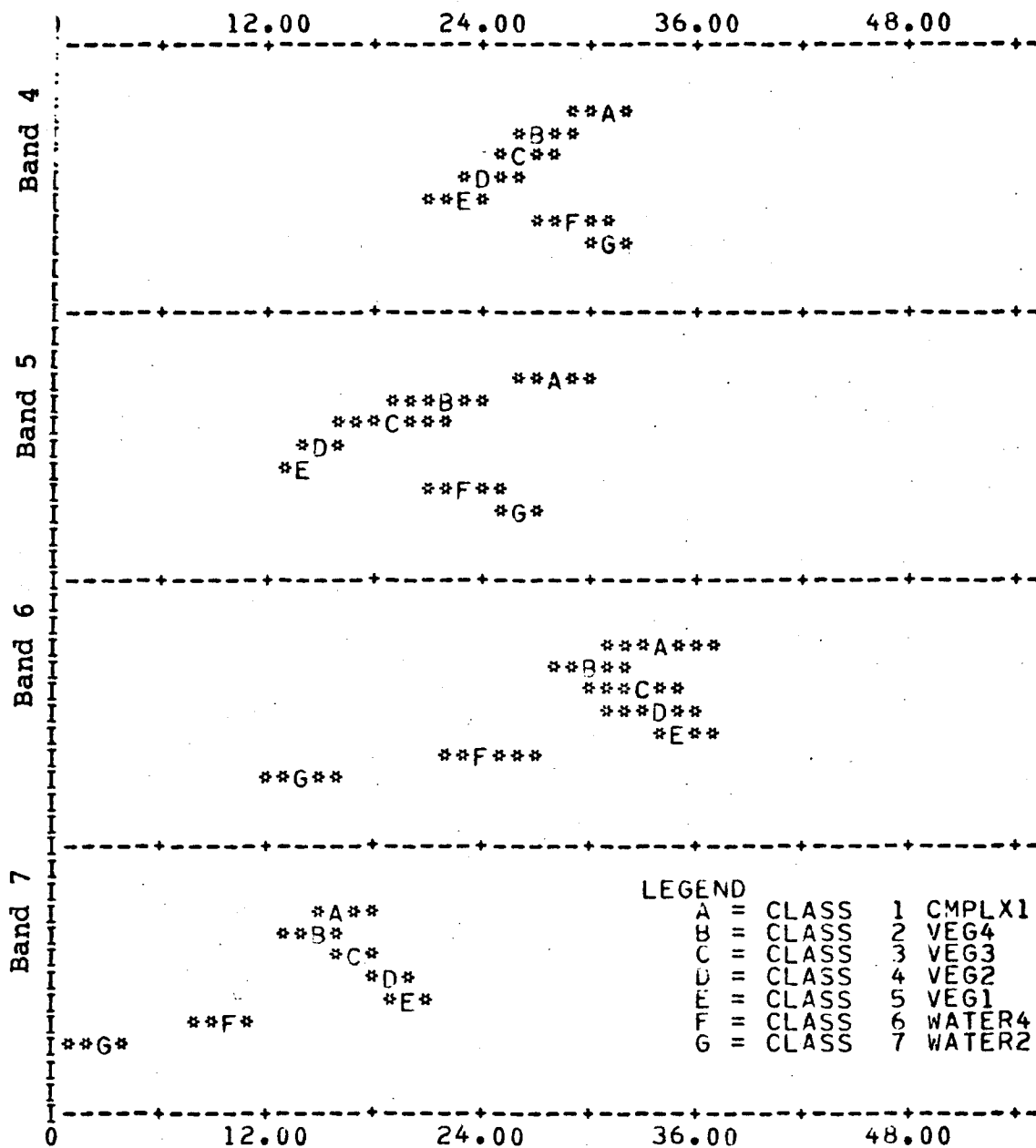


Figure 13. Coincident spectral plot of 7 combined cluster classes for training site 2.

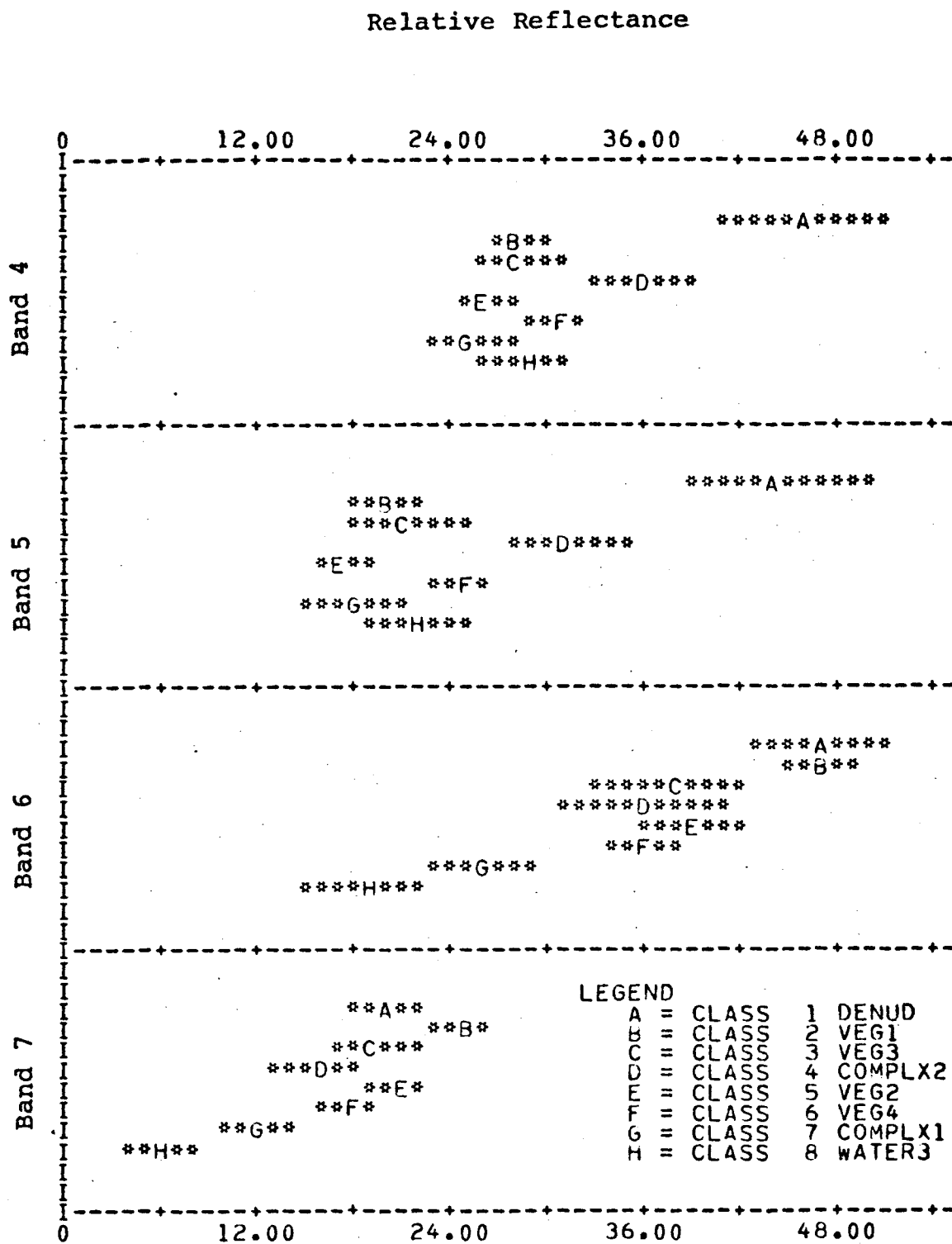


Figure 14. Coincident spectral plot of 8 combined cluster classes for training site 3.



