C. 1

USING SPECTRAL REFLECTION AND MULTI-DYE LAYER PIXEL VALUES TO QUANTIFY SOIL PATTERNS FOR ASSESSING FIELD FERTILITY CONDITIONS

by

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ABSTRACT

The variability of soil chemical properties exerts a great influence on the practice of fertilization and other soil management. Quantitative reliable measurements of the soil variability are vital to the accuracy of fertilizer recommendations and the effective uses of fertilizer. The aim of the thesis is to determine whether soil classifications and variability assessments can be facilitated by the use of quantitative remote sensing techniques.

An agricultural field with very contrasting soils was selected for this study and field variability in total and organic C, exchangeable cations, CEC, major fertility elements N, P, and K, soil water content and coarse fragments was examined using three different sampling techniques and laboratory analysis.

The remote sensing techniques evaluated in this study were: 1) laboratory spectral reflection measurements of soil samples in the green, red and two near IR bands using a multi-channel radiometer, and 2) multi-dye layer pixel value analysis of digitized color aerial photos taken at the time of sampling.

Conventional, selective and stratified random sampling techniques were used to quantify the soils in the field and although the variability in K, Ca, and P was high no significant differences were obtained in the mean values among the three techniques. Three distinct soil types were

identified in the field, which included type I - very dark soils, type II - gravelly, very light colored soils, and type III - average brown or dominant soils. All three categories could be separated by Munsell value and chroma data. Significant differences in C, N, K, CEC, moisture content and coarse fragment content were obtained among the three soil types. Once the chemical data were translated into fertilizer requirements it became evident that soil type II (gravelly light colored soils) needed a higher K fertilizer rate than either type I or type III, thus suggesting that a differential fertilizer rate application within the field should be beneficial to crop performance.

Correlation and regression studies of soil parameters with spectral reflection and dye-layer pixel values revealed the nature of the relationships between soil spectral properties and physical and chemical conditions. Significant correlations were found between reflectance values and most of the chemical parameters, and between pixel values, soil chemistry and moisture content. In both cases, % organic C showed the highest correlation. The results from stepwise regression and discriminant analysis revealed that organic C, water content and color value were the most dominant soil parameters to influence spectral or pixel value variations. The relationship between water content and pixel value was significant suggesting that the variation in water content mignt be quantified by an analysis of dye-layer pixel values. Soil organic matter and soil color proved to be best predicted by laboratory reflectance measurements.

Multi-variate cluster and discriminant analysis revealed that the soil types could be quantified with both spectral and multi-dye layer pixel value analysis and that the remote sensing data were best related to organic matter, soil color and soil moisture content in the field. The pattern of soil types in the field was determined visually by planimetry and by quantitative dye-layer pixel value analysis. The two results were found to be in close agreement and provided quantitative values for the spatial extent of the three soil types. These values were used to determine the total amount of fertilizers required for the field and the quantified spatial pattern is an excellent medium to facilitate soil sampling for fertilizer assessment for future cultivation.

TABLE OF CONTENTS

LIST OF TABLES

LEAF x OMITTED IN PAGE NUMBERING.

FEUILLET x NON INCLUS DANS LA PAGINATION.

page x.

Table Page

LIST OF FIGURES

Figure Page

LIST OF ABBREVIATIONS

Symbol	Variable	Unit
MC	Soil moisture content	%
CF	Soil coarse fracton (> 2 mm)	%
pH	pH value in 1:1 soil:water solution	-
TC	Total carbon	%
OC	Organic carbon	%
CA	Exchangeable Ca	+cmol/kg
MG	Exchangeable Mg	+cmol/kg
K	Exchangeable K	+cmol/kg
NA	Exchangeable Na	+cmol/kg
CEC	Cation exchange capacty	+cmol/kg
P	Available phosphorus content	μg/g
N	Total nitrogen	%
V	Munsell color value	-
CH	Munsell color chroma	-
B4	Landsat 1-3 MSS Band 4 (0.5 - 0.6μm)	-
B5	Landsat 1-3 MSS Band 5 (0.6 - 0.7μm)	-
B6	Landsat 1-3 MSS Band 6 (0.7 - 0.8μm)	-
B7	Landsat 1-3 MSS Band 7 (0.8 - 1.1μm)	-
RED	Red filter pixel value(cyan dye-layer)	-
GREEN	Green filter pixel value(magenta dye-layer)	-
Ln(variable)	Natural log transformed variable	-

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Chapter I

INTRODUCTION

A. PROBLEMS AND AIMS

The spatial variability of soil chemical properties often leads to a serious problem in soil fertility management. Beckett and Webster (1971) in their review quote median coefficients of variation (CV) of 35 percent for organic matter and total N, and 60 percent for available K, P, Mg and Ca within topsoils of a given soil series. Furthermore, the results they consider show that much of the variability in a field or landscape as a whole is already present within a distance of a few meters. In many circumstances, fertilizer recommendation based on mean sample values is inadequate and knowledge of soil variability and its subsequent effects on the precision of predicting field fertility is needed.

The conventional study of soil variability requires the collection and analysis of a very large number of soil samples, chosen on a probability basis (Ball and Williams, 1968, 1971; Beckett and Webster, 1971). This work is laborious and tedious. Consequently information on soil variability is rarely included in the soil test/fertilizer recommendation programs, notwithstanding its importance. The difficulty is the lack of efficient methods to quantify soil variability. The traditional way of using standard deviations or coefficients of variation as a measure of variability gives the magnitude or degree of the variability of individual soil properties, but it cannot indicate the spatial trends of those properties nor provide a simple picture of changing soil patterns.

Multivariate techniques have been used to quantify soil variability. Bank (1984) used a cluster analysis to determine soil management units within fields in order to determine different fertilizer responses, and the classification results were fairly successful. However, the lack of contiguousness of unit members in some fields, and the need for more than one P and K recommendation within many of the cluster units reduced the possible practical uses of these units. Furthermore, to perform such analysis requires a large amount of work devoted to sample analysis, which is likely to discourage the frequent use of this approach.

Remote sensing has achieved increasing recognition as being able to make important contributions to the solution of many resource related problems. Remote sensing images are capable of providing a spectral picture showing the spatial distribution of earth surface features. With the aid of quantitative remote sensing techniques it is likely possible to quantify the spatial pattern of soils and to predict selective soil properties. So far, few quantitative investigations have been carried out to assess soil spatial variability with regard to fertility status. It is the aim of this thesis to examine soil variability and fertility conditions in an agricultural field, linking conventional methods with multi-variate remote sensing techniques.

The specific objectives are:

1. To determine soil variability and how it affects conventional soil fertility assessments in an agricultural field with a high degree of variability.
2. To divide the field into distinct soil units which have different fertilizer requirements.
3. To quantify the soil pattern from a digital analysis of the dye-layers from color aerial photographs.
4. To determine if spectral reflection measurements and multi-dye layer pixel values of soil samples can be used to differentiate soils with different fertility status.
5. To relate and compare the remote sensing data with data obtained from conventional analysis of soil samples, so as to determine the potential of predicting soil chemical properties from quantitative remote sensing techniques.

B. STUDY DESIGN

An agricultural field with a high degree of variability was chosen for this study. The soil variability was determined using conventional, stratified random, and selective soil sampling techniques. Simultaneously with the sampling a set of color aerial photographs was flown. The chemical and spectral properties of all the soil samples were then examined in the laboratory and related to the dye-layer pixel values from aerial photographs. An overview of the analysis procedure is provided in Figure 1.1.

C. SITE DESCRIPTION

The study site is a field of approximately 2.9 ha located near the Abbotsford Airport in the Lower Fraser Valley, British Columbia, immediately north of the Canada-United States border. The soils in this field were mapped as a pure unit belonging to the Abbotsford soil series (Luttmerding, 1980).

The Abbotsford soil has generally developed from 20 to 50 cm of medium-textured eolian deposits underlain by stratified gravelly glacial outwash. The surface and subsurface texture is mostly silt loam, varying sometimes to loam or fine sandy loam where the surface capping is thin. The underlying gravel and gravelly sand is usually stony and contains lenses of coarse and medium sands. In some places, tree uprooting and land clearing has mixed some gravels and stones into the surface soils, as in the case of the study site. The drainage classes are well to rapidly drained. Soil classification is Orthic Humo-ferric Podzol.

The reason for selecting this field as a test site is that very contrasting soils exist within the field as a result of unusual cultivation practices. The agricultural use in this area started in 1970, shortly after the land was cleared from forests in 1969. Land clearing left the soils on the site with a large number of distinct patches: light,

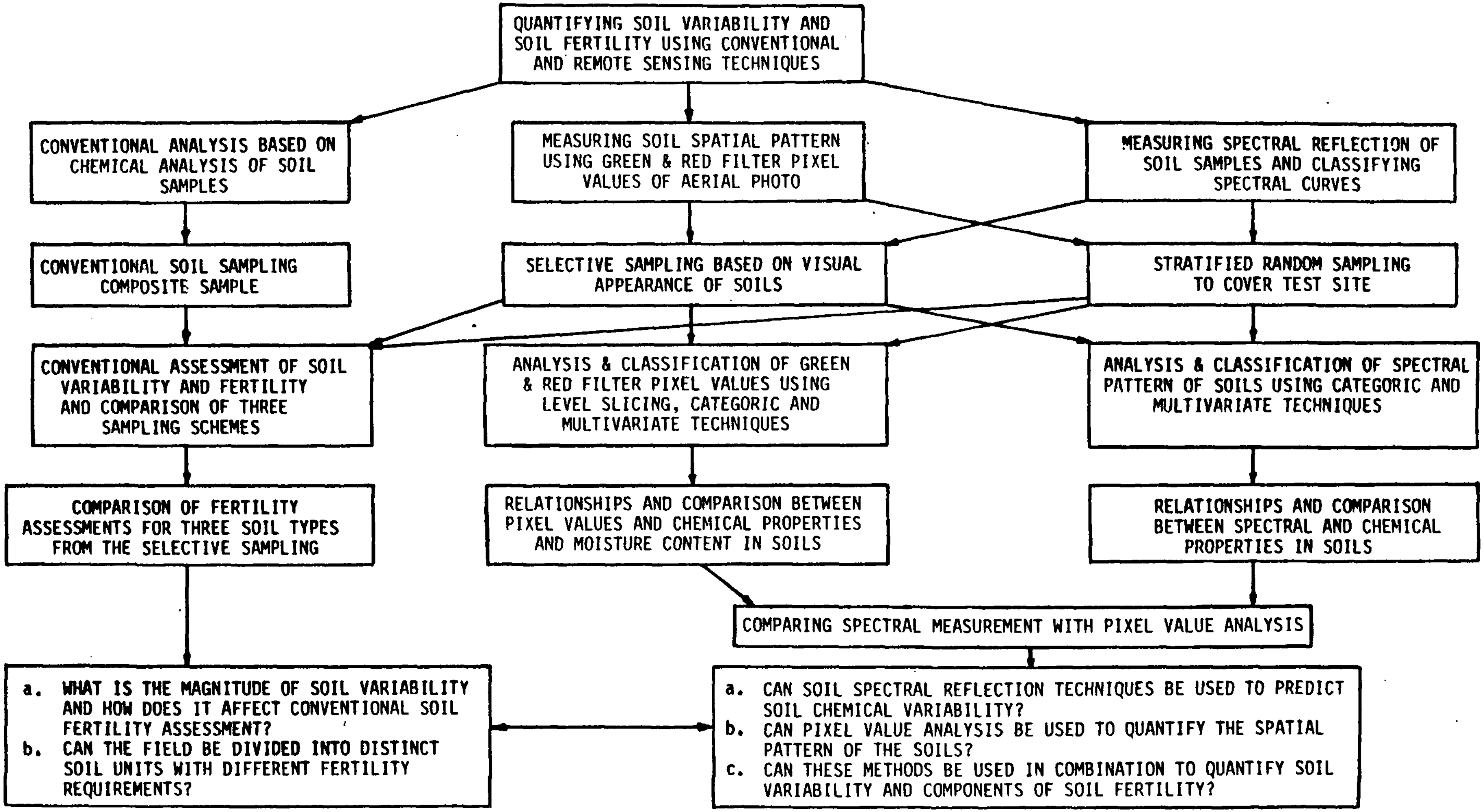


Figure 1.1 Study Design

gravelly areas showing the underlying coarse material exposed, dark surface soils having higher content of organic matter caused by burned tree residue, and average brown soils. These patterns remain clearly visible today although the contrasts have been marginally reduced through the cultivation.

The field had peas grown on it in the previous year, and was bare at the time of sampling. An aerial view of the study site is provided in plate 1.

PLATE 1. STUDY SITE.

Chapter II

LITERATURE REVIEW

A. THE DEVELOPMENT OF REMOTE SENSING

1. AERIAL PHOTOGRAPHY

Resource managers require rapid and accurate methods to acquire and interpret data for the development and management of our natural resources. Since 1929 when remotely sensed data in the form of black and white panchromatic aerial photographs were first used to prepare base maps for a soil survey in Indiana (Bushnell, 1951), aerial photographs have been conventionally used by soil scientists for soil-boundary detection, land form analyses and visual perception of tonal qualities associated with the spatial patterns of soils (Myers, 1983). Aerial photography has been shown capable of increasing both the speed and accuracy of soil mapping because of the wealth of ground detail shown, the availability in areas of difficult access, and the three-dimensional view of the soil landscape (Stoner and Baumgardner, 1980).

The multi-stage photographs were found suitable for different levels of detail in the preparation of large as well as small scale soil maps. Repetitive aerial images also proved useful in identifying and monitoring seasonal and long-term changes of soil parameters and patterns (Milfred and Kiefer, 1976). The development of color and color infrared aerial photography expanded the potentials of remote sensing for differentiating the boundaries among soil types, identifying soil drainage characteristics and slopes, and quantifying organic matter content (Parry et al., 1969). Near infrared film has the advantage that it allows people to see past the range of the eye perception into the infrared region of the spectrum.

2. MULTISPECTRAL SCANNER

Success in discerning objects with aerial photography prompted scientists to investigate more sophisticated remote sensing techniques involving digitized photographs, optical-mechanical scanners, and multi-images (Weismiller and Kaminsky,1978). The advent of instruments such as spectroradiometers and multispectral scanners(MSS) along with computer-assisted pattern recognition techniques for sorting and classifying quantitative multispectral data made it possible to extend the study of the spectral properties of soils beyond the visible portion of the spectrum and provided increased information for soil survey. The techniques for overlaying and analyzing of multi-date and multi-image data also became available in integrating existing surveys into an updated monitoring system.

Preliminary studies of soil mapping using airborne multispectral scanner data indicated that soil surface conditions, from dark to light soils, could be mapped with reasonable accuracy by computer techniques (Kristof, 1971).

Another investigation used similar multispectral scanner data to delineate and map surface soils containing different levels of soil organic matter (Kristof et. al., 1973). Other scientists studied the interrelationships among the spectral responses of soils and their physical and chemical properties with laboratory instruments (Obukhov and Orlov, 1964; Bowers and Hanks, 1965; Shields et al., 1968; Beck et al., 1976, Montgomery et al., 1974, 1976; Schreier, 1977, 1985; Stoner and Baumgardner, 1980; and Vinogradov, 1981).

3. LANDSAT IMAGERY

The launch of the Landsat-1 satellite in 1972 began a new era in the acquisition and availability of remotely sensed data (Baumgardner, 1982). The Landsat-1, -2 and -3 were equipped with the four-channel multispectral scanner (MSS) and the three-camera return beam vidicon (RBV). The MSS obtained spectral data in four bands (0.5 - 0.6 μm, 0.6 - 0.7 μm, 0.7 - 0.8 μm and 0.8 - 1.1 μm) in 18-day repetitive cycles and viewed a ground swath approximately 185 km wide, with a ground resolution for each pixel of about 79 by 79 m. These data were processed to provide images in the form of various photographic products as well as numerical format magnetic tapes for digital analysis. Landsat-4 and -5 were also launched in 1982 and 1984 respectively. In addition to the same four band MSS employed by the earlier Landsats, new equipment was added in the form of the advanced MSS called the thematic mapper (TM). This new sensor system operates over seven bands including two new bands in the mid-infrared region and one in the thermal infrared region, and has a ground resolution of 30 m by 30 m for all reflective bands (band 1 through 5 and 7). The improved spectral, spatial and radiometric resolution of TM compared to earlier sensors provides the opportunity to examine details that had previously been available only from aircraft-acquired data over small areas (Thompson and Henderson, 1984).

Certain unique characteristics of Landsat imagery were recognized as advantageous over aerial photographs in low intensity soil surveys for delineation of soil association boundaries (Westin and Frazee, 1976). The main characteristics are: 1) the synoptic view of almost 3.4 million ha on which the conditions of soils and vegetation were recorded at almost same moment and could be compared across the entire scene; 2) the near-orthographic character of the scenes, allowing for the construction of mosaics and the overlaying of ancillary maps with little distortion; 3) the multispectral capability, permitting establishment of unique signatures for vegetation and soil-related features, and 4) the temporal feature for the study of multispectral changes in the soil/vegetation complex with time. The application of Landsat data to soil investigation has progressed beyond the research stage to be used in extensive soil surveys, generally conducted at the reconnaissance level (Myers,1983).

Remote sensing as an aid in delineating soil differences for soil surveys and detecting special soil problems such as soil erosion and salinity will continue to develop with further improvements in sensors and data processing techniques and better understanding of the spectral properties of the soil and their relation to important physical, chemical and site characteristics.

B. REMOTE SENSING TECHNIQUES

Remote sensing is the acquisition of information about an object without physical contact (Colwell, 1983). Although many forms of remotely sensed information exist, photography, scanners and radar are considered as the major components in any earth resource remote sensing package. The remotely sensed data can be gathered from the ground, but most commonly from aircraft and satellite sources, and processed either manually or automatically by computer-assisted analyses.

Only those remote sensing techniques pertaining to this study are reviewed.

1. BASIC CONCEPTS

The detection, recording and analysis of interactions between the subject and electromagnetic radiation is the foundation of remote sensing. Most remote sensing techniques involve the use of different wavelengths of electromagnetic energy that are reflected or emitted from the sensed object as the means of measuring target characteristics. The electromagnetic spectrum is a continuum of electric and magnetic wavelengths which is subdivided into various bands or spectral regions, such as X-ray, ultraviolet, visible, infrared, and microwave.

The level of energy reflected or emitted from objects normally varies with frequency or wavelength throughout the electromagnetic spectrum. The spectral behavior, or 'signature' of the imaged object is characterized by the difference in the amount of energy incident upon and reflected from the object, along with the wavelength sensitivity of the sensor at the time the image is acquired (Estes, 1983). A unique signature of an object, therefore, can often be identified by selective recording of energy within particular wavelength band or bands. That is one of the most important features of multiband , multispectral remote sensing.

Typical spectral curves have been plotted for three basic types of earth features: green vegetation, bare soil, and water (Figure 2.1). The horizontal axis represents wavelengths in the visible and reflective infrared portions of the electromagnetic spectrum. The vertical axis represents the intensity of reflected energy or reflectance as measured by a spectroradiometer. These curves reveal that there are certain wavelengths that are much better than others for separating green vegetation, soil and water. However, spectral analysis becomes more difficult and

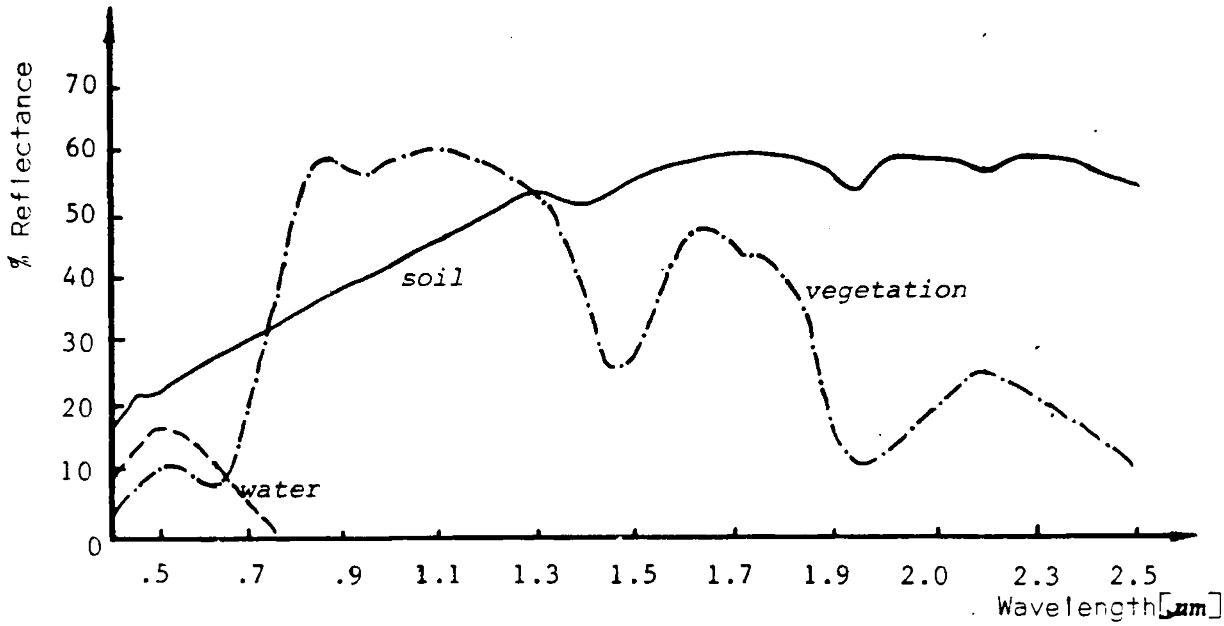


Figure 2.1 Typical spectral curves of green vegetation, bare soil, and water. (Adapted from Baumgardner, 1982)

sophisticated when the objective is to classify the ground scene into different subcategories of green vegetation, soil and water. Another use of spectral curves is to provide a comparison standard for identifying spectra of unknown features.

The spectral behaviors of materials derive from a series of complex internal and external interactions between energy-matter-environment. Laboratory studies of visible and infrared spectra of minerals, rocks and soils were initiated in the late 1960's (Hunt and Ross, 1967; Hunt and Salisbury, 1970, 1971; Hunt et al. 1971). They revealed that intrinsic spectral properties of materials were caused by a variety of electronic and vibrational processes. Electronic process is the electron transformation from one ion to another, absorbing or reflecting electromagnetic energy. This process normally produces broad band changes in visible wavelength. Vibrational process is the excitation of the fundamental mode of anions within the crystalline structure. This process often produces relatively sharp bands, more frequently in the infrared region. These two processes change reflectance spectra of materials in the form of bands and slopes, providing the basis for the measurement of the spectral properties of the mineral and soil constituents.

2. SPECTRORADIOMETRIC MEASUREMENT

Detection and recording of spectral responses of objects to radiant energy can be performed either photographically as in the case of aerial photography or electronically as in the cases using radiometers or scanners. One of the commonly used techniques for remotely sensed data acquisition in the laboratory and field is the spectroradiometric measurement of soil reflectance.

The spectroradiometric technique is to determine or measure the spectral properties of objects in terms of total reflectance or reflectance factor (Stoner and Baumgardner, 1980), or coefficient of spectral radiance (Vinogradov, 1981). A reflectance factor is defined as the ratio of the radiant flux actually reflected by a sample surface to that reflected by an ideal, perfectly reflecting, perfectly diffusing standard surface, irradiated in exactly the same way as the sample (Robinson and Biehl, 1979). The measured reflectance value, often expressed in percentage, of a target surface for a given wavelength will depend on the geometry of the arrangement of radiation source, surface and detector; the polarization of the irradiance; and the spectral distribution of the irradiance at the surface (Colwell, 1983) Since the directional characteristics of the reflection process are crucial to remote sensing studies, a method of measuring the bidirectional reflectance factor (BRF) has been devolped in the Laboratory for Applications of Remote Sensing at Purdue University and become a standard procedure in the study of soil spectral properties (Stoner and Baumgardner, 1980).

For small fields of view (less than 20 solid angle) the term bidirectional reflectance factor has been used to describe the measurement: one direction being associated with the viewing angle and the other direction being the solar zenith and azimuth angles. (Robinson and Biehl, 1979). A BRF reflectometer developed as an accessory to a field spectroradiometer permits the measurement of variable incident irradiance of a horizontally placed soil surface. In this manner, specially prepared soil samples can be irradiated and viewed from above, thus simulating the remote sensing situation as closely as possible. Quantitative measurements of soil reflectance using this instrument setup have been successful in relating BRF to important soil properties (Beck et al., 1976; Montgomery and Baumgardner, 1974; Montgomery et al., 1976; Stoner and Baumgardner, 1980; Latz et al., 1981)

The technical basis for BRF measurements allows for direct comparison of field-collected data with laboratory-collected data when a standard calibration procedure is closely followed (Stoner and Baumgardner, 1980). Field and laboratory calibration procedures consist of a comparison of the response of the instrument viewing the subject to the response of the instrument viewing a level reference surface, often barium sulfate. Experimental results verified the validity of comparing laboratory-measured soil spectra under controlled moisture equilibria to field-measured soil spectral response of bare moist soils from Indiana (Stoner et al.,1980).

In addition to laboratory measurements of soil spectral properties, similar spectroradiometric techniques have been extended to obtain the multispectral data of soils and vegetation canopy in the field (Gausman et al., 1975, 1977; Stoner et al., 1980), from the air (Schreier, 1977; Kondratyev and Fedchenko, 1982; Kondratyev et al., 1983; Huete et al., 1984, 1985) and used to simulate and compare to Landsat digital data (Cipra et al., 1980; Thompson et al., 1983). Results showed that the laboratory and field measurements of soil reflectance could be used as reliable ground references or calibration basis for the characterization of soils from air- and space-borne multispectral measurements (May and Peterson, 1975; Cipra et al., 1980).

3. DIGITAL ANALYSIS OF AERIAL PHOTOGRAPHIC DENSITY

Before the mid 60's, most remote sensing specialists used aerial photographs from multispectral cameras and manual photointerpretation with some simple classical instruments such as stereoscopes to recognize scene features and extract required information. A black-and-white photographic print is an image containing a continuum of shades of gray. The photographic density at any point in the image is a measure of the integrated brightness or relative reflectance, in the visible and/or infrared band of wavelengths, of the corresponding area in the referent world scene (Kelley, 1983). The image is, therefore, an analog model of the scene, in which relevant world brightness is modelled as shades of visual gray in the image. These analog models contain the wealth of information that can be extracted by skilled interpreters. They can be manipulated photographically to isolate areas of similar gray levels or to enhance the zones where photographic density changes rapidly. With the development of digital computer and analysis techniques during the past two decades, computer-assisted image analysis has now become possible, providing the capability to store, retrieve, analyze and interpret vast quantities of multispectral images from aircraft and satellites.

Any image may be thought of as consisting of tiny equal areas called picture elements or pixels arranged in regular lines and columns. The brightness of each pixel has a numerical value ranging from zero for black to some higher number for white. An image may be recorded originally in digital format, as in the case of Landsat MSS, with numerical terms on a three-coordinate system with X and Y locating each pixel and Z giving the pixel brightness value. An analog image recorded initially on photographic film may be converted into numerical format by a process known as digitization. High-speed scanning microdensitometers are available for this task and capable of digitizing image pixels as small as 50 μm by 50 μm square. An ordinary 35mm slide digitized to this resolution would contain approximately 323,000 pixels in a pixel matrix.

A multiband image may be digitized into several pixel matrices, each containing relative reflectance or brightness values for a different band of the spectrum. Thus, a normal color aerial photograph can be converted into at least three pixel matrices according to its brightness values of three dye-layers: yellow, magenta and cyan, and one matrix results from the digitization or scanning with one of the three fitlters: blue, green and red. Resulting pixel matrix data are usually recorded on computer-compatible tapes and may be read into a computer for various processing operations.

One of the simplest methods of digital analysis is called density slicing which only deals with one pixel matrix or single-channel data. Density slicing broadly refers to a process that converts the continuous gray tone of an image into a series of density intervals, each corresponding to a specified digital range (Sabins, 1978). Each digital slice may be displayed in a separate color, as line printer symbols or bounded by contour lines. This technique is used to identify where, within the scene, the area of interest is located. It can also be employed as a simple classification procedure to separate the features with different spectral responses. Some features, such as water, can be isolated successfully by density slicing. Many features are not nearly so homogeneous. Variations in time, growing season, spatial location, and other factors occur. Thus single-channel density slicing as a classification logic is likely to be less dependable than the multichannel methodology (Kelley,1983).

4. COMPUTER-ASSISTED PATTERN RECOGNITION TECHNIQUES

The analysis of multichannel remote sensing images can be accomplished by computer-implemented pattern recognition techniques. One of the most important applications of these techniques is to group data points (pixels) with similar spectral characteristics into spectral classes representing different objects or features. The multispectral classification by pattern recognition techniques not only examine the relationships between the brightness or reflectance value for a given pixel and its spatial neighbors in a given band but also compare that value with its spectral neighbors, that is, the pixel values at the same spatially registered location in the pixel matrices of all other bands.

The basis of multispectral classification is illustructed in Figure 2.2 using the same data for plotting the spectral curves in Figure 2.1. The reflectance values for each landscape feature (vegetation, soil, water) at three different wavelengths, represented by λ_1, λ_2, and λ_3, were plotted in three-dimensional space. Spectral separation between the classes is obvious. During the classification, the computer retrieves the three values for each pixel and determines the position of this data point in the classification space and, finally, assigns each of the data points to one of the resulting categories according to appropriate algorithms developed for analysis of multispectral data. Although human experience is limited to only three-dimensional perception, the computer can operate in n-dimensional space and examine vast quantities of multispectral data such as Landsat MSS and TM data.

Pattern recognition techniques generally follow one of two approaches. One approach, clustering or non-supervised classification, uses a mathematical algorithm to direct the computer to examine the spectral data for the area of interest and to assign each pixel to a cluster of pixels having similar spectral characteristics. The number of cluster classes to be spectrally separated generally is set

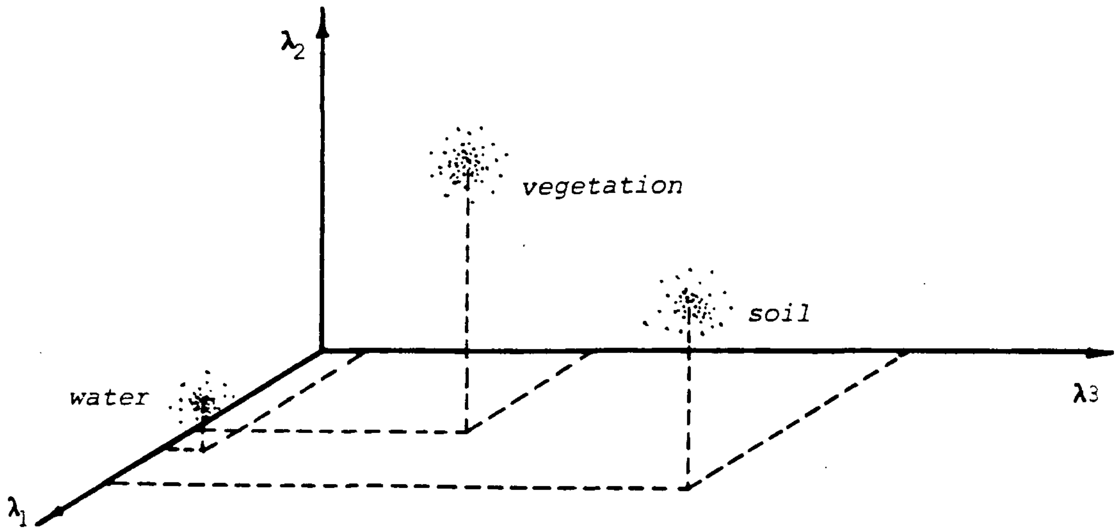


Figure 2.2 Spectral separation of green vegetation, bare soil, and water in three-dimentional space. (Adapted from Baumgardner, 1982)

arbitrarily by the analyst and may or may not be determined by the analyst's prior knowledge of the area being analyzed.

In the another approach, supervised classification, the analyst provides the computer with a spectral definition in the form of a set of training samples of known identity from specific addresses within the multispectral data. The quality of the resulting supervised classification depends on the spectral separability of the desired classes with existing spectral data and on the degree to which the training samples selected by the analyst represent the features to be classified (Baumgardner, 1982).

The multispectral analysis by computer-assisted pattern recognition techniques was initiated in the early 1970's by a group of scientists at Purdue University (Al-Abbas et al., 1972; Baumgardner et al., 1970; Kristof, 1971; Kristof and Zachary, 1974; Kristof et al., 1973, 1975). Using airborne multispectral scanning data, the spectral maps were produced and related to important soil properties and conditions such as the levels of organic matter content, drainage classes, parent materials, as well as soil types. Such investigations were further extended by using Landsat MSS and TM (Weismiller et al., 1977; Kirschner et al., 1978; Thompson et al., 1981, 1983) and other satellite data (Kondratyev and Fedchenko, 1980), along with certain ancillary data such as aerial photographs or digitized topography data.

