THE USE OF REMOTE SENSING TECHNIQUES IN THE DETECTION OF UPLAND VEGETATION COMMUNITIES IN THE NORTH YORK MOORS NATIONAL PARK

Priyadi Kardono

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The Use of Remote Sensing Techniques in the Detection of Upland Vegetation Communities in the North York Moors National Park

by

Drs. Priyadi Kardono M.Sc.

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ABSTRACT

The North York Moors National Park was designated in 1952 to conserve the extensive area of open dry upland heath dominated by *Calluna vulgaris*. However, problems of moorland management have occurred with the loss of open moorland to agriculture, and forestry. Bracken encroachment, over-aging of heather, and soil erosion are further problems. In attempts to solve these problems, it is necessary to produce vegetation and land cover maps which can be achieved by using remote sensing techniques. This thesis examines the use of Landsat TM data and remote sensing techniques to produce an upland vegetation distribution map which may be useful as a data input for management planning.

Landsat TM data acquired on 31st May 1985 were used to discriminate the upland vegetation communities in five sample areas: Blakey, Egton, Farndale, Glaisdale, and Whitby. A supervised box and maximum likelihood classification from the R-CHIPS image processing system is used to determine the distribution of vegetation classes. Spectral coincident plots and scatter diagrams of the training data were examined to produce classmaps.

The Habitat maps, used as a guide during computer training stages were also used for assessing the accuracy of classification results. It is shown that the average accuracy of box classification result is about 77%. whilst using maximum likelihood classification, overall accuracy of 85% has been achieved. It is shown that bracken, mature *Calluna*, young *Calluna*, coniferous plantation, improved grassland, and

bryophytes were better discriminated whilst acid flush, acid grassland, and semi-improved acid grassland were less successfully identified.

The potential and problems of the techniques are discussed and alternatives strategies to achieved better results are suggested. Using high spatial resolution data such as SPOT imagery, multitemporal data acquisition, and image filtering may increased the classification accuracies. The combined use of image masking and maximum likelihood classification will reduce generalisation giving high classification accuracy.

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Declaration

(a) I **Priyadi Kardono** hereby certify that this thesis has been composed by myself, that is a record of my own work, and that is has not been accepted in partial or complete fulfilment of any other degree of professional qualification.

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(b) I was admitted to the Faculty of Science of the University of St. Andrews under Ordinance General No 12 on 10th October 1988 and as a candidate for the degree of Ph.D. on 29th September 1989.

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CHAPTER 1

INTRODUCTION

1.1 Research Background

At present, there is no definitive dividing line between lowlands and uplands in Britain (Usher and Gardner, 1988). Ball *et al.*, (1982) describe the upland environment as land with a mean altitude over 122 metres, but land above the limits of arable farming is more usually defined as upland (Ratcliff and Thompson, 1988). A great variety of landscape and dependent biotic communities are the most common features of the British uplands. This variety is created by differences in geology, topography, climate, soils and past land uses (Ratcliff and Thompson, 1988). The uplands make up almost one third of Britain, and despite being sparsely populated they are still an important and complex component of British landscape (Gimingham, 1988; Jones and Wyatt, 1988).

Upland ecology is mostly dominated by physical environment factors such as climate, geology and topography. The pattern and composition of this landscape is not static, but affected by changes of past, present, and new land use patterns. These changes include loss of moorland, agriculture improvement, deforestation, bracken encroachment, afforestation and building construction (Ball *et al.*, 1982; Birks, 1988; Jones and Wyatt, 1988; Ratcliff and Thompson, 1988; Williams, 1988).

The North York Moors National Park, which is located on an upland plateau of northern England and covers an area of about 1432 square kilometres, was designated in 1952 (North York Moors National Park, 1986; Alam and Harris, 1987). One of the main reason for this designation was the conservation of the extensive area of open dry upland heath which is interspersed with blanket bog and peat and their associated wet moorland/bog communities (Brown, 1986). About 40% of this area is dominated by moorland, and *Calluna vulgaris* (common heather) is the dominant species. There is no other area in Britain which has such extensive area of common heather (Ordnance Survey, 1987). This moorland is used for extensive sheep grazing, the rearing of grouse for shooting and recreation (Brown, 1986). Management problems arise as there is conflict between these land uses. The loss of open moorland to agriculture and plantation/forestry, encroachment by bracken, and changing management practise are the most common problems in the management of North York Moors National Park (Ball *et al,* 1982; Parry *et al.,* 1981). Between 1950 and 1975, about 22,1% of moorland area was converted to agriculture and forestry (North York Moors National Park, 1977), and between 1950 and 1984 about one quarter of the moorland has been reclaimed for both these purposes, but this trend has recently been slowed (Brown, 1986).