## Relative Reflectance

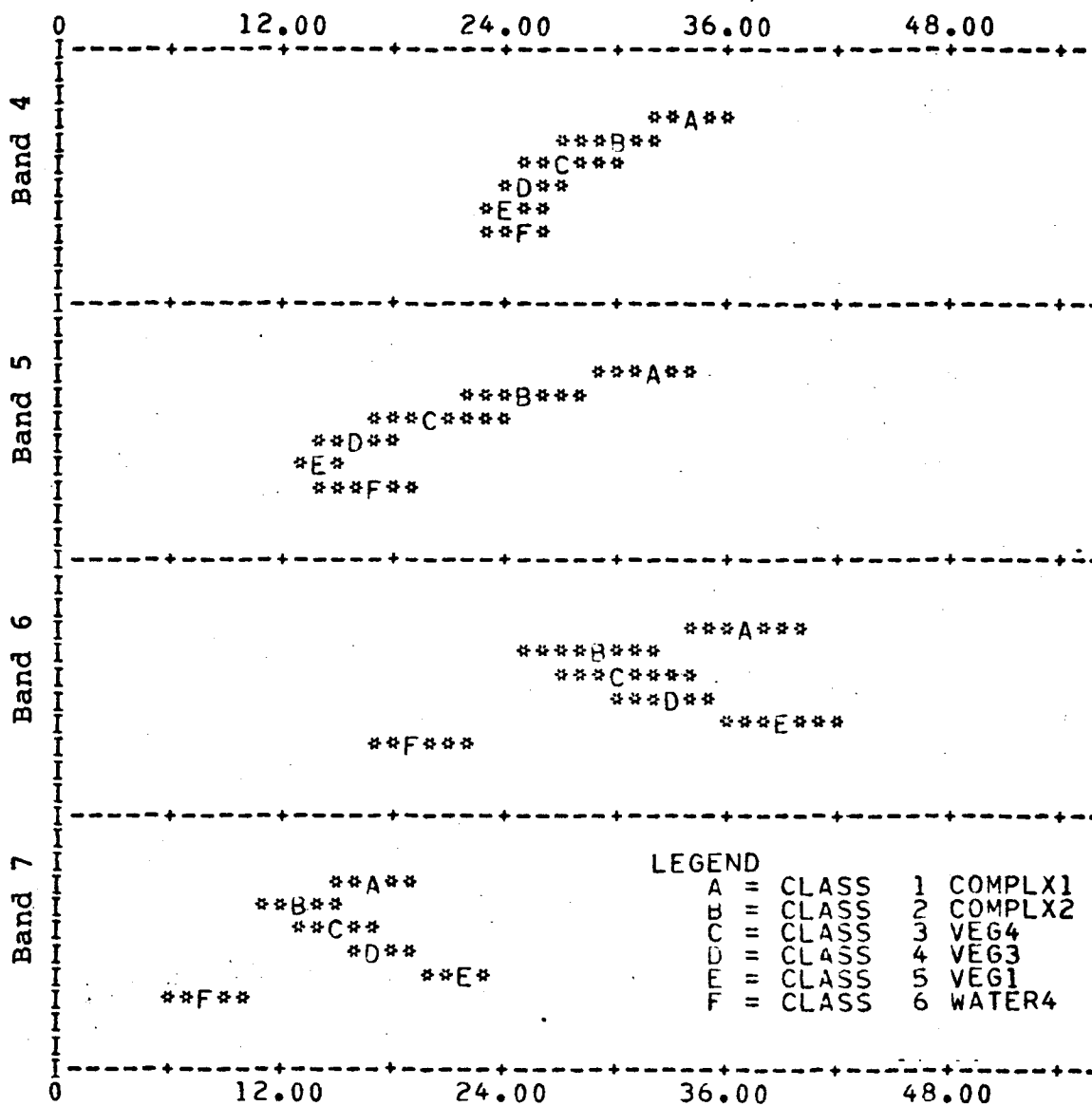


Figure 15. Coincident spectral plot of 6 combined cluster classes for training site 4.

## Relative Reflectance

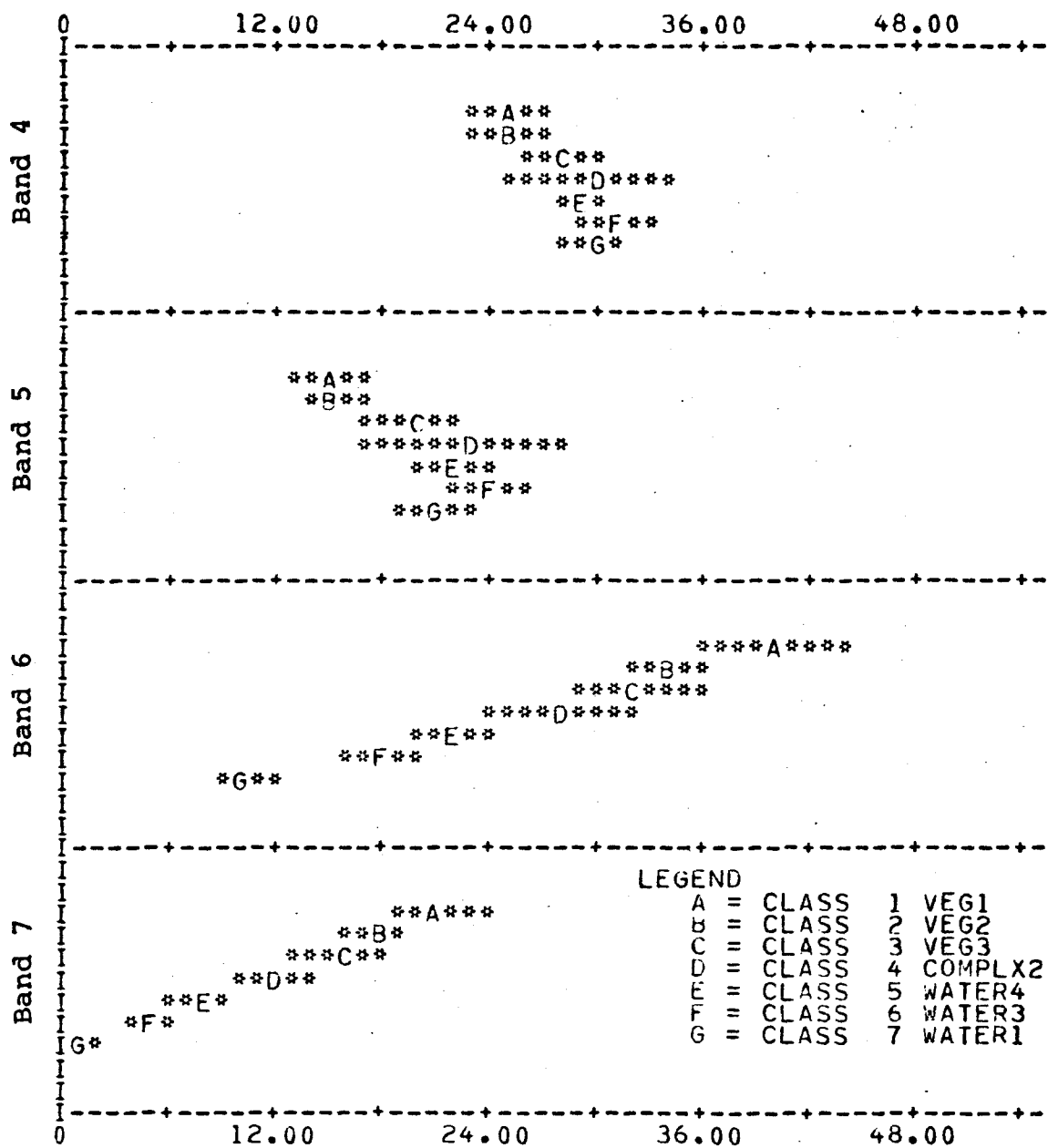


Figure 16. Coincident spectral plot of 7 combined cluster classes for training site 5.

Denuded 1 has a very high reflectance and variance in bands 4, 5 and 6. Vegetation 2 and Complex 1 give essentially the same reflectance and are therefore inseparable in bands 4 and 5. However, in the infrared bands (6 and 7) these two classes are easily separable. On the other hand, Complex 1 and Urban 2 are spectrally similar in bands 6 and 7 but easily separable in bands 4 and 5. Urban 1 and Urban 2 are spectrally separable in all four bands.

A comparison of the coincident spectral plots for all five training sites reveals that Water 1 in training site 5 and Vegetation 1 in training site 2 have the greatest uniformity or least variance in reflectance. A relatively high variance in reflectance is exhibited by Denuded 1 and Complex 1 in training site 1, Denuded 2 in training site 3 and Complex 2 in training site 5.