C. RELATING REMOTE SENSING DATA TO SOIL PARAMETERS

1. SOIL COLOR

Soils types can often be distinguished from one another by their photographic tones and color characteristics. The color is the electromagnetic radiation derived from the properties of the soil materials which can be sensed by human eye. The color imparted to a soil may be due to specific absorption in the visible region or may be caused by intense absorptions in either or both the ultraviolet and near infrared, the shoulders of which may extend forward or back into the visible region (Stoner and Baumgardner, 1980)

Surface soil colors that differ from one another or those of parent materials are usually used to indicate the processes involved in soil formation and may also be indicative of other factors such as excessive soluble salts or erosion. The most important factors influencing soil color are mineralogy and chemical constituents, soil moisture, soil structure, particle size and organic matter. Da Costa (1979) quantified several important relationships for a number of soils from a broad climatic area when he published regression equations relating clay content, organic carbon, soil moisture retained at 15 bars and CEC with soil color measured as both Munsell notation and soil reflectance.

The quantitative relationship between soil properties and soil color exposes the possibility of using remote sensing techniques to quantify soil properties. Obukhov and Orlov (1964) found that all of the soils that they investigated had spectral reflectance characteristics related to soil color. Minimum reflectance occurred in the blue-violet portion of the spectrum and ranged from 13% for the A horizon of thick Chernozem to 18% for the same horizon of Sod-Podzolic soils. Maximum reflectance was in the red region where the reflection coefficient of the same samples increased from 15 to 44 percent. They concluded that the visible red region and the near infrared region are the most favorable for a qualitative and quantitative decription of soil. Shields et al. (1968) converted spectrophotometric measurements of soils at different moisture contents to Munsell notations in order to relate soil color to organic matter. The color value was most highly correlated to organic matter content. Page (1974) also related reflectance measurements from a color-difference meter to organic matter in Atlantic coastal plain soils. Within the 0 - 5% range, reflectance measurements provided a reliable estimate of organic matter in soils at a considerably faster and cheaper rate than traditional methods. In all those studies, spectroradiometric measurements were proved useful in providing a basis for establishment of quantitative relationship between soil color and soil characteristics.

2. ORGANIC MATTER

Organic matter in soils, consisting of decomposed residues and its constituents, has a profound influence on soil color. The dark color of surface soils is often associated with high organic matter content. This suggests that soil organic matter content is inversely related to the spectral reflectance.

It is generally concluded that organic matter is the single most important variable in the visible and near infrared bands for explaining reflectance. Baumgardner et al. (1970) found that soils containing more than 2% organic matter content appeared to mask out the contributions of other soil parameters, whereas soils with less than 2% organic matter were harder to separate spectrally due to iron or manganese interference. Stoner and Baumgardner (1980) observed that when mineral soils were grouped into three levels of organic matter content (0-3%, 3-5% and 5-10%), the reflectance curves, which decreased with increasing organic matter content throughout the 0.52 to 2.32 μm wavelength region, behaved differently. Soils in the 5-10% organic matter range showed the concave-shaped curves while soils in the 0-3% and 3-5% range followed the convex-shaped curves. These two types of spectral curve also corresponed respectively to the Type 1 and Type 2 of soil reflectance curves recognized by Condit (1970), which represented the high surface organic content Mollisols and low surface organic content Alfisols.

Many studies concluded that reflectance in wavelengths from 0.5 μm to 1.2 μm were the best for separating organic matter levels in soils (Mathew et al., 1973b; Beck et al., 1976; Montgomery et al., 1976; Stoner and Baumgardner,1980; Vinogradov,1981). Krishnan et al. (1980) reported that reflectance measurements from the visible region were more closely correlated to the organic matter content of the soil than the measurements from the infrared region. Regression studies indicated that organic matter content could be related to soil reflectance by a curvilinear exponential function (Schreier, 1977). Vinogradov (1981) supported the finding by publishing a general equation which describes the exponential relationship between humus content and reflection in the orange-red part of the spectrum(0.6 -

0.7 μm). The equation could be used to explain many data reported by previous investigators.

The quantitative relationship between organic matter content and soil reflectance from Landsat bands was investigated by Da Costa (1979). He found that organic carbon was negatively correlated with Landsat MSS bands 4, 5 and 6. However, correlation coefficients higher than 0.50 were concentrated within the 0.5 to 0.74 μm range and the correlation decreased from band 4 to band 6. This study supports previous findings that the best correlation corresponds to the visible and a small part of the reflected infrared region of the spectrum. Although total nitrogen was not correlated with spectral reflectance, C/N ratio relationships were negatively correlated up to 1.89 μm of the spectrum in his studies.

3. IRON OXIDE AND CLAY MINERALS

Iron oxide is another major 'pigment' influencing soil color and reflectance. Of the cations, iron is the most common source of electronic processes which change the reflectance characteristics of soil minerals (Hunt et al., 1971b). The ferric iron response bands are at approximately 0.4, 0.7 and 0.87 μm, and the ferrous ion response bands are at 0.43, 0.45, 0.51, 0.55 and 1.0 μm. Stoner and Baumgardner (1980) described the iron absorption bands either as well resolved dips in the reflectance curve or as broad features centered on specific wavelengths but extending their influence over a wide range of wavelengths.

In general, an increase in iron oxide content can cause a decrease in visible reflectance of soils. Obukhov and Orlov (1964) demonstrated that soils with an elevated content of iron could be easily distinguished by the reflection characteristics for pure Fe_2O_3. The intensity of the reflection in the region from 0.5 to .64 μm is inversely proportional to the iron content. Mathews et al. (1973b) reported that high free iron oxide content reduced reflectance intensity in the 0.5 to 1.2 μm region. Stoner and Baumgardner (1980) reported high iron content Oxisols decreased in reflectance with increasing wavelength because of strong absorption features in the infrared region. Absorption bands of ferric iron at 0.7 and 0.9 μm impart spectral reflectance curve forms to soils with moderate to high amounts of free iron oxides. Ferrous iron absorption as well as hydroxyl absorption, both centered at 1.0 μm, can also be seen to influence the shape of soil reflectance curves.

Most correlations between iron oxide content and spectral reflectance remained low. However, Montgomery et al. (1976) indicated that the presence of organic matter might not diminish the contribution of iron to soil reflectance. In carbon free samples originating from mine tailings, Schreier and Lavkulich (1980) and Schreier (1985) found good correlations between reflection and total iron content but the introduction of organic matter to the soils tends to obscure this general relationship. Stoner and Baumgardner (1980) reported that the correlation could be much improved when samples were separated into the specific climatic zones where the soils were developed.

In a summary of the spectral features of some common minerals in the visible and near-infrared portions of the electromagnetic spectrum, Da Costa (1979) revealed that several minerals, including quartz and feldspar, were spectrally featureless. Others such as kaolinite, gibbsite, and muscovite, exhibit spectral response due to hydroxyl effects. Oxides and hydroxides of iron, aluminum, and titanium are important for soils in general.

4. PARTICLE SIZE AND SOIL TEXTURE

Soil particle size and soil aggregates influence reflectance and thermal diffusivity of soils and, indirectly, soil moisture and other measurements. It is generally concluded that increasing particle diameter results in a decrease of reflectivity. Bowers and Hanks (1965) measured reflectance of pure kaolinite in size fractions from 0.022 to 2.68 mm diameter (coarse silt to very coarse particle size classes) and found a rapid exponential increase in reflectance at all wavelengths between 0.4 and 1.0 μm with decreasing particle size. The most notable increases in reflectance occurred at sizes less than 0.4 mm diameter.

Similar results were obtained by Obukhov and Orlov (1964). They found that the change in reflectivity was associated only with the diameter and shape of the aggregates and not with their chemical or mineralogical composition. The fractions less than 0.25 mm in diameter have maximum reflectivity, while fractions from 5 to 10 mm diameter have the minimum. Orlov (1966) demonstrated that the artificial breakdown of aggregates usually led to an increase in the reflection coefficients caused by the character of mutual position of aggregates. Fine particles fill the volume more completely, thus providing a more even surface. Coarse aggregates, having irregular shapes, form a very complex surface with a large number of interaggregate spaces.

The conclusion that reflection increases with decreasing particle diameter is true only for the laboratory case of dispersed soils. Stoner and Baumgardner (1980) observed that decreasing the particle size among sand-textured soils increased soil reflectance, possibly due to forming a smoother surface with fewer voids to trap incoming light. The inverse response appears for medium to fine textured soils, possibly because increased moisture content and organic matter content associated with higher clay content lead to lower reflectance.

Variations in soil reflectance are known to be affected by soil texture, the relative porportion of sand, silt and clay in the soil. The reflectances from varying mixtures of clay and sand were measured by Gerbermann and Neher (1979) at five wavelengths. Soil samples with low sand levels (10-30%) had the lowest reflectance while pure sand had the highest reflectance. As the sand level increased from 0 to 100%, percent reflectance increased in the 0.4 to 0.8 μm region, while the percent reflectance for a particular level of sand increased as wavelength increased. Any one of the five wavelengths could be used for discriminating among sand levels in a clay soil.

Soil clays occur in intimate combination with other soil constituents. Mixed clay mineralogies are common in most soils. Montgomery et al. (1976) analyzed separately a group of soils rich in montmorillonite and noted little difference between correlations of reflectance and soil properties for this group and for soils as a whole. The contribution of the clay fraction to soil reflectance may be more important than that of clay types. Al-Abbas et al. (1972) stated that decreasing the clay content of soils increased the spectral response, but found no clearly defined relationship between clay content and relative reflectance, hypothesizing that the relationship may be secondary due to the high correlation between organic matter and clay content. The contribution of surface soil texture to soil reflectance is difficult to separate from other soil parameters such as organic matter and oxides which coat soil particles to varying degree. However, multispectral analysis and pattern recognition techniques may be used to delineate and map gross textural differences in surface soils (Myers, 1983).

Cation exchange capacity (CEC) is frequently to have a high negative correlation with reflectance, especially in the middle-infrared region (Montgomery et al., 1976; Stoner and Baumgardner, 1980). Although there is not a direct physical basis for this relationship, it seems that CEC is acting as a natural integrating factor for clay type and content as well as organic matter content which exhibit inherent spectral behavior.

5. MOISTURE CONTENT

Most soils appear darker when wet than when dry and the decrease in reflectance with increasing moisture is apparent throughout the reflective wavelengths (Bauer et al., 1981). The effect of moisture on soil reflectance is due to the internal total reflection within the thin water film covering soil particles. A portion of the energy reflected from the soil surface would not be reflected to space but would be re-reflected between the surface of the particle and the surface of the water layer (Stoner and Baumgardner, 1980).

The absolute magnitude of reflectance changes with soil water content and varies considerably because of differences associated with other soil parameters and site characteristics. Bower and Hanks (1965) demonstrated a potential for measuring surface moisture content by the reflectance methods and noted a lowering in reflectance for Newtonia silt loam at six increasing soil moisture contents over the wavelength range of 0.5 to 2.5 μm. The amplitude and shape of soil reflectance curve is affected by the presence of strong water absorption bands at 1.45 and 1.94 μm. The band at 1.94 μm is the most sensitive to water, and has been found best for relating reflectance measurements to soil moisture content. Unfortunately, this band is also a region of strong atmospheric water absorption, which makes it impractical to measure soil moisture in the field by reflectance method.

Another absorption band at 2.2 μm was identified as a vibrational mode of the hydroxyl ion (Hunt and Salisbury, 1970). They found that absorption due to the hydroxyl ion also gave rise to 1.45 μm band, the same as that of liquid water. The appearance of the 1.45 μm band without the 1.95 μm band in the reflectance curve indicates that hydroxyl groups and not free water are present in the material. Sharp bands at 1.45 and 1.95 μm indicate that water molecules are located in well defined ordered sites while broad bands at these wavelengths indicate that they are relatively unordered, as is often the case in naturally occurring soils.

Idso et al. (1975) measured bare soil albedo (0.3 to 2.5 μm) and water content for a smooth Avondale loam at various depth intervals from 0 to 10 cm. A linear relationship with soil moisture was found over the range of

0 to 0.18 cm/cm in the 0 to 0.2 cm layer. They also found similar relationships for deeper layers apparently due to the close correlation between soil moisture at the surface and at deeper layers. Reflectance measurements in the field and from the air- or space-craft seem to be only sensing the moisture content in a layer of 5 to 10 cm thick at the surface. This limitation implies that remote sensing approaches may not be able to directly satisfy the application which requires knowledge of the moisture condition in the root zone of the soil. Meyer (1983) cited that Moore et al. correlated Skylab S-192 multispectral scanner measurements at six wavelength range from 0.56 to 2.35 μm with soil moisture content of three different layers (0 to 2, 2 to 14, and 10 to 30 cm) for 13 fields. The most highly significant correlation was obtained for the 2.10 to 2.35 μm band and for a depth of 0 to 2 cm. Wavelengths greater than 2.10 μm were required to reliably separate wet and dry bare surfaces. From a laboratory study with controlled moisture tensions, Stoner and Baumgardner (1980) also found a negative correlation existed between reflectance and moisture percentage by weight of 481 soils in the 2.08 to 2.32 μm wavelength band.

D. SPECTRAL CHARACTERIZATION OF SURFACE SOILS

1. <u>SOIL SPECTRAL CHARACTERISTIC CURVES</u>

Soil spectral curve, representing an overall reflected radiation of soils as a function of the visible and infrared regions of the spectrum, can be used to identify some soil features and differentiate among soil groups.

Classification of soils with respect to their curve shape has been done successfully by Condit (1970). Spectral reflectance values extending from 0.32 to 1.00 μm wavelengths were obtained for 100 soil samples collected from 36 states. Measurements were made of both wet and dry samples, which varied widely in color and reflectance. Procedures were established for classifying the soil spectra into three general types with distinct curve shapes. As a result of a characteristic vector analysis of the spectral reflectance data it was concluded that reflectance of a wide variety of soils for all wavelengths could be predicted with sufficient accuracy from measurements at five wavelengths 0.45, 0.54, 0.64, 0.74 and 0.86 μm. However, Condit's study did not relate these general soil spectral curve types to soil characteristics or classification. Cipra et al. (1971), based on field spectroradiometric studies, showed the properties and classification of seven soil series in terms of Condit's spectral curve types.

A comprehensive study of the reflectance properties of soils conducted by Stoner and Baumgardner (1980), using a spectroradiometer in the laboratory, measured the spectral reflectance of 485 surface soil samples from the U.S. and

Brazil. Five distinct soil spectral reflectance curve types were identified according to curve shape and the presence or absence of absorption bands. These curve types were distinguished as having in common certain differentiating characteristics pertaining mainly to the organic matter and iron oxide content of the soils. Drainage characteristics were also taken into account. The first three curves were similar to those described by Condit (1970), which dominated the soils (Stoner and Baumgardner, 1981a).

Soil parameters which influence spectral reflectance curve were summarized by Stoner and Baumgardner (1980, 1981a). Based on a statistical discriminant analysis, Thompson et al. (1983) noted that Stoner's five curve types for different soils represent genetically homogeneous soil properties and are generally separable within simulated Landsat greenness and brightness vector space.

2. FIELD CHARACTERISTICS OF SOIL SPECTRA

Field spectra of soils measured by either ground-based spectroradiometer or airborne or spaceborne sensors may differ substantially from spectra measured under laboratory conditions due to the differences of the environmental and radiation factors experienced in two situations. Aside from the atmospheric conditions and solar radiation change itself, soil surface conditions such as green vegetative cover, nonsoil residue, and surface soil structure and other factors all have a substantial influence on reflectance spectra of surface soils.

Spectral composition of the reflected radiation from green vegetation is strikingly different from that from bare soils. Much work relating to soil-vegetation interactions on reflectance of the earth canopy has been done recently though the effort is often devoted to the effect of soil background on vegetation discriminations. Hoffer and Johannsen (1969) indicated that density, morphology, and condition of the geometrical arrangement of leaves in a plant canopy were the factors which determined the extent to which green vegetative cover affected the reflectance from surface soils.

Although dense vegetative cover of crops or natural plants may mask soils themselves, inherent fertility, drainage pattern, and moisture holding capacity differences among soils tend to influence the vegetation growth on these soils. Thus although the soil itself eventually is masked by plant canopies, different soil features may still be identified to some degree by means of the canopy variation in phenological and morphological characteristics (Westin and Lemme, 1978). Even at the point of maximum canopy devolopment, soil patterns have been observed in aircraft MSS data of crop land (Kristof and Baumgardner, 1975).

Dead or diseased leaves behave differently in the near infrared wavelength region in comparison with live, healthy leaves. Field spectroradiometeric investigations showed that sugarcane crop residue littered on the soil surface had higher reflectance than bare soils, but that standing crop residue had lower reflectance than bare soils (Gausman et al., 1975). Residue-covered soils for a variety of crops and grasses were best discriminated from bare soils with Landsat reflectance measurements from 0.5 to 0.6 μm. Further work with wheat straw suggested that the near-infrared region from 0.75 to 1.3 μm was best for distinguishing among reflectances of soil-tillage-straw treatments (Gausman et al., 1977).

Surface roughness (soil aggregation), as governed by tillage treatments, affects soil reflectance by means of reflectance surface and shadows. The general conclusion has been reached that rougher soil surface results in lower reflectance (Myers, 1983). Cipra et al.(1971) found that crusted surfaces gave higher reflectance values in the 0.43 to 0.73 μm wavelengths than did soils with the crust broken. The lower reflectance of the disturbed soil was attributed to the rough surface which presumably caused scattering of light as well as a shadowing effect.

Reflectance of undisturbed soils measured in the field is generally the inverse of that measured in the laboratory. This is readily apparent on aerial photos which show sands to have higher reflectance than silts and clays (Myers, 1983). This is because fine-textured soils in the undisturbed condition generally have structure, which gives them the characteristic of aggregates coarser than sand. Thus, measurements for the identical soils, in an undisturbed condition in the field, shows sand having the highest reflectance whereas the fine-textured soil the lowest. Obukhov and Orlov (1964) showed that soils with well-defined structure in the plow layer were found to reflect 15 to 20% less light energy than structureless soils.

Technically, many methods can be used to reduce the influences of illumination variation and soil surface conditions on spectral interpretation of soil properties or patterns. One promising technique is ratioing of multiband images or multispectral data. Although the ratio approach is particularly used to enhance differences associated with soil conditions such as color, drainage and texture, it has the effect of reducing spectral or image tone variations related to directional and intensity variation of scene illumination caused by sun angle, slope, aspect, surface roughness etc. (Wagner et al., 1973). The technical assumption for a successful ratio method is that those variations which can be eliminated or reduced are not or only slightly wavelength dependent.

3. IDENTIFICATION AND CHARACTERIZATION OF SOIL PATTERNS

The understanding of soil inherent behavior resulting from soil parameters along with the knowledge of field spectral properties of surface soils provides the basis for soil pattern identification and characterization by airborne and spaceborne remote sensing. Shockley et al. (1962)

demonstrated the value of a soil moisture signature in identifying soils. Some soils that were otherwise difficult to differentiate could be distinguished from each other when using values of reflectance measured with variable moisture contents. If reflectance at six wavelengths - 1.40, 1.75, 1.94, 2.25, 4.00 and 4.50 μm - were known, any soil that they tested could be identified.

The good relationship between soil organic matter and reflectance has been utilized to produce spectral maps relating to soil types (Baumgardner et al., 1970; Kristof et al., 1973). Prairie soils, forest soils and transitional soils were included in their studies. By using airborne MSS data and computer classification, they successfully delineated and mapped surface soil area into five spectral classes which represented five levels of organic matter ranging from 1.5 to 7%. Since the organic matter content in the soil affects the color, heat capacity, water holding capacity, CEC, soil structure and erodability, the spectral maps can be of special importance in soil productivity assessment. Erosion classes separated spectrally were reported to be comparable in location and extent to field observations (Mathews et al., 1973a). This is attributable to the close relationships between erosion classes and surface organic matter and iron oxide contents.

Extending laboratory and field results of spectroradiometry to the level of airborne or spaceborne remote sensor, it is likely that reflectance data from carefully selected wavelength bands can be used to extract information from bare soil areas that may be related to levels of organic matter, soil moisture, particle size distribution , iron content, or used as an indicator of potential productivity such as CEC (Myers, 1983). Where prior information is available about soil drainage and parent materials, even better correlations can be expected within more homogeneous areas of soil inference.

As a site characteristic integrating the effects of climate, local relief, accumulated organic matter and soil texture, soil drainage can be expected to be closely associated with surface reflectance (Stoner and Baumgardner, 1981b). Kirshner et al.(1978) used digital analysis of Landsat MSS data to produce a spectral map of non-vegetated soils interpreted according to drainage characteristics. By correlating drainage classes with the soil series, soil mapping units could be more accurately defined. A procedure of partitioning the area into different parent material areas based on photointerpretation together with automatic spectral classification within parent material zones led to the preparation of 1:15,840 scale spectral map sheets which was intended for use in a soil survey (Weismiller et al., 1979). Again, spectral classes represented were most closely correlated with soil drainage. Although it was sometimes possible to correlate soil properties such as organic matter and surface texture with the spectral classes, these correlations did not prove as consistent as those with drainage characteristics.

Weismiller et al. (1977) and Wong et al. (1977) point out that a spectral analysis of soils alone cannot distinguish between widely different soils exhibiting similar spectral responses. The accuracy of soil identification has been considerably degraded by data noise characteristics. By combining quantitative ancillary data such as digital terrain factors with MSS data, a more reliable delineation of soils can be provided than can be derived solely from spectral classification. Following this approach, Weismiller et al. (1977), by utilizing soil spectral information combined with digitized topographic boundary and parent material boundary data, has presented a detailed soil map showing 14 subgroups, 7 soil families and 18 soil series classes.

The usefulness of spectral information for soil pattern recognition over a vast territory in the U.S.S.R. has been tested by Kondratyev and Fedchenko (1980). Spectral brightness coefficients (SBC) were measured from an altitude of 100-150 m by an aircraft equipped with a high-speed field spectrometer with discrete spectral scanning in the wavelength region of 0.4 to 0.9 μm. A supervised approach of pattern recognition was performed, under a test site which included all types of soils in arable lands of the region under investigation. The final product was a soil map for the entire area of Ukraine and Moldavia territories. This map was then compared to the conventionally accepted map with a coincidence level of 94.3%.

Kondratyev and Fedchenko (1982) made another spectral map for identification of soil organic matter contents for the same area. In this study, the ground measurements of spectral brightness coefficients for selected plots measuring 50 by 50 m with different contents of organic matter instead of soil types were performed for the construction of a calibration curve. Again, the air-measurements were carried out by an AN-2 aircraft with the same spectrometer at an average flight altitude of about 100 m. Because all measurements were in cloudless sunny weather at a solar elevation of no less than 40° and after plowing, the influences of soil moisture content, degree of cultivation, and illumination conditions on spectral properties were assumed to be eliminated, thus, the readings from ground measurements used in the calibration procedure would be approximately the same as those from air-measurements. They used this approach to map soil organic matter for entire areas of the Ukraine and Moldavia. This work was further extended to other areas but combined with a density analysis of Meteor satellite images (Kondratyev et al., 1983). The results of aircraft measurements were used to construct a training sequence from which they could estimate organic matter content in the soils of an area where no aircraft measurements were performed in that period, but which appeared on the same space photograph.

Although the aerial photographic images have been long used for identification of soil features, the use of airphoto tone (density) as a measure of the variability of individual soil properties cannot be regarded as promising as the multispectral classification. Cihlar and Protz (1972) found that infrared color film recorded some specific information about soil mapping units but correlation between photo-density values and soil properties was poor. Evans et al. (1976), after examining the correlations of photo densities with organic matter contents within an area of 60 km^2 and with organic matter contents as well as other soil properties within fields, concluded that tonal patterns were good indicators of different soils but the correlation between tonal densities and specific soil properties was not good enough for those properties to be accurately predicted. Moreover, correlations were even lower when larger areas were involved. They suggested that tonal values are best used in conjunction with other criteria, such as pattern and landform analysis. In another study, Evans (1979) evaluated aerial photos collected over bare soils and found that the color changes related to soil moisture varied with different soils. He concluded that it was unlikely that changes in soil water-content could be estimated using photo density. The level of importance of tone varies between localities, and tonal density could not always be used as a definitive criterion for a particular soil nor predicting particular soil properties.

However, Piech and Walker (1974) reported that an empirical reflectance ratio method obtained from the red and blue spectral bands of conventional color air-photos could be used to delineate relative soil moisture and texture patterns. If the darker soil element has a greater red-to-blue reflectance ratio than the lighter soil element, the tonal variation between the soil elements is caused principally by moisture. If the darker soil element has a smaller red-to-blue reflectance ratio, the soil elements differ principally due to texture. To perform the ratio analysis, the interpreter must relate soil image densities to reflectances by calibrating the color imagery through density variations in shadow images.

E. SUMMARY

Based on this literature review it is evident that that remote sensing techniques show significant promise as a tool to predict soil properties and soil variability. However, a lot of parameter interactions influence and reduce the predictive reliability of such methods. The most promising direction is in the spatial delineation of soil types and the quantification of organic matter and soil moisture. The former must be based on an analysis using spectral curves over a wide wavelength range while the latter can most likely be predicted from the reflection at specific wavelength bands. How this can be applied to detailed soil assessments on a field specific basis and how this can be translated into fertility assessments will be the focus of the present thesis research.

Chapter III

MATERIALS AND METHODS

A. SAMPLING DESIGN

The soil variability in the test field was examined using three different sampling schemes: conventional, selective, and stratified random. The sample collection took place on May 13, 1984, when the field was prepared for planting and prior to fertilizer application. The surface soils were sampled at 0-20 cm depth using a shovel and the sample collection was carried out independently for each sampling scheme.

1. CONVENTIONAL SAMPLING

Conventional sampling was carried out according to the B.C. Ministry of Agriculture (BCMAF, 1978) guidelines and consisted of collecting 12 soil samples in a subjective manner so as to sample only the dominant soil conditions and to avoid extreme dark or gravelly patches which were present in the field. Twelve samples were then combined into one bulk sample for subsequent analysis.

2. SELECTIVE SAMPLING

Selective sampling was carried out to show the contrast of the soil pattern and to determine if the visual perception of the surface soils could be translated into chemical differences in the field. Forty-seven soil samples were selected and the samples could visually be classified into three groups: dark soils (approximately 20% of all samples) gravelly soils (approximately 20% of all samples), and dominant, brown soils (approximately 60% of the samples). The samples were selected in such a way that the dominant soils in each of 28 equal size grid cells were examined. The field was stratified into grid blocks of 30 m by 30 m dimensions and these were the same units used for the stratified random sampling, except that the samples collected in each grid cell were chosen subjectively on the basis of visual appearance (Appendix 1).

3. STRATIFIED RANDOM SAMPLING

The plot design for the stratified random sampling is illustrated in Figure 3.1. The entire study site was divided into 28 equal-sized, 30 m by 30 m squares. Because of the uneven shape of the field, 6 additional half size plots were also sampled. Two random samples were collected in each full size plot and one random sample was collected for each half size plot. Pairs of random numbers selected from random number tables provided the coordinates for the sample location. Sixty-one samples were collected independently using the stratified random sampling technique which was assumed to provide best estimates of true field conditions.

All samples were described in the field and the location of the sample points was recorded in coordinate numbers in order to facilitate the sample location

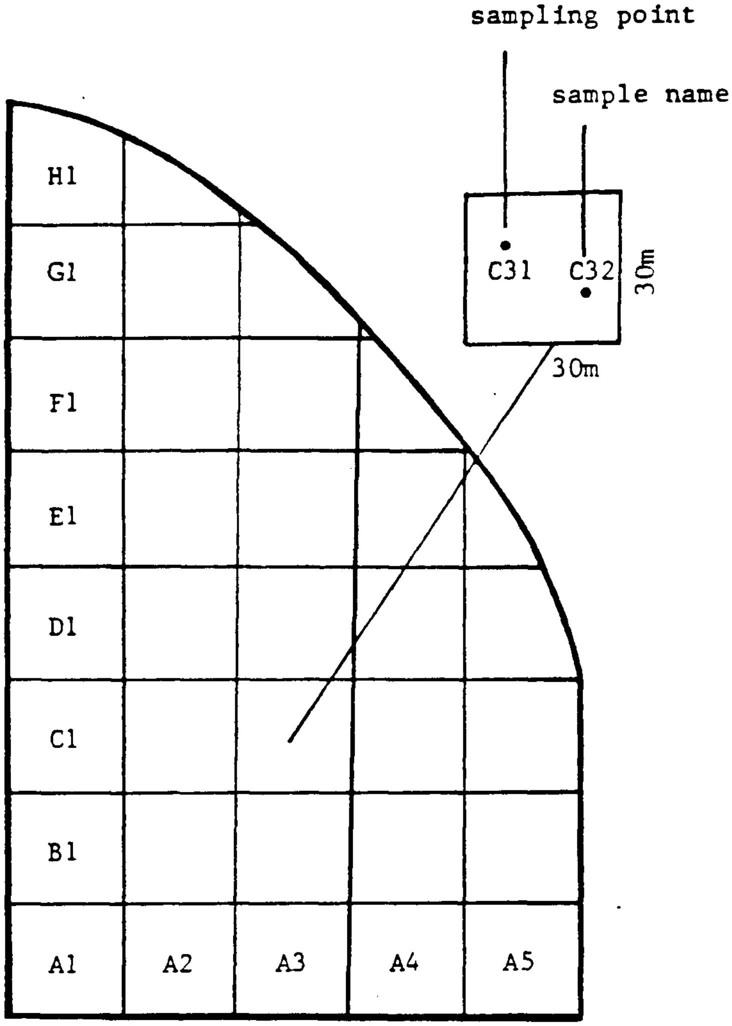


Figure 3.1 Illustration of stratified random sampling plot design: two samples were randomly taken from each plot.

identification on aerial photographs.

In addition, small metal cans with tight-fitting lids were filled with soils from each of those sampling locations for gravimetric soil moisture determination.

B. SOIL PHYSICO-CHEMICAL ANALYSES

1. SAMPLE PREPARATION AND PHYSICAL MEASUREMENTS

Samples were air-dried in the laboratory, crushed with a wooden rolling pin, and passed through a 10 mesh sieve to remove all coarse materials larger than 2 mm in diameter. Coarse fragment content was measured by weighing and then discarded. Sieved soil samples were stored in air-tight containers for further chemical and reflectance measurements.

Soil moisture content was determined gravimetrically by drying in the oven at 110°C. Munsell color notations were taken from each of the soil samples in both moist and dry conditions.

2. CHEMICAL ANALYSIS

All chemical analyses were carried out on sieved, air-dried soil samples, following standard analysis methods.

Soil pH was measured in 1:1 soil water solution by a Radiometer pHM62 Standard pH meter. Total carbon analysis was conducted using a Leco Carbon Analyzer(Leco, 1959). Organic matter content was determined by the Walkley-Black method and expressed as % organic carbon (Allison, 1965). Exchangeable calcium, magnesium, sodium, and potassium were determined by the ammonium acetate extraction method at pH 7.0 (Chapman, 1965). The concentrations of cations in the extracts were measured on a Perkin Elmer 306 atomic absorption spectrophotometer. Cation exchange capacity was determined by the analysis of NH_4 concentration of the extract with a Technicon Autoanalyzer II (Technicon, 1974).

Total nitrogen was determined using the colorimetric method under the Technicon Autoanalyzer II (Technicon, 1974). The Bray P-1 method was employed for determining available phosphorus (Olsen and Dean, 1965). The concentration of P was measured colorimetrically with a Gilford Stasar II spectrophotometer at 660 μm (Murphy and Riley, 1962).

C. CONVENTIONAL VARIABILITY AND FERTILITY ASSESSMENT

The variability of soil chemical properties was determined and assessed in a conventional analysis based on soil data from samples collected by stratified random sampling technique, following the methods used by Beckett and Webster (1971). Comparisons were made using sample data from the selective sampling as well as the conventional sampling.

Fertilizer requirement assessment and recommendation were made for P and K only. The soil test value was estimated using the composite sample from the conventional sampling method which consisted of 12 sub-samples. The fertilizer rate and the amount of fertilizer required for the field were then determined according to the guidelines in the Soil Testing Methods and Interpretations published by BCMAF (Neufeld, 1980). This manual is routinely used for soil testing and for making fertilizer recommendations in the province, including the Lower Fraser Valley.

D. REMOTE SENSING TECHNIQUES

1. SPECTRAL REFLECTANCE MEASUREMENTS

Bidirectional reflectance factor measurements of soil samples were performed in the laboratory under artificial illumination condition, using a multi-channel spectrometer (Exotech Model 100 A). The samples were distributed on a flat 30 cm * 30 cm surface and the spectrometer was mounted in a fixed position approximately 50 cm above the sample stage with a field of view about 15°. A barium sulfate paint, Eastman Kodak white reflectance standard, was used to calibrate spectral readings for all sample measurements. After every sixth soil sample the $BaSO_4$ paint was measured to account for any changes in instrument setup and illumination condition. The calibration and measuring procedure outlined by Robinson and Biehl (1979) was followed in this study.

Spectral readings (expressed as % reflection) in Landsat spectral band 4(0.5 - 0.6 μm), 5(0.6 - 0.7 μm), 6(0.7 - 0.8 μm, and 7(0.8 - 1.1 μm) were obtained for each sample and were placed in a computer file for subsequent statistical analysis.