Pteridium aquilinum (bracken) which is spreading to areas previously occupied by *Calluna vulgaris* (heather) and to agricultural land has attracted considerable interest on a national scale. This problem has occurred not only in the North York Moors, but also in many other areas such as Scotland (Birnie and Miller, 1986), and Wales (Williams *et al.,* 1987). The area of bracken in the North York Moors has been estimated at 11,600 hectares (Barber, 1986) and the encroachment of bracken is increasing rapidly, estimated at 120 hectares per annum (Jewell and Brown, 1987). There are five main reasons for bracken becoming the focus of management concern. Firstly, it infests agricultural fields, mainly improved pasture, and makes them less productive. Secondly, when it is dry, it is a fire risk. Thirdly, it is toxic to stock if grazed causing stomach and rectal cancer. Fourthly, it harbours ticks which can kill sheep and grouse, and lastly it destroys other moorland plant species, prevents the regeneration of heather stands, and discourages recreational access (Brown, 1986; Jewell and Brown, 1987).

Approximately 40% of the National Park area consists of Moorland and upland heath. The conservation of this moorland has been dependent on a management scheme which includes sheep grazing and controlled heather burning (Brown, 1986). However, many moorland areas are now outside the normal burning pattern which gives a more extensive area of over-aged heather (Weaver *et al.*, 1989). Therefore, it is essential, for management purposes, to produce maps showing areas of mountain, heather, moorland and forest which are important to conserve. Nevertheless, these maps should be updated at an interval not exceeding five years (Jewell and Brown, 1987). In the past, much of the mapping was undertaken using traditional methods based on ground survey, and in the North York Moors, this mapping was done using aerial photograph and field survey (Jewell and Brown, 1987). However, given the area involved and rapid changes from year to year, it is not realistic to use such conventional survey methods (Weaver, 1986). Physically inaccessible and rough terrain of upland areas are a common problem for conventional ground survey. Accordingly, remote sensing techniques may offer an available alternative tool for mapping of relatively difficult terrain (Kardono, 1988). Remote sensing has a considerable potential for reducing time spent on field work (Budd, 1987). Imagery can show the current pattern of vegetation cover for extensive areas at the same time, which is particularly useful for such inaccessible upland areas (Stuart and Hogg, 1987). Therefore, it allows the ground information sample to be interpolated across extensive areas and reduce the area to be covered by the surveyor. Advances in remote-sensing systems and the availability of satellite imagery (which is provided every 16 days by Landsat satellite) are advantageous for mapping and monitoring of land use/land cover and vegetation changes (Morton, 1986). By using data from Landsat Thematic Mapper (Landsat TM), the time and cost of map preparation could be reduced. These useful data could be provided for mapping and detection of dominant plant communities, detection of loss of open moorland to agriculture and forestry, and detection of changes in moorland management (mainly in cyclical heather burning) (Jewell and Brown, 1987; Ward *et al.*, 1987; Williams, 1988). In comparison with Landsat Multispectral (MSS) data, the Landsat TM data are expected to increase the accuracy of vegetation identification. Better spatial resolution and more numerous spectral regions are the most important characteristic of Landsat TM (Atkinson *et al.*, 1985).

1.2. The Aims of the Study

Remote sensing is a valuable tool in the detection, grouping and monitoring of ground surface information. It has considerable potential for routine monitoring, so that management practices can be less expensive, less time consuming and more efficient. However, remotely sensed data has many problems which influence the interpretation.

The main aim of the research presented in this thesis is to evaluate remote sensing techniques for detection and classification of the vegetation communities in the North York Moors using Landsat TM data. This research will examine and develop a routine image processing methodology for producing detailed upland vegetation distribution maps, in order to provide a regular input of vegetation maps for management planning.

1.3. Methodology

In this research, the methodology of image interpretation focuses on the problem of classification of upland vegetation communities. It is based on the assumption that a) the nature of upland vegetation communities can be described and classfied by their spectral response in the Landsat TM wavebands, and b) the distribution of vegetation classes, when characterized by spectral response, will be similar to their distribution on the Habitat maps. Various techniques will be used to classify TM imagery, including Box classification and Maximum likelihood classification. The classification results will then be compared with vegetation habitat maps, produced by North York Moors National Park at a scale of 1:10,000.