#### Interpretation of Images of Combined Cluster Classes

The same portions of each of the training sites for which the cluster maps were presented (Figures 7, 8, 9, 10, 11) and described were reclassified into a total of 37 combined cluster classes. The 1:25,000 printouts of these combined classes (Figures 17, 18, 19, 20, 21) are much more interpretable and less complex than are the original cluster maps. A comparison of these figures representing the combined cluster classes reveals distinct differences in land use patterns in the five training sites. One of the most difficult problems to discern is the differences













between the patterns of Vegetation 1 ("C") and Vegetation 2 ("J") in training sites 2 and 3. These classes have very similar spectral properties.

A study of the locations of these classes with respect to other classes in each of the training sites was helpful in developing the final description of informational classes.

#### Interpretation of Training Data

A 1:250,000 scale land use map of the study area was used as a reference for this investigation (Figure 22). Although a map at this scale provides limited detail, it was useful to confirm classes which were suggested on the basis of spectral characteristics. The analyst's knowledge of the Bangkok area also was important in the interpretation and description of spectral classes. With this limited set of ground information and the spectral statistics, the decision was made to merge the statistics of the 37 combined cluster classes to produce a final training set of 14 classes (Table 4). Available ground information made it possible to relate informational or functional classes to the merged classes (Table 5). In the final 14 classes, four vegetation classes, four classes of water, two complex classes, two urban, and two denuded classes were identified and described. A summary of the spectral statistics and the area estimates for these 14 classes in the five training sites was compiled (Table 6).



Table 5. Association of cluster classes and information classes.

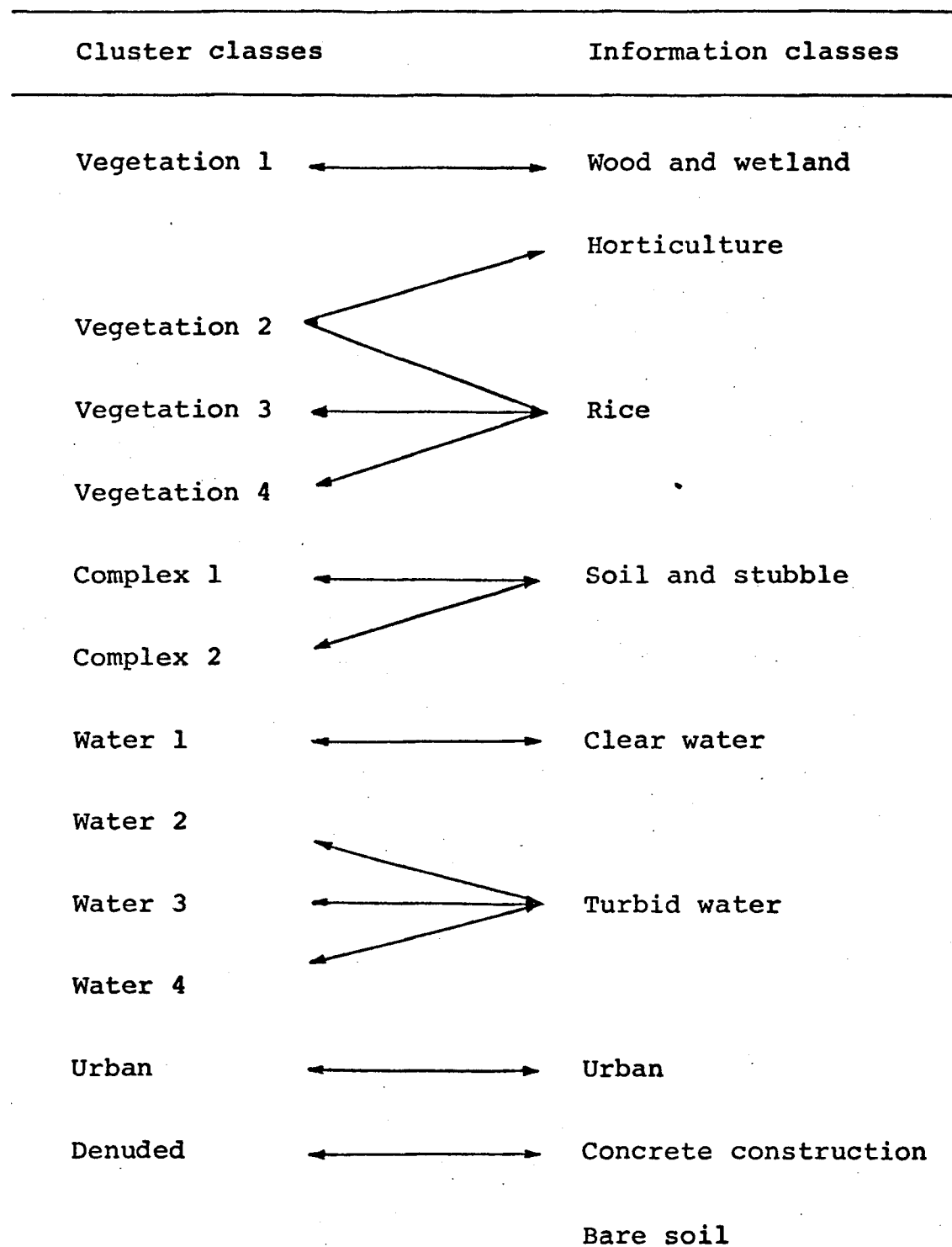


Table 6. Summary of spectral statistics and area estimates for 14 land use classes in five training sites.

Class	Sym	Magni- tude*	Ratio** (V/IR)	No. of Data Points	Area Estimates			
					Acres	Hectares	Km <sup>2</sup>	%
Denuded 1		151.1	1.53	1,317	1,499	659	6.59	1.09
Denuded 2	"	157.2	1.34	534	587	267	2.67	0.44
Urban 1	/	118.4	1.61	3,172	3,489	1,586	15.86	2.62
Urban 2	=	94.5	1.74	7,195	7,915	3,598	35.98	5.95
Complex 1	*	98.8	1.17	14,977	16,475	7,489	74.89	12.38
Complex 2	+	99.7	1.35	11,478	12,626	5,738	57.38	9.49
Horticulture/Tree	T	92.6	0.69	17,439	19,182	8,720	87.20	14.41
Woodland/Wetland	F	98.8	0.63	5,315	5,847	2,658	26.58	4.39
Rice 1	R	100.8	0.74	15,159	16,675	7,580	75.80	12.53
Rice 2	J	99.3	0.96	27,251	29,976	13,626	136.26	22.52
Water 1	W	62.2	4.37	1,374	1,511	687	6.87	1.14
Water 2	O	72.8	3.28	3,297	3,627	1,649	16.49	2.72
Water 3	M	77.9	2.28	4,336	4,770	2,168	21.68	3.58
Water 4	X	79.9	1.64	8,156	8,972	4,078	40.78	6.74
TOTAL				121,000	133,100	60,500	605.00	100.00

\* Sum of relative reflectance for all four MSS bands.

\*\*Ratio between visible (Bands 4 and 5) and infrared (Bands 6 and 7) reflectance.

Of the four classes of water, the clearest or least turbid water appears along the coast and for some distance up the Chao Phraya River. The load of pollutants in the river in the Bangkok area changes the reflectance dramatically. This difference in water quality can easily be observed in the classifications.

Although some classes of vegetation were easily identified, a considerable amount of difficulty arose in the interpretation of other vegetation classes. Spectral statistics (Tables 3 and 4) reveal that the accuracy for identifying and mapping woodland is quite good. Most of the woodlands or forests in the study area are in lowland or depressional areas, and there was relatively high spectral separability of forest from other cover types.

The spectral statistics suggest that there might be confusion between some of the four vegetation classes. For example, in an irrigated area dense tree canopies along the canals might cause misclassification of rice along the field edges. While confusion may arise between rice and trees, two categories of rice were established spectrally. Reflectance in the infrared is quite different for these two classes. At the time the Landsat data were acquired on 6 January 1973 many fields of rice had reached maturity and senescence was well advanced. Some rice fields had been harvested, and fields were being prepared for a new crop. The area estimate for Rice 2 (mature) was quite a

bit higher than for Rice 1 (immature) as shown in Table 6. The variances in reflectance of these two classes of rice are greater than those of all other classes except Denuded 1 and 2.

The agricultural fields which had been harvested or plowed or replanted appear in the final classification as Complex 1 and 2. These classes may include cover types of rice stubble, grass, and dark soil and have high variances of reflectance. That is, these classes are quite heterogeneous. Spectral statistics suggest that more stubble is present in Complex 1 than in Complex 2. Complex 1 may be considered a transition class between Rice 2 and bare soil.