2. AIRPHOTO PIXEL VALUE ANALYSIS

A Wild RC-10 camera with a 152 mm focal length and Kodak 2445 color negative film was used for the aerial mission. The test area was covered at the time the soil samples were collected in the field, and the 1:4000 scale 9 * 9 inch color prints obtained from the air photo mission were used for the quantitative multi-dye layer pixel value assessment of the spatial pattern of the soils. Color infrared film at the time was not available for this study.

The field test area which was identified on the aerial photos was digitized using an Optronics C-4500 color film scanner. The scanning was done for both the magenta and the cyan dye-layers using the green and the red filters. The optical aperture of detection was selected at 100 μm and the data was stored on the computer tape for digital analysis on a Raster Technology (Model 25) image analysis system. The blue sensitive layer was not chosen because the light in this wavelength band is subject scattering by haze and dust particles in the atmosphere and the contrast and detail of the image would be reduced (Carroll, 1973).

After digitization, the pixel matrices of both dye-layers were read into a computer, with the numerical scale of pixel values from 0 for black to 255 for white. The pixel size is 100 μm by 100 μm and represents the ground spatial resolution about 0.4 m by 0.4 m. The digitized image, then, was portrayed on a Raster Technology color display screen for various analyses such as area delineation, histogram and classification.

The area of the study site was delineated on the display screen and all areas outside the target field were eliminated. Reflectance or pixel value variations were examined by profiling and frequency distribution analysis. The latter showed the relative frequency of appearance of given pixel values for the entire study site.

Before using a line printer to output pixel matrix data, a computer program was written and used to average the pixel values for every 10 by 10 pixels, with a resultant ground resolution of about 4 m by 4 m in area per pixel point. The reason for reducing the volume of data is the difficulty of handling such a large volume of original data. Printer outputs of the image pixel value matrices in individual dye-layers (magenta and cyan) for the entire site were obtained and pixel values for each sampling location were taken from the printouts according to the sample point coordinates on record. The printout data were also used for cluster analysis to classify the pixel values of soil samples into groups in two dimensional space (similar to non-supervised classification).

E. STATISTICAL METHODS

An outline of the statistical methods used in this study is presented in Figure 3.2. All analyses, if not specified, were performed using the procedures in the MIDAS package (Fox and Guire, 1976).

1. VARIABILITY ASSESSMENTS

Various descriptive statistics were calculated for soil variability assessments. They are the mean, standard deviation, minimum, maximum, and coeffecient of variation (%CV). CV is a unitless value defined as:

$$\%CV = \text{standard deviation/mean} * 100$$

CV was used to express the variability of parameters because it accounts for both mean and range(standard deviation) differences, and the results can be directly compared one another.

2. SIGNIFICANCE TESTS

T-test compares the means from two sets of samples by calculating student's T value and tests the significance of the difference between the means. The T-test was used to test soil differences between samples from different sampling methods at the 95% confidence level when both sample sizes were larger than 12 samples.

The Mann-Whitney U-test (Siegal, 1959) was also a significance test used for comparing sample differences. The Mann-Whitney U-test is a nonparametric test with minimal

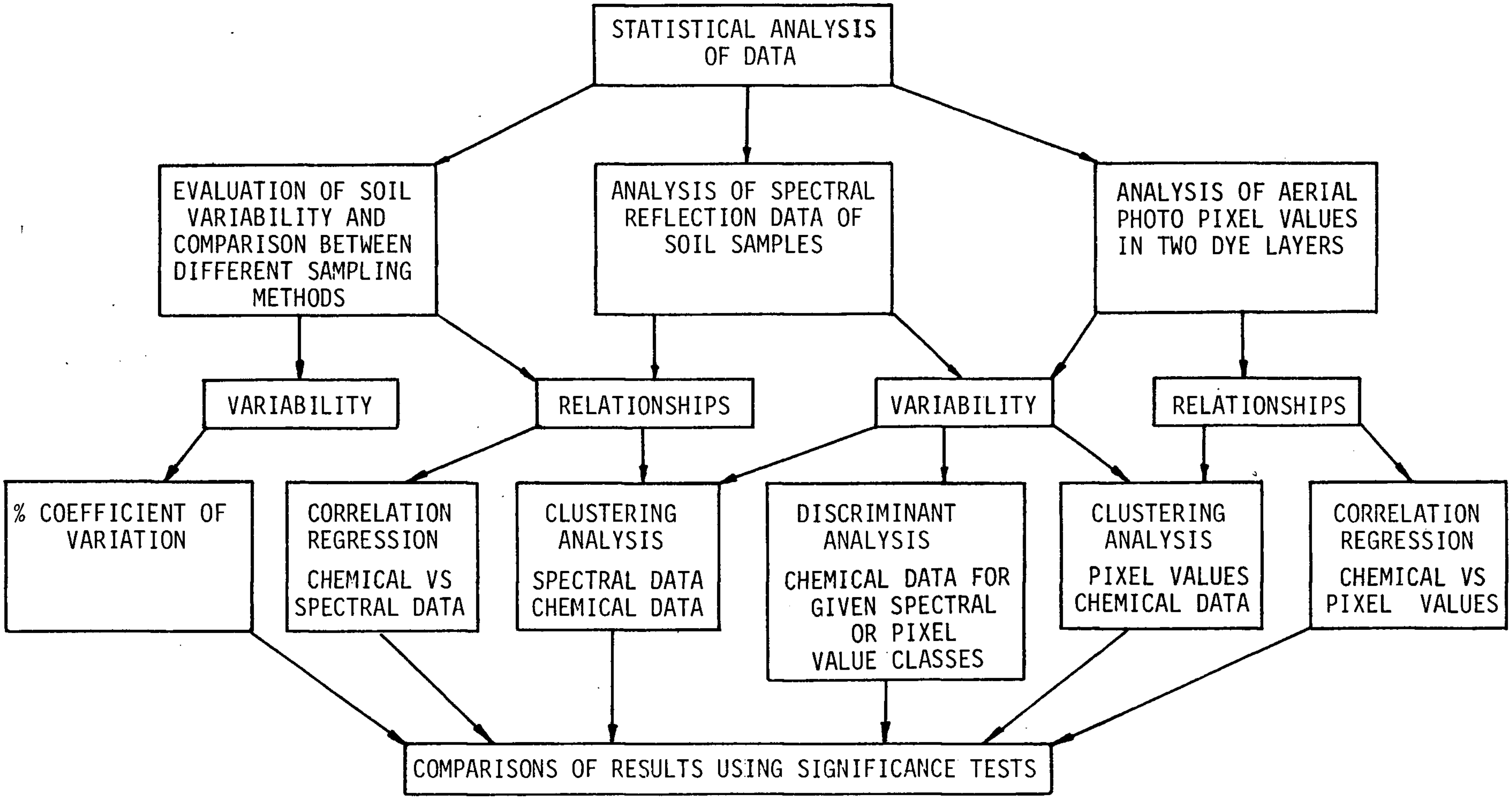


Figure 3.2 Statistical Methods

assumptions on sample data, permitting sample size of less than 12 to be compared. The Mann-Whitney U-test was performed mainly to determine if the cluster analysis groupings were significantly different from one another at the confidence level of 95%.

3. RELATIONSHIP ANALYSIS

A collinearity study of the data was performed by means of a correlation matrix, which expressed the linear relationship between any two variables in the form of a correlation coefficient. All basic data: soil parameters, % reflectances, and pixel values for soil samples were entered into the program. Spectral band ratio and band combination were also considered, and for some soil parameters, a logarithmic transformation was performed. The resulting r values for the soil properties gave a first order indication of how well each property could be predicted from spectral reflectances and pixel values and which spectral band was best.

For those properties and bands which showed high prediction potential, scattergrams were generated, and simple linear regressions were performed. The four spectral bands and two dye-layers were used as independent variables, respectively, whereas the soil properties were chosen as predictive variables.

The stepwise multiple regression was carried out to determine which soil properties and parameter interactions were best related to reflectance or pixel values. Soil parameters which entered in stepwise regression at the significance level of 90% were used to express the variations in reflectance or pixel value.

4. CLASSIFICATION

The procedure outlined by UBC CGROUP (Patterson and Whitaker, 1978) was employed to perform a cluster analysis for soil samples on the basis of soil spectral reflection and dye-layer pixel values. Cluster analysis is a multivariate classification method based on the statistical similarity of individuals or groups of individuals. The hierarchical average distance linkage grouping (Ward, 1963) was used in this procedure. Another program, UBC CORDER, was used in combination with CGROUP to rearrange the original data set in a manner which is comparable to the grouping order. CGROUP output included a dendrogram of the grouping and indexes associated with each grouping step which indicated the compactness of clusters relative to the separation between clusters. The properties associated with the soils in each cluster were averaged to indicate the nature of each cluster in terms of its soil physical and chemical properties.

5. DISCRIMINANT ANALYSIS

Discriminant analysis is a multivariate statistical method in which linear combinations of variables are used to distinguish between two or more categories of samples. Stepwise discriminant analysis chooses the linear combination of variables that best separates groups in a stepwise manner and, after the discriminant functions have been computed, group membership can be predicted using coefficients. The discriminant analysis can be used not only to classify a sample in which actual group membership is unknown but also to identify the misclassified samples and place them into their proper groups.

Stepwise discriminant analysis was carried out using the UBC-BMD07M program (Dixon and Brown, 1979). The groups obtained from a cluster analysis of the spectral and pixel value analysis served as a basis for the discriminant analysis and the analysis was performed in order to determine which of the chemical and physical properties best differentiated the spectral reflective properties of the soil samples and soil types. The output from the procedure included a list of those properties which appeared significant in distinguishing among clusters at the confidence level of 95%. The classification aspect of the discriminant analysis was not emphasized in the present study.

Chapter IV

RESULTS AND DISCUSSION

The laboratory results of soil physical, chemical, reflection and digitized airphoto measuremnts on soil samples are presented in Appendix 2 and 3. Appendices 4 and 5 give the computer printouts of green and red filter pixel value data for the entire test field. Results interpretation and discussion are given in the following four sections.

A. CONVENTIONAL ASSESSMENT OF SOIL VARIABILITY AND FERTILITY

The principal aim under this section is to determine the lateral variability of soil properties within the field using mean sample values and coefficients of variation and compare the different sampling techniques and sample groupings. The emphasis is placed upon those soil parameters pertaining to soil fertility status.

1. THE MAGNITUDE OF SOIL VARIABILITY

The overall variability of selected soil properties obtained from the different sampling schemes are displayed in Table 4.1.1. The %CV values for all 108 samples (selective + stratified random sampling) were compared with data obtained from the stratified random and selective sample sets and literature values.

Considerable variations were present in all parameters except pH. In eight out of nine parameters, the data from the selective sampling showed the highest variability. This

Table 4.1.1 Within-field variability (%CV) of selected soil properties and comparison with the median values from Beckett and Webster (1971).

SOIL PROPERTY	COEFFICIENT OF VARIATION (%)			
	Stratified random samples n = 61	Selective samples n = 47	Combined samples n = 108	Beckett and Webster's Median Value
MC	21.5	34.8	29.1	-
CF	26.4	38.4	31.4	-
pH	4.3	5.2	4.6	-
OC	23.3	37.2	30.3	25-30
N	21.4	35.7	27.8	25-30
P	37.6	44.6	40.6	45
K	46.9	79.9	62.7	70
Ca	43.7	41.4	42.6	30
CEC	19.3	30.5	25.8	-

is expected because the selective sampling placed more emphasis on the extreme conditions in the field. If we combine the data from the stratified random and the selective sample set then the variability is slightly higher than in the set sampled with the stratified random technique but smaller than in the selectively sampled data set. These trends and comparisons were consistent for all parameters except Ca, which was more variable in the stratified random sample set.

K was found to be the most variable parameter showing the highest %CV and the greatest difference between sample sets. Ca and P had %CV above 40% and moisture content, coarse fragment content, % organic C, N and CEC all showed %CV values which were in the range of 25-30%. This implies that K, Ca and P are the most variable parameters in the field and are, therefore, more difficult to quantify for fertilizer recommendation work.

The values obtained in this study compared very favorably with those obtained by Beckett and Webster (1971) which were based on a literature review. The median values were all very close except for Ca which had a coefficient of variation approximately 10% higher in the study site than that quoted in the literature.

2. COMPARING MEAN VALUES OF THREE SAMPLING METHODS

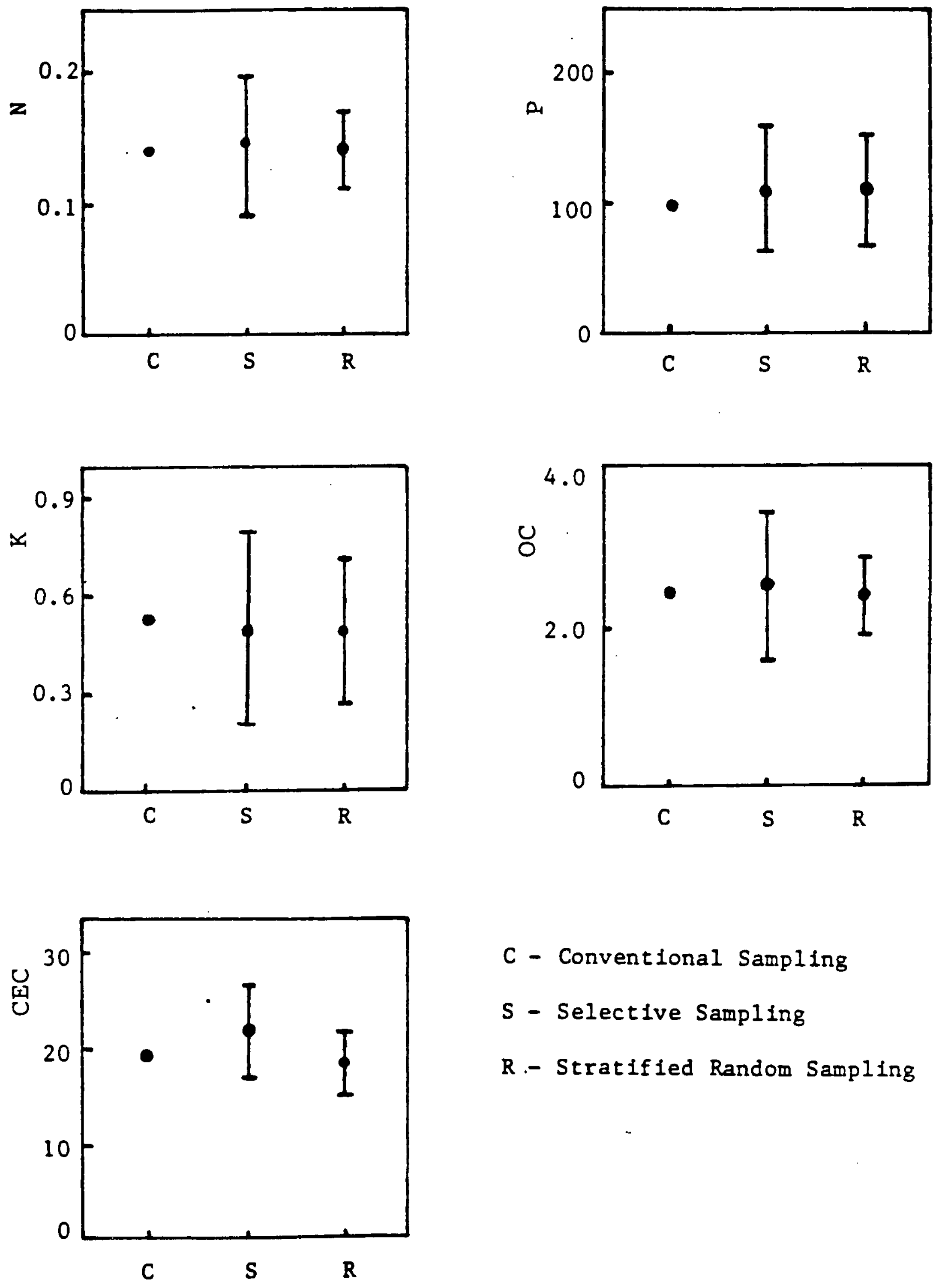
The mean and range values obtained from the conventional, stratified random and selective sampling data set were compared in Figure 4.1.1. In spite of large differences in %CV values between different sampling methods, the mean values were very close. Based on a further comparison showing the % differences between means, the difference was in all cases less than 12% using the stratified random data set as a basis for comparison (Table 4.1.2). The mean differences between the stratified random and the selective sampling were checked by a student-T test and the results showed that there were no significant difference for any of the tested soil properties at the confidence level of 95%. This indicated that the selective sampling, which was based on selecting the dominant soil types in each 30m by 30m sampling grid, was representative of the field conditions.

Similar results were obtained when the conventional sample mean was compared with the other data sets (Table 4.1.2 and Figure 4.1.1). The estimates never differed by more than 13.1% from the stratified random sampling. The latter method was considered the most objective method of sampling for assessing soil variability (Ball and Williams, 1971; Bank, 1984) and should therefore be used as a base for comparison. We can thus conclude that the mean values obtained from the three sampling methods are representative of the field conditions with the exception of P values which show a 13% difference between conventional sampling and the other two methods.

Table 4.1.2 Comparisons of three sample sets from conventional, stratified random and selective sampling.

SOIL PROPERTY		CONVENTIONAL SAMPLING	SELECTIVE SAMPLING	STRATIFIED RANDOM SAMPLING
MC	MEAN	27.6	29.6	26.5
	SD	-	10.3	5.7
	% D#	4.2	11.7	-
CF	MEAN	28.2	29.4	29.7
	SD	-	11.3	7.8
	% D	-5.1	-1.0	-
pH	MEAN	6.87	6.94	6.97
	SD	-	0.36	0.30
	% D	-1.4	-0.4	-
OC	MEAN	2.41	2.53	2.4
	SD	-	0.94	0.56
	% D	-0.4	5.4	-
N	MEAN	0.142	0.145	0.143
	SD	-	0.051	0.031
	% D	-0.7	1.4	-
P	MEAN	95.1	108.9	109.4
	SD	-	48.4	41.1
	% D	-13.1	-0.7	-
K	MEAN	0.53	0.50	0.49
	SD	-	0.27	0.23
	% D	8.2	2.0	-
Ca	MEAN	10.3	10.3	10.8
	SD	-	4.2	4.7
	% D	-4.6	-4.6	-
CEC	MEAN	19.8	20.1	18.1
	SD	-	6.14	3.50
	% D	9.4	11.0	-

Percent mean difference from the sample set of the stratified random sampling.



C - Conventional Sampling

S - Selective Sampling

R - Stratified Random Sampling

Figure 4.1.1 Comparison of mean values from three sampling methods for N, P, K, OC, CEC, error bars represent one standard deviation.

3. <u>IDENTIFYING THREE SOIL TYPES FROM THE SELECTIVELY COLLECTED SAMPLES</u>

As previously discussed, there were no significant differences between means among the different sampling methods. However, the samples collected selectively can be grouped into three categories based on their visual appearance (see Appendix 1). The three categories of samples represent very dark soils (Type I), gravelly, light colored soils (Type II) and generally brown or dominant soils (Type III) respectively. The average Munsell color notations of hue, value and chroma measured on the air-dry condition for each of three soil sample categories are given in Table 4.1.3. The distributions of these three soil types is readily visible on the aerial photograph (Plate 1).

Although color hue was similar among the three soil sample categories, the measurements of color value and chroma were different from each other, with the highest numerical values for soil type II and the lowest values for type I. It is noted, however, that the differences between type II and III are much smaller than the differences between type I and other two types, which implies that the same trend may be observed in soil chemical differences. The Mann-Whitney test showed that the differences of color value and chroma between soil type II and type III were not significant at the confidence level of 95%

Figure 4.1.2 and Table 4.1.4 show the mean values and standard deviations of selected soil fertility properties

Table 4.1.3 Average Munsell color notations for three soil categories from the selective sampling.

SOIL TYPE	HUE	VALUE	CHROMA
I	10YR	4.50	3.10
II	10YR	6.11	4.33
III	10YR	5.86	4.04

obtained from these three categories of the soil that were classified according to their visual appearence using the selective sampling method. Mean values from the stratified random sampling and the percent mean differences of the three soil sample categories from the stratified random method are also provided in Table 4.1.4 for comparison. The Mann-Whitney U-test was used to test the significant difference between means for selected soil fertility properties from various sample groups and results are given in Figure 4.1.3.

Significant differences were obtained between all three soil types , and OC, N, K and CEC were found to be the best distinguishing parameters. Soil type I and II were also found to be significantly different from the soil data set collected using the stratified random method. Soil type III as shown in Figure 4.1.3 did not differ from the stratified

Table 4.1.4 Comparisons of three soil categories from the selective sampling and samples from the stratified random sampling.

SOIL PARAMETER		SELECTIVE SAMPLES GROUP I	II	III	STRATIFIED RAMDOM SAMPLE SET
MC	MEAN	44.7	19.5	27.6	26.5
	SD	6.8	6.8	5.1	5.7
	% D#	68.7	-26.4	4.1	-
CF	MEAN	21.2	43.1	28.2	29.7
	SD	3.6	12.4	9.4	7.8
	% D	-28.6	45.1	-5.1	-
pH	MEAN	6.79	7.18	6.92	6.97
	SD	0.30	0.34	0.36	0.30
	% D	-2.6	3.0	0.7	-
OC	MEAN	3.96	1.90	2.21	2.40
	SD	0.43	0.62	0.58	0.56
	% D	65.0	-20.8	-7.9	-
N	MEAN	0.210	0.108	0.133	0.143
	SD	-0.053	0.027	0.032	0.031
	% D	46.9	-24.5	-7.0	-
P	MEAN	156.6	93.2	95.3	109.4
	SD	67.1	24.3	34.9	41.1
	% D	43.4	- 14.8	-12.9	-
K	MEAN	0.70	0.26	0.50	0.49
	SD	0.20	0.11	0.27	0.23
	% D	42.9	-46.9	2.0	-
Ca	MEAN	14.3	7.7	9.6	10.8
	SD	4.0	2.5	3.9	4.7
	% D	32.0	-28.7	-11.1	-
CEC	MEAN	28.9	14.5	18.8	18.1
	SD	5.45	3.57	3.13	3.5
	% D	58.7	-19.9	3.9	-

Percent mean difference of three soil categories from the samples of the stratified random sampling.

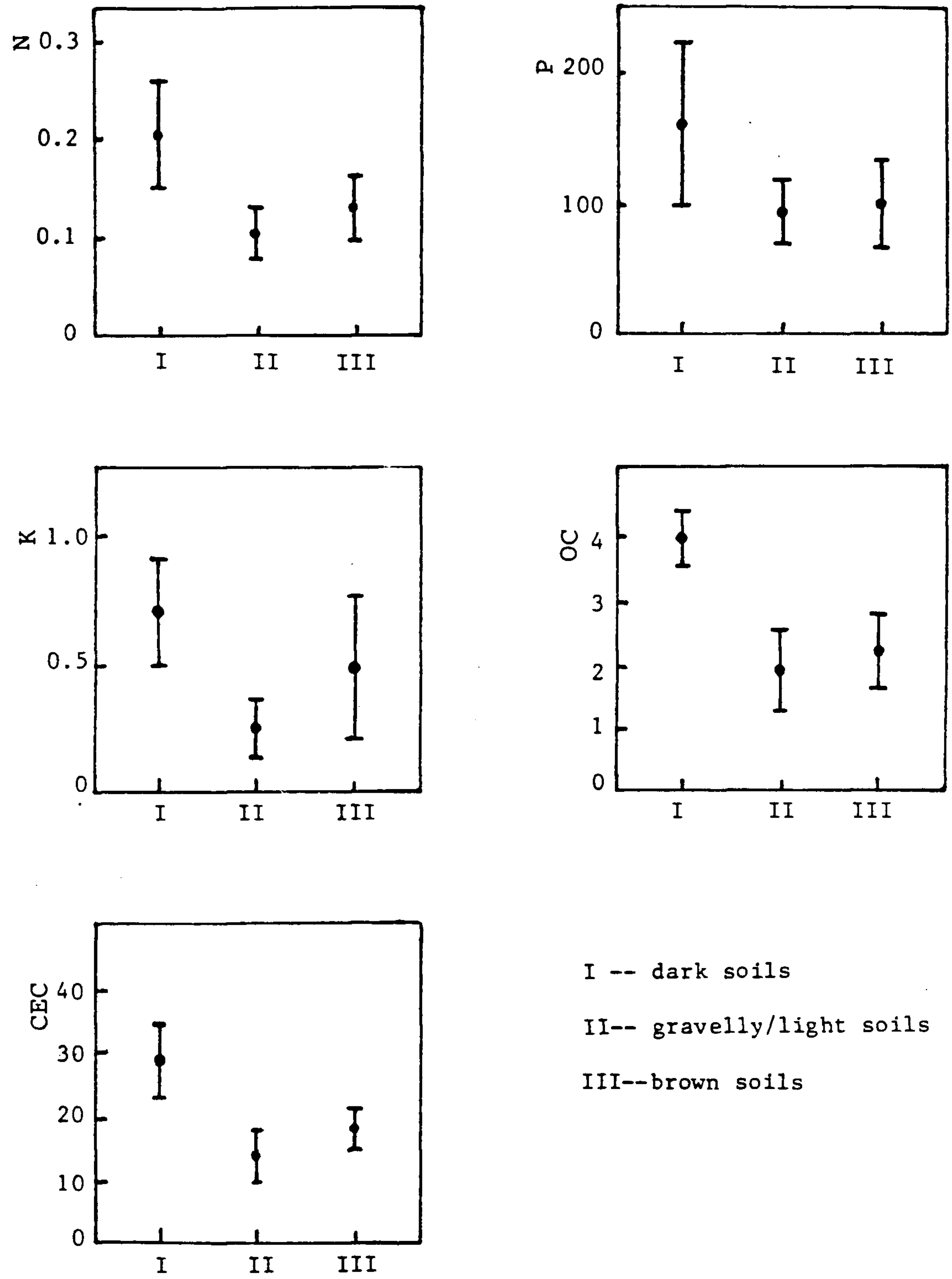


Figure 4.1.2 Comparison of mean values from three soil categories selective sampling for N, P, K, OC and CEC, error bars represent one standard deviation.

	I	II	III
II	pH, OC, N, P, K, CEC, VALUE, CHROMA		
III	OC, N, P, K, CEC, VALUE, CHROMA	pH, OC, N, K, CEC	
SRS	OC, N, P, K, CEC, VALUE, CHROMA	OC, N, K, CEC	

I: dark soils (Type I), II: gravelly/light soils (Type II), III: dominant soils (Type III), SRS: stratified random samples.

Figure 4.1.3 Significant differences between three soil types from selective sampling and stratified random sample set by Mann-Whitney U-test (α=0.05), tests were made on pH, OC, N, P, K, CEC, and color value and chroma.

random soils and was thus representative of the average field conditions.

The samples from soil type I tend to overestimate the stratified random means, and the samples from soil type II underestimate the means for most soil properties. The exception is the coarse fragment content which shows an opposite trend. However, the differences between type II and the randomly selected samples are much smaller than those between type I and the random samples for all soil properties but coarse fragment content and K. Differences larger than 40% appear in soil moisture content, OC, N, P, K and CEC between soil type I and the randomly selected samples and in coarse fragment content and K between soil type II and the random samples. Significance tests indicated that the soil types could be differentiated at the confidence level of 95% based on soil fertility parameters (Figure 4.1.3) as well as moisture content and coarse fragment content. Only P does not appear on the significance table between soil type II and the random sample set or type III.

These results show that the three soil types which can be identified visually from the aerial photographs and in the field are also chemically different. What is now needed is to examine whether these soils require different fertilizer treatments and whether their spatial extent is large enough to be considered of importance in applying variable rates of fertilizers.

4. EFFECT OF DIFFERENCES AMONG THREE SOIL TYPES ON FERTILIZER RECOMMENDATION

Table 4.1.5 presents the results of P and K fertilizer recommendations for corn which is in crop Group 3 specified by the BCMAF handbook (Neufeld, 1980). This was based on mean values estimated from conventional composite samples and the selective samples in which three soil types were considered separately. An attempt was made to show how the variability of soil fertility led to different fertilizer rates recommendations.

The calculations for P fertilizer recommendation showed that the P values were well above the required levels for all soil types in spite of significantly higher mean value observed for soil type I. In fact, all soil test values are higher than the critical value needed for fertilizer application listed in the BCMAF handbook. This suggests that heavy application of P fertilizer has likely taken place in the recent past.

The same situation occurred for K, where large differences between soil type I and the other soil types were present. Once again the values were above the necessary test value, therefore, only a minimum rate of fertilizer (starter effect) was needed for type I and III. However, the low mean K value for soil type II did show the need for a higher K fertilization rate for those soils than the rate for the average soil condition estimated by the conventional method. This means that a different rate of K should be

Table 4.1.5 P and K fertilizer recommendations for crop group three based on the conventional sampling and the selective sampling (three soil types).

	SOIL SET	SAMPLE NUMBER	MEAN (ppm)	FERTILIZER RATE (kg/ha)	TOTAL FERTILIZER APPLICATION (kg)*
	Conventional composite	1	95	28 (P_2O_5)	81
P	Type-I	10	157	28 (P_2O_5)	-
	Type-II	10	93	28 (P_2O_5)	-
	Type-III	28	95	28 (P_2O_5)	-
	Conventional composite	1	207	45 (K_2O)	130
K	Type-I	10	273	45 (K_2O)	-
	Type-II	9	101	67 (K_2O)	-
	Type-III	28	195	45 (K_2O)	-

* Total fertilizer applications for three soil types from the selective sampling can not be determined based on the presently available information.

applied to the light colored gravelly soils in order to achieve a maximum yield.

These calculations were based on mean values obtained from chemical analyses of soil samples less than 2 mm in particle size and, accordingly, the coarse fragment content was not taken into account in determining different rates of fertilizer application for different soils. Considering the nearly 43% of coarse fragments in soil type II (Table 4.1.4), one can anticipate that actual soils would show even larger chemical differences between type II and other soil types. This would likely result in a higher application rate of K than that showed in Table 4.1.5 for type II, and may have a similar effect on P recommendations which showed only one rate was needed for all soil types in the present study.

Total fertilizer applications for the study site (2.90 ha) were estimated using the conventional composite sample. Since the areas represented by individual soil types are unknown, we are not able to determine how much fertilizers should be applied to each of three soil types at the present stage.

No recommendations of different rates of N fertilizer were made in this study because presently no such standard soil testing method for N is available in the Lower Fraser Valley area.

5. SUMMARY

Reliable soil sampling is a prerequisite to accurately carry out soil-fertility tests. The conventional sampling provided results comparable to the detailed stratified random sampling with respect to the prediction precision of the mean values of soil qualities. This statement also applies to the selective sampling data and the combined data set. By grouping samples according to their visual appearence, three general categories were identified. They could be separated on the basis of mean values and range differences for most soil properties. The significance test proved that the major soil fertility elements behaved differently among the soil groups and the importance of this effect on soil management and crop performance should not be underestimated. This is of particular importance in intensively managed fields.

Based on the current observations, it is obvious that high rates of fertilizer were being applied to the study field, and a different rate is required only for K for soil type II at the present. With a more moderate fertilizer application rate the differences among the soil types will be more dramatic in successive years and application of variable rates would then be of greater importance. It is expected that in other fields, where the soil tests are low, the soil fertility variability within the field will be larger, therefore, further justifying the use of different fertilizer recommendations and soil management practices.

B. SPATIAL ANALYSIS OF SOIL PATTERNS FROM THE AIRPHOTO

In the previous section, soils from the selective sampling were grouped into three categories based on the visual appearance on the ground. Each of these categories represented a certain portion of the field in which the soils were sampled. The differences on the ground are easily detected from the aerial photos on the basis of differences in tone and density patterns. In this section the airphoto pattern and its relationships to soil properties and soil types will be evaluated. The objective is to differentiate the field into soil units which correspond to the three soil groups obtained from the selective sampling analysis, i.e., to divide the study field into very dark soils, gravelly soils and dominant soils.

1. QUALITATIVE DELINEATION OF PHOTO TONAL PATTERNS

Tonal variations in the airphotos are significantly affected by soil texture, water content and organic matter. Sands and gravels, which are generally well drained and low in organic matter, are light in tone and may even appear white when they are fully exposed. Fine textured soils often present dark tones, since their moisture and organic matter contents are generally high. Three distinct tonal patterns were clearly recognized from the airphoto within the study site (Plate 1).

The very dark tones can be considered to be associated with soil type I which represents dark soils with high organic matter and/or high soil water content. In contrast, very light to white tonal patterns are attributable to soils containing large amounts of gravel and low organic matter content (Type II). The other areas which show moderate grey tones are dominant brown soils (Type III). The three contrasting tonal patterns were delineated from the air photo. Using a digital planimeter (LASICO Model 1250D) the areas of these soil patterns were estimated and the results showed that approximately 10.5% and 11.5% of the total 2.90 ha in area were occupied by the dark and gravelly soils respectively, and the rest (78%) was represented by the dominant soils. This method is easy and fast, but the accuracy is questionable because of the limitaton of human eyes and the subjective nature of the analysis.