1.4. Upland Vegetation Communities in North York Moors.

The existence and distribution of plants has been influenced by many different environmental factors including rainfall, temperature, soil moisture content, nutrient content and depth. It is also influenced by the type of land management. In particular, most of vegetation in upland areas may appear to be natural, nevertheless, it has been considerably modified by man. Notably, these changes occurred through removal of the extensive woodland cover during prehistoric and historic times (NERC and ITE, 1978). In the North York Moors, the natural vegetation was deciduous forest which was cleared in the Bronze Age around 2,000 BC. (Ball *et al.*, 1981; Dimbleby, 1952).

The British moorlands are typically dominated by dwarf shrub heaths. It is woody vegetation, usually less than one meter tall and dominated by one or several species (NERC, ITE, 1978). In the North York Moors, heather is the most dominant species which covers about one third of the area. In particular, there are four categories of common moorland plant communities in the North York Moors, namely drier areas of the plateaux, damper areas, flushes and dry moorland slopes (North York Moors National Park, 1979).

In the drier areas, *Calluna* is the dominant species, which covered the widest area on the high ridges and the dales, and have most vigorous and luxuriant heather growth (Elgee, 1914). In the very dry area, various vegetation groups can be found with *Vaccinium myrtillus* (bilberry) becoming the most common sub-dominant vegetation. *Erica cinerea* (bell heather), *Empetrum nigrum* (crowberry) are the co-dominant vegetation in the peaty surface. *Potentilla tormentilla* (tomentil), *Vaccinium vitis-idaea* (cowberry), *Agrostis tenuis* (common bent grass), *Festuca ovina* (sheeps fescue) and *Nardus stricta* (mat grass) are also found in the drier areas (North York Moors National Park, 1979). On wetter area, *Erica tetralix* (cross leaved heath) is often sub-dominant (Carroll and Bendelow, 1981).

The damper areas occur around the highest parts of the watershed with the altitude ranging from 240 m to 450 m. The surface is generally flat, rainfall is high and very wet all times of the year (Elgee, 1914). This has lead to the build-up of the deepest peat. Heather is nearly always present, but *Erica tetralix* (cross leaved heath) is often dominant. In some areas, *Eriophorum vaginatum* (Hare's tail grass) is also found to be dominant whilst *Molinia caerulea* (purple moor grass) is found interspersed among heather. *Juncus squarrosus* (heath rush) and *Sphagnum* (bog moss) are commonly found in the wettest areas (Elgee, 1914).

In the flush or spring areas, *Juncus effusus* (soft rush) and *Sphagnum* are commonly found in the upper and lower reaches, where peaty water is more highly mineralized and more aerated (Carroll and Bendelow, 1981; Elgee, 1914). *Carex echinata* (star sedge) and *Agrostis canina* (velvet bent) are also commonly found in this area (North York Moors National Park, 1979).

The various combinations of altitude, steepness, contour and direction will influence the vegetation in the dry moorland slopes areas.

Therefore the conditions in these areas favour a more varied and luxuriant vegetation (Elgee, 1914). *Pteridium aquilinum* (bracken) is the dominant vegetation on many slopes. However, upstream in shallow valleys, bracken becomes more rare on the slopes. Among *Calluna* and *Pteridium, Vaccinium myrtillus* (bilberry) and *Deschampsia flexuosa* (wavy hair grass) are also found in these areas (North York Moors National Park, 1979), whereas *Vaccinium* cover dominates on slopes facing north and east (Carroll and Bendelow, 1981).

Cundill (1971) suggested that formerly there was slightly more varied vegetation species in the upland moors, however, the variety of vegetation species has been reduced as a result of human interference, particularly by burning and grazing.

1.5 **The Structure of the Thesis.**

This thesis is organized into six chapters. In the first chapter, the introduction, the background and the aims of the research are discussed. The following section describes the research methodology concerned. The distribution of common vegetation communities in the study area is also discussed in this chapter.

In Chapter 2, the remote sensing system which includes the Landsat Thematic Mapper sensor and some aspects which affect the spectral properties of soil, leaves and vegetation canopy are discussed. This is followed by the description of the potential of remote sensing techniques for upland vegetation mapping. The effects of temporal, spectral and spatial characteristics are the main subject in this section.

The remainder of this chapter describes various studies of upland vegetation mapping using remote sensing techniques.

The first section of Chapter 3 introduces the physical features of the study area and also the land use and management problems which occur. The geographical location of the study area, physiography, geology, soils and climate are outlined. It is followed by a brief description of the imagery of the National Park and the choice of the study extracts. Another part of this chapter describes the ground information acquisition and the ground radiometer measurements. This includes a discussion of using field spectroscopy in remote sensing, the Macaulay portable radiometer and the results of ground radiometer measurements.