A careful examination has been made of the soils and their effects on the reflectance in the four MSS bands. Most of the soils in central plain of Thailand are alluvial soils and are characterized by high organic matter content, high water table, and a relatively dark surface. The higher the moisture content, the higher the water table, the lower the spectral reflectance. The spectral properties of Complex 2 suggest a greater influence of soil on the reflectance than for Complex 1.

While the area to the east of Bangkok is irrigated and is covered extensively with rice, horticulture has dominantly been grown to the northwest of Bangkok. Successful spectral classification of the horticultural area is possible largely because of the homogeneity of that

area. Although it is the most spectrally homogeneous, several factors must be considered in classifying the area. These factors include total relative reflectance, location, other agricultural patterns, plant geometry, and growing season. The horticultural area contains coconut, truck crops, and citrus orchards.

To the south of Bangkok, the horticultural land has mainly included intensively cultivated crops, truck crops, and small areas of vineyards.

Spectral classification results have been compared to the land use map of Thailand. The spectral classification suggests that some horticultural land has changed to other land uses. Recent housing development and highway construction extending from Bangkok southward into the horticultural land in Samut Prakan Province is evident in the Landsat data. This scattered development also expands eastward from Bangkok into some cultivated areas.

In this study the relative homogeneity in spectral characteristics of the horticultural areas is an interesting contrast to the heterogeneity of the urban area. As usual, the urban class is quite complex. In a general land use classification many different cover types are combined into a single class. In this study the urban class is identified based on spectral characteristics of all data points or the components in its class and its location. Different surface features may include concrete and asphalt

surfaces, a variety of lawn in residential areas and recreation areas, industrial sites, and other manmade features.

A comparison of the spectral characteristics of Bangkok with those of other large metropolitan areas reveals some interesting differences about Bangkok. In the final classification for this study the central city is represented as Urban 2 which has a relatively low total mean relative reflectance compared to that of other central metropolitan areas. This may be explained by the fact that the central city of Bangkok is located in a depression area along the Chao Phraya River. This flood plain is characterized by dark, high organic matter soils and a relatively high water table. In addition, there are many canals throughout the central city. In recent years some of the canals, no longer needed for transportation, have been filled and put to use for streets, small shopping centers and housing. Many canals remain for commercial purposes. The low reflectance in the central city may be attributed at least in part to the effects of the large amount of surface water interspersed with the other surface features.

Urban 1 has a somewhat higher reflectance than Urban 2 in all wavelength bands, giving a greater total reflectance. The Urban 1 class generally occurs on higher ground around the central city and represents more recent suburban and housing developments. In recent years this extension of



the city and change in land use patterns has been particularly rapid toward the northeast, east and southeast, especially along transportation arteries (Figure 23). The development has occurred primarily at the expense of horticultural areas and paddy fields.

Industrial development has occurred rapidly on both sides of the river extending from the upper part of Bangkok in Nonthaburi Province all along the river to the south. Results from this classification illustrate that digital analysis of Landsat data can be used to monitor land use changes in and around the Bangkok area. Classification from Landsat data reveals great changes in urban development when compared to the land use map derived from aerial photography obtained from 1962 to 1965. The small scale land use map (1:250,000) presents extremely limited information about the pattern of urban development. The results of this study indicate dramatic changes in land use during the period from 1965 to 1973.

There are 2 spectral classes that do not fit into any of the others. These consist of isolated small areas having extremely high reflectance in all wavelength bands. These characteristics suggest flat, dry, hard surfaces. Features exhibiting these properties might include bare soil, monuments, concrete structures, sports arenas, and transportation arteries. These two classes, called Denuded 1 and Denuded 2, have very high reflectance.

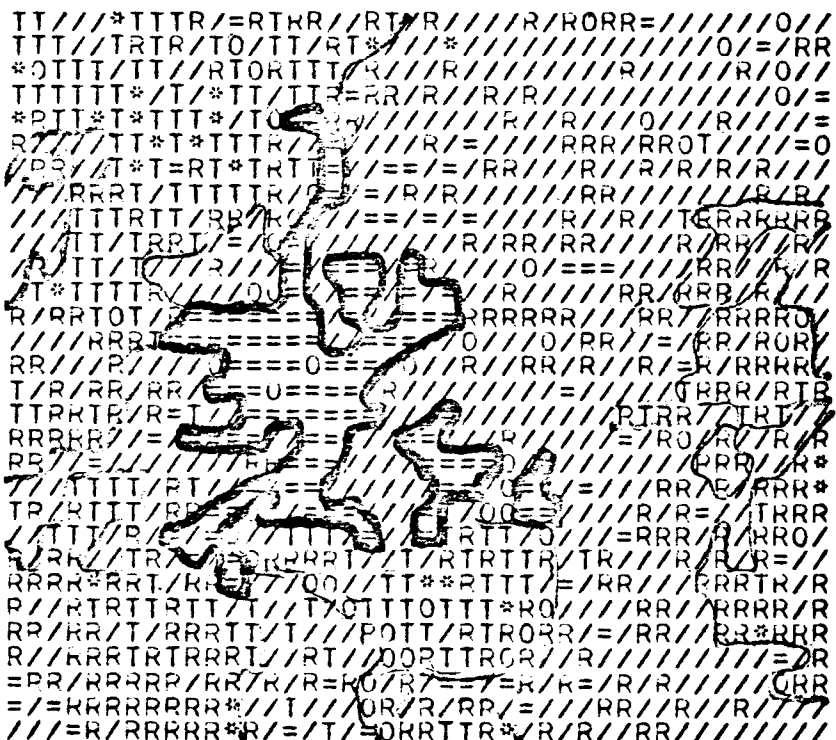
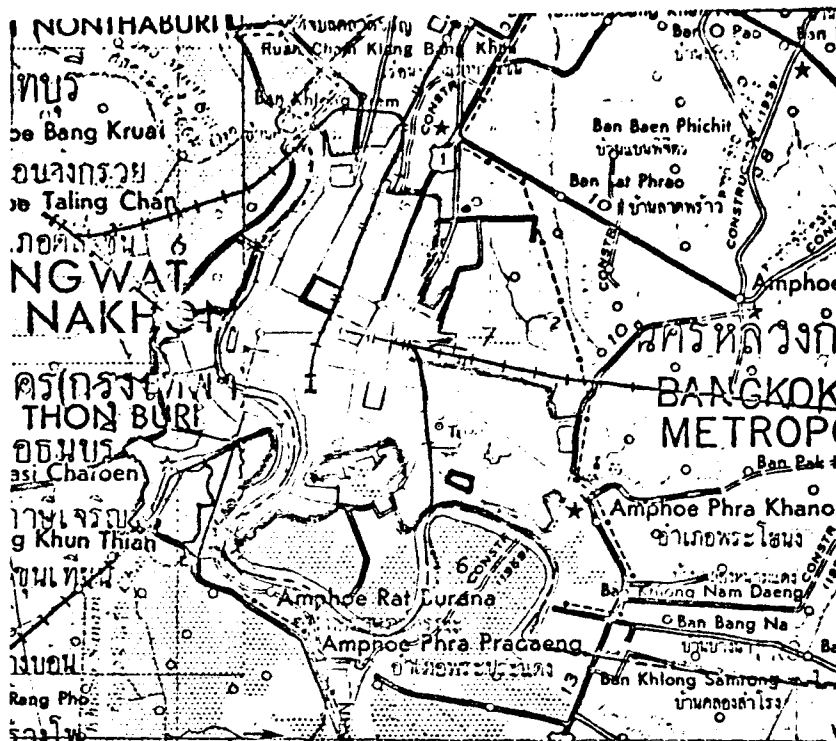


Figure 23. Land use changes observed by comparing land use maps of Bangkok derived from aerial photography (1962-1965) and from digital analysis of Landsat data (1973). Scale 1:250,000.

A summary of the interpretation of reflectance properties of land use classes is presented in Table 7.

Methods of Presenting Results of Land Use Classification  
by Digital Analysis of Landsat MSS Data

A coincident spectral plot of the 14 land use classes obtained in the final classification was generated (Figure 24). This plot indicates that the fourteen classes were easily separable spectrally in one or more of the four MSS bands. It also indicates the relatively high variance in reflectance in the following classes: Denuded 1 and 2, Urban 1 and 2, and Complex 1 and 2. In general, the variance for the classes of water and vegetation was much lower.