2. QUANTITATIVE DETERMINATION OF REFLECTION VARIATION

A more objective method to define photo tonal or density patterns was carried out by a quantitative analysis of dye-layer pixel values. This was examined by scanning micro density of the aerial image, using an Optronics C-4500 color film scanner with the scanning interval of 100 μm. Two pixel matrices of dye-layers using green and red fitlers were obtained with the numerial scale of the pixel values from 0 for black to 255 for white. Three methods were used: i.e. profiling, analysis of pixel value frequency distribution, and multi-dye layer pixel value classification in a Raster Technology (Model 25) image analysis system.

Two transects across the study field were selected to compute the pixel value profiles using original (unaveraged) data. The red and the green fitler pixel values were presented in Figure 4.2.1. These profiles revealed that high reflection variation existed across the field and provided a general idea about median value and range of pixel values.

Profile B, which was in W-E direction and 40 m from the northern end of the field, crossed two very dark soil patches which showed the low pixel values (160 and 170 or below for green and red layers, respectively) comparing with the median level pixel values as around 180 to 200. Profile A was also in W-E direction but 160 m to the north and had several high pixel value peaks (210 and 220 or above), which indicated that the profile transected the gravelly areas. The reflectance curve shapes across the field in the red and the green filter pixel values resembled each other and the values of red filter pixels were slightly higher than those of green filter pixels.

The pixel value frequency distribution within the entire field was examined using the histogram method and the results were shown in Figure 4.2.2. Again the histograms were computed using unaveraged pixel value data. The frequency distributions of pixel values is somewhat skewed and partially polymodal. No obvious classification is possible based on single dye-layer pixel value frequency distributions. These histograms were further modified to show the four pixel value classes obtained from a multi-dye

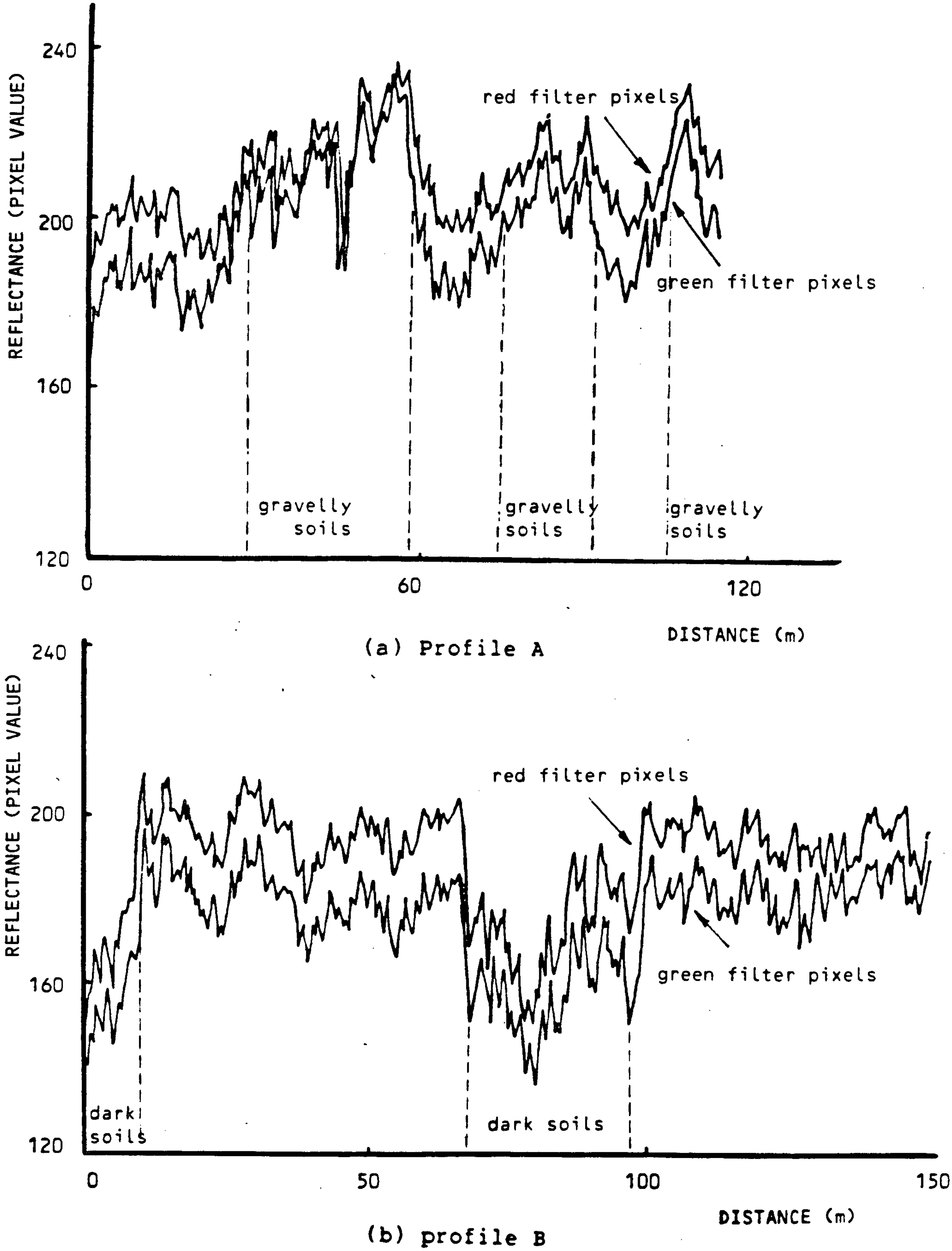


Figure 4.2.1 Pixel value profiles showing reflection variation across the field.

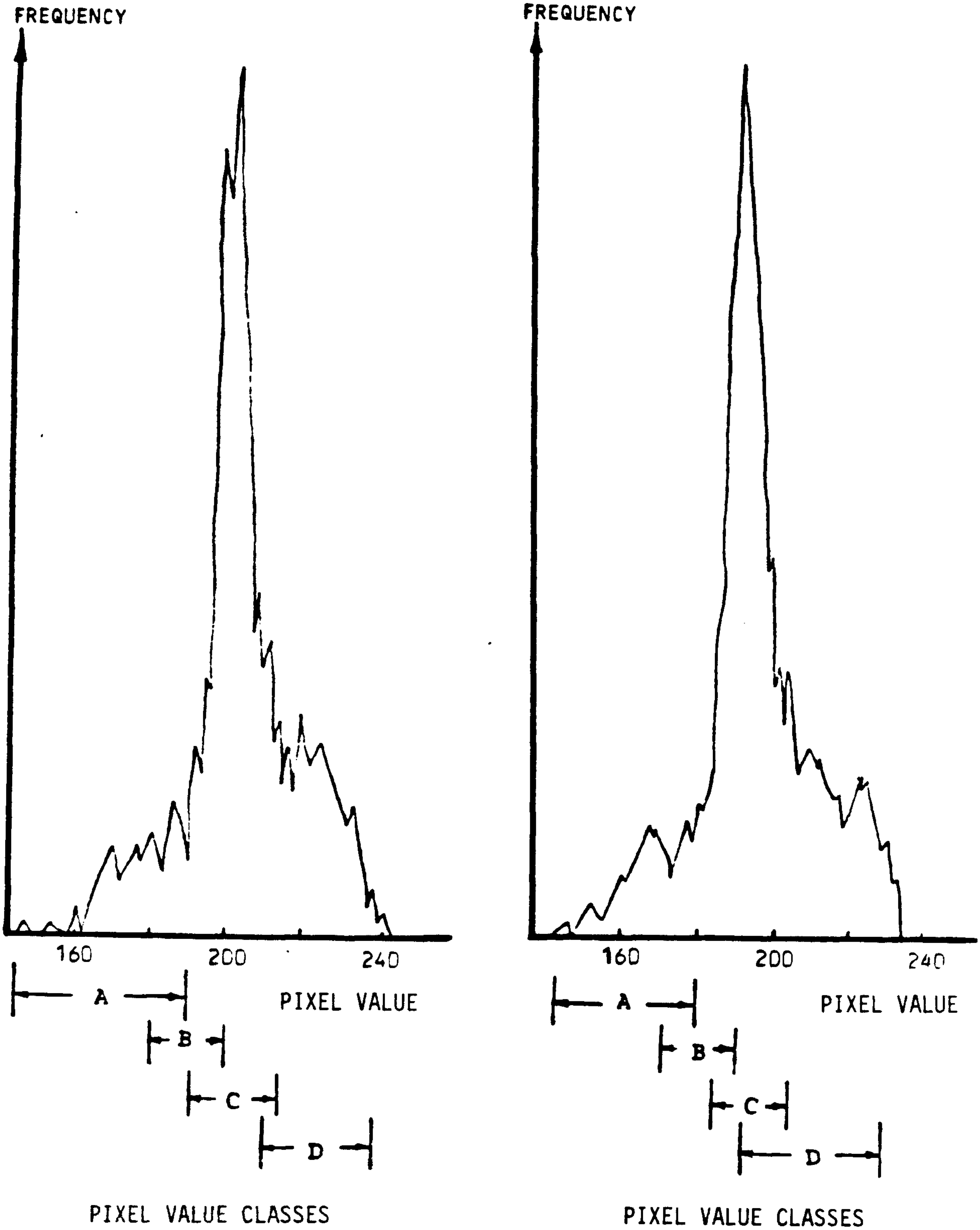


Figure 4.2.2 Pixel value frequency distributions in two dye layers and the ranges of four pixel value classes, left: red filter pixel values(magenta dye-layer), right: green filter pixel values (cyan dye-layer).

pixel value classification.

The multi-dye layer pixel value classification was carried out using an unsupervized average distance linkage cluster analysis on the computer data using two dimensional space. Four classes were identified as the result of the classification (Table 4.2.1). 242 out of 1862 pixels were classified as class A, which represents 13.0% of the total. For other pixel value classes B, C and D the pixels counts were 682, 676 and 262 and the areas represented are approximately 36.6%, 36.3% and 14.1%,respectively. The mean values observed from each of four classes were clearly different from one another, with class D having the highest mean pixel value and class A the lowest. Similar trends were found for both red and green filter pixel values, indicating the close relationship between the two dye-layers. Overlapping pixel values only occurred between immediate neighbors among the classes, as shown in Figure 4.2.2. Statistically, these classes were found to be different based on the Mann-Whitney U-test at the confidence level of 95%. Figure 4.2.3 illustrates that the four groups are separable within the two dimensional vector space.

The four distinct clusters can be related to the tonal patterns shown on the airphoto and, indirectly, to ground soils distribution. Class A, which has the lowest mean pixel values, corresponds to very dark tones and class D which has high overall pixel values shows the pattern where light tones are dominant. Pixel value classes A and D are further

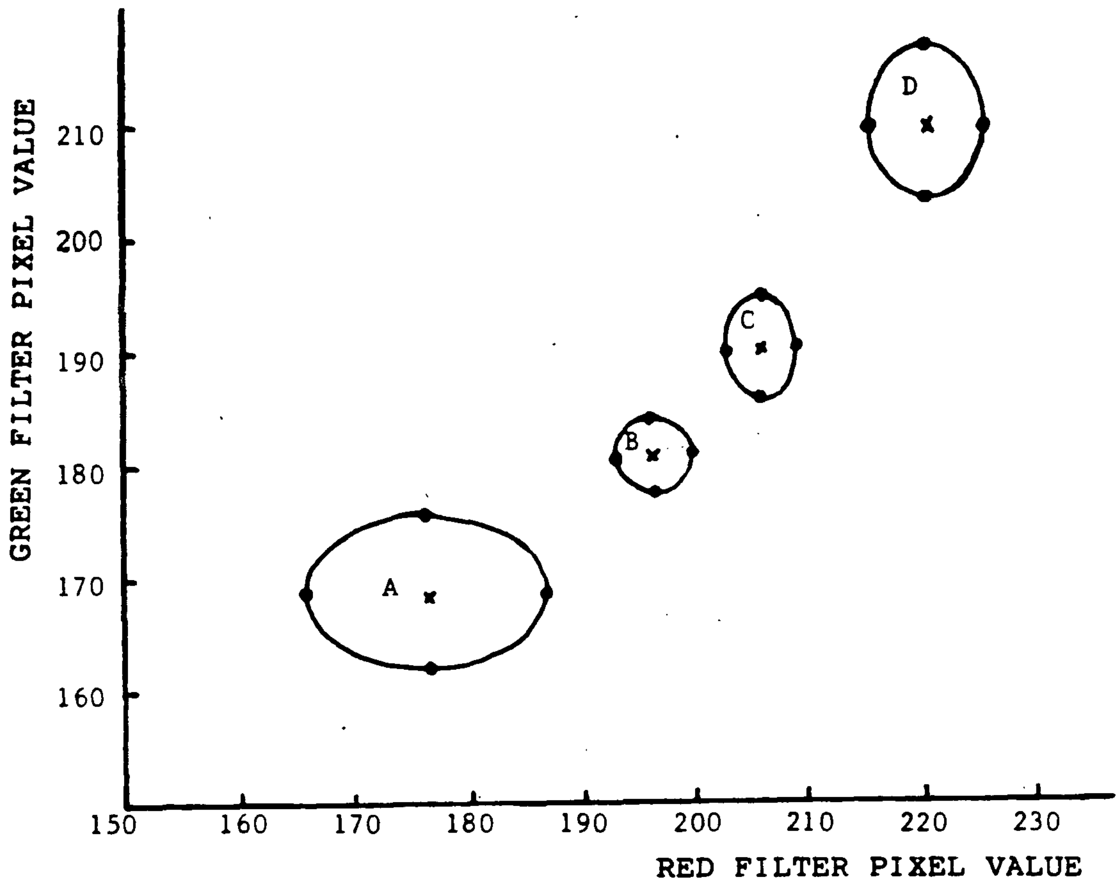


Figure 4.2.3 Cluster separation within the two dimensional pixel value vector space, the center represents mean pixel values and the diameter represents plus and minus one standard deviation.

Table 4.2.1 Summary of classification results from the cluster analysis on the red and green filter pixel values for the entire study site.

PIXEL VALUE CLASS	n	MEAN VALUE		RANGE (min to max)	
		Green	Red	Green	Red
A	242	168.7	176.7	147-188	139-191
B	682	181.3	196.4	173-192	181-201
C	676	191.2	205.0	185-204	192-216
D	262	210.3	220.2	194-230	210-236

Table 4.2.2 Area estimation for different soil types by planimetry and multi-dye layer pixel values classification.

METHOD	TYPE I dark tones)		TYPE II (average tones)		TYPE III (light tones)		TOTAL
	area (ha)	%	area (ha)	%	area (ha)	%	area (ha)
Planimetry	0.305	10.5	2.262	78.0	0.334	11.5	2.90
Pixel value classification	0.387	13.0	2.173	72.9	0.419	14.1	2.98

inferred to be associated with soil type I (dark soils) and type II (gravelly soils), respectively. Pixel value class B and C generally refer to soil type III, that is, dominant soils. Although manual interpretation failed to discern the subtle tonal differences between moderate grey tones, the cluster analysis allowed their separation into two classes (B and C). The separation between the classes may be attributable to the combination or interaction of densities in two spectral bands, though the real mechanism remains unknown.

3. COMPARING THE PIXEL VALUE CLASSIFICATION TO THE SUBJECTIVE DELINEATION OF SOIL TYPES BY PLANIMETRY

The results from the pixel value classification can be utilized to calculate the areas that each of the pixel value groups represents, using the pixel counts of each class and its spatial resolution (one pixel point = 4 m * 4 m). Table 4.2.2 shows these estimates and compares them with the results from the manual delineation of photo tone pattern by a planimeter. Pixel value class B and class C were combined in order to make the results comparable.

The comparison showed that the two methods were in close agreement and the largest relative error was less than 20%. Generally, the planimetry method estimated either dark or gravelly soil areas to be slightly less than the cluster analysis did, but the difference cannot be regarded as substantial.

In the previous section when we discussed whether variable fertilizer recommendation rates should be applied to different soil types, we found soil type II, gravelly, light colored soils, need a higher rate of K than the average and dark soils. According to the area estimates from this section approximately 10 to 14% of the total area belongs to this type of soils. This means that if we apply an average rate to the field, 12% of area will receive insufficient K-fertilizer.

In summary, the spatial delineation of soils from remote sensing images is possible since differences are clearly reflected on the image by changing tonal or pixel value patterns. Both subjective method (e.g. planimetry) and objective method (e.g. multispectral classification) can be used for this task. The quantitative multispectral analysis generally provides more reliable information in differentiating soil patterns and quantifying soil variability.

C. PREDICTING SOIL VARIABILITY USING SPECTRAL REFLECTANCE VALUES

The prediction potential of soil properties and types with respect to their spatial distributions via quantitative remote sensing techniques depends on the nature of the relationships between soil parameters and spectral reflection characteristics. It is evident from the literature that a number of physical and chemical properties have a profound influence on soil spectral reflectance in certain sensitive wavelengths and thus have great predictive value. However, such relationships are usually very complicated and in some cases may not appear distinct due to the interactions of soil properties. Furthermore, a prediction model well suitable for this area may not be applicable to other areas in different climatic regions.

The principal aim of this section is to determine whether the relations between soil properties and spectral characteristics appear significant and whether these relationships can be utilized to quantify soil chemical properties and types from spectral reflectance measurements of soil samples.

These questions are to be examined in two ways: (a) a correlation/regression study to examine the relationship between the spectral measurements and the observed physical and chemical properties of soils on a single parameter basis using all sample data, and (b) a clustering/discriminant multivariate analysis to determine soil spectral categories to be used for prediction of important soil properties and soil types. The multivariate method is likely more useful because it allows for a determination of parameter interactions.

1. CORRELATIONS OF SOIL PARAMETERS WITH SPECTRAL REFLECTION VALUES

Using spectral reflectance values in the four Landsat MSS bands versus individual soil parameters, a correlation analysis was carried out for all 108 soil samples. A matrix showing correlation coefficients is given in Table 4.3.1, and serves as an indication of the degree in collinearity among the variables. The original correlation matrices of all soil parameters, reflection bands and pixel values in two dye-layers, as well as ratioed or logarithmic transformed variables can be found in Appendix 6 and 7. With the exception of pH and exchangeable Na, significant correlations were found between most soil parameters, spectral reflectance bands and pixel values (Table 4.3.1). The organic matter content, expressed by percent organic C showed the highest correlation coefficient with reflectance Band 4 ($r=0.80$), followed by total N, though this relationship may be attributed to the fact that C and N were correlated. CEC, exchangeable Ca and Mg, and available P all showed significant correlations with reflectance but the correlation coefficients obtained were low (generally around 0.50), in comparison with r values for reflection and organic C. This indicates that the influence of these parameters on reflection may be of secondary nature and considerably smaller than the contribution from organic matter. Also, their predictivity will likely be of lower accuracy.

Coarse fragment content and moisture values cannot be used in predictive equations in this study because the

Table 4.3.1 Correlation matrix showing correlation coefficient between any two variables. (R@ 0.05=0.1891 0.01=0.2469)

Soil Parameters vs Reflectance and Density Values

VARIABLE	15. B4	16. B5	17. B6	18. B7	35. B4/B5	36. B5/B6	37. B6/B7	38. BANDS	19. RED	20. GRE	39. GRE/RED	40. GRE+RED
1. MC	-.4324	-.2859	-.3806	-.2559	-.3895	.1560	-.4289	-.3562	-.6870	-.7360	-.3819	-.7191
2. CF	.0765	-.0039	-.0123	-.0673	.1266	-.0189	.1831	-.0054	.3257	.4346	.4758	.3847
3. PH	.1306	.0388	.0292	-.0756	.1939	.0205	.2996	.0275	.0572	.1180	.2395	.0888
4. TC	-.7914	-.7541	-.7696	-.7188	-.3510	-.1164	-.2608	-.8010	-.7499	-.6974	-.0461	-.7309
5. OC	-.7950	-.6850	-.7015	-.5904	-.4637	-.0973	-.4245	-.7287	-.7508	-.7282	-.1519	-.7470
6. NA	-.0972	-.1524	-.1496	-.0474	.0509	-.0313	-.2932	-.1168	-.0881	-.0580	.0721	-.0737
7. K	-.2125	-.1907	-.1923	-.1225	-.1119	-.0189	-.2187	-.1878	-.1859	-.1799	-.0408	-.1847
8. CA	-.4056	-.3990	-.4073	-.3744	-.1606	-.0663	-.1511	-.4190	-.5002	-.4290	.1126	-.4690
9. MG	-.5261	-.4757	-.5445	-.4314	-.2850	.0508	-.4100	-.5223	-.5791	-.5595	-.1210	-.5751
10. CEC	-.5667	-.4673	-.4893	-.3610	-.3619	-.0302	-.4474	-.4941	-.5850	-.5960	-.2196	-.5967
11. P	-.5106	-.5060	-.5385	-.4951	-.2073	-.0439	-.2129	-.5425	-.3743	-.3089	.1052	-.3448
12. N	-.7403	-.6659	-.6229	-.5281	-.3880	-.2263	-.3673	-.6705	-.6259	-.5877	-.0540	-.6129
13. V	.5756	.6115	.6916	.6548	.1807	-.0403	.2115	.6735	.5839	.5360	.0124	.5655
14. CH	.2563	.2707	.3866	.3470	.0928	-.1750	.1566	.3379	.2806	.2302	-.0864	.2578
24. LNTC	-.8062	-.7646	-.7365	-.7102	-.3488	-.1965	-.1940	-.7952	-.6794	-.6305	-.0351	-.6615
25. LNOC	-.8213	-.7014	-.6733	-.5835	-.4761	-.1824	-.3644	-.7291	-.6753	-.6503	-.1175	-.6695
27. LNK	-.3163	-.2684	-.2870	-.1775	-.1824	.0017	-.3379	-.2746	-.2570	-.2605	-.0906	-.2615
28. LNCA	-.5468	-.5093	-.4911	-.4618	-.2499	-.1327	-.1591	-.5290	-.5065	-.4534	.0425	-.4847
29. LNMG	-.5786	-.4950	-.5333	-.4188	-.3430	-.0142	-.4043	-.5328	-.5169	-.5093	-.1338	-.5184
30. LNCEC	-.5648	-.4616	-.4590	-.3350	-.3595	-.0755	-.4299	-.4761	-.5487	-.5653	-.2235	-.5629
31. LNP	-.5317	-.5188	-.5269	-.4920	-.2215	-.0935	-.1850	-.5466	-.3184	-.2666	.0755	-.2953
32. LNN	-.7819	-.6889	-.6136	-.5402	-.4201	-.2833	-.3098	-.6869	-.5857	-.5570	-.0721	-.5771

effect of these parameters on soil reflection was removed by screening and drying of the samples in the laboratory prior to spectral measurements. Good relationships between soil moisture and spectral reflectance were found in the 2.02-2.32 μm region of wavelengths (Moore et al., 1975; Stoner and Baumgardner, 1980). However, soil moisture content was found to be the second highest soil parameter next to organic matter to be correlated with pixel value data, especially in green sensitive dye-layer. It is evident that soil moisture content is also an indirect factor since it is connected with soil texture, drainage and organic matter, all of which influence surface soil reflectance characteristics in visible and near infrared wavelength bands.

Many studies have noted that the relationship of laboratory-measured soil spectral reflectance versus soil chemical properties can best be described as a curvilinear function. Scatter diagram of reflectance in the specific bands plotted against total carbon revealed a definite negative curvilinear relationship between soil organic matter and reflectance (Figure 4.3.1). A natural logarithmic transformation was performed prior to the correlation analysis with spectral reflectance values (Table 4.3.1). It was found that the natural Log C content was best for relating organic matter to reflection in two visible bands (B4 and B5) and the correlation coefficient was found to be highest between Band 4 and Ln OC (r=0.82). Considerable

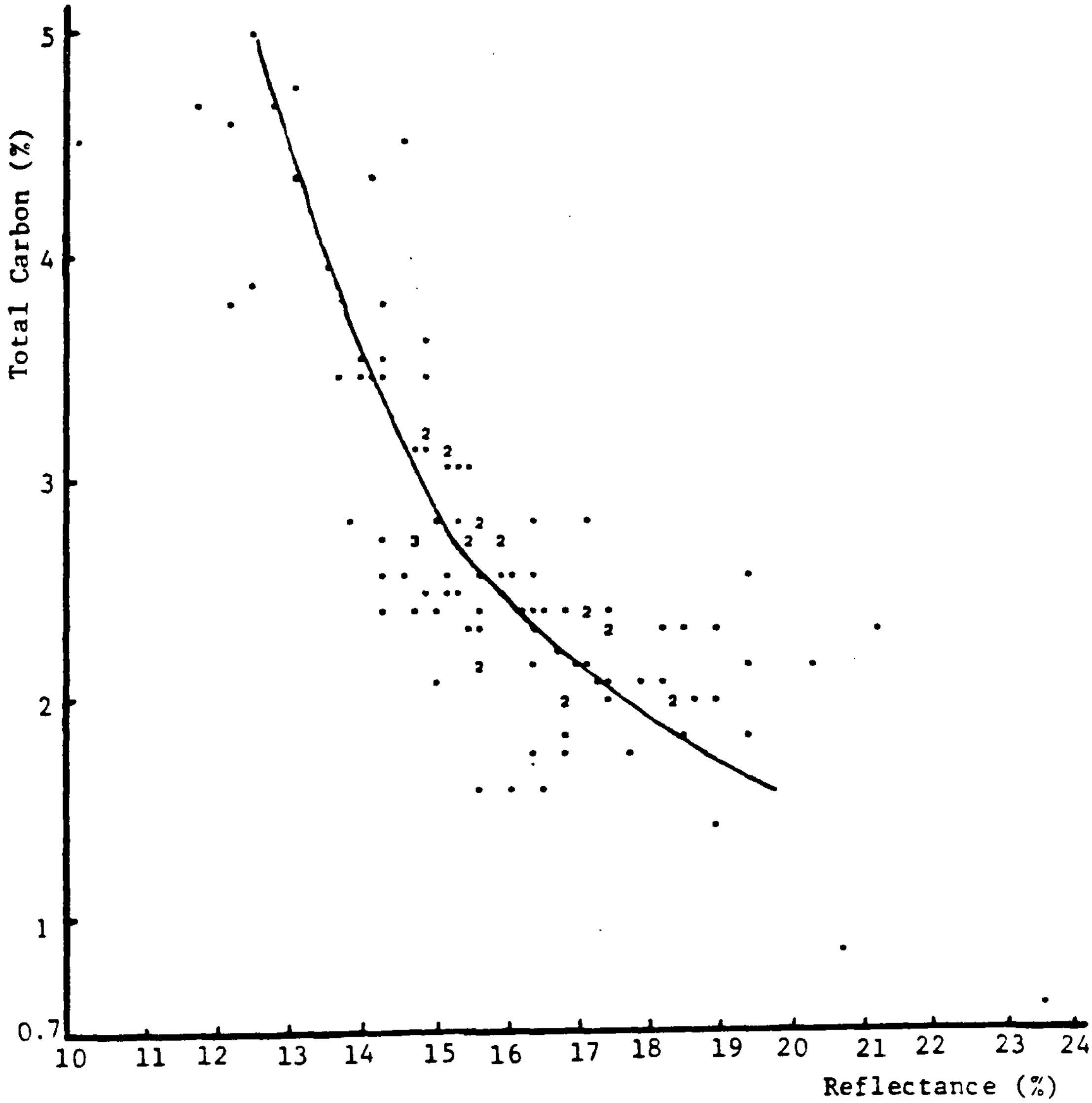


Figure 4.3.1 % total carbon carbon plotted against reflectance in Band 4 (0.5-0.6 m) showing a negative curvilinear relationship.
* Numbers indicate overlapping points

improvements were observed in most relationships after log-transformation and these results are in agreement with the findings reported by Schreier (1977). The log-transformed N and P also showed a higher correlation coefficients with the visible bands. No significant improvement was observed between the transformed CEC and the spectral bands, but r values for transformed Ca, Mg and K were higher.

Band ratios and combinations were considered in this correlation study and lower r values were found for band ratios than for spectral bands. Table 4.3.1 also shows no significant improvements over individual bands using additive band combinations. It is likely that the individual band will be superior to band ratios and combinations in predicting soil parameters.

The Munsell color notations, especially color value, were found to be significantly correlated with spectral reflectance and dye-layer pixel values. Their correlations with soil parameters such as percent OC were also noted. Quantitative relationships between color and organic matter of soils were found to be significant but r values were lower than those obtained from the use of spectral values and organic matter.

The conclusions drawn from the correlation results are in agreement with previous findings from the literature. The logarithmic transformation of organic matter accounts for the highest correlation with reflectances, which means that on the basis of all measured soil properties organic C has the highest potential to be predicted from spectral remote sensing data. The correlations of spectral data with Munsell color value, CEC, and exchangeable cations are also significant but their predictions are more complicated and simple linear relationships are insufficient because the presence of soil organic matter may mask the effects of other properties on reflectance characteristics of soils. The importance of water content is evident, however, it is unlikely to be predicted using the spectral bands employed in this study.

2. REGRESSION ANALYSIS FOR PREDICTING SOIL PARAMETERS AND SPECTRAL VARIATIONS

Although the degree of correlation between the soil properties and the individual spectral bands has been seen in Table 4.3.1, the significance of each band in predicting the level of certain soil parameters is not fully understood. This was examined by using a stepwise multiple regression procedure to develop regression equations for prediction of selected soil parameters from reflectance data in four spectral bands. Independent variables also included the pixel values of two dye-layers because our purpose here was to determine the relative contributions of individual wavelength reflectance or pixel values to the prediction of soil parameters rather than to use these band values together for predictions. Dependent variables, or the variables being estimated from reflectance data were the natural logs of total C, organic C , N, moisture content, CEC and color value.

Spectral bands which entered the regression equations with their significance levels and the cumulative R^2 values are given in Table 4.3.2 for each of the predictive soil parameters. R^2 values as high as 0.78 for prediction of OC, 0.66 for N, 0.59 for moisture content were obtained at the significance level of 90%. Approximately 50% of the variability of color value and CEC can be explained by spectral reflectance and pixel values. The low R^2 values in this study compared with those from literature reported by Stoner and Baumgardner (1980) are attributable to broad bands and few observations used in this study. This means that the satisfactory prediction equation may not be established for those soil parameters having low R^2 values.

In order to summarize the important contributions of each band in predicting the overall soil parameters and identify optimum wavelengths for future uses, the number of times each band or dye-layer entered into the prediction equations at the 90% significance level was counted in the order of entry and total inclusions. The results are presented in Table 4.3.3. Clearly, the green portion of wavelength is the most promising band to predict soil properties. Band 4, which entered the regression three times in the first place position, is the most important for spectral band predicting soil organic matter-related

Table 4.3.2 Stepwise multiple regression of spectral band and pixel value as predictors of soil parameters at a significance level of 90%.

SOIL PROPERTY	SPECTRAL BAND B4	B5	B6	B7	PIXEL VALUE GRE	RED	CUMULATIVE R^2
TC	1* 0.0000#		3 0.0153			2 0.0000	0.76
OC	1 0.0000		4 0.0068	3 0.0390		2 0.0000	0.78
N	1 0.0000	4 0.0308		3 0.0355		2 0.0155	0.66
MC			3 0.0024	2 0.0665	1 0.0000		0.59
VALUE			1 0.0000			2 0.0031	0.52
CEC	2 0.0003		4 0.0177	3 0.0408	1 0.0000		0.49

* Order of inclusion of the variable(band) into regression equation.
\# Significant level obtained for the variable.

Table 4.3.3 Frequency of inclusion of spectral bands into regression (Table 4.3.2) at a significance level of 90%.

BAND	ORDER OF ENTRY* 1st	2nd	3rd	4th	TOTAL#
B4	3	1			4
B5				1	1
B6	1		2	2	5
B7		1	3		4
GREEN	2				2
RED		4			4

* Only the first four entries were counted.
\# All entries were included.

parameters and green filter pixel value which was first included in moisture content and CEC regression equations, shows its potential for predicting these parameters and soil texture-related parameters. Near infrared Band 6 is of most importance, in relating color value with spectral properties, which is in agreement with the correlation study discussed earlier. This band, as well as B7, another infrared band, also contributed to variations of many other soil parameters, but to a lesser extent. Red filter pixel value often entered the equation as the second largest contributor to the prediction model for soil parameters.

The ultimate objective of the correlation regression study is to be able to predict the level of soil parameters using optimum spectral reflectance band values. Simple linear or curvilinear regressions were carried out using soil parameter values versus their best correlated spectral bands. The examples are only given for OC and N. Their natural log transformed values against the corresponding spectral values in Band 4 were plotted in Figure 4.3.2 and Figure 4.3.3. The best regression equations for Ln OC and Ln N were obtained with the highest correlation coefficients. Nearly 67% of the total variability for OC and 61% for N were found to be accounted for by the spectral reflection values in 0.5-0.6 μm wavelength region. In the cases of other soil parameters, the regression lines are not as significant and, accordingly, accurate predictions are not expected.

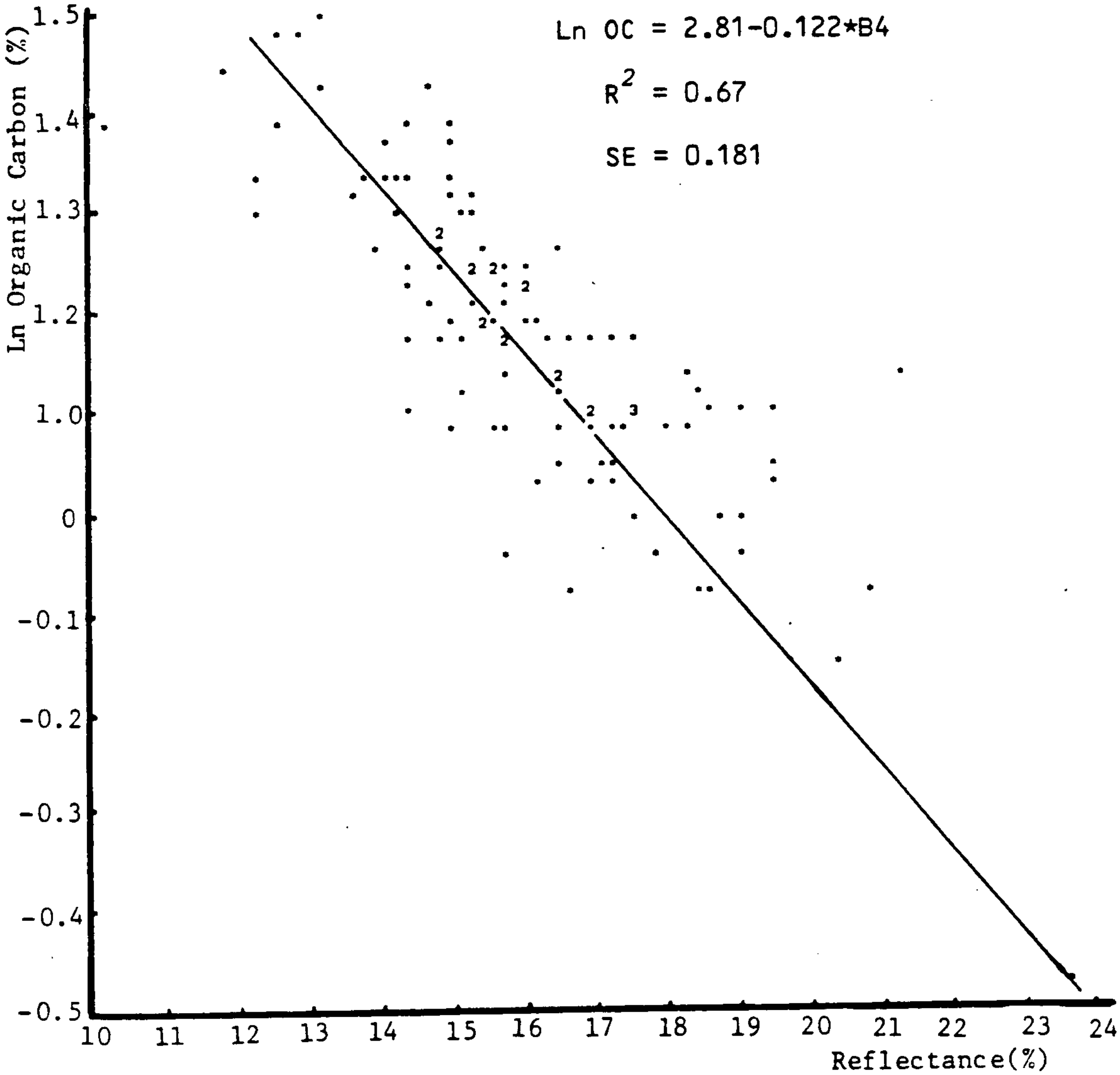


Figure 4.3.2 Regression: Log OC vs reflectance in Band 4.
* Numbers indicate overlapping points.

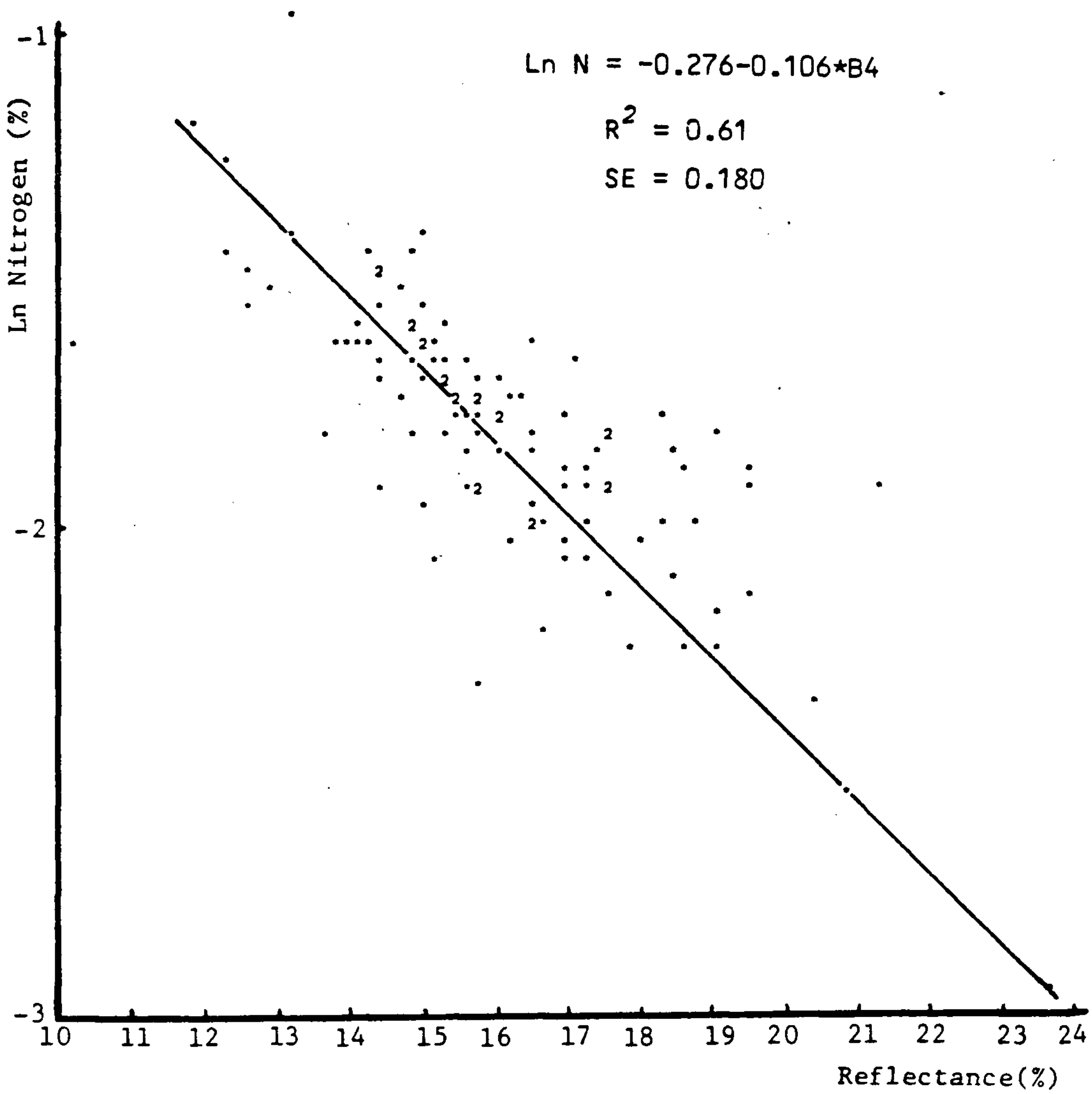


Figure 4.3.3 Regression: Log N vs reflectance in Band 4.
* Numbers indicate overlapping points.

The spectral variations in soil reflectance in given wavelength regions in terms of observed soil parameters were examined again by employing a stepwise multiple regression model. The approach has proved to be useful in identifying the important contribution of individual soil parameters and parameter interactions responsible for spectral variations. This time, soil data were entered into the regression model as estimators of spectral reflectance values of all samples in four wavelength bands. The 10 independent variables used were coarse fragment content, % organic C, K, Ca, Mg, CEC, P, N, color value and chroma. The use of the natural log transformation values of some soil parameters for the given spectral band was decided according to the r values obtained in the correlation analysis.

The results are provided in Table 4.3.4. The order of inclusion of the independent variables into regressions for individual spectral bands reveals the importance of the specific soil parameters in explaining spectral variations. Organic C was found to be the first variable to enter the regression equation for all given spectral bands except for Band 7 which had the Munsell value as the first entry. This suggests that the influence of soil organic matter on spectral variations in near infrared bands is less effective than in the visible bands. In addition to Band 7, color value was also selected to enter the regression equations for Band 5 and 6 as the second variable and for Band 4 as the third variable, indicating its close relationship with

Table 4.3.4 Stepwise multiple regression of soil parameters as predictors of reflectance bands at a significance level of 90%.

BAND	CF	OC or LNOC	K or LNK	MG or LNMG	CA or LNCA	CEC	P or LNP	N or LNN	VALUE	CHROMA	CUMULATIVE R^2
B4	2* 0.0133#	1 0.0000							3 0.0338		0.71
B5		1 0.0000			6 0.0847	4 0.0237	3 0.0185		2 0.0001	5 0.0552	0.63
B6		1 0.0000			6 0.0678	5 0.0127	4 0.0021		2 0.0000	3 0.0020	0.70
B7				5 0.0079	4 0.0067		2 0.0001		1 0.0000	3 0.0041	0.60

* Order of inclusion of the variable (soil parameter) into regression equation.
# Significance level obtained for the variable.

spectral measurements. Coarse fragment content was included in the regression as the second important soil parameter for predicting spectral reflectance values in green band (Band 4). The inclusion of this parameter may imply that there is a relationship between reflectance and soil texture. Other parameters such as P, Ca and CEC played a role in the equations, but to a lesser extent. Total N was not observed to be included into the regressions where organic C was dominant. This suggests that the role of N in explaining spectral variations has already been accounted for since they are closely correlated with soil organic matter. The frequency of each soil parameter to enter the regressions is summarized in Table 4.3.5.

The cumulative R^2 values in Table 4.3.4 indicate to what extent the variability of spectral reflection in specific bands can be explained by the interactions of variables included in the regressions. R^2 values varied from the highest (Band 4) to the lowest (Band 7). In the case of reflectance values in Band 4, 71% of the variability was accounted for by the interactions of three variables. The significance of the next variable entered dropped to less than 90%. For the Band 7 values, five variables were needed and explained only 60% of the variability. The prediction of reflectance difference in Band 4 seems to require the fewest soil parameters and obtain the highest estimation accuracy. However, overall R^2 values obtained in this study are lower in comparison with the literature data (Stoner and

Table 4.3.5 Frequency of inclusion of soil parameter into regressions (Table 2.3.4) at significance level of 90%.

SOIL PROPERTY	1st	2nd	3rd	4th	TOTAL#
		ORDER OF ENTRY*			
OC	3				3
V	1	2	1		4
CF		1			1
P		1	1	1	3
CHROMA			2		3
CA				1	3
CEC				1	2

* Only the first four entries were counted.
\# All entries were included.

Baumgardner, 1980). This is suggestive that other parameters, such as site characteristics may be involved in this process and account for an important part of spectral variations.

The significance of the results developed from these regression studies is twofold. First, with respect to soil parameters the results are consistent with the findings from correlation analysis and further explain why those relationships are significant and how the spectral properties of soils are affected. Soil organic matter and color value are most important among soil parameters in terms of being able to explain the difference of spectral values, especially in Band 4. The variations of these properties, in turn, are likely to result in spectral reflectance curve changes, thus, the prediction becomes possible. The prediction model for organic C using a single spectral band was illustrated. Secondly, the regression models help us to identify the optimum spectral wavelength band for prediction. Variable results were found in this study and even with the best band such as Band 4, the predictions are not entirely satisfactory. This leads to the use of multivariate methods to quantify the spectral reflectance curves for predicting soil properties and types.

3. MULTIVARIATE CLASSIFICATION OF SOILS USING SPECTRAL REFLECTANCE VALUES

Over the years, many quantitative numerical methods have been developed to quantify soil types and the variability of soil properties. A cluster analysis was used by Schreier and Lavkulich (1980) and Schreier (1985) to predict soil and mine sample types in terms of their organic matter, iron content and sample origin based on the characteristic spectral curves. Crouse et al., (1983) also used cluster/discriminant analysis to identify the important soil parameters which were highly correlated with six TM reflectance bands. The same approach was used in this study in order to examine how well it can be used to predict the variability of important soil properties and define soils with different fertility conditions.

The spectral reflectance data in four dimensional space were classified with an average distance linkage cluster analysis. The total 108 soil samples from the stratified random and selective sampling sets were grouped into five unique spectral classes and the resulting dendrogram which provided a measure of the degree of similarity between the various spectral characteristics of soil samples is shown in Figure 4.3.4. The summary data of each of the spectral classes are given in Table 4.3.6 and the data from reflectance and pixel value measurements are also included. Although the spectral differences among clusters can be seen in an individual band by band basis, it is difficult to visualize the overall spectral separation among five spectral classes. Figure 4.4.5 gives the characteristic spectral reflectance curves of each spectral class, where means, plus and minus one standard deviation, were plotted.

The individual soil spectral classes (A to E), as illustrated in Figure 4.3.5, were found to be very different from one another. Significant differences between classes, on a parameter-by-parameter basis, were further examined by using a Mann-Whitney U-test with a confidence level of 95%, and the results are shown in Figure 4.3.6. The significant separation was obtained between any pair of classes in all spectral bands. This suggests that each class has formed a distinct spectral category.

Since significant correlations have been found between the spectral reflection values and a number of soil physical

Table 4.3.6 Summary of soil data for different spectral classes obtained from cluster analysis.

(a) Physical and chemical data

Unit	n	MC	CF	pH	TC	OC	K	Ca	Mg	CEC	P	N
A	24	32.5*	30.7	6.91	3.78	3.29	0.555	12.82	0.750	22.7	145.9	0.186
		11.5#	12.4	0.36	0.71	0.69	0.24	4.08	0.47	7.0	56.5	0.05
B	39	26.6	29.0	6.93	2.71	2.47	0.557	11.04	0.472	18.8	106.2	0.146
		6.2	7.7	0.27	0.44	0.50	0.28	5.37	0.17	3.2	38.2	0.03
C	10	24.0	30.3	6.83	1.94	1.66	0.379	6.73	0.327	15.3	83.6	0.101
		5.5	11.1	0.37	0.62	0.50	0.28	2.34	0.28	4.01	32.2	0.03
D	15	23.9	33.6	7.16	2.22	1.83	0.387	9.29	0.334	16.3	95.0	0.113
		5.3	9.4	0.32	0.20	0.27	0.14	3.68	0.13	2.67	25.5	0.02
E	20	29.4	26.1	6.98	2.55	2.30	0.549	9.80	0.417	18.7	93.6	0.133
		6.9	6.9	0.33	0.60	0 58	0.53	2.78	0.19	3.56	26.9	0.03

(b) Color, spectral and pixel value data

UNIT	n	Value	Chroma	B4	B5	B6	B7	Red	Green
A	24	4.38*	3.17	13.6	17.5	23.1	24.6	183.2	170.1
		0.70#	0.48	1.2	1.4	2.0	2.1	15.7	16.7
B	39	5.64	3.79	15.6	19.8	26.5	28.0	199.9	186.1
		0.54	0.80	0.8	0.7	0.6	0.8	10.2	10.4
C	10	5.90	3.90	20.2	23.5	30.2	31.7	207.9	194.6
		0.57	0.88	1.61	1.7	1.2	2.0	7.2	9.6
D	15	5.87	4.07	18.1	21.1	27.8	28.6	204.0	190.9
		0.35	0.59	0.6	1.4	0.5	0.9	7.5	7.9
E	20	5.95	3.95	16.3	21.7	28.7	30.1	200.0	185.2
		0.22	0.60	0.8	1.0	0.7	0.6	8.8	9.9

* mean # standard deviation

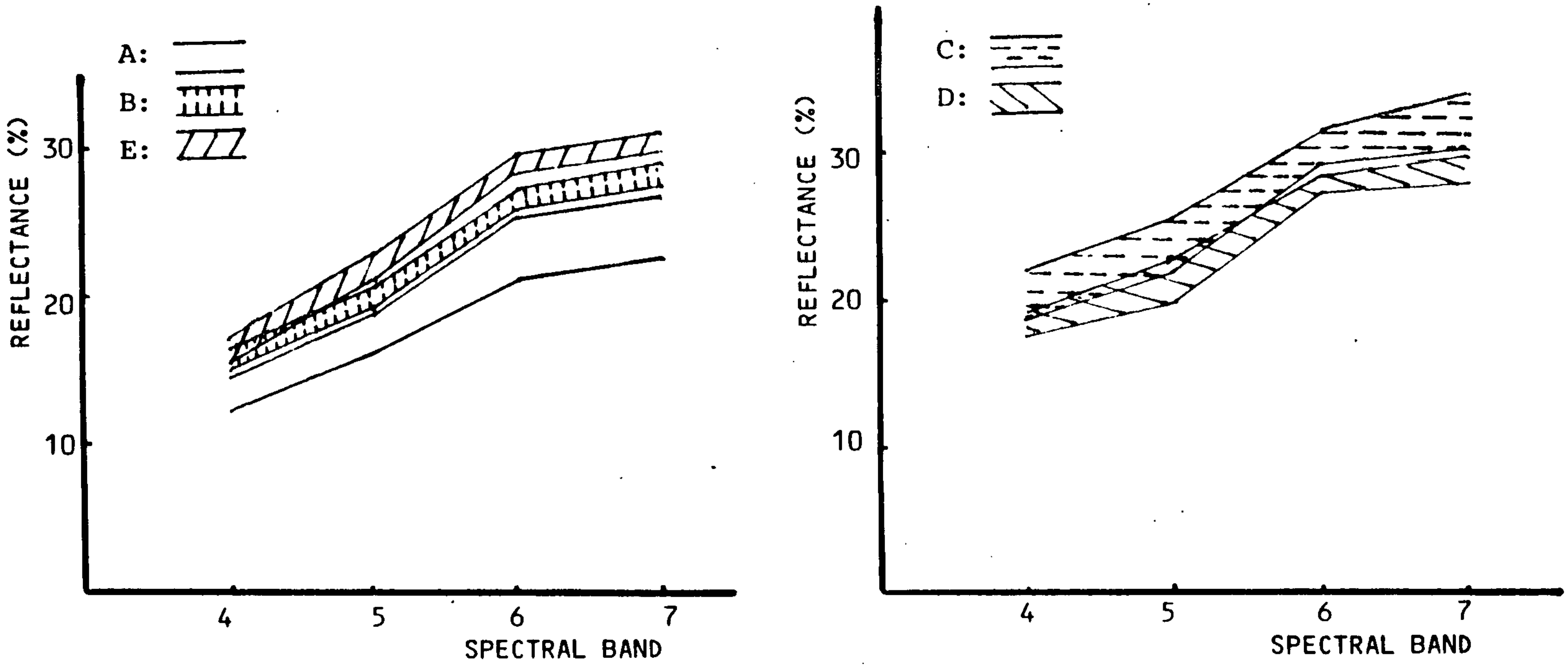


Figure 4.3.5 Spectral reflectance curves of spectral classes (A to E) from cluster analysis.

	A	B	C	D
B	TC, OC, CA, MG CEC, P, N, VALUE, CHROMA, B4, B5, B6, B7, RED, GREEN			
C	TC, OC, CA, MG, CEC, P, N, VALUE, CHROMA, B4, B5, B6, B7, RED, GREEN	pH, TC, OC, K, MG, CEC, N, B4, B5, B6, B7		
D	MC, pH, TC, OC, K, CA, MG, CEC, P, N, VAULE, B4, CHROMA, B5, B6, B7, RED, GREEN	TC, OC, K, CA, MG, CEC, N, B4, B5, B6, B7, RED, GREEN	pH, B4, B5, B6, B7	
E	TC, OC, CA, MG, CEC, P, N, VALUE CHROMA, B4, B5, B6, B7, RED, GREEN	NA, VALUE, B4, B5, B6, B7	TC, OC, CA, CEC, N, B4, B5, B6, B7, RED, GREEN	MC, CF, TC, OC, CEC, N, B4, B5, B6, B7, GREEN

Figure 4.3.6 Parameters separated between soil spectral classes identified by Mann-Whitney U-test (α=0.05).

and chemical properties, it is possible to characterize each cluster class in terms of soil parameters. Table 4.3.6 provides the soil parameter mean and standard deviation for each spectral class. A comparison can be made among classes using single soil parameters. To get a statistical evaluation of the soil properties which best separate the multi-spectral classes, the Mann-Whitney U-test was again used to test significant differences of individual soil parameters between classes (Figure 4.3.6). If a soil parameter is identified to be significantly different between spectral classes, it suggests that the spectral classification by the clustering is successful and can thus be used for predictive purposes.

It is evident from these figures that no single soil property was separated by spectral classes in all cases. It means that those spectral classes cannot be differentiated on the basis of any one soil parameter. The best parameters were TC, OC, N and CEC, in which cases 80% of all classes appeared to have unique characteristics of those properties. About 70% of classes showed that they could be separated by green filter pixel value, and followed by Ca, Mg, red filter pixel value (60%), and color value (50%). For the rest of the soil parameters, only a partial classes separation was observed. The results reveal a good relationship exists between multi-spectral reflectance data and soil properties with high degree of separation such as organic matter and CEC.

The results shown in Figure 4.3.6 can be used to evaluate the spectral class separations in terms of overall soil characteristics or soil types. Highly successful separation was found between spectral class A and the rest of classes. Almost all soil properties that were highly correlated with spectral reflectance were differentiated. A good classification was achieved between class B and D, only P and moisture content were not separated in this case. The results of class B vs C, C vs E and D vs E are also fairly good. The poorest differentiations of soil parameters were found between class C and D, and class B and E, though they did show distinct spectral separations.

By examining the soil data across spectral classes from Table 4.3.6, we found class A represents the type of soils with high fertility status in terms of high average levels of organic matter, CEC and fertility elements N and P (Type I). The average concentration of K in class A is among the highest but it is not different from the levels of class B and E. Class C with highest spectral values corresponds to an overall low levels of soil chemical properties including organic matter content, CEC, and N, P, K, although this class is very close to class D. Spectral class D shows the lowest soil water content and the highest coarse fragment content. Its overall soil chemistry and fertility status are a little higher than those of class C but substantially lower than those in other classes except for P content which is similar to class E. Classes B and E generally represent average soil conditions (Type III) and hold over 55% of soil samples studied.

4. IDENTIFICATION OF SIGNIFICANT SOIL PARAMETERS FOR DIFFERENTIATING SOIL SPECTRAL CLASSES

In order to evaluate the role of each soil parameter in the contributions of overall soil characteristics to spectral curve separations, an investigation was undertaken to identify which soil property and property combination could actually serve to discriminate among spectral classes. This is of particular importance if soil parameter interactions are common in the data set. Some soil parameter, which appears to be distinguished between spectral classes, may not present cause and effect relationships with spectral characteristics, but may be the result of auto-correlation and associated indirect relationships.

A stepwise discriminant analysis was run on five spectral classes with all thirteen soil parameters as variables in order to evaluate which soil properties could best be used to discriminate spectral classes. Total C was not entered simply because a very large part of its contribution had been accounted for by organic C. The results identified that organic C, color value and moisture content were the first three variables that entered the discriminating function to separate spectral classes at a probability of 95%. Table 4.3.7 lists, in order of entry, the selected parameters. The separability of these properties among clusters is shown in Figure 4.3.7, in which the property means and standard deviations were plotted on a cluster-by-cluster basis.

As illustrated in Table 4.3.7, organic C appears as the most influential soil property for spectral class separations. The appearance of Munsell color value as the second most important variable is not unexpected due to its high correlation with spectral reflection. Although CEC and N appeared most of the times separated by spectral classes, they were excluded from the list of discriminant variables. This can be explained by their close relationships with organic C ($r = 0.81$ and 0.87 for CEC and N, respectively). It is an important feature of the stepwise discriminant analysis that once a variable is entered into the model, variables which are highly correlated to the entered variable will have less chance of being selected on the next step since most of their discriminanting power has already been accounted for. The selection of moisture content is somewhat suspect since no direct relationship was measured between this parameter and reflectance in this study. Its selection may be due to the associations of water content with other soil properties. When those soil properties are removed, the importance of the moisture content increases. The inclusion of color chroma is more difficult to explain, it seems to be attributable to the big separation between class A and other classes.

Table 4.3.7 Soil properties selected by discriminant analysis for discriminating among spectral classes ($\alpha = 0.05$).

PROPERTY	U-STATISTIC	F PROB
OC	0.5060	0.0000
VALUE	0.4176	0.0006
MC	0.3574	0.0033
CHROMA	0.3162	0.0148

Figure 4.3.7 visually illustrates some points made in the above discussion. It is evident that none of these single properties can be used to differentiate spectral classes. Considerable overlaps exist between classes, especially in the cases of moisture content and chroma. The successful results obtained by cluster analysis with respect to soil parameter separation must thus be viewed as the result of the combination of these discriminating properties and their interactions with other important properties.

D. QUANTIFYING SOIL CONDITIONS USING PIXEL VALUE DATA OF SOIL SAMPLES

In the spatial analysis discussed in section B, we have determined soil patterns based on digitized airphoto dye-layer pixel value data and using an unsupervised multivariate classification procedure. The assumption was

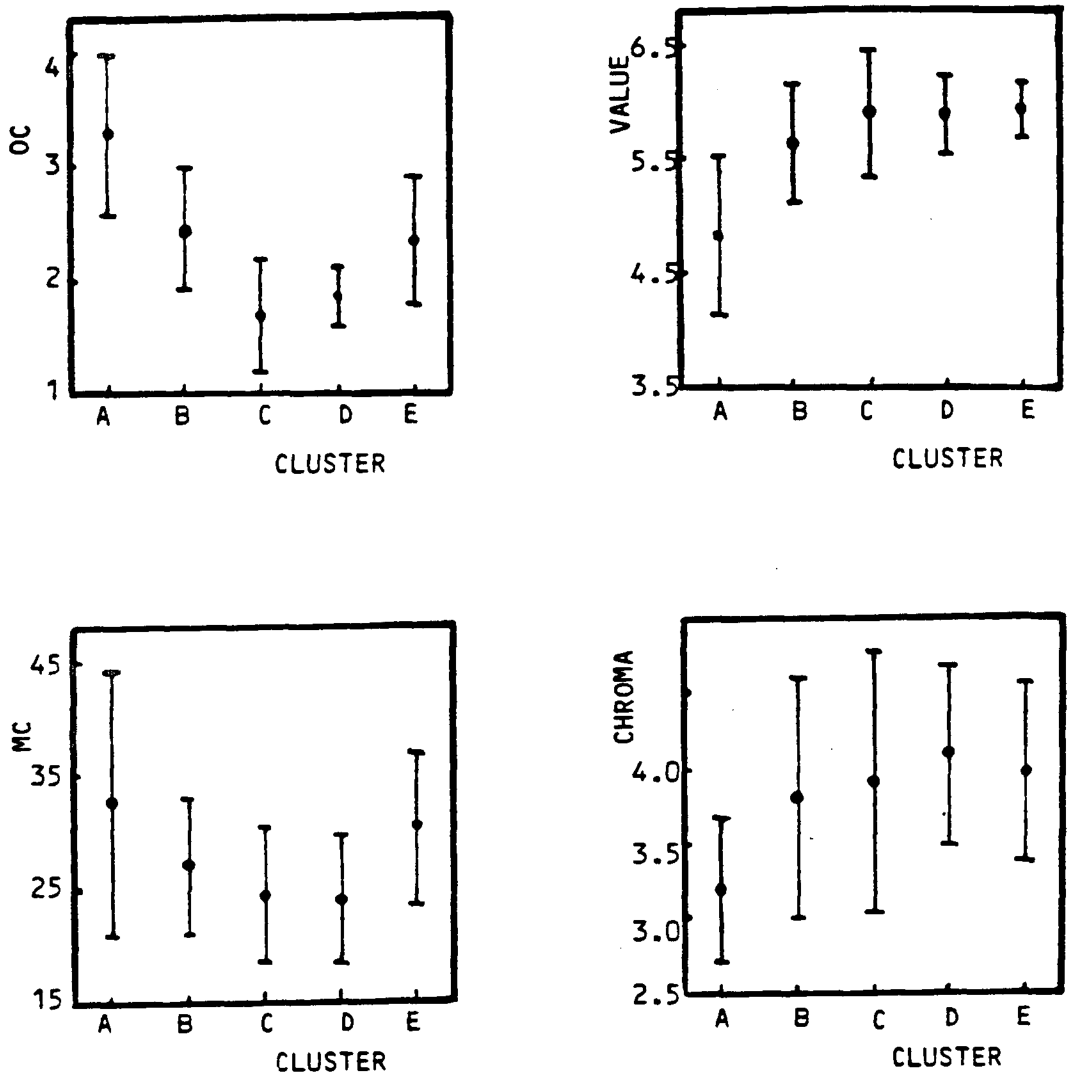


Figure 4.3.7 Soil properties as discriminants in each spectral class (A to E).

made that a good relationship must exist between the soil parameters and the pixel values. If this is true it should be possible to quantify the soil pattern on the aerial photograph by numerical analysis using the digital pixel values. This will allow us to determine how well we can rely on the pixel value data to predict the variability of soil parameters and types. It is the objective of this section to compare the relationship between the 108 soil samples with the corresponding red or green filter pixel values. The numerical methods used to relate soils to spectral properties were once again used to compare soil properties with pixel values.

1. DETERMINATION OF THE RELATIONSHIPS BETWEEN PIXEL VALUES AND SOIL PROPERTIES VIA CORRELATION/REGRESSION ANALYSIS

A correlation analysis was carried out for all 108 soil samples using individual soil variables versus the green and red dye filter pixel value data obtained from computer printouts in each sample location. Some results have already been discussed in the last section where a correlation matrix was presented (Table 4.3.1). Generally, most soil properties showed a significant correlation with both the green and the red filter pixel values except for pH and exchangeable K and Na. Among these highly correlated soil parameters, organic C received the highest coefficient (r=0.75) with red filter pixel value, followed by soil moisture content (0.69) and total N (0.63). For the green filter pixel value, the carbon-pixel value relationship was lower than the moisture-pixel value relationship which showed the highest r value of 0.74. A scatter diagram was plotted in Figure 4.4.1, to show their close relationship. Moisture proved to be more highly correlated with pixel values than with spectral data because spectral reflection measurements were performed on air dry samples whereas dye-layer pixel values which accounted for photo tonal variations represented the undisturbed site conditions at the time of the flight. This indicates that soil water in the field exerts a large influence on soil spectral variations and this may have a larger effect on relection than organic matter. Spectral analysis of soils under different moisture conditions needs to be carried out to determine the ultimate effect. Since water itself is not sensitive to absorbed light in the visible bands, the influence of soil moisture content on photo pixel values is attributed to its association with other soil and site characteristics, such as texture and drainage.

The correlations between exchangeable cations, CEC, and pixel values in both red and green fitler dye-layers were also significantly higher. The exception was K which only showed a low correlation coefficient with the pixel value data after logarithmic transformation. However, the correlation coefficients with Ca, Mg, and CEC were usually within the range of 0.5 to 0.6, this means that predictions may not entirely be reliable based on the values from a single dye-layer pixels. Coarse fragment content also showed a moderate correlation with pixel value data and correlation coefficients were significantly improved in comparison with correlations with spectral reflection.

Dye-layer ratioing and additive combination were considered, but rejected because almost no advantage over correlations with individual dye-layers was expected. It is also noted from the correlation matrix(Table 4.3.1) that the correlation between green and red filter pixel values was very high (r=0.95), but they behaved differently with regard to soil properties.

Simple linear regressions were performed for % organic C and moisture content, as well as other soil parameters with red and green filter pixel values. Two examples of these results are provided in Figure 4.4.1 and Figure 4.4.2. Although the correlations were highly significant, the variance explained by the respective regression equations was at best 56% for organic C versus red filter pixel value, and 54% for moisture content versus green filter pixel value. In most instances, the correlation of single dye-layer data with specific soil properties was not good enough for predictive purposes.