Classification results were generated in several formats. The electronic printer/plotter may be used to produce a black and white image from the classification results on digital tape. Three examples of such results were selected from the final classification of the study area (Figures 25, 26, 27, 28). Figure 25 provides the legend which relates specific land use classes to the different textural classes of the printout. The scale of the final product can easily be adjusted. The results presented here represent a scale of 1:50,000.

Two different color coded classification results are presented. The first (Figure 29) was produced by displaying the classification results on the digital image display

Table 7. Interpretation of reflectance properties of land use features identified by digital analysis of Landsat-1 MSS data.

<u>Informational Classes</u>	<u>Interpretation</u>
Denuded	Variable high reflectance, spectral characteristics at considerable variance from those of typical urban and vegetated agricultural scene in Bangkok area; spectral characteristics suggest concrete surfaces and bare soils in urban or residential areas.
Agriculture	Relatively high, uniform reflectance; variations in reflectance caused by differences in conditions and maturity of crops; large areas of alluvial soils and depressions characterized by lower reflectance; double cropping following rice harvest provides additional variable in scene; analyst's knowledge of area made it possible to separate subclasses of dense green vegetation--coconut, sugar palm, citrus, truck crops surrounded by paddy fields.
Woodland/ wetland	Very high, uniform relative reflectance; clear cut area or isolated area with the appearance of drainageways surrounded by depressions and paddy fields.
Complex	Variable medium responses representing soil and rice stubble; low to medium reflectance variations are a result of differences in moisture and tillage conditions.
Urban	Variable low to medium reflectance; low reflectance in central city partly as a result of large amount of surface water; medium reflectance in residential areas, mixture of housing, dry soil, vegetation, streets.
Water	Low, uniform reflectance; increase in reflectance from water related to increasing level of suspended solids.

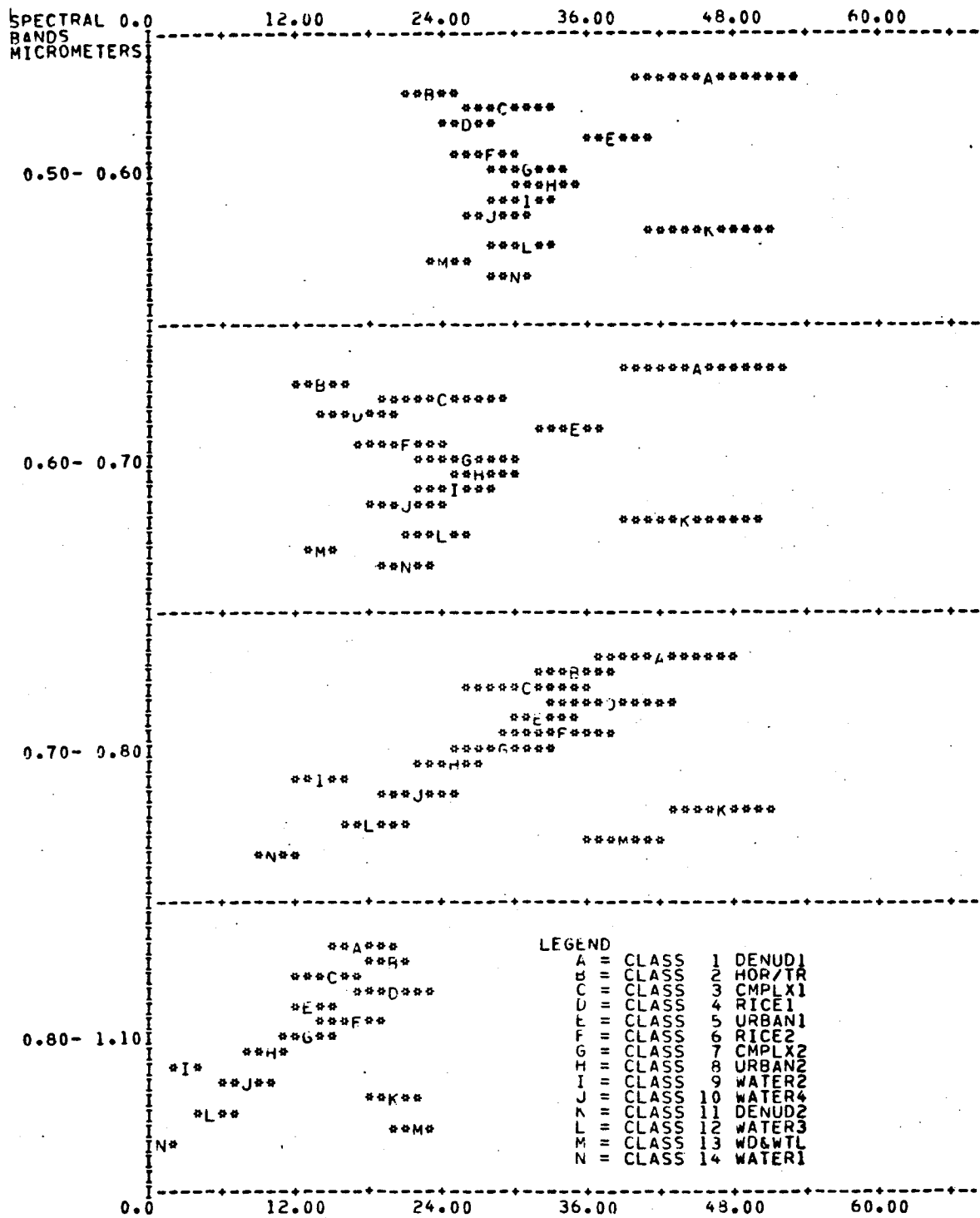


Figure 24. Coincident spectral plot of 14 land use classes obtained in final spectral classification.


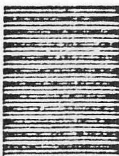

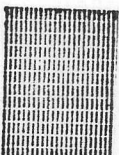

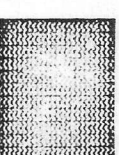



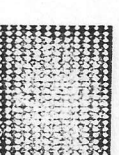

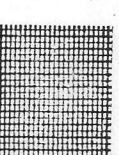

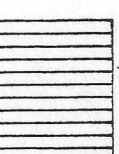
LEVEL	CLASS	LEVEL	CLASS
	1 WATER1		8 URBAN1
	2 RICE1		9 WATER2
	3 RICE2		10 WATER3
	4 HOR/TR		11 WATER4
	5 WD&WTL		12 DENUD1
	6 CMLX1		13 DENUD2
	7 CMLX2		14 URBAN2

Figure 25. Legend for relationship between textural classes and land use classes for Figures 26, 27 and 28.



Figure 26. Final land use classification of central city and surrounding area of Bangkok; produced on electronic printer plotter. Scale 1:50,000.