In order to examine to what extent the pixel value data can be explained by soil parameters, a stepwise regression analysis was carried out with the green and the red filter dye-layer pixel values as dependent variables. The independent variables entered into the regression were

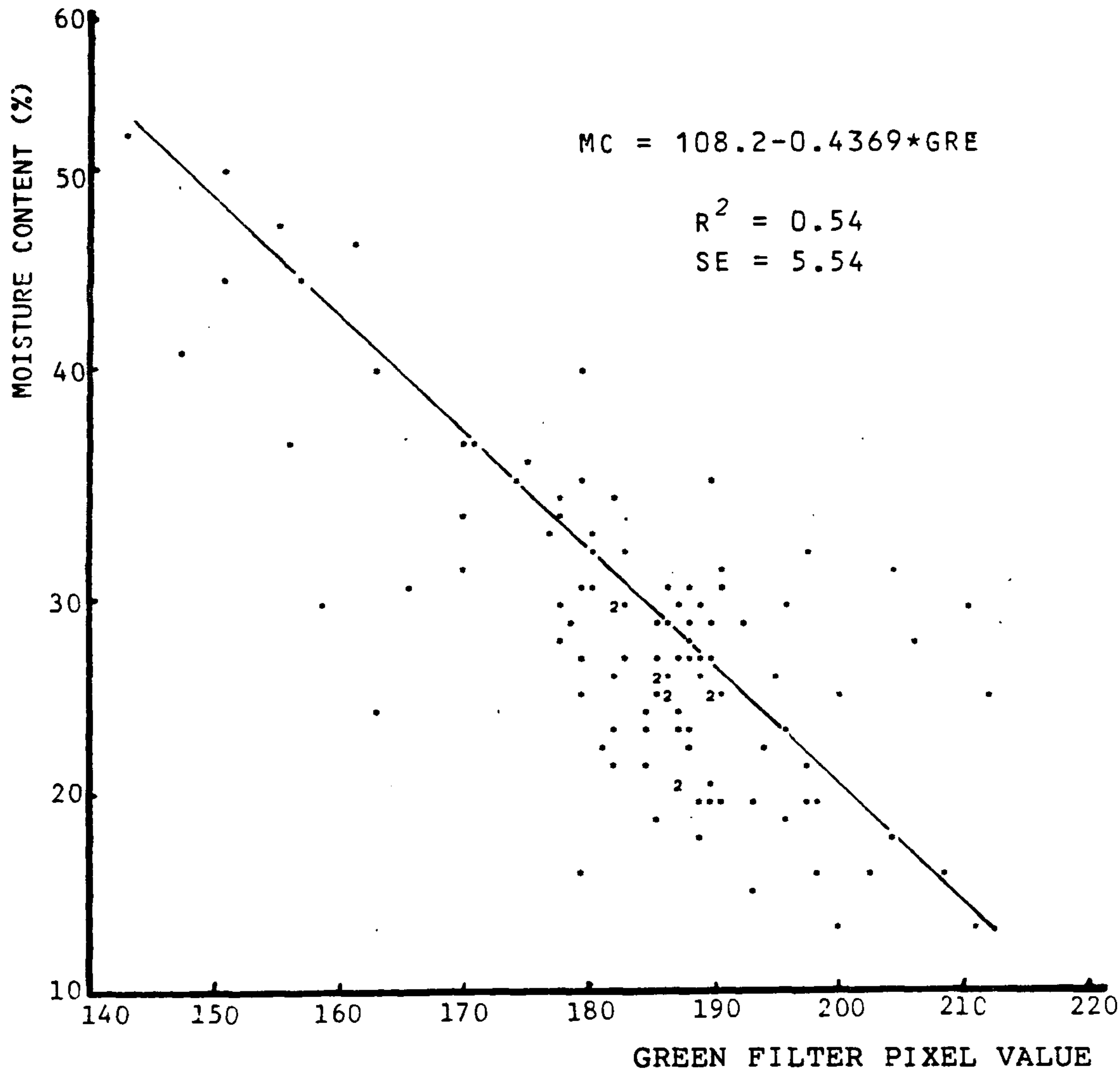


Figure 4.4.1 Scatter diagram of soil moisture content plotted against green filter pixel values.
* Numbers indicate overlapping points

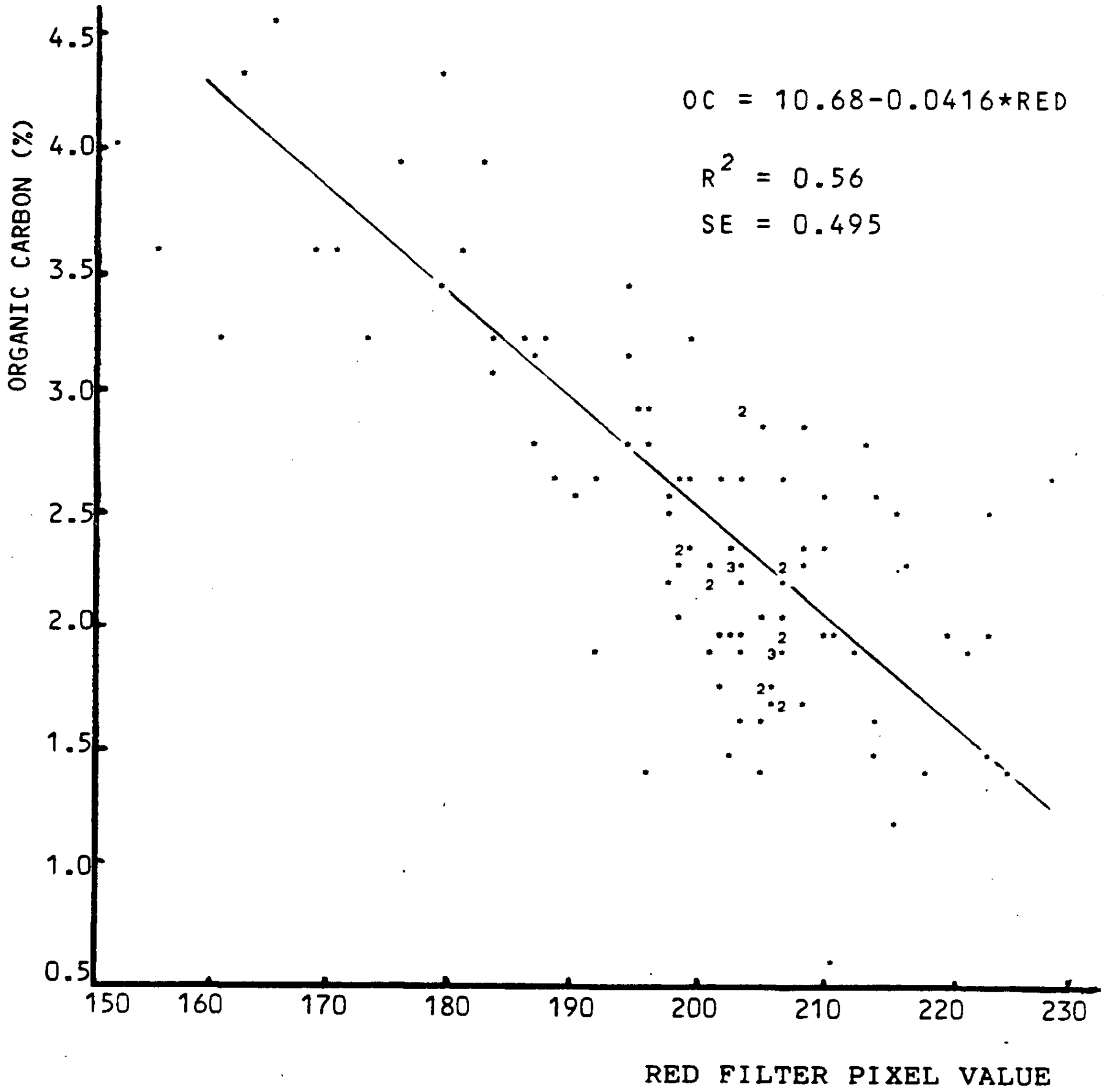


Figure 4.4.2 Scatter diagram of % organic carbon plotted against red filter pixel values.
* Numbers indicate overlapping points

moisture content, coarse fraction, % organic C, Ca, Mg, CEC, P, N, Munsell color value and chroma. No log transformed or ratioed data were used, since the previous correlation study showed that the transformation did not significantly improve the relationships.

The order of inclusions of the independent variables into the regressions with individual dye-layers was shown in Table 4.4.1. Soil moisture content and organic C were found to be the first two soil parameters to enter the regression equations. These two parameters explained most of the variability in pixel values. The moisture content entered first in the estimation of green filter pixel value whereas organic C was selected to be the largest contributor to the variation of red filter pixel value. These results were consistent with the order of correlation coefficients obtained between moisture, organic C and pixel value data. Munsell color value was the third important soil parameter included into the regressions for predicting both green and red filter pixel values. Coarse fragment content was selected as the fourth variable in the regression of the green filter pixel value, but it did not appear to be able to predict the red filter pixel value. The color chroma and CEC were active in explaining the red filter pixel value variation but to a lesser extent. The frequency of each soil parameter to enter the regressions is summarized in Table 4.4.2.

Table 4.4.1 Stepwise multiple regression of soil parameters as predictors of red and green pixel values at a significance level of 90%.

PIXEL VALUE	MC	CF	OC	MG	CA	CEC	P	VALUE	CHROMA	CUMULATIVE R^2
GREEN	1* 0.0000#	4 0.0576	2 0.0000					3 0.0143		0.66
RED	2 0.0004		1 0.0000			5 0.0873		3 0.0027	4 0.0286	0.67

* Order of inclusion of the variable (soil parameter) into regression equation.
\# Significance level obtained for the variable.

The cumulative R^2 value for each of the regression models indicated to what extent the variability of pixel values in the two dye-layers could be explained by the interactions of variables. Similar R^2 values were found for predicting both green and red filter pixel values. These R^2 values were lower, in comparison with the values obtained for corresponding visible reflectance bands (Section 4.3) which suggests the site characteristics have more influence on photo dye-layer pixel value than on spectral reflectance in visible bands and account for large portion of reflection variation.

Table 4.4.2 Frequency of inclusion of soil parameter into regressions (Table 4.4.1) at a significance level of 90%.

SOIL PROPERTY	ORDER OF ENTRY* 1st	2nd	3rd	4th	TOTAL#
OC	1	1			2
MC	1	1			2
VALUE			2		2
CF				1	1
CHROMA				1	1
CEC					1

* Only the first four entries were counted.
\# All entries were included.

2. MULTIVARIATE CLASSIFICATION OF SOILS USING TWO DYE-LAYER PIXEL VALUE DATA

The correlation and regression analysis revealed that photo dye-layer pixel values were highly correlated with organic matter, moisture content and exchangeable cations. However, linear regression equations to predict these properties from single dye-layer pixel values were not very satisfactory because of the variablilty of soils, the surface conditions and the parameter interactions. Also, the conditions associated with image processing and the image quality all play a role in affecting the prediction accuracy. More complex models are needed in order to predict individual soil properties and quantify soil types.

It is evident from the stepwise multiple regression study that several soil parameters which act together appear to have a profound influence on pixel value variation. This implies that the relationship of pixel values with overall soil characteristics may be of more importance than with a single parameter. In order to examine this relationship, the same clustering procedure used in the spectral analysis was used to classify 108 soil samples according to their two dimensional pixel value data. The resulting dendrogram shown in Figure 4.4.3 revealed that four pixel value groupings existed based on the degree of similarity of soil samples. The soil data for each of those pixel value classes (A to D) are summarized in Table 4.4.3, which provides the means and standard deviations of all 20 observed parameters.

STEP	I	J	ERROR
1	31	80	0.0015234
2	54	102	0.0021119
3	9	32	0.0031045
4	61	97	0.0091508
5	24	83	0.0093608
6	36	82	0.0099898
7	86	95	0.0141539
8	77	101	0.0151566
9	60	73	0.0157521
10	25	100	0.0170560
11	69	71	0.0178820
12	3	30	0.0182681
13	41	59	0.0185247
14	53	78	0.0238209
15	15	81	0.0285540
16	84	89	0.0304407
17	43	47	0.0343943
18	56	63	0.0353520
19	21	92	0.0366493
20	8	39	0.0371830
21	20	27	0.0388274
22	24	28	0.0412375
23	31	70	0.0455656
24	18	69	0.0543602
25	40	96	0.0545213
26	36	76	0.0553001
27	53	103	0.0586790
28	3	68	0.0605721
29	14	66	0.0665315
30	24	75	0.0730882
31	26	36	0.0733716
32	74	86	0.0797524
33	10	52	0.0831572
34	31	72	0.0857667
35	7	48	0.0956763
36	1	58	0.1126693
37	51	87	0.1170821
38	22	24	0.1282070
39	19	20	0.1319296
40	8	99	0.1324154
41	12	13	0.1417703
42	43	105	0.1419029
43	29	94	0.1452256
44	38	85	0.1473102
45	56	84	0.1539029
46	3	18	0.1566277
47	33	41	0.1619460
48	21	55	0.1637803
49	53	65	0.1682788
50	49	50	0.2038878
51	4	34	0.2227173
52	31	54	0.2301221
53	62	64	0.2375805
54	40	88	0.2441363
55	93	98	0.2454364
56	53	91	0.2484574
57	60	90	0.2607248
58	57	74	0.2610338
59	21	106	0.2694564
60	15	19	0.2883817
61	43	44	0.2974484
62	23	26	0.3278202
63	67	77	0.3594868
64	2	5	0.3677722
65	3	6	0.3938651
66	93	108	0.4128096
67	7	35	0.4225624
68	22	25	0.4461067
69	42	107	0.4876448
70	45	49	0.4961520
71	23	60	0.5261777
72	38	43	0.5753487
73	10	14	0.6192126
74	9	40	0.6404803
75	15	33	0.6746864
76	16	17	0.8373251
77	67	104	0.9266634
78	29	57	0.9435863
79	2	4	0.9952325
80	22	31	1.0287867
81	53	61	1.0945663
82	9	56	1.1118593
83	45	62	1.2942438
84	10	23	1.3349457
85	37	67	1.4941339
86	7	51	1.5434189
87	1	45	1.5777578
88	3	22	2.0254555
89	9	21	2.1892500
90	8	29	2.2560501
91	38	93	2.5441036
92	53	79	3.0197706
93	2	12	4.3378839
94	38	46	4.5830660
95	42	53	4.8109102
96	3	15	4.9206371
97	7	16	5.5081062
98	10	38	5.7200251
99	1	42	7.1225071
100	2	11	7.6004057
101	3	9	7.9215746
102	8	37	9.5199118
103	1	7	19.899689
104	8	10	28.321533
105	3	8	40.392319
106	1	2	58.852600
107	1	3	183.15953

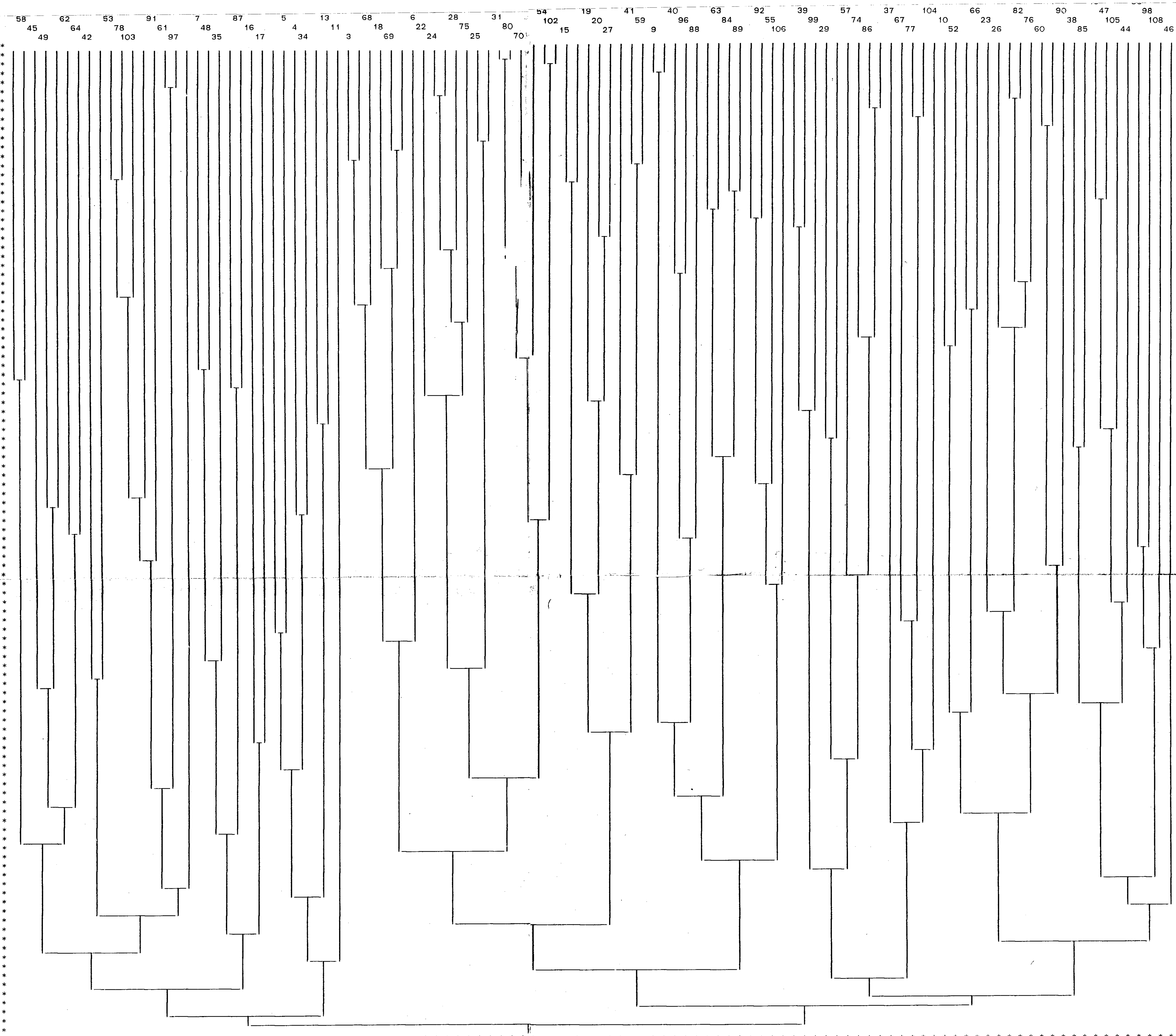


Table 4.4.3 Summary of soil data for different pixel value classes obtained from cluster analysis.

(a) Physical and chemical data

UNIT	n	MC	CF	pH	TC	OC	K	Ca	Mg	CEC	P	N
A	12	41.7*	23.5	6.91	4.32	3.87	0.660	15.16	0.984	27.4	148.1	0.205
		9.4#	9.1	0.38	0.50	0.45	0.19	4.7	0.55	6.0	64.1	0.05
B	33	29.4	27.7	6.89	2.96	2.68	0.598	11.58	0.524	19.6	116.6	0.152
		6.4	10.0	0.36	0.58	0.51	0.43	5.0	0.21	3.6	49.9	0.02
C	45	25.3	30.1	7.02	2.40	2.08	0.398	9.35	0.349	16.8	92.1	0.129
		4.3	7.1	0.29	0.48	0.46	0.22	3.8	0.11	2.7	30.0	0.03
D	18	21.9	35.8	6.94	2.35	2.04	0.558	8.73	0.454	17.7	111.4	0.124
		6.3	10.8	0.31	0.51	0.52	0.32	2.2	0.25	4.4	26.4	0.04

(b) Color, spectral and pixel value data

UNIT	n	Value	Chroma	B4	B5	B6	B7	Red	Green
A	12	4.50*	3.17	13.1	17.5	22.9	24.8	168.8	155.0
		0.80#	0.58	1.3	1.9	3.0	3.3	8.6	7.0
B	33	5.52	3.79	15.5	19.7	26.3	27.7	192.0	178.9
		0.51	0.86	1.3	1.5	2.0	2.2	5.4	4.8
C	45	5.82	3.84	16.8	20.7	27.5	28.7	202.6	188.3
		0.49	0.74	1.99	2.1	2.0	2.1	2.3	3.1
D	18	5.78	3.72	17.2	21.3	27.7	29.4	214.1	202.3
		0.43	0.46	2.0	1.3	1.3	1.5	5.0	6.1

* mean # standard deviation

The separations among pixel value classes were best illustrated in two dimensional vector space using mean pixel values, and plus and minus one standard deviation (Figure 4.4.4). It is evident that each pixel value class had formed a unique characteristic category which was different from all other categories. Figure 4.4.5 shows the result of the Mann-Whitney U-test which identified the parameters which best separated the cluster categories. The result proved that all pixel value classes were significantly different from one another with respect to their mean pixel value value separations in both dye-layers. The mean pixel values from the lowest to highest classes were identifed as group A-B-C-D.

The characterization of each pixel value cluster in terms of soil properties was performed in two ways: Mann-Whitney U-test to examine the significant differences between clusters on a parameter-by-parameter basis, and by employing a stepwise discriminant analysis to examine the nature of the cluster separations and identify those soil parameters that were best able to serve as discriminants among the pixel value classes.

Table 4.4.3 gave soil property mean and range values within each pixel value class. A statistical comparison was carried out using significance tests and Figure 4.4.5 shows these results. Tests were made for all soil parameters as well as spectral bands. The success of classifications in terms of specific soil properties can be evaluated by

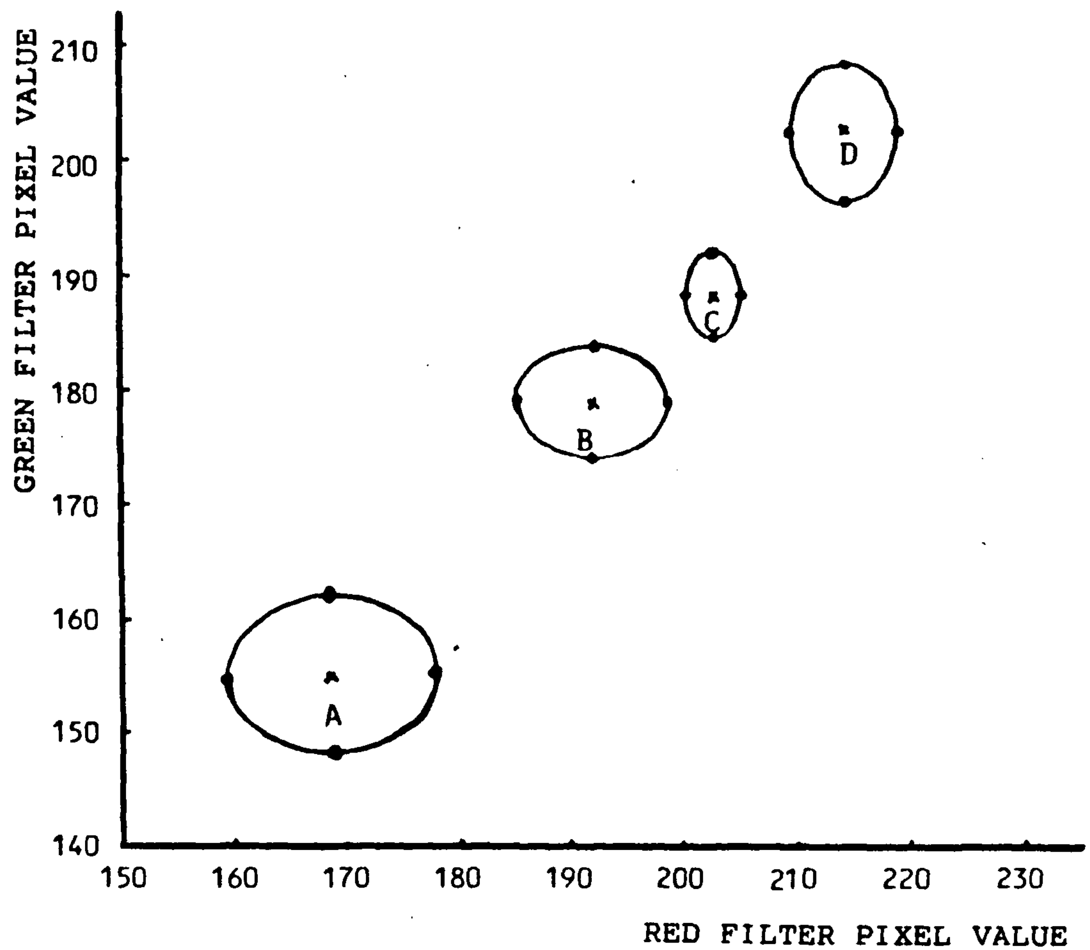


Figure 4.4.4 Pixel value classes (A to D) separation within the two dimensional pixel value vector space, the center represents mean pixel values and the diameter represents plus and minus one standard deviation.

	A	B	C
B	MC, TC, OC, CA, MG, CEC, N, VALUE, CHROMA, B4, B5, B6, B7, RED, GREEN		
C	MC, CF, TC, OC, K, CA, MG, CEC, N, P, VALUE, B4, CHROMA, B5, B6, B7, RED, GREEN	MC, TC, OC, K, CA, MG, CEC, P, N, VALUE, B4, B5, B6, RED, GREEN	
D	MC, CF, TC, OC, CA, MG, CEC, N, VALUE, CHROMA, B4, B5, B6, B7, RED, GREEN	MC, CF, TC, OC, CA, N, B4, B5, B6, B7, RED, GREEN	MC, K, P, RED GREEN

Figure 4.4.5 Parameters separated between pixel value classes identified by Mann-Whitney U-test ($\alpha = 0.05$).

examining whether the soil property can be separated between two classes.

The successful separation of most soil properties is evident from the results of classification (Figure 4.4.5). Soil moisture content was the best parameter to separate the soil types and showed to be significantly different in all cases. This indicates that soils with different soil moisture conditions have been distinguished by the combination of two airphoto dye-layer pixel value data. The potentials of using the multi-dye layer pixel value classification to quantify soil types were also demonstrated as the good separability of TC, OC, N and Ca between classes. In five out of 6 cases the class separation could be made on the basis of these parameters. In about 67% of cases, significant differences were observed in terms of color value, CEC and Mg, and 50% were separated by coarse fragment content, P, K, and chroma.

With respect to overall soil properties or soil types, the pixel value classes were significantly different from one another. The only poor separation was seen between class C and D, for which only moisture content and two fertility components have been differentiated. Most soil parameters were apparently discriminating factors for separating classes A and B from the rest of classes. This suggests that class A and B are the most distinct units in which a unique soil characteristic category has been established.

The relationships between the four pixel value classes from cluster analysis and the field soil conditions and variability of soil properties were further examined by using the average values of soil properties in Table 4.4.3. Clearly, class A is the most distinct class with very low mean pixel values and the levels of soil moisture content and overall chemistry (organic matter and CEC) in class A are much higher than those from other classes. The soil fertility levels are also distinctly higher for class A than for any other class, although P and K were not different from class B. In contrast, coarse fragment content in class A is considerably lower in comparison with other classes. Class B, which is also distinct from other classes, represents soils with moderately high soil chemical contents and fertility status, but the mean values of P and K are not different from those in class D.

Although class D represents the type of soils with the largest volume of gravel and the lowest water content, its overall soil chemistry was not found to be distinguishable from class C which holds over 40% of all collected soil samples and corresponds to the most common soil type in the study site. This is in partial agreement with the results from data obtained from the selective sampling (Section 4.1) in which we found no substantial differences in soil fertility between soil type II (gravelly soils) and type III (average soils). This implies that the soil type with high coarse fragment content is not necessarily different in fertility status from average soil condition in the field under investigation. It is anticipated that if we account for coarse fragment content in the measurements of soil chemical conditions, the difference between the two types of soils would probably then be displayed.

Soil spectral reflectance values within each pixel value class were quantified in order to test whether soil groups with distinct difference in pixel values were also separated by their spectral characteristic curves. The results from the Mann-Whitney U-test (Figure 4.4.5) clearly showed that class A and B were significantly different in terms of their spectral band separations. It was also found that these two classes were spectrally distinguished from other classes and only spectral Band 7 did not appear on the list between class A and B. None of the spectral bands were found to differentiate class C from class D, indicating that the two classes were very close not only chemically but also spectrally, in spite of their distinct difference in pixel values. The only reason to cause pixel value separation between these classes is due to their difference in moisture and, possibly, K content. Spectral separations among pixel value classes are illustrated in Figure 4.4.6, which provides the spectral characteristic curves (mean relectance value and plus and minus one standard deviation) for each of the pixel value classes. Considerable overlaps are evident between class C and D. Class B and D appear to have some separation, but it is not as good as the separation of class

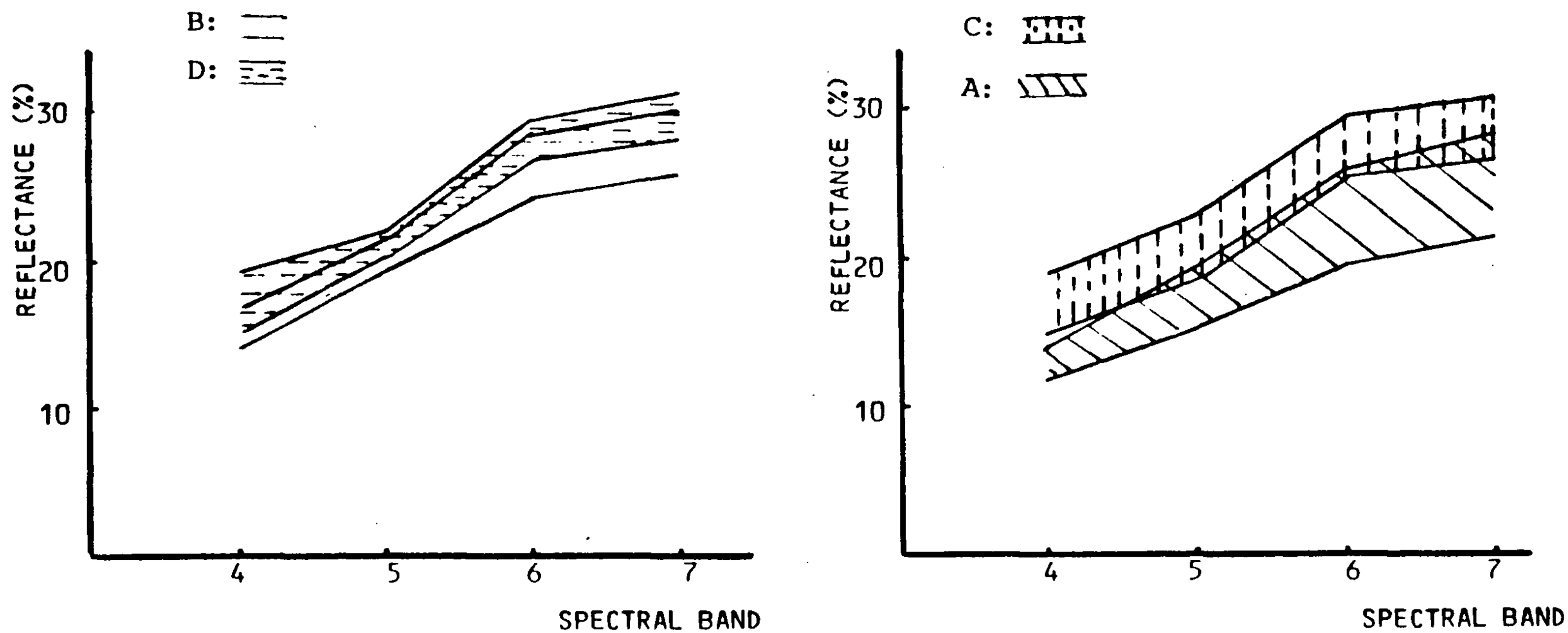


Figure 4.4.6 Spectral reflectance curves of pixel value classes (A to D) from cluster analysis.

A from other classes.

Again, a stepwise discriminant analysis was carried out on four pixel value classes to determine the role and contribution of individual soil parameters in separating pixel value classes. All thirteen soil properties were entered into the analysis as variables. Table 4.4.4 gives the result and lists the soil properties, in order of entry, that could serve as discriminants among pixel value classes. The mean values, plus and minus one standard deviation, were plotted for each pixel value cluster (Figure 4.4.7). One can subjectively determine the extent to which each soil parameter performed as discriminanting factors in separating the classes.

The results presented in Table 4.4.4 are generally consistent with the earlier conclusions from correlation and stepwise regression analyses. It is evident that organic matter and moisture content are the most influential discriminants among soil properties and seem to take a dominant part of the contribution to pixel value class separations. Color value which appears on the list is also not unexpected since its correlation with pixel value is significantly high. The soil parameters such as N and CEC do not appear on the list because their discriminating power has already been accounted for by OC which entered the discriminating function as the first parameter. The inclusion of K is interesting, but difficult to explain. However, when we check the results from the significance

Table 4.4.4 Soil properties selected by discriminant analysis for discriminating among pixel value classes (α= 0.05).