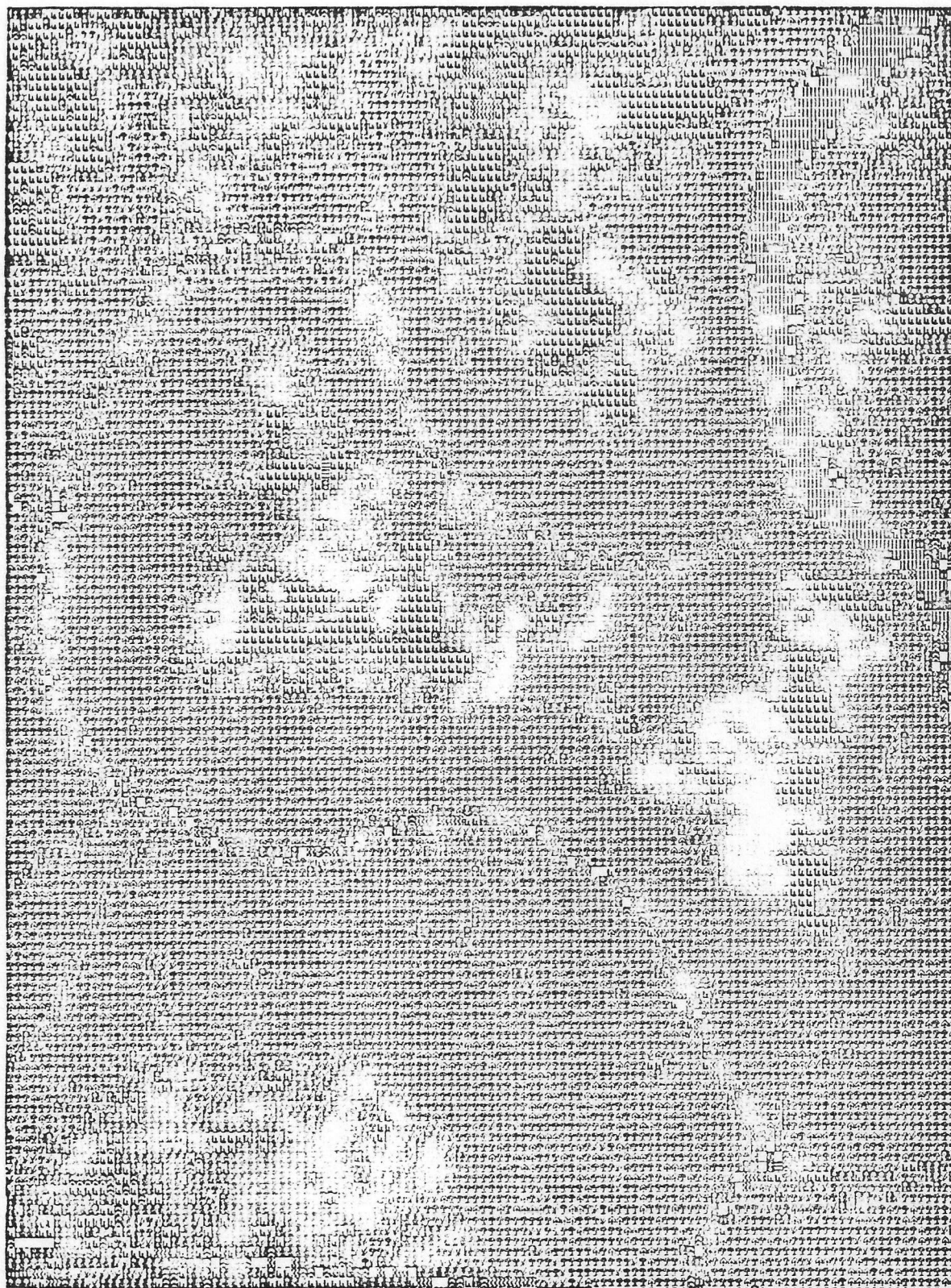
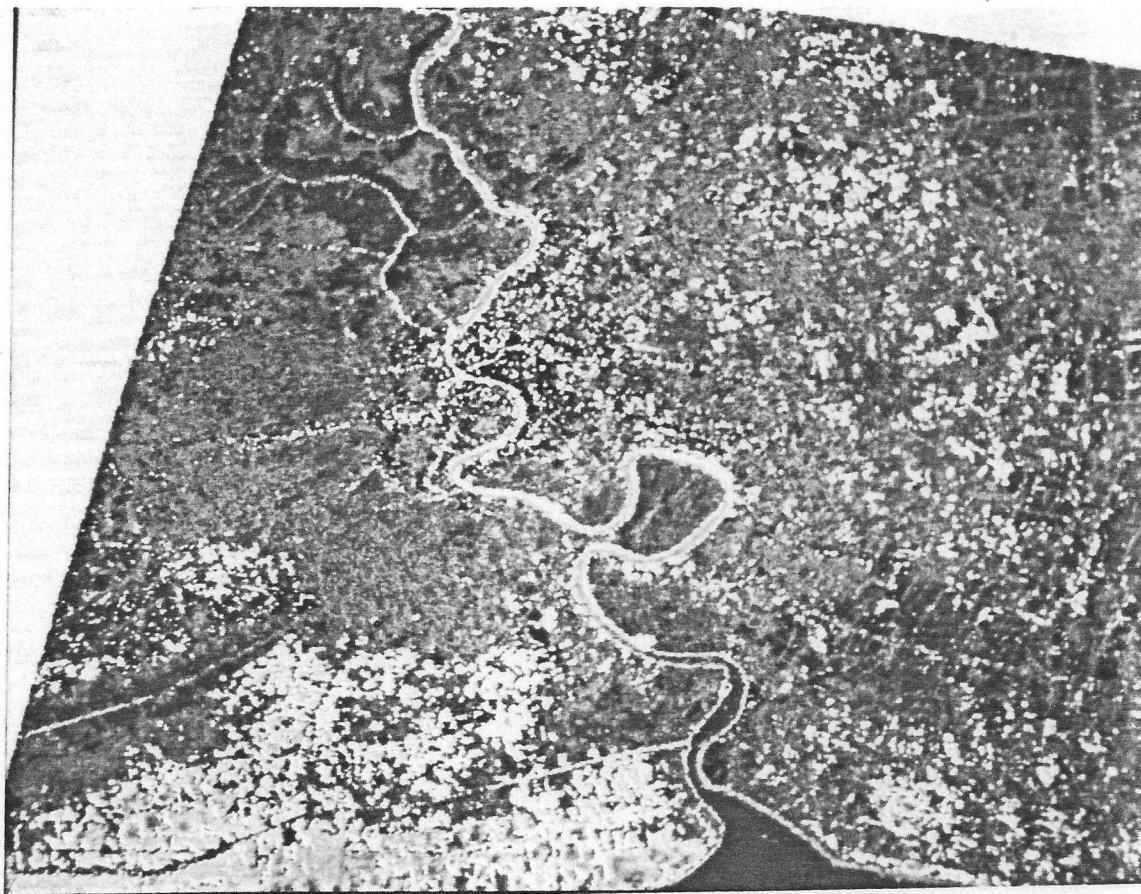


Figure 27. Final land use classification of horticultural area northwest of Bangkok; produced on electronic printer plotter. Scale 1:50,000.





Figure 28. Final land use classification of area along Chao Phraya River near Gulf of Siam; produced on electronic printer plotter. Scale 1:50,000.



Purple - Urban 1  
 Red - Urban 2  
 Yellow - Rice  
 Green - Orchard/Tree  
 Ivory - Denuded 1,2

Navy blue - Water 1  
 Blue - Water 2  
 Light blue - Water 3 and 4  
 Tan - Complex 1  
 Olive - Complex 2

Figure 29. Color coded classification of Bangkok, Thailand study area produced on LARS digital image display. Approximate scale 1:1,000,000.

and photographing the image through a series of color filters by multiple exposure of the color film. This product is very useful for general interpretive and illustrative purposes, but the distortion inherent in the system provides a product of unacceptable cartographic quality.

The second color coded classification was generated by Mead Technology with a laser film writer to produce a Chromalin print (Figure 30). The LARS classification results tape served as the source of data for the 14 color classes. A distinct advantage of this method is that it retains the geometric fidelity of the data tape, so that the final product is of cartographic quality.

A common method of presenting classification results is by the computer-driven line printer in alphanumeric format. Several examples of this product appear earlier in the thesis.

#### Comparison of Land Use Classification from Digital Analysis of Landsat Data and Land Use Classification System of Thailand

One of the deficiencies of this study was the limited amount of ground observation data of the study area available to the analyst. In the digital analysis of Landsat data of the Bangkok area it was obvious that far more spectral classes could be separated and mapped than could be related to land use features of interest.

The approach used in this study was to begin with a large number of spectrally separable clusters or classes



Red	- Urban 1	Navy blue	- Water 2
Maroon	- Urban 2	Blue	- Water 3
Beige	- Rice 1	Light blue	- Water 4
Yellow	- Rice 2	Ivory	- Complex
Green	- Orchard	Tan	- Tree

Figure 30. Color coded classification of a portion of the Bangkok, Thailand study area, image produced by Mead Technology from LARS classification tape. Approximate scale 1:50,000

and then to combine clusters on the basis of spectral similarity and limited knowledge of the area--general distribution of land use patterns, soils, locations, associations between certain features. From the original 70 cluster classes a final classification of 14 informational classes was derived. In general, these classes which were identifiable by spectral analysis compare well with many of the major classes included in the land use classification system of Thailand (Table 8).

Satellite data have been used successfully in many areas of the world to produce level 1 land use maps (Anderson, 1976). Many level 2 land use classes may also be delineated by digital analysis of Landsat data. In most instances the detail required for identifying levels 3 and 4 land use classes is not available in the present Landsat scanner data. Improved scanner systems in future earth observation satellites will greatly enhance the use of this technology for more detailed land use mapping.

Table 8. Comparison between land use classes separable by digital analysis of Landsat MSS data and some classes in the land use classification system of Thailand.

Spectrally Separable Classes	Land Use Classification of Thailand
1. Urban 1.1 Residential 1.2 Central city	1. Urban 1.1 Residential 1.1 Residential
2. Denuded 2.1 Denuded 1 2.2 Denuded 2	1. Urban 1.3 Institutional 1.3 Institutional
3. Agriculture 3.1 Horticulture 3.2 Rice 1 3.3 Rice 2	2. Agriculture 2.1 Horticulture 2.2 Perennial crop 2.4 Paddy fields 2.4 Paddy fields
4. Wood/Wetland	4. Forest 4.3 Mangrove
5. Complex 5.1 Complex 1 5.2 Complex 2	
6. Water 6.1 Water 1 6.2 Water 2 6.3 Water 3	6. Water 6.4 Water body 6.4 Water body 6.3 Fish pond 6.2 Shrimp pond 6.1 Salt pan 6.1 Salt pan
6.4 Water 4	5. Marsh and Swamp

## CHAPTER V - CONCLUSIONS AND RECOMMENDATIONS

### Conclusions

Digital analysis of Landsat-1 MSS data was used to identify and map six major land use classes and twelve subclasses in the Bangkok, Thailand area. Even with a limited amount of ground observation data it was possible to generate a high quality level 1 land use map at a scale of 1:25,000. The wide range of spectral properties of the different land use classes in the Bangkok area required the use of all four MSS bands in the analysis.

Although some of the level 1 land use classes have relatively high variance of reflectance, it was possible by digital analysis to separate 4 distinct classes of water, 4 distinct classes of vegetation, and 2 classes each of urban, denuded, complex 1 and complex 2. Had sufficiently detailed ground observation data been available, each of the 14 spectral classes could have been described in greater detail.

From this study it can be concluded that digital analysis of Landsat-1 MSS data can play a significant role in more detailed mapping and monitoring of land use in Thailand.

### Recommendations

The primary data for this study were obtained by the Landsat-1 MSS scanner on 6 January 1973. Available ground observation data were severely limiting. Land use classification results might be somewhat altered if Landsat data from a different date were used and if an adequate statistical sample of ground observation data were used. With these facts in mind, the following recommendations are presented:

1. Examine Landsat data from different dates to quantify the temporal changes in spectral characteristics of land use classes in Thailand.
2. Similar studies in the future should include a well planned ground observation component for more accurate selection of training sets and for adequate evaluation of classification results.
3. A methodology should be developed for identifying and mapping significant changes in land use. Sequential coverage by Landsat can be useful in performing this task.
4. The technology used in this study should be evaluated over a wide range of geographic areas in Thailand.
5. Further studies should be conducted to determine the best methods of supplementing Landsat data with up-to-date high altitude aerial photography.



6. Better techniques are needed for comparison of classification results and evaluation of their accuracy.

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Table A-1. Summary of spectral statistics for fourteen cluster classes in each of five training areas.

		Mean Relative Reflectance Values				Magnitude*	Vis/IR**
Symbol		Band 4	Band 5	Band 6	Band 7		
Training Site 1	.	46.26	45.02	42.44	17.34	151.07	1.5270
	.	29.61	21.26	46.00	24.14	121.02	0.7252
	/	35.94	30.95	39.57	18.41	124.87	1.1536
	J	29.85	23.10	38.97	19.63	111.54	0.9036
	L	38.49	34.58	32.19	13.10	118.37	1.6134
	S	30.00	23.41	34.24	16.66	104.30	1.0493
	3	33.26	28.01	32.17	14.42	107.86	1.3152
	Y	34.33	29.03	26.58	10.61	100.56	1.7036
	8	30.67	25.05	26.88	11.54	94.14	1.4504
	G	28.85	22.31	29.93	14.20	95.30	1.1593
	B	24.62	15.37	32.50	17.57	90.07	0.7988
	R	26.77	19.23	25.81	11.95	83.76	1.2183
	Q	30.55	25.06	22.40	8.72	86.73	1.7870
	M	30.30	24.92	14.25	2.81	72.27	3.2364
Training Site 2	.	31.88	29.53	36.53	17.66	115.59	1.1332
	.	30.07	27.00	32.23	15.69	104.99	1.1912
	/	27.97	22.81	31.16	15.60	97.55	1.0859
	J	28.04	22.20	35.75	18.20	104.19	0.9313
	L	26.64	19.21	32.61	17.13	95.59	0.9217
	S	25.08	15.69	33.92	18.86	93.55	0.7725
	3	25.73	16.71	37.09	19.82	99.35	0.7457
	Y	22.62	13.55	36.90	20.52	93.59	0.6299
	8	22.46	13.52	34.08	19.72	89.77	0.6688
	G	23.34	14.08	32.10	18.75	88.27	0.7359
B	25.00	16.39	30.57	16.40	88.35	0.8813	

Table A-1. (Continued)

		Mean Relative Reflectance Values				Magnitude*	Vis/IR**
Symbol		Band 4	Band 5	Band 6	Band 7		
Training	R	26.42	19.35	27.68	13.38	86.83	1.1143
Site 2	Q	29.02	23.10	24.36	9.71	86.18	1.5299
(Cont.)	M	31.09	26.12	14.30	2.61	74.13	3.3821
Training		45.93	44.14	47.12	20.05	157.23	1.3411
Site 3	.	28.47	19.76	47.17	24.67	120.06	0.6714
	/	33.70	28.01	42.79	20.61	125.11	0.9734
	J	38.50	33.93	40.10	17.80	130.33	1.2512
	L	29.89	22.79	41.97	21.48	116.14	0.8303
	S	26.87	17.89	41.75	21.98	108.49	0.7023
	3	27.72	20.72	37.70	19.19	105.32	0.8516
	Y	30.91	24.62	36.28	17.71	109.51	1.0285
	8	25.96	17.06	36.75	19.28	99.04	0.7678
	G	27.06	20.63	27.85	12.79	88.33	1.1733
	B	25.73	17.61	32.19	16.31	91.84	0.8935
	R	23.48	15.62	23.90	10.68	73.68	1.1309
	Q	34.33	29.21	31.95	13.85	109.35	1.3872
	M	28.89	22.01	18.86	5.93	75.69	2.0531
Training		34.24	31.57	36.78	17.01	119.60	1.2235
Site 4	.	31.82	28.41	31.88	14.57	106.69	1.2965
	/	28.57	22.75	32.07	15.50	98.88	1.0787
	J	30.55	25.48	36.74	17.68	110.46	1.0297
	L	26.65	17.66	35.46	18.32	98.10	0.8238
	S	24.74	14.09	42.99	23.46	105.29	0.5844
	3	24.17	13.96	38.92	21.54	98.59	0.6306
	Y	23.76	13.89	35.40	19.70	92.75	0.6833



Table A-1. (Continued)

		Mean Relative Reflectance Values				Magnitude*	Vis/IR**
Symbol		Band 4	Band 5	Band 6	Band 7		
Training Site 4 (Cont.)	8	26.70	19.42	29.57	14.69	90.38	1.0423
	G	24.33	15.05	31.11	16.51	87.00	0.8272
	B	29.25	24.86	28.08	12.66	94.85	1.3282
	R	27.42	21.51	24.92	10.88	84.73	1.3668
	Q	24.95	16.54	26.45	12.85	80.79	1.0555
	M	24.55	16.61	19.28	7.54	67.99	1.5344
Training Site 5	.	27.34	16.59	47.04	24.91	115.88	0.6105
	/	25.73	15.43	40.81	21.59	103.57	0.6596
	J	22.97	13.47	36.63	19.96	93.03	0.6440
	L	26.12	16.17	35.86	18.62	96.75	0.7762
	L	23.99	14.55	32.23	17.25	88.01	0.7789
	S	29.66	22.46	36.90	17.91	106.92	0.9511
	3	27.07	18.50	30.37	14.59	90.53	1.0135
	Y	40.32	36.55	40.27	17.09	134.23	1.3399
	8	27.19	19.21	25.72	11.19	83.31	1.2572
	G	32.78	27.49	30.55	13.07	103.89	1.3819
	B	29.02	21.88	21.85	7.70	80.45	1.7225
	R	31.09	24.22	18.33	5.04	78.67	2.3666
	Q	30.84	22.76	10.91	1.51	66.02	4.3155
	M	28.06	19.16	9.49	1.16	57.87	4.4337

\* Sum of relative reflectance for all four MSS bands.