PROPERTY	U-STATISTIC	F PROB
OC	0.4130	0.0000
MC	0.3640	0.0046
VALUE	0.3223	0.0060
K	0.2932	0.0192

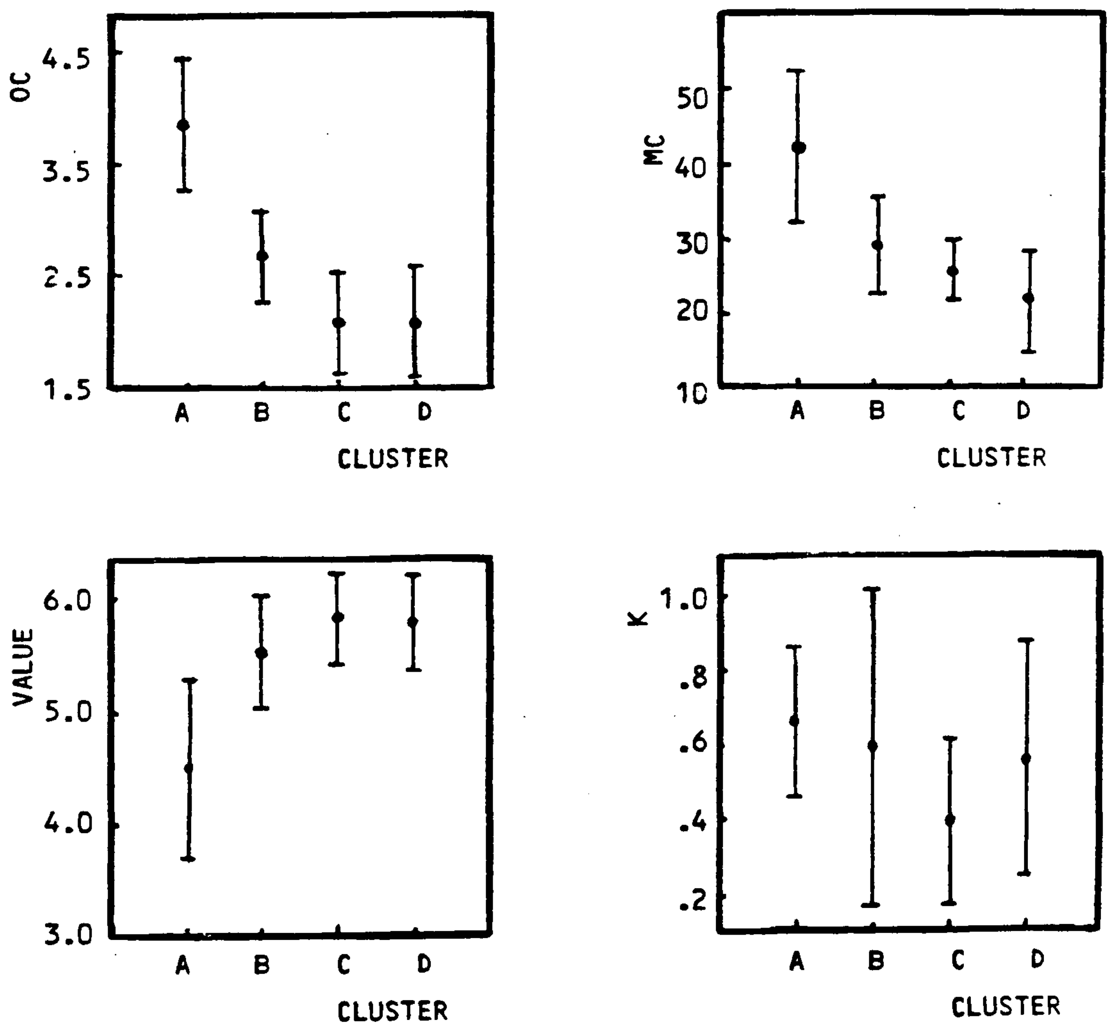


Figure 4.4.7 Soil properties as discriminants in each pixel value class (A to D).

test in Figure 4.4.5 and Figure 4.4.7, it was shown that K had a significant separating capability between class C and other classes, which probably explains the selection of K.

The most notable absence from the list is the coarse fragment content. We expected that differences in this parameter would facilitate class separation. It suggests that a secondary relationship exists between this soil property and pixel values in this study. The role of coarse fragment content has probably been masked by good correlations between pixel value and organic matter or moisture content.

The result in Table 4.4.4 was compared with soil properties listed in Table 4.3.7, which were selected by the same discriminant procedure but for different spectral classes. The first three soil parameters are the same, indicating that they are the most promising soil properties to influence both pixel value and spectral variations. The difference in the order of importance is obvious since moisture content was held constant in the spectral measurements. It suggests that the moisture content is best quantified by using pixel value data and color value is best quantifyed by spectral reflectance measurements. The Mann-Whitney U-test also proved that the moisture content was the only soil parameter which separated pixel value classes in all cases.

E. SUMMARY AND COMPARISONS

1. SPECTRAL REFLECTION VS DYE LAYER PIXEL VALUE

In this study, soil parameters and conditions have been determined by two remote sensing techniques: laboratory spectral reflection measurement and airphoto digital analysis. A comparison made on summary of results from this two methods is given in Table 4.5.1.

It is evident from this comparison that slightly better relationships exist between spectral reflection values and overall soil chemical parameters than between pixel values and soil properties. This is because spectral reflection measurements were conducted in a controlled laboratory environment and were exclusive of the effects of surface variation, site and atmospheric factors, and soil moisture conditions, all of which influenced the airphoto dye-layer pixel value measurements. In both cases, % organic C was found to be the most important soil chemical parameter which related to spectral reflection and pixel values. Soil moisture content was another important soil parameter which entered the stepwise regression and discriminant function, but its importance was only relevant in relation to the dye-layer pixel value. Soil moisture was found to be best predicted using green filter pixel values.

Cluster analyses using 4-dimensional spectral data and 2-dimensional pixel value data have classified 108 soil samples into five soil spectral classes (A to E) and four

Table 4.5.1. Summary and comparisons of two remote sensing techniques to quantify soil parameters and types.

	LABORATORY SPECTRAL REFLECTION MEASUREMENT	MULTI-DYE LAYER DIGITAL ANALYSIS
Number of variables	4 spectral bands	2 dye layer pixel values
Best correlation with soil parameters	Band 4 vs Ln Organic Carbon $r = 0.82$	Red Filter Pixel Value vs Organic Carbon $r = 0.75$
Best regression for prediction of soil parameters	$\ln OC = 2.81-0.122*B4$ $R^2 = 0.67$ $SE = 0.18$	$OC = 10.68-0.0146*Red$ $R^2 = 0.56$ $SE = 0.495$
Best stepwise regression for prediction of spectral or pixel value variables	$\text{Band 4} = a_0+a_1*\ln OC+a_2*CF$ $+a_3*\text{Value}$ $R^2 = 0.71$	$\text{Red Filter Pixel Value} = a_1+a_2*OC+a_3*MC$ $+a_4*\text{Value}+a_5*\text{Chroma}$ $R^2 = 0.67$
The importance of soil parameters in discriminant functions	OC > Color Value	OC > MC > Color Value
Multi-variate classification (cluster analysis)	Five Spectral Classes	Four Pixel Value Classes
Soil Type I	A (n=24)	A'(n=12)
	10 samples identical	
Soil Type II	C,D (n=25)	D'(n=18)
	8 samples identical	
Soil Type III	B,E (n=59)	B',C'(n=78)
	47 samples identical	

pixel value classes (A' to D'), respectively. A comparison between these two classifications was made in Table 4.5.1 on the basis of three soil types which were visually identified by the selective sampling. In the case of soil type I, which was considered as dark soils with high MC, OC, CEC, N, P and K contents and low CF, color value, spectral and pixel values, 10 out of 12 soil samples in pixel value class A' were in common with the corresponding spectral class A. About 80% of spectral classes B and E were found within the pixel value class B' and C'. These spectral or pixel value classes were representative of soil type III, the dominant soils with median values for all soil, spectral and pixel value variables. The poorest correspondence was found between spectral classes C and D and pixel value class D', all of which related to soil type II, with the lowest soil chemistry and moisture content and the highest spectral and pixel values as well as coarse fragment content. In this case, only 8 samples were found to be identical, which accounted for 32% of spectral classes C and D and 44% of pixel value class D'. This implies that very different classifications of gravelly soils can be obtained using different techniques. Since spectral reflection measurements did not take coarse fragments and moisture content into account, digital pixel value analysis should be considered as a more reliable procedure to quantify this type of soils.

The disagreement is partially due to the sample size differences between corresponding spectral and pixel value classes. For example, the spectral classification identified 24 soil samples which were representative of soil type I (class A) while the pixel value classification only identified 12 samples for this soil type (class A'). The differences in soil sample size can be reduced if we use the same dimensional classification procedures. An increasing degree of agreement is likely to be achieved between spectral and pixel value classifications if color infrared photographs would have been flown so that the pixel values in IR dye layers could have been included in the analysis.

2. LINKING REMOTE SENSING MEASUREMENTS WITH CONVENTIONAL METHOD FOR SOIL FERTILITY ASSESSMENT

The approach used to make soil fertility assessments in this study can be described as follows: 1) to sample soils according to the visual appearance of the soil pattern and 2) to determine different fertilizer rates based on the laboratory measurements of each individual soil sample group. The soil type distribution in the field, which is directly related to total fertilizer applications, can be estimated by field observations or, more precisely, determined with a planimeter from aerial photographs.

The application of remote sensing techniques to soil fertility assessments was found useful in the following two aspects. First, these new techniques had an advantage over the conventional method with regard to spatial pattern delineations and area measurements for different soil types.

Secondly, since good relationships were often found between chemical, spectral reflection and pixel value data, predictions could be made for some soil chemical properties, such as organic matter, which provided a general picture of field fertility status.

The use of soil spatial pattern delineation and soil chemistry prediction is illustrated in Table 4.5.2. The measurement of areas represented by three soil types was conducted using the multi-dye layer analysis which was discussed in Section 4.2. Using the regression equation shown in Figure 4.4.2 % organic C for each photo pixel was calculated and average values for each of four pixel value classes are presented in Table 4.5.2. This method can be used to produce a soil organic matter distribution map which provides a spatial picture of general fertility of the field. Higher accuracy of prediction and spectral maps can be obtained with higher resolution multi-spectral data and narrower wavelength bands.

It is noted that remote sensing measurements can not replace the conventional approach, but can provide a better assessment of the spatial pattern and extent of soil types and organic matter distribution. To this end it may be more desirable to use these techniques in combination with the conventional soil fertility assessment. The conventional method gives fertilizer rates for different types of soils from field sampling and laboratory measurements.

Table 4.5.3 presents the results of K fertilizer recommendation for the three different soil types identified by the selective sampling (Section A) and quantitative remote sensing measurements (Section C and D). The two different rates were translated into total fertilizer application for three soil types, according to the area estimations from the planimetry method and the multi-dye layer pixel value classification, both were discussed in Section B. Table 4.5.4 provides a direct comparison on the total amount of K fertilizer required for the entire field estimated by various methods, including the conventional one-rate blanket application. The higher rate of K recommendation for soil type II resulted in an increase in total fertilizer application over conventional one-rate recommendation, especially in the case of using the multi-dye layer pixel value classification to measure soil type areas. Using the multi-variate classification, the area estimates of soil type I and II were slightly higher than the values obtained by the planimetry method. This resulted in 5 kg difference in the total amount of fertilizer applied. Since the former is generally considered to be more objective and more accurate than the latter, the quantitative remote sensing measurements are more advisable to be used in the future.

The effort devoted to field sampling and laboratory work can be much reduced using remote sensing data in fertility assessment, without affecting the fertilizer

Table 4.5.2 Average organic carbon contents of three soil types estimated by red filter pixel values.

Pixel Value Class	Soil Type	Area (%)	% Carbon mean	% Carbon range
A	I	13.0	3.33	2.73-4.90
B	III-1	36.6	2.51	2.32-3.15
C	III-2	36.3	2.15	1.69-2.69
D	II	14.1	1.52	0.86-1.94

Table 4.5.3 K fertilizer recommendations for three soil types using the planimetry and multi-dye layer pixel value analysis to measure areas of soil types.

Soil Type	Rate	Area (ha)		Total Application (kg)	
	(kg/ha)	planimetry	dye layer analysis	planimetry	dye layer analysis
I	45 K_2O	0.305	0.387	14	17
II	67 K_2O	0.334	0.419	22	28
III	45 K_2O	2.262	2.173	101	98

Table 4.5.4 Comparison of total K fertilizer application estimated by different methods

Recommendation	Area Measurement (ha)	Total Application (kg)
1 blanket rate	planimeter	131
2 variable rate	planimeter	138
2 variable rate	dye layer analysis	143

recommendation accuracy. It is thought that the number of soil samples which is needed to determine variable fertilizer rates for specific types of soil can be reduced to a lowest limit if we select sampling points based on remote sensing images or, more desirably, the spectral maps showing current fertility status, i.e. digital soil organic matter map. Such maps should be available in the near future.

Chapter V

CONCLUSIONS

The aims of this thesis were to evaluate the extent to which remote sensing techniques can be used to facilitate the quantification of soil variability in agricultral fields. The thesis research was carried out in a field which contained three very contrasting soils. The spatial distribution of the soil pattern was quantified using multi-dye layer analysis of digitized color aerial photographs. The actual chemical and spectral differences among soil types were determined from soil sample analysis in the laboratory. These methods were examined to determine if fertilizer effectiveness can be improved by considering the application of variable rates of fertilizers in accordance to the soil pattern.

The following conclusions can be made from the present study:

1. DETERMINING SOIL VARIABILITY WITHIN THE FIELD

Analysis of overall variability of selected soil properties showed that K, Ca and P were the most variable parameters in the field with the highest CV values (above 40%). However, these large within-field variabilities can not be taken into account in making fertilizer recommendations by different sampling methods. The conventional sampling and selective sampling method generally provided comparable results to the detailed stratified random sampling technique with respect to the prediction accuracy of the mean values of major fertility qualities. This implies that there will be no significant differences in the one-rate fertilizer recommendations based on the mean values estimated by any one of three sampling methods.

2. VARIABLE FERTILIZER REQUIREMENTS FOR DIFFERENT SOIL TYPES

By grouping samples according to their visual appearance from selective sampling, three general categories which represent three different soil types were identified: very dark soil (Type I), gravelly and very light soils (Type II) and dominant soils (Type III). These three soil types were found to be statistically different on the basis of mean values and ranges for most soil properties and these soil types should be treated differently in making fertilizer application recommendations. For P application only the minimum starting fertilizer rate was required for all three soil types, and this despite large differences in mean P values among soil types. This likely represents heavy applications of fertilizer in the past. However, for K application two different rates were identified and recommended for the three soil types. Type II (gravelly, light colored) requires a higher application rate than either soil type I or III. This suggests that the application of variable rates of K fertilizer is desirable within the field.

3. QUANTITATIVE AERIAL MEASUREMENTS OF SOIL TYPES

The areal extent of the three soil types in the field was determined quantitatively using a multi-variate analysis of airphoto dye-layer pixel values. As the result 13.0%, 14.1% and 72.9% of a total field area of 2.98 ha were found to be represented by soil types I, II and III, respectively. These results were comparable with the results from the subjective delineation of airphoto tonal pattern of three soil types by a digital planimeter. In the latter case, the areas occupied by soil types I, II and III were 10.5%, 11.5% and 78%, respectively, of the total 2.90 ha in area.

4. PREDICTING SOIL CONDITIONS FROM SPECTRAL REFLECTANCES

Spectral reflection measurements on soil samples revealed that good relationships existed between reflection values in the four spectral bands and such soil chemical properties as organic C, N, CEC, and exchangeable Ca and Mg, as well as Munsell color value. The best correlation was found in the case of spectral band 4 vs natural log transformation of % organic C which presented the highest r value (0.82). This relationship can be used to predict % organic C from reflection, as expressed by a simple linear regression model:

$$\text{Ln OC}=2.81-0.122*B4 \quad (R^2=0.67 \text{ and } SE=0.18)$$

Using the stepwise multiple regression and discriminant analysis, it was found the % organic C and Munsell color value were the most important soil parameters which influenced spectral reflection variations. The multi-spectral cluster analysis successfully classified soils according to their spectral differences and the resulting five spectral classes were separated on the basis of important soil parameters. The classification results were related to soil conditions and a good agreement was achieved between spectral classes and the three soil types in the field.

5. PREDICTING SOIL CONDITIONS FROM DYE LAYER PIXEL VALUE DATA

Good relationships were found between dye-layer pixel values from color aerial photographs and corresponding soil properties. The highest correlations were found in the cases of red filter pixel value vs % organic C ($r=0.75$) and green filter pixel value vs water content ($r=0.73$). A stepwise regression and discriminant analysis showed that organic matter, water content, and Munsell color value were the the most dominant soil parameters to influence pixel value variations. However, correlation/regression analysis was not found to be satisfactory for predicting individual soil parameters from pixel value data. Cluster analysis was thus used to quantify soil conditions and the resulting four pixel value classes could be separated on the basis of important soil parameters, which proved to be representative of the three soil types in the field.

6. COMPARISON BETWEEN SPECTRAL REFLECTION, PIXEL VALUE DATA AND SOIL CONDITIONS

Evidence was produced to show that the relationships between spectral reflection and chemical soil conditions were better than those between dye-layer pixel values and soil chemistry. The opposite trend was found in the relationship between spectral reflection, pixel value and soil water content. The difference is due the fact that soil moisture was held constant during the spectral reflection measurements. The airphoto measurements represented the undisturbed site condition and were subject to be influenced by factors other than soil chemistry. The results suggest that organic matter and other soil chemical parameters can best be quantified using spectral reflection data and moisture content can best be predicted by dye-layer pixel values, but further testing is needed. Soils grouped according to their spectral reflection and pixel values showed a partial agreement between corresponding classes, but this correspondence needs to be improved and this can be accomplished by examining the spectral response to moisture variations and using the additional IR dye-layer data in the pixel value classification.

7. FERTILIZER REQUIREMENT PREDICTION LINKING REMOTE SENSING MEASUREMENTS TO THE CONVENTIONAL ASSESSMENT.

An approach integrating remote sensing measurements into conventional assessment and prediction of field fertility was explored. The conventional field sampling was used to determine different soil fertility requirements and the multi-spectral measurements were carried out to quantify the soil patterns. The technique allows the prediction of the general soil fertility status and measurement of the extent of different soil types and, therefore, can be used to facilitate the determination of the amounts of fertilizer required. The results were compared with the conventional sampling method as well as with the planimetry method in making K fertilizer recommendation. A total 131 kg K fertilizer is required if only one blanket rate is applied to the entire field. Using planimetry and multi-spectral classification to determine the areas represented by the different soil types, a two-rate application is suggested, which leads to 138 and 143 kg of total K fertilizers. It is anticipated that with the development of higher resolution, multi-spectral devices, the prediction accuracy for fertility status and fertilizer requirements can be considerably improved. Further investigations involving these techniques are likely to be a promising direction of research.

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Appendix 1
Sample Descriptions of Selective Sampling Method

Sample ID	Plot	Description	Class#
s-1	A1	first dark spot	1
s-2	A2	dark	1
S-3	A2	light brown	3
s-4	A3	dark	1
s-5	B3	very dark	1
*s-6	A4	light brown	3
s-7	A5	light	3
s-8	A5	very light grey/gravel	2
*s-9	A4	light brown	3
s-10	B5	light	3
s-11	B4	dark, depression	1
s-12	B4	very dark	1
s-13	B3	very dark	1
s-14	B2	light	3
*s-15	B2	light	3
s-16	B1	first dark spot	1
s-17	B1	very dark, wet	1
*s-18	C1	light brown	3
s-19	C2	brown	3
*s-20	C2	light brown	3
s-21	C3	dry, light/gravel	2
s-22	C3	dark brown	3
s-23	C4	dark brown	3
*s-24	C4	dry, brown	3
*s-25	C5	dark brown	3
s-26	C5	light brown	3
s-27	D5	light brown gravel	2
s-28	D4	dark brown	3
s-29	D4	brown	3
*s-30	D3	brown	3
s-31	D3	brown	3
s-32	D2	light	3
*s-33	D2	brown	3
s-34	D1	very dark, second spot	1
*s-35	D1	brown	3
s-36	F3	brown/gravel	2
s-37	F3	dry, light/gravel	2
s-38	F2	dry, light/gravel	2
s-39	F2	light brown	3
*s-40	F1	brown	3
s-41	F1	brown	3
s-42	G1	dry brown	3
s-43	G1	dry, light grey/gravel	2
s-44	G2	dry, light grey	2
*s-45	H1	brown	3
s-46	H2	light brown	3
s-47	G2	light grey/gravel	2

\# Classes were assigned according to visual appearance of soils. Class 1 -- dark wet soils; class 2 -- dry, gravelly soils; class 3 -- generally brown soils.

* Samples were also used to compose of a bulk sample in the conventional spmpling.

Appendix 2. Selective Sampling Data

SAMP	Mo.Ct	Cs.Fg	PH	Tot.C	Org.C	EXCHANGEABLE CATION (meg/100g)					Ava.P	Tot.N	COLOR		--- SPECTRAL BAND ----				PIXEL VALUE	
NAME	%	%	1:1	%	%	Na	K	Ca	Mg	CEC	ppm	%	V	C	4	5	6	7	red	green
S-01	41.6	17.9	6.5	3.5	3.3	0.00	0.65	10.24	0.55	23.7	97.0	0.177	5	3	14.3	19.0	24.2	25.7	182	179
S-02	49.1	23.8	6.9	4.8	4.6	0.10	0.95	19.01	1.66	33.1	200.0	0.336	4	3	13.2	17.1	23.0	25.3	166	154
S-03	27.9	26.9	6.6	2.3	1.9	0.06	1.29	9.84	0.78	19.8	84.8	0.122	6	4	15.7	20.3	26.1	29.3	218	207
S-04	46.2	21.4	7.2	4.7	4.4	0.04	0.54	14.96	1.17	28.6	193.9	0.186	4	3	12.9	16.5	20.0	22.0	163	150
S-05	53.4	14.0	7.2	4.7	4.1	0.05	0.87	21.29	2.28	33.2	315.1	0.269	4	3	11.8	15.9	20.1	22.7	154	142
S-06	29.6	23.7	6.4	2.1	2.0	0.09	0.98	8.62	0.94	22.4	151.5	0.136	6	4	19.1	21.6	29.1	30.7	219	211
S-07	31.2	33.2	6.8	2.6	2.5	0.06	0.96	11.14	0.69	24.6	133.3	0.157	6	4	15.3	20.0	26.1	29.0	219	205
S-08	17.5	61.8	7.3	4.0	3.2	0.01	0.38	11.55	0.40	19.0	109.1	0.137	6	4	13.6	18.1	23.0	24.0	192	189
S-09	25.2	30.0	6.6	3.1	2.7	0.04	0.98	7.90	0.63	22.6	109.1	0.139	6	4	15.3	20.6	26.7	28.7	224	213
S-10	20.0	19.9	6.9	2.4	1.6	0.04	0.40	6.18	0.22	17.9	74.0	0.094	6	4	19.1	16.1	29.1	30.3	202	187
S-11	30.7	25.6	6.4	4.4	4.0	0.00	0.41	8.94	0.50	40.3	169.7	0.213	4	3	13.2	18.1	24.2	26.7	181	165
S-12	38.1	19.9	6.8	3.9	3.6	0.00	0.54	13.03	0.76	27.1	133.3	0.179	4	3	12.5	16.8	21.8	24.0	169	155
S-13	42.3	24.3	6.6	4.5	3.6	0.02	0.67	10.86	0.73	26.5	121.2	0.164	4	2	10.1	13.8	17.0	18.2	157	146
S-14	25.5	18.0	7.1	1.7	1.4	0.01	0.23	7.90	0.36	16.6	82.0	0.090	6	4	16.7	23.0	29.0	29.7	202	186
S-15	32.2	20.4	6.8	2.7	2.5	0.00	0.44	9.90	0.56	20.5	139.4	0.124	6	4	15.8	22.3	29.7	31.0	212	198
S-16	46.5	19.6	6.9	3.8	3.6	0.01	0.53	17.20	0.69	21.1	90.9	0.191	6	4	14.3	19.7	26.7	29.0	170	156
S-17	47.7	24.9	7.0	4.5	4.0	0.07	0.81	15.38	1.02	26.8	133.2	0.187	6	4	14.6	21.0	27.9	30.7	175	160
S-18	28.8	36.4	7.3	1.9	1.8	0.00	0.35	10.33	0.40	18.3	97.0	0.115	6	4	16.5	23.0	29.1	31.0	202	190
S-19	32.6	24.2	7.1	2.1	2.0	0.00	0.46	10.22	0.42	19.5	67.0	0.123	6	4	16.9	21.6	28.9	31.2	200	183
S-20	29.8	16.4	7.0	2.5	2.3	0.00	0.40	10.94	0.53	19.1	39.4	0.148	6	4	16.4	22.3	29.5	30.6	198	182
S-21	23.2	25.2	7.1	2.9	2.4	0.00	0.42	11.40	0.60	19.3	127.2	0.151	6	4	15.5	19.7	27.1	28.0	197	182
S-22	27.1	24.4	6.8	2.3	1.8	0.02	0.33	7.50	0.34	16.9	107.7	0.161	6	4	17.1	22.3	29.5	30.6	199	183
S-23	28.1	24.4	7.0	2.4	1.9	0.00	0.31	8.60	0.32	11.8	97.0	0.120	6	4	15.6	21.0	28.3	29.9	201	186
S-24	25.8	20.8	7.1	2.3	1.9	0.00	0.55	8.16	0.37	15.5	52.0	0.121	6	4	17.2	22.3	29.5	30.6	204	189
S-25	29.3	21.9	6.8	2.5	2.3	0.00	0.38	6.97	0.27	15.6	97.0	0.129	6	4	17.2	23.9	29.3	30.1	204	189
S-26	24.7	18.6	7.0	2.3	1.7	0.00	0.30	6.02	0.22	13.3	92.0	0.096	6	6	19.6	23.2	29.9	29.4	204	190
S-27	31.4	25.4	6.4	2.4	2.2	0.00	0.15	4.97	0.26	18.4	73.0	0.120	6	4	21.3	24.5	31.6	31.4	204	191
S-28	26.2	38.0	7.1	2.4	2.0	0.00	0.38	8.12	0.30	16.6	60.0	0.126	6	4	18.7	21.9	28.1	29.4	199	195
S-29	18.7	52.0	7.0	2.8	2.4	0.00	0.39	9.40	0.50	18.9	115.1	0.160	5	4	15.6	20.6	27.5	28.8	207	196
S-30	26.5	27.7	7.4	2.2	1.9	0.00	0.34	11.14	0.34	19.4	109.1	0.131	6	4	17.4	22.6	29.9	30.7	203	188
S-31	24.4	35.7	7.4	2.5	2.3	0.01	0.33	9.52	0.32	18.2	73.0	0.113	6	3	16.7	21.6	28.5	29.4	200	186
S-32	25.6	26.5	7.1	3.1	2.7	0.00	0.41	11.93	0.48	22.3	97.0	0.132	6	3	15.6	21.0	28.5	29.4	199	185
S-33	35.6	27.1	6.5	2.8	2.7	0.00	0.64	8.64	0.48	19.5	73.0	0.145	6	3	15.6	20.3	27.9	29.4	196	179
S-34	51.6	20.8	6.4	5.0	4.4	0.00	0.98	12.17	1.33	28.4	115.1	0.197	4	3	12.6	16.5	21.8	23.0	178	150
S-35	37.2	26.0	7.2	2.8	2.7	0.00	2.69	14.12	0.44	22.4	109.1	0.153	6	4	16.0	20.3	28.5	29.4	190	175
S-36	26.4	42.1	7.0	2.0	1.8	0.00	0.26	6.80	0.22	14.5	53.0	0.123	6	4	19.5	22.2	30.3	31.7	203	189
S-37	15.9	50.3	7.5	2.3	1.2	0.00	0.14	7.24	0.16	9.8	93.0	0.075	7	5	20.4	23.5	29.3	30.1	212	203
S-38	14.6	36.7	7.4	3.3	1.9	0.00	0.18	9.69	0.26	12.1	103.0	0.116	6	4	14.9	17.8	25.1	24.3	203	193
S-39	19.1	43.4	7.1	4.6	3.3	0.00	0.29	13.58	0.54	17.9	212.1	0.204	5	4	12.3	15.9	22.1	23.0	197	185
S-40	28.0	20.2	6.7	3.2	3.0	0.00	0.45	10.96	0.44	20.6	84.8	0.163	6	6	15.3	19.0	27.5	29.0	193	177
S-41	35.4	17.9	6.6	2.5	2.3	0.05	0.74	7.70	0.28	18.5	75.0	0.143	6	4	16.9	22.2	29.3	30.4	196	182
S-42	23.6	50.4	7.8	4.4	3.3	0.00	0.56	24.94	0.47	20.8	98.1	0.199	4	3	14.2	17.1	23.9	24.0	162	162
S-43	15.3	44.4	7.2	1.7	1.5	0.00	0.26	6.03	0.14	11.8	76.9	0.081	6	4	15.8	21.9	27.6	29.9	219	209
S-44	13.0	48.4	7.5	2.0	1.4	0.00	0.38	8.49	0.14	14.1	117.3	0.086	6	4	18.7	21.2	27.6	27.0	221	212
S-45	35.4	29.6	6.0	2.7	2.5	0.00	0.25	4.84	0.14	22.9	90.4	0.151	5	6	14.6	20.0	27.6	29.9	195	177
S-46	19.0	35.6	6.5	0.8	0.6	0.03	0.33	2.50	0.20	13.1	48.1	0.041	7	4	23.8	27.5	32.4	35.8	208	191
S-47	13.2	47.4	7.2	1.9	1.5	0.00	0.19	5.44	0.16	11.6	113.5	0.085	6	6	17.9	21.2	27.1	28.0	211	200

Appendix 3. Stratified Random Sampling data

SAMP NAME	Mo.Ct. %	Cs.Fg %	PH 1:1	Tot.C %	Org.C %	EXCHANGEABLE CATION (meg/100g) Na	K	Ca	Mg	CEC	Ava.P ppm	Tot.N %	COLOR V	C	--- SPECTRAL BAND ---- 4	5	6	7	PIXEL VALUE red	green
A-11	31.9	27.2	6.8	3.2	2.8	0.04	0.68	11.60	0.71	23.9	257.6	0.170	6	4	14.8	19.4	26.5	28.0	185	180
A-12	37.8	25.7	6.5	3.2	3.1	0.01	0.74	9.33	0.87	25.9	199.1	0.182	5	3	15.0	19.4	24.3	25.3	182	169
A-21	33.6	28.0	6.7	3.5	3.0	0.05	0.87	10.70	0.87	24.2	184.6	0.164	5	3	14.2	17.6	22.6	24.0	194	180
A-22	33.9	30.9	6.7	3.3	3.3	0.00	0.39	11.05	0.57	25.1	128.8	0.169	6	3	14.9	19.4	24.3	26.7	184	169
A-31	23.2	22.4	7.1	2.1	1.6	0.03	0.58	8.55	0.45	18.4	111.5	0.112	6	4	18.8	21.2	27.8	28.7	211	196
A-32	29.0	26.2	6.7	2.7	2.6	0.04	0.71	9.80	0.62	20.3	78.8	0.145	5	3	16.0	20.6	26.7	28.3	207	196
A-41	25.0	24.4	7.1	2.7	2.0	0.03	0.53	10.21	0.38	18.9	113.5	0.125	6	4	19.6	22.4	28.4	31.0	216	200
A-42	19.4	33.2	6.7	2.5	2.3	0.03	0.64	9.34	0.59	20.8	134.6	0.146	6	3	15.8	20.0	26.1	27.8	213	199
A-51	29.5	31.7	6.9	2.9	2.7	0.04	0.36	10.56	0.41	19.2	84.6	0.135	6	4	15.8	20.0	26.1	27.8	204	187
A-52	21.0	45.9	6.5	3.6	2.7	0.06	0.89	8.20	1.05	15.5	190.4	0.161	5	3	14.4	17.9	25.5	25.8	187	182
B-11	41.9	20.3	6.8	3.5	3.5	0.02	0.53	12.17	0.62	21.8	109.6	0.176	5	3	14.1	19.1	24.9	26.5	178	162
B-12	35.9	33.5	6.3	2.6	2.4	0.07	0.80	8.05	0.54	19.1	184.6	0.147	6	3	15.5	20.1	25.5	26.8	205	190
B-21	21.6	46.4	6.7	2.2	1.9	0.03	0.50	6.33	0.38	14.8	138.5	0.107	6	4	18.0	22.1	27.8	29.7	209	194
B-22	30.0	27.5	7.1	2.1	2.1	0.01	0.17	9.74	0.47	18.3	121.2	0.133	5	6	18.4	22.1	28.4	29.5	204	188
B-31	33.8	16.7	6.5	3.5	3.5	0.01	0.51	10.18	0.55	22.4	94.0	0.168	5	4	15.0	19.1	25.5	27.3	192	177
B-32	28.2	21.6	7.1	2.9	2.6	0.01	0.45	12.01	0.48	20.0	90.1	0.143	6	3	15.8	20.3	27.2	27.6	188	178
B-41	29.5	17.1	6.9	3.6	3.3	0.01	0.53	12.01	0.58	20.7	97.0	0.168	5	4	14.1	17.9	23.2	25.7	173	158
B-42	33.0	15.6	6.9	3.1	2.8	0.02	0.62	10.91	0.56	19.3	115.1	0.144	5	3	15.4	20.3	26.1	28.9	192	176
B-51	26.8	22.7	8.0	2.1	1.4	0.02	0.46	20.43	0.34	15.0	51.0	0.101	6	4	18.4	22.1	27.8	27.9	194	179
B-52	24.5	30.0	8.0	2.4	1.6	0.04	1.50	28.94	0.46	15.3	42.0	0.095	5	3	17.6	20.3	25.1	26.2	201	190
C-11	28.1	36.4	7.2	2.1	2.0	0.01	0.43	9.83	0.37	20.8	83.0	0.122	6	4	17.6	21.4	27.4	28.9	204	188
C-12	28.8	28.7	7.3	2.2	2.0	0.01	0.64	11.64	0.54	19.0	103.0	0.124	6	4	17.6	21.4	28.0	29.2	207	192
C-21	22.6	33.7	7.0	2.4	2.3	0.01	0.44	9.60	0.49	17.8	90.9	0.138	6	4	17.6	20.9	27.4	28.6	204	188
C-22	27.8	30.3	7.3	2.5	2.0	0.01	0.47	12.05	0.42	18.3	101.9	0.135	6	4	17.6	21.4	28.0	28.9	204	188
C-31	26.1	23.9	7.2	2.3	2.2	0.01	0.57	10.41	0.48	17.4	155.8	0.148	6	3	15.8	19.7	26.3	27.1	198	182
C-32	23.0	36.8	7.3	2.4	1.9	0.01	0.28	9.80	0.31	15.0	111.5	0.114	6	4	18.3	20.8	27.0	27.3	198	187
C-41	24.2	28.1	7.1	2.7	2.2	0.01	0.32	9.91	0.44	15.8	107.7	0.131	5	4	16.5	19.2	25.9	27.3	195	184
C-42	23.9	23.9	6.7	2.5	2.1	0.01	0.27	7.32	0.37	15.9	92.3	0.118	6	3	16.5	20.8	27.6	28.5	202	187
C-51	24.4	25.0	6.8	2.5	1.8	0.01	0.26	7.27	0.28	15.1	88.5	0.114	6	4	17.3	20.8	27.9	27.9	202	186
C-52	20.3	18.1	7.0	2.9	1.7	0.01	0.41	6.43	0.30	13.5	63.5	0.105	5	3	17.3	20.8	25.9	26.1	204	187
D-11	30.3	27.7	6.8	2.7	2.7	0.01	0.53	10.22	0.50	20.6	150.0	0.153	5	6	15.2	19.2	25.9	27.9	197	180
D-12	37.6	19.2	6.6	3.5	3.3	0.02	0.41	12.19	0.54	13.2	117.3	0.169	5	3	13.8	17.8	23.3	26.0	186	170
D-21	24.7	33.9	7.0	2.5	2.3	0.01	0.52	10.11	0.47	18.4	117.3	0.136	6	4	14.8	18.9	26.1	27.3	200	185
D-22	30.6	32.1	7.2	2.7	2.4	0.04	0.67	11.88	0.54	20.5	126.9	0.148	6	4	16.2	19.4	26.7	27.9	196	179
D-31	26.3	31.6	6.8	1.9	1.7	0.01	0.34	6.03	0.30	14.3	92.3	0.103	6	4	16.9	20.6	27.2	28.5	203	187
D-32	25.9	26.7	7.1	2.1	2.0	0.01	0.45	9.08	0.32	15.4	107.7	0.126	6	4	16.9	20.0	26.7	28.5	201	185
D-41	26.8	26.7	7.1	2.8	2.7	0.01	0.55	10.10	0.34	18.9	98.1	0.159	6	3	14.8	18.9	25.6	27.3	201	185
D-42	19.0	33.3	6.9	2.4	1.9	0.03	0.33	7.40	0.22	12.1	80.8	0.113	6	6	16.5	20.9	26.7	27.3	203	190
D-51	22.4	30.9	7.1	2.6	2.4	0.01	0.37	9.18	0.30	16.2	57.7	0.145	5	4	16.0	20.3	27.2	28.5	196	181
E-11	35.6	18.2	6.9	3.7	3.6	0.09	1.10	34.67	1.06	25.9	151.9	0.207	6	4	14.9	19.1	26.1	28.2	180	174
E-12	30.9	20.8	7.1	3.2	3.2	0.06	0.39	14.03	0.46	23.5	78.8	0.170	6	3	15.3	20.3	27.2	29.1	185	169