\*\*Ratio between visible (Bands 4 and 5) and infrared (Bands 6 and 7) reflectance.

Table A-2. Summary of spectral statistics for fourteen classes from five training sites for final supervised classification of Bangkok, Thailand study area.

Class	Symbol	Mean Relative Reflectance Values				Magnitude*	Vis/IR**
		Band 4	Band 5	Band 6	Band 7		
Denuded 1		46.26	45.02	42.44	17.34	151.07	1.5270
Horticulture/Trees	T	23.43	14.36	35.01	19.81	92.61	0.6894
Complex 1	*	29.50	23.84	30.96	14.54	98.84	1.1722
Rice 1	R	25.94	16.78	38.00	20.07	100.79	0.7357
Urban 1	/	38.49	34.58	32.19	13.10	118.37	1.6134
Rice 2	J	27.84	20.66	33.82	16.96	99.28	0.9551
Complex 2	+	31.32	25.94	29.43	12.96	99.65	1.3507
Urban 2	=	32.68	27.29	24.75	9.78	94.50	1.7365
Water 2	0	30.53	25.27	14.26	2.75	72.82	3.2791
Water 4	X	28.27	21.32	22.09	8.21	79.89	1.6366
Denuded 2	"	45.93	44.14	47.12	20.05	157.23	1.3411
Water 3	M	30.51	23.63	18.47	5.27	77.88	2.2800
Woodland/Wetland	F	24.21	13.98	39.04	21.55	98.77	0.6302
Water 1	W	29.55	21.08	10.25	1.34	62.22	4.3661

\* Sum of relative reflectance for all four MSS bands.

\*\*Ratio between visible (Bands 4 and 5) and infrared (Bands 6 and 7) reflectance.

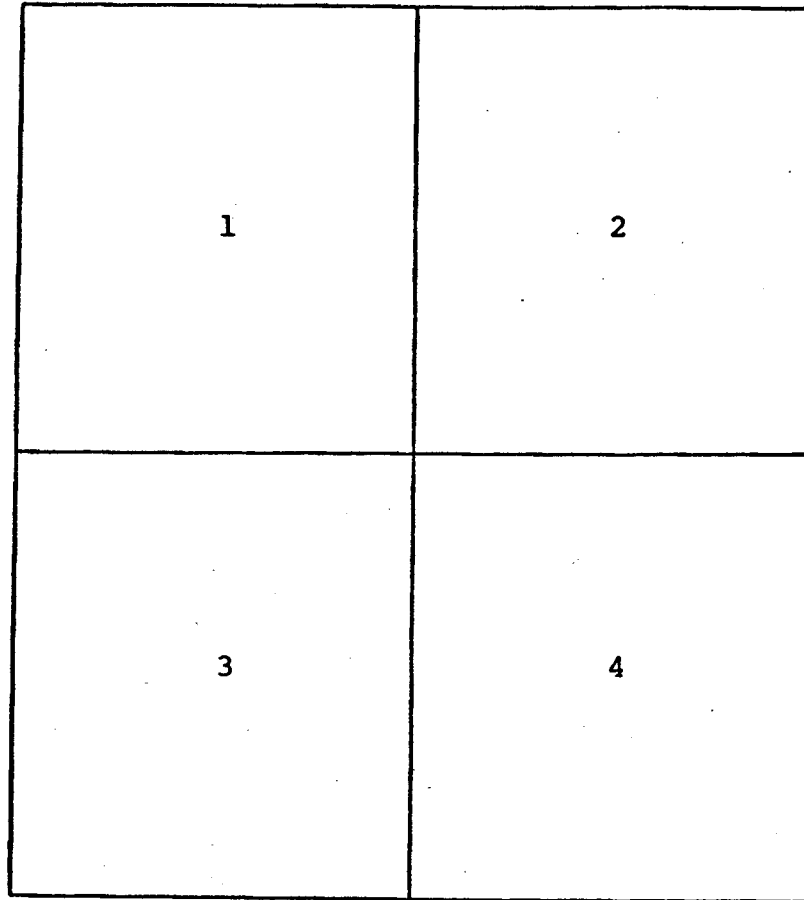


Figure B-1. Map sheet index for Figure B-2, B-3, B-4, B-5, and B-6.

































Training Site 4 Sheet 3

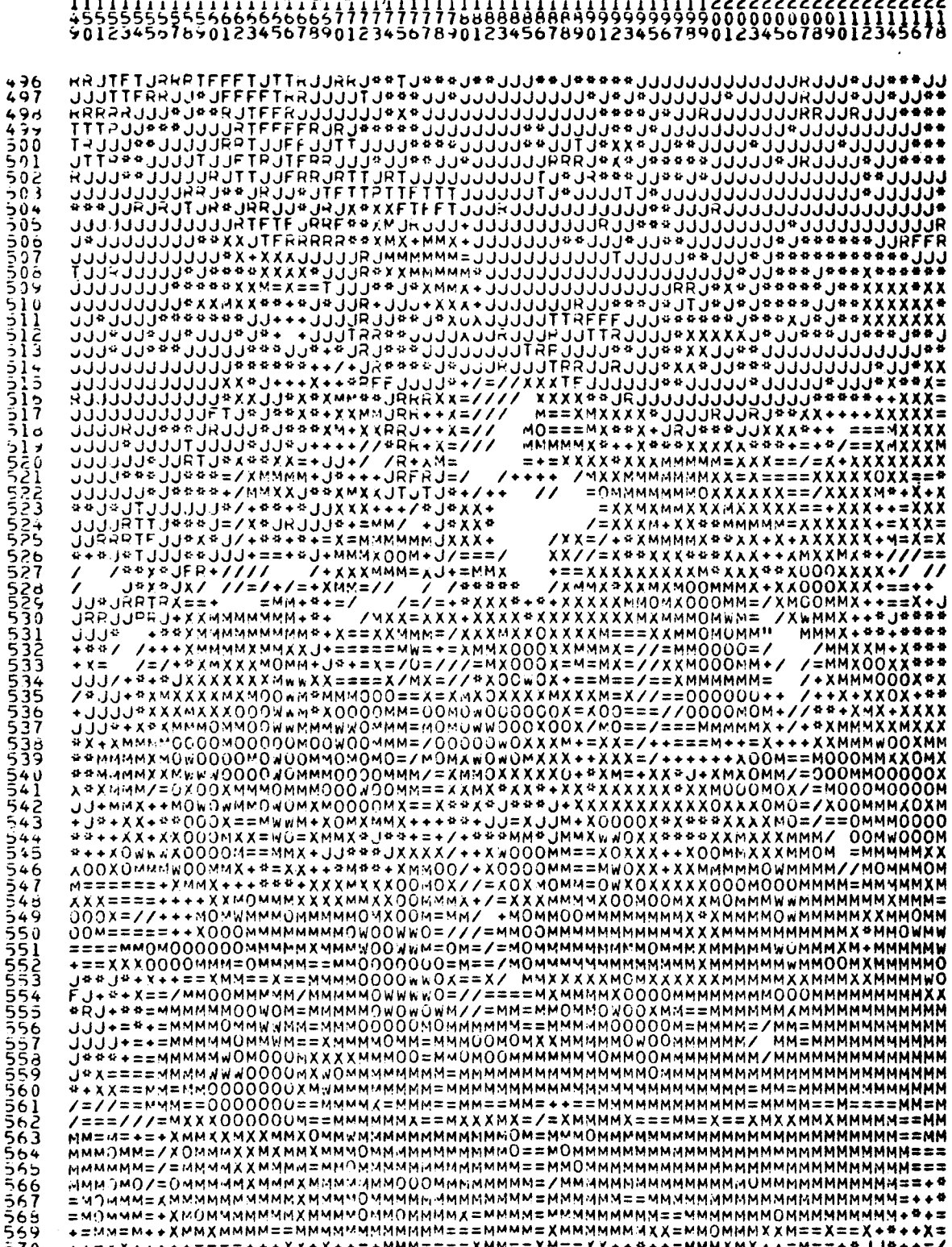


Figure B-5c. Fourteen land use classes in the marshland area along the coast southwest of Bangkok. Scale 1:40,000.