SAMP	Mo.Ct	Cs.Fg	PH	Tot.C	Org.C	EXCHANGEABLE CATION (meg/100g)					Ava.P	Tot.N	COLOR		--- SPECTRAL BAND ----				PIXEL VALUE	
NAME	%	%	1:1	%	%	Na	K	Ca	Mg	CEC	ppm	%	V	C	4	5	6	7	red	green
E-21	25.2	23.8	7.1	2.8	2.6	0.02	0.56	12.68	0.52	18.6	128.8	0.134	6	4	16.0	20.9	27.8	29.8	195	179
E-22	20.9	21.1	6.7	1.6	1.5	0.00	0.12	6.86	0.10	13.6	75.0	0.087	6	4	19.1	22.8	30.1	29.8	200	184
E-31	26.5	28.4	7.0	2.8	2.9	0.01	0.42	12.26	0.50	19.2	90.4	0.202	5	3	14.8	18.8	24.6	27.7	205	190
E-32	22.8	36.2	6.9	2.6	2.4	0.01	0.76	9.45	0.47	20.6	115.4	0.155	6	4	15.0	19.4	27.4	28.3	200	184
E-41	20.6	31.7	7.1	2.4	2.3	0.01	0.28	9.94	0.37	16.1	98.1	0.155	6	3	15.7	19.4	26.9	28.6	205	190
E-42	15.3	42.7	7.0	2.7	2.6	0.01	0.30	10.69	0.35	17.9	119.2	0.191	5	4	14.4	18.8	26.9	28.6	211	199
E-51	21.6	27.9	7.3	2.5	2.3	0.03	0.24	11.81	0.32	16.1	117.3	0.166	5	4	15.1	18.8	26.9	27.1	200	188
F-11	30.1	22.8	6.9	2.9	3.0	0.01	0.43	11.16	0.50	21.6	94.2	0.158	6	3	15.1	18.8	26.9	27.7	201	191
F-12	29.9	20.4	6.6	2.2	2.2	0.06	0.71	9.41	0.69	18.3	88.5	0.145	5	4	18.3	22.4	30.3	33.6	198	182
F-21	19.1	45.1	7.0	2.8	2.3	0.02	0.13	7.08	0.20	12.8	94.2	0.122	6	3	14.3	17.6	24.6	26.3	201	189
F-22	19.4	43.5	7.2	3.8	3.0	0.01	0.24	13.71	0.52	17.4	210.8	0.242	5	4	12.2	15.2	21.7	22.9	201	198
F-31	28.7	35.2	7.1	2.3	2.2	0.02	0.32	9.05	0.24	16.1	71.2	0.137	6	4	16.5	20.6	25.7	29.0	201	185
F-32	19.3	35.3	6.8	1.7	1.7	0.01	0.33	5.50	0.16	12.9	65.4	0.109	5	4	16.2	20.0	26.9	27.2	205	193
F-41	24.5	36.9	7.3	2.5	2.0	0.05	0.50	13.37	0.40	18.8	88.5	0.156	6	4	14.4	18.2	25.7	26.6	208	191
G-11	29.4	36.6	7.1	2.9	2.8	0.07	0.65	15.30	0.62	19.4	123.1	0.168	5	4	13.9	17.5	24.0	24.8	194	177
G-12	29.2	39.9	6.9	2.0	1.9	0.02	0.23	5.87	0.14	11.7	59.6	0.109	5	4	17.0	21.3	28.0	27.9	190	183
G-21	17.5	41.7	7.1	1.0	1.4	0.02	0.27	4.62	0.10	10.8	48.1	0.064	6	3	20.9	24.4	30.3	33.3	215	205
G-22	20.7	30.9	7.0	2.9	2.8	0.04	0.50	13.54	0.60	20.2	126.9	0.168	6	4	16.5	21.3	28.6	29.1	210	198
H-11	30.1	42.9	6.7	2.8	2.9	0.02	0.53	9.76	0.34	19.8	92.3	0.171	4	4	14.8	18.8	25.7	27.3	202	186
H-22	15.3	36.9	6.9	2.2	2.1	0.00	0.41	7.36	0.30	16.8	63.0	0.105	6	3	15.1	19.4	26.9	28.8	196	179

Appendix 4. Red Filter Pixel Values for the Field.
(One number represents 4*4 m in area)

194	185	155	179
189	185	179	186	188	173
184	187	187	188	186	187	190	174
183	184	186	178	179	184	188	187	178
181	181	180	176	178	183	191	190	192	188
176	179	189	177	179	182	186	190	192	193	184
179	179	177	175	180	180	182	189	189	190	194	181
178	179	175	178	182	185	186	205	202	195	197	207	175
177	177	175	180	189	204	210	217	221	208	205	219	216	171
176	177	177	181	188	199	209	214	221	213	214	219	226	210
179	183	183	183	184	181	192	208	213	213	215	222	220	222	199
182	186	188	178	180	186	209	215	212	215	218	217	223	230	221	175
179	183	182	180	189	209	220	218	215	214	222	215	230	230	231	207
176	182	178	187	208	219	216	219	204	201	212	211	232	219	231	209	184
179	181	177	196	211	219	214	209	198	200	198	219	229	227	227	204	196	167
184	181	181	196	207	218	220	211	205	196	200	221	220	226	220	205	202	191	179
185	183	183	209	215	215	218	219	206	189	195	215	209	215	219	210	204	196	191	190
168	183	182	185	208	207	211	215	206	206	185	189	207	201	203	220	218	210	204	191	197
164	179	179	185	190	187	203	205	203	199	187	198	218	209	205	224	223	212	208	199	204	193
167	178	177	183	182	182	196	201	192	186	191	211	216	221	209	224	221	212	213	204	198	199	177
164	180	178	180	179	178	183	198	190	193	202	219	211	208	209	209	215	214	220	206	191	200	196	173
173	182	183	185	179	175	185	193	202	211	206	219	206	194	202	206	217	213	217	203	190	197	202	192	181
179	181	184	188	177	180	192	198	212	213	212	220	211	189	193	200	213	213	215	207	196	186	191	208	208	193
180	182	184	187	181	192	206	205	209	198	219	221	215	201	196	195	207	217	209	201	192	194	190	206	216	197	172
169	181	181	187	183	185	196	204	202	212	215	218	224	215	186	186	192	200	206	199	191	197	194	195	211	200	191
173	183	184	186	177	176	191	199	203	208	214	215	212	194	175	179	187	200	195	189	187	199	190	193	204	202	199	178
171	183	180	183	176	170	178	194	202	204	207	209	206	190	180	173	182	188	188	193	181	194	193	191	201	205	212	205
173	177	178	181	178	171	171	175	193	206	208	211	197	186	181	177	179	179	187	187	181	182	193	196	202	194	212	219	186
178	178	173	179	179	172	171	187	194	212	211	198	189	186	180	182	182	174	183	181	180	178	195	196	193	195	208	206	197
180	179	175	176	176	173	176	177	187	208	211	187	185	183	182	178	185	180	183	182	182	176	191	196	199	197	199	205	192
174	174	179	176	175	176	179	177	184	187	186	180	183	183	179	177	179	188	187	190	184	180	190	196	200	203	198	205	207	181
174	171	175	169	171	175	179	180	181	185	181	179	181	180	182	180	176	186	190	193	184	184	187	190	201	189	188	198	210	190
174	167	175	169	168	172	178	184	183	183	181	180	180	181	183	181	176	188	189	194	181	191	192	184	179	186	189	197	199	192	161
174	165	156	157	165	172	180	184	182	182	183	179	178	184	184	182	183	191	185	191	185	189	193	191	184	176	184	187	199	198	198	179
168	166	168	157	158	161	182	186	187	180	179	180	180	181	185	182	185	189	187	186	191	191	189	185	184	184	190	192	194	195	199	192
163	167	173	166	162	160	175	181	181	180	177	179	179	182	183	181	187	195	191	192	198	182	183	192	194	195	195	194	188	190	191	194	167
159	166	173	170	167	163	181	185	187	182	178	178	178	180	184	183	188	191	192	194	188	184	192	211	204	196	195	197	190	184	183	188	187
159	164	174	169	170	169	185	188	186	185	183	185	184	183	183	185	185	165	188	187	185	189	194	201	194	194	197	198	201	184	176	181	191
150	154	171	169	163	177	180	182	185	183	182	185	184	185	186	185	187	186	185	183	187	179	188	196	193	192	188	190	195	184	181	176	184	167
139	163	165	165	171	179	178	181	183	177	179	188	185	185	187	186	198	186	181	182	182	185	188	190	190	186	182	185	186	180	181	178	183	177
144	174	175	173	177	181	179	181	179	177	180	185	186	187	186	186	185	184	183	181	187	182	190	191	190	187	183	181	182	188	192	191	185	186	185
167	171	181	183	186	183	179	185	182	180	179	181	185	183	185	188	187	184	185	188	187	187	190	187	185	184	183	182	180	184	189	197	193	189	183
176	178	185	185	187	184	186	185	182	182	181	180	180	183	182	187	188	184	181	190	188	188	186	186	186	182	183	180	181	186	184	189	197	187	186
186	181	187	183	188	184	188	183	183	184	184	181	177	182	180	184	183	185	182	182	183	184	180	184	186	184	181	181	183	195	184	184	191	188	186
192	191	188	182	189	184	183	184	185	188	186	181	179	179	185	182	181	183	182	182	181	178	188	182	182	178	176	184	187	186	184	185	188	185	183
192	190	186	187	183	190	180	183	182	187	186	183	179	180	183	182	181	183	184	183	182	182	188	185	186	179	176	180	183	185	186	190	193	188	181
191	188	186	187	187	189	183	186	183	188	194	180	179	180	178	182	186	182	178	183	182	183	186	188	187	185	184	182	189	191	189	186	192	196	189	179
186	192	188	184	188	192	189	185	188	188	186	185	182	180	180	182	183	181	179	181	179	181	185	190	186	184	183	187	193	194	190	186	188	196	180	184
186	187	185	181	189	187	188	188	188	189	185	184	183	184	183	183	180	176	176	179	181	182	186	189	187	187	184	183	186	192	188	184	190	194	190	186
186	189	184	183	187	188	189	193	188	184	184	181	182	182	184	183	180	179	179	180	180	180	188	185	189	187	186	185	187	191	189	186	192	196	189	179
189	187	185	181	188	196	195	188	185	184	186	183	182	182	185	182	182	187	185	183	179	175	177	179	183	188	189	189	187	189	187	181	185	182	184	191
176	184	183	187	197	199	191	188	186	185	187	183	183	183	186	183	185	187	185	177	177	171	170	173	176	183	185	185	184	190	198	184	180	182	176	183
162	186	188	188	184	191	190	190	187	189	185	185	189	184	188	186	187	189	181	180	171	161	172	178	166	174	181	184	180	180	187	194	191	185	182	177	179
161	160	184	189	190	187	190	190	191	188	189	187	186	185	184	184	180	184	186	178	159	154	166	158	170	170	181	184	176	182	183	183	188	186	182	179	179
161	162	177	187	192	187	192	194	193	192	190	188	185	177	172	178	173	180	180	170	154	141	148	154	166	165	179	183	177	183	170	178	182	184	184	177	173
157	158	164	182	190	193	190	192	195	192	190	183	177	165	171	174	172	174	175	158	151	148	152	158	165	165	176	185	177	184	180	178	181	184	187	190	185
158	156	162	181	179	189	190	194	198	189	186	180	172	167	169	172	177	176	171	152	146	157	155	163	166	177	180	184	181	181	182	180	182	184	203	218	189
156	155	163	184	174	191	195	195	196	189	185	176	173	177	175	176	170	180	166	142	150	154	163	169	174	180	180	181	179	183	189	184	182	187	219	229	192
162	157	158	171	161	176	188	189	190	190	189	178	176	181	182	178	180	184	170	159	178	168	166	180	175	179	181	185	184	181	182	186	183	183	193	216	219	189
170	167	162	160	157	157	175	190	183	181	185	184	179	174	169	172	175	181	186	181	188	180	174	177	184	188	189	192	186	180	195	197	188	187	197	219	223	195
170	169	166	172	157	158	182	188	172	180	190	189	184	180	182	181	185	192	196	191	192	192	186	191	189	190	192	199	194	185	202	204	202	210	214	226	230	199
177	169	157	160	154	184	183	189	181	186	192	193	192	192	192	191	191	195	196	192	197	197	196	193	194	203	201	202	194	195	210	208	204	209	214	218	224	192
182	168	152	166	178	201	198	205	197	193	196	197	201	203	207	206	202	207	201	197	206	201	201	198	200	199	200	206	205	205	203	205	205	203	207	209	213	185
183	176	167	185	201	197	200	197	198	197	198	203	204	201	202	207	206	208	204	202	193	194	197	198	200	202	202	203	199	199	197	198	200	196	201	202	200	159
185	188	183	189	196	197	198	197	190	194	190	193	196	203	207	207	201	196	194	197	198	197	195	198	200	197	201	204	201	200	179	188	187	194	198	198	183	167
175	176	180	185	191	179	176	178	188	189	168	174	178	166	168	174	185	191	188	194	173	182	183	183	189	179	172	179	179	180	177	181	188	187	188	185	183	177

Appendix 5. Green Filter Pixel Values for the Field.
(One number represents 4*4 m in area)

210	197	146	189																																		
206	202	195	202	204	173																																
202	204	203	205	202	203	204	171																														
200	201	203	196	197	201	205	204	181																													
199	199	197	194	197	201	208	207	208	197																												
194	196	196	195	198	201	204	207	209	209	195																											
197	197	195	194	198	198	199	205	205	207	210	185																										
195	196	193	196	198	201	202	217	215	209	211	219	168																									
195	195	192	196	202	214	220	225	228	218	217	228	225	159																								
194	194	194	197	202	210	219	223	228	221	224	227	233	215																								
195	198	199	199	199	197	206	218	221	220	223	230	227	229	198																							
197	201	203	195	197	202	219	224	221	222	226	225	229	236	229	162																						
190	199	198	196	203	219	229	226	223	223	229	222	235	236	236	216																						
181	199	195	201	218	227	226	228	213	210	221	219	237	227	237	219	193																					
188	198	194	208	221	228	223	219	208	209	210	226	236	234	234	215	209	163																				
198	197	196	207	216	226	228	220	215	209	211	228	228	232	227	214	213	204	185																			
201	200	198	219	222	224	226	227	216	202	207	223	218	224	226	219	213	208	209	203																		
162	199	198	198	218	216	221	223	215	217	199	212	216	212	214	227	226	218	214	205	209																	
157	196	195	200	202	198	213	214	212	211	201	210	225	218	215	231	230	220	217	211	214	203																
168	195	194	198	196	196	206	211	197	200	201	220	224	227	218	231	228	221	221	214	208	210	180															
170	196	195	196	194	193	197	208	197	205	213	225	219	216	219	218	222	222	226	215	203	211	209	176														
186	198	198	201	194	190	199	203	210	219	216	226	215	206	213	215	223	220	223	212	203	209	214	205	184													
195	197	200	203	193	194	202	205	220	220	221	226	220	203	205	210	220	220	222	217	210	201	204	219	219	207												
196	198	200	202	195	204	216	213	216	201	227	228	223	212	207	206	216	224	219	213	206	208	205	207	226	212	174											
167	197	197	202	199	197	204	213	211	218	210	225	230	216	202	201	204	210	216	210	206	211	209	209	222	214	206											
177	199	201	202	193	189	201	209	213	216	221	222	220	207	201	195	200	210	206	203	201	213	211	208	217	215	213	185										
175	199	197	198	191	186	192	205	211	212	215	218	215	204	196	190	106	201	201	206	196	208	208	207	215	217	223	217										
182	192	194	196	193	189	188	191	205	214	215	220	209	202	198	194	195	194	201	201	196	197	208	210	215	209	223	229	188									
191	193	189	195	195	189	188	188	207	220	219	210	203	202	196	198	197	190	196	195	196	194	209	210	208	209	219	219	210									
193	194	190	192	194	190	193	194	201	218	220	201	201	199	197	195	200	194	196	196	196	192	205	210	213	211	212	218	207	163								
189	191	194	193	192	193	196	194	199	201	200	196	199	199	197	194	195	201	200	203	200	196	205	211	213	215	211	217	219	188								
190	187	191	186	187	191	196	197	197	200	196	195	198	197	198	197	192	200	203	206	200	199	202	205	214	202	202	211	221	204								
190	183	191	185	194	188	194	200	199	198	197	197	197	197	199	197	193	202	202	206	197	205	207	200	194	200	203	209	211	205	157							
189	179	171	171	181	188	196	200	199	199	199	195	195	200	200	198	199	204	200	205	200	203	207	206	200	193	199	202	212	211	210	190						
172	180	182	170	102	176	187	200	202	196	196	197	195	197	201	198	201	203	201	201	205	206	201	201	199	199	203	205	207	208	211	206						
172	181	187	179	176	175	190	197	197	196	194	195	194	198	199	198	202	208	205	206	211	198	199	205	296	207	207	206	202	203	204	207	161					
172	181	188	186	191	177	196	200	201	197	194	193	194	196	200	199	203	205	206	207	203	199	204	219	214	207	207	208	203	198	198	203	196					
172	178	190	184	186	184	199	202	200	200	198	200	199	199	200	200	201	201	203	202	200	203	205	211	207	207	209	210	212	199	192	196	204					
162	166	186	185	188	193	197	197	199	198	197	199	200	201	202	201	202	200	200	198	201	194	200	206	205	205	203	203	208	199	197	192	198	161				
150	176	180	180	187	195	196	197	199	193	195	203	201	201	203	202	203	201	197	197	196	199	201	202	203	201	197	199	200	195	196	193	197	182				
155	189	190	188	193	198	196	197	196	194	196	201	202	202	202	202	201	199	198	197	201	196	204	205	204	202	198	197	197	203	206	205	198	201	197			
177	184	196	198	201	199	197	201	198	197	195	196	201	200	201	203	203	200	200	202	201	201	205	202	201	200	199	198	196	200	204	211	208	204	196			
190	192	200	201	202	200	202	201	200	199	198	195	196	199	198	202	203	199	196	203	202	202	201	201	200	197	199	196	197	201	199	204	212	202	197			
201	196	201	199	204	200	203	200	200	202	200	198	194	198	196	200	199	200	198	198	198	198	195	198	201	199	196	197	199	208	200	199	205	202	197			
207	205	204	199	204	201	200	200	201	204	203	198	195	195	200	198	197	198	198	197	196	193	197	197	196	193	191	198	201	201	199	199	202	200	195			
207	205	202	202	207	205	198	200	198	203	201	199	195	195	198	198	197	199	199	197	197	197	203	200	202	195	191	195	199	200	202	204	207	202	192			
206	204	203	202	202	204	199	203	200	204	200	198	196	196	194	197	201	198	194	198	198	198	200	203	202	201	198	197	204	206	204	201	206	210	202	189		
196	207	203	200	203	207	204	202	203	203	202	202	199	197	197	198	199	196	195	197	194	196	200	205	202	199	198	202	207	208	205	201	203	210	204	190		
201	203	202	198	204	203	203	204	204	205	201	201	200	201	200	201	197	192	192	195	197	198	201	204	203	203	199	198	200	207	203	199	204	208	204	197		
202	204	200	200	203	204	204	208	204	200	200	198	199	200	201	201	197	197	196	197	197	196	203	201	205	204	201	199	201	206	204	199	202	202	203	199		
205	203	201	198	204	209	209	204	201	201	202	200	200	199	202	199	200	200	202	200	195	190	192	195	199	205	204	204	202	204	202	197	200	197	198	202		
193	201	200	203	210	211	206	203	202	201	203	200	200	199	202	199	202	203	201	194	192	186	186	190	192	199	202	201	200	205	212	199	195	197	192	195		
178	201	204	204	209	206	205	205	203	205	201	201	205	201	204	202	203	205	198	196	188	177	199	194	181	191	197	199	195	195	202	208	205	200	197	192	192	
164	175	200	204	207	203	206	206	206	204	205	202	202	201	200	201	196	198	202	195	175	168	182	173	184	186	197	201	191	197	198	198	203	199	196	194	191	
171	177	193	203	207	203	207	209	208	207	206	203	201	194	197	193	191	196	197	186	168	153	161	168	180	181	195	199	192	197	194	192	196	198	199	191	193	
168	173	180	198	205	208	206	208	210	208	206	199	193	181	185	190	188	190	190	173	164	160	165	182	180	181	192	201	192	199	195	194	192	194	200	201	194	
167	170	177	197	194	204	205	209	212	206	203	197	188	182	185	187	192	192	188	167	157	172	169	178	181	192	196	200	196	197	196	194	195	195	211	225	197	
169	169	178	199	189	204	209	210	211	204	200	191	188	193	192	193	187	195	180	154	163	168	177	186	193	195	196	197	194	198	203	199	198	200	226	229	196	
175	170	172	185	173	190	203	204	206	205	203	194	191	195	198	194	196	200	185	172	194	185	181	185	192	198	197	201	200	196	197	202	198	198	207	224	228	192
176	181	176	174	170	167	188	204	198	197	201	198	194	189	184	188	191	198	201	198	205	195	190	192	200	205	206	207	202	196	209	212	203	202	211	229	231	195
181	182	179	185	169	169	193	201	187	196	204	204	199	194	195	195	210	208	212	208	211	208	202	206	204	204	211	214	209	201	216	218	216	223	224	233	238	198
191	182	169	173	166	197	196	203	195	201	210	209	208	207	205	206	207	210	211	208	213	213	207	210	210	213	213	216	209	210	222	221	218	222	226	228	233	187
196	181	163	178	190	215	212	219	212	208	213	212	216	217	221	219	217	221	216	213	220	216	215	217	224	213	215	220	219	219	215	219	219	217	220	222	224	178
198	191	180	198	214	211	213	212	213	212	213	218	219	215	217	221	229	221	218	216	210	210	213	215	213	217	217	218	214	214	211	212	214	211	216	216	207	131
197	202	198	204	211	205	209	210	215	209	193	198	203	211	218	220	215	211	219	212	210	212	210	212	214	200	209	215	214	215	168	180	181	196	207	206	176	144
153	157	171	185	196	160	155	162	179	184	151	157	165	153	145	157	179	190	189	199	153	169	176	176	184	164	156	166	163	169	151	156	173	178	180	177	173	161

Appendix 6 Correlation matrix for all variables on 108 soil samples (R@ 0.05=0.1891 0.01=0.2469)

VARIABLE	1. MC	2. CF	3. PH	4. TC	5. OC	6. NA	7. K	8. CA	9. MG	10. CEC	11. P	12. N	13. V	14. C	15. B4	16. B5	17. B6	18. B7	19. RED	20. GRE
1.MC	1.0000																			
2.CF	-.5900	1.0000																		
3.PH	-.3410	.2803	1.0000																	
4.TC	.5788	-.1721	-.1220	1.0000																
5.OC	.7064	-.2664	-.2622	.9211	1.0000															
6.NA	.2901	-.1308	-.1637	.1806	.2237	1.0000														
7.K	.4200	-.2161	-.0713	.2635	.2992	.4243	1.0000													
8.CA	.3711	-.1694	.4200	.5214	.4958	.3527	.4392	1.0000												
9.MG	.6908	-.3337	-.1657	.6862	.7120	.5193	.4787	.5306	1.0000											
10.CEC	.7063	-.3715	-.2989	.7065	.8018	.3033	.4188	.4247	.7268	1.0000										
11.P	.3461	-.0305	-.1436	.5720	.5381	.3401	.2340	.2916	.6953	.5430	1.0000									
12.N	.5915	-.2046	-.1652	.8059	.8676	.3163	.2856	.5406	.7286	.7381	.6310	1.0000								
13.V	-.3805	.0060	.0888	-.6436	-.6098	-.0540	-.1058	-.2918	-.4612	-.4553	-.3633	-.5769	1.0000							
14.C	-.1175	-.0553	-.0437	-.2910	-.2542	-.0828	-.1213	-.1434	-.2491	-.1913	-.1207	-.1513	.2222	1.0000						
15.B4	-.4324	.0765	.1306	-.7914	-.7950	-.0972	-.2125	-.4056	-.5261	-.5667	-.5106	-.7403	.5756	.2563	1.0000					
16.B5	-.2859	-.0039	.0388	-.7541	-.6850	-.1524	-.1907	-.3990	-.4757	-.4673	-.5060	-.6659	.6115	.2707	.8529	1.0000				
17.B6	-.3806	-.0123	.0292	-.7696	-.7015	-.1496	-.1923	-.4073	-.5445	-.4893	-.5385	-.6229	.6916	.3866	.8317	8835	1.0000			
18.B7	-.2559	-.0673	-.0756	-.7188	-.5904	-.0474	-.1225	-.3744	-.4314	-.3610	-.4951	-.5281	.6548	.3470	.7665	8583	.9379	1.0000		
19.RED	-.6870	.3257	.0572	-.7499	-.7508	-.0881	-.1859	-.5002	-.5791	-.5850	-.3743	-.6259	.5839	.2806	.6002	.5616	.6098	.5636	1.0000	
20.GRE	-.7360	.4346	.1180	-.6974	-.7282	-.0580	-.1799	-.4290	-.5595	-.5960	-.3089	-.5877	.5360	.2302	.5675	.5113	.5551	.4904	.9593	1.0000

Appendix 7 Correlation matrix for ratioed and log transformed variables on 108 soil samples. (R@ 0.05=0.1891 0.01=0.2469)

VARIABLE	15. B4	16. B5	17. B6	18. B7	19. RED	20. GRE	51 B4/B5	52 B5/B6	53 B6/B7	54 B45/B67	55 B4+B5	56. B6+B7	57. B4567	58. RED/GRE	59. GRE+RED
21.LNMF	-.3837	-.2299	-.3111	-.1882	-.6352	-.6920	-.3784	.1412	-.4151	-.2281	-.3185	-.2533	-.2915	-.6707	-.3863
22.LNCF	.1018	.0196	.0203	-.0336	.3730	.4647	.1382	-.0322	.1863	.1281	.0630	-.0069	.0255	.4237	.4308
24.LNTC	-.8062	-.7646	-.7365	-.7102	-.6794	-.6305	-.3488	-.1965	-.1940	-.4575	-.8159	-.7348	-.7952	-.6615	-.0351
25.LNOC	-.8213	-.7014	-.6733	-.5835	-.6753	-.6503	-.4761	-.1824	-.3644	-.5702	-.7909	-.6382	-.7291	-.6695	-.1175
27.LNK	-.3163	-.2684	-.2870	-.1775	-.2570	-.2605	-.1824	.0017	-.3379	-.2182	-.3037	-.2356	-.2746	-.2615	-.0906
28.LNCA	-.5468	-.5093	-.4911	-.4618	-.5065	-.4534	-.2499	-.1327	-.1591	-.3153	-.5486	-.4839	-.5290	-.4847	.0425
29.LNMG	-.5786	-.4950	-.5333	-.4188	-.5169	-.5093	-.3430	-.0142	-.4043	-.3463	-.5575	-.4833	-.5328	-.5184	-.1338
30.LNCEC	-.5648	-.4616	-.4590	-.3350	-.5487	-.5653	-.3595	-.0755	-.4299	-.4301	-.5331	-.4029	-.4761	-.5629	-.2235
31.LNP	-.5317	-.5188	-.5269	-.4920	-.3184	-.2666	-.2215	-.0935	-.1850	-.2775	-.5457	-.5175	-.5466	-.2953	.0755
32.LNN	-.7819	-.6889	-.6136	-.5402	-.5857	-.5570	-.4201	-.2833	-.3098	-.6093	-.7639	-.5858	-.6869	-.5771	-.0721

VARIABLE	51. B4/B5	52. B5/B6	53. B6/B7	54. B45/B67	55. B4+B5	56. B6+B7	57. B4567	58. RED/GRE	59. GRE+RED
1.MC	-.3895	.1560	-.4289	-.2262	-.3729	-.3230	-.3562	-.7191	-.3819
2.CF	.1266	-.0189	.1831	.1308	.0376	-.0406	-.0054	.3847	.4758
3.PH	.1939	.0205	.2996	.2373	.0879	-.0239	.0275	.0888	.2395
4.TC	-.3510	-.1164	-.2608	-.4060	-.8027	-.7559	-.8010	-.7309	-.0461
5.OC	-.4637	-.0973	-.4245	-.5037	-.7687	-.6559	-.7287	-.7470	-.1519
6.NA	.0509	-.0313	-.2932	-.1027	-.1297	-.0998	-.1168	-.0737	.0721
7.K	-.1119	-.0189	-.2187	-.1533	-.2094	-.1597	-.1878	-.1847	-.0408
8.CA	-.1606	-.0663	-.1511	-.1978	-.4179	-.3970	-.4190	-.4690	.1126
9.MG	-.2850	.0508	-.4100	-.2561	-.5204	-.4954	-.5223	-.5751	-.1210
10.CEC	-.3619	-.0302	-.4474	-.3940	-.5370	-.4316	-.4941	-.5967	-.2196
11.P	-.2073	-.0439	-.2129	-.2324	-.5280	-.5249	-.5425	-.3448	.1052
12.N	-.3880	-.2263	-.3673	-.5562	-.7303	-.5844	-.6705	-.6129	-.0540
13.V	.1807	-.0403	.2115	.1379	.6167	.6838	.6735	.5655	.0124
14.C	.0928	-.1750	.1566	-.0522	.2738	.3725	.3379	.2578	-.0864