The analysis of Landsat TM data for vegetation mapping within the five study extracts of the North York Moors National Park are discussed in Chapter 4. The first part of this chapter considers image processing and the R-CHIPS image processing system. This is followed by a discussion of image classification systems and the training stage which is very important in the image classification algorithm. The main part of this chapter is the detection of upland vegetation communities. This reports on the analysis of Landsat TM data for the five study extracts for box and maximum likelihood classification. The results of classifications are outlined briefly and summarized in the last section.

In Chapter 5, the accuracy of the classification results are examined. An accuracy assessment approach is presented in the first part of this chapter. Following this are the reports of the accuracy results of the box and maximum likelihood classification compared with the Habitat maps. This is summarized and presented in the last section.

The last chapter, Chapter 6, considers the potential and the problems of remote sensing techniques for the detection of upland vegetation communities, particularly in the North York Moors. The recommendations for achieving a better result is considered in the final section.

CHAPTER 2

THE APPLICATION OF REMOTE SENSING FOR UPLAND VEGETATION MAPPING

2.1 **Introduction.**

Remote sensing techniques have been widely used for many purposes in earth resource surveys such as agriculture, geology, hydrology, oceanography, land use / land cover, etc., particularly to provide accurate and timely information (Quirk and Scarpace, 1982). Until the 1960s, aerial photography was the principle method of remote sensing (Everet and Simonet,1976). However, since the Landsat satellite become operational in 1972, more researchers and resource managers have used Landsat Multispectral Scanner (MSS) data as a major input. High speed processing, continuity in providing new data and production of print-out maps at relatively low cost, are the main advantages of Landsat images (Gordon, 1980). Nevertheless, one of the disadvantages of the Landsat MSS data is that the images cannot provide information for detailed planning purposes owing to the low spatial resolution.

Starting from the middle of 1982 , when Landsat 4 was launched, the MSS sensor on board the Landsat satellite has been enhanced with a new sensor system called Thematic Mapper (Landsat TM). Landsat TM data are more useful and have much wider range of application than Landsat MSS (Lillesand and Kiefer, 1987). This is the result of increasing the number of spectral bands and an improvement in spatial resolution as compared with the MSS.

The aim of this chapter is to describe the remote sensing system particularly for Landsat TM, the potential of remote sensing for upland vegetation mapping and the use of Landsat TM for vegetation mapping.

2.2 The Remote Sensing System.

Remote sensing is the science and art of physical data acquisition of an object, area, or phenomenon through the analysis of data which is acquired without direct contact with the object (Lillesand and Kiefer, 1987; Lintz and Simonet, 1976). It is usually concerned with the use of electromagnetic radiation sensors to obtain data on the environment which can than be analysed to provide useful information on such topics as land use / land cover, vegetation, etc.

There are four main components of a remote sensing system using electromagnetic energy (Curran, 1985). Firstly, the system requires a source of electromagnetic radiation which either occurs naturally such as the Sun's (source 1) reflected light or the earth surface emitted heat (source 2), or is man made such as microwave radar (source 3). Secondly, interactions take place between electromagnetic radiation and the earth's surface, with soil, vegetation, water, urban areas, etc. The amounts and characteristics of radiation reflected or emitted from the earth surface are based upon the characteristics of the objects on the earth surface. Thirdly, interactions exist between electromagnetic energy and the atmosphere. When electromagnetic energy passes through the atmosphere, it will be distorted by reflection, scattering and absorption of cloud (water droplets), water vapour, ozone and carbon dioxide. The fourth component is the sensor, which will record the electromagnetic radiation that has interacted with the atmosphere and the objects on the earth surface. This could be a camera, radiometer or imaging radar either in the satellite, aircraft or possibly held in the hand (Figure 2.1).

Electromagnetic energy which is reflected, emitted or back scattered (radar) from the earth surface occurs as a continuum of wavelengths and frequencies. These are present as short wavelengths to long wavelengths or from cosmic rays to television/radio waves (Lillesand and Kiefer, 1987). However, only a few of these are useful in an environmental remote sensing system. Visible light, infrared and microwave are the most common wavebands used by the earth resources satellite (Figure 2.2).

The electromagnetic energy has to pass through the atmosphere both before and after interacting with the earth's surface, and before being detected by a satellite remote sensor. During its passage through the atmosphere, the electromagnetic radiation interacts with particles suspended in the atmosphere. This will change the radiation's speed, direction, frequency, spectral distribution, and intensity as a result of atmospheric scattering, absorption and refraction. Atmospheric scattering particularly affects the direction of short visible wavelength; the blue band is scattered about four times as much as red band (Campbell, 1987). Absorption of radiation affects wavelengths which are both shorter and longer than the visible band. In particular, there are three gases which are responsible for most absorption of solar radiation.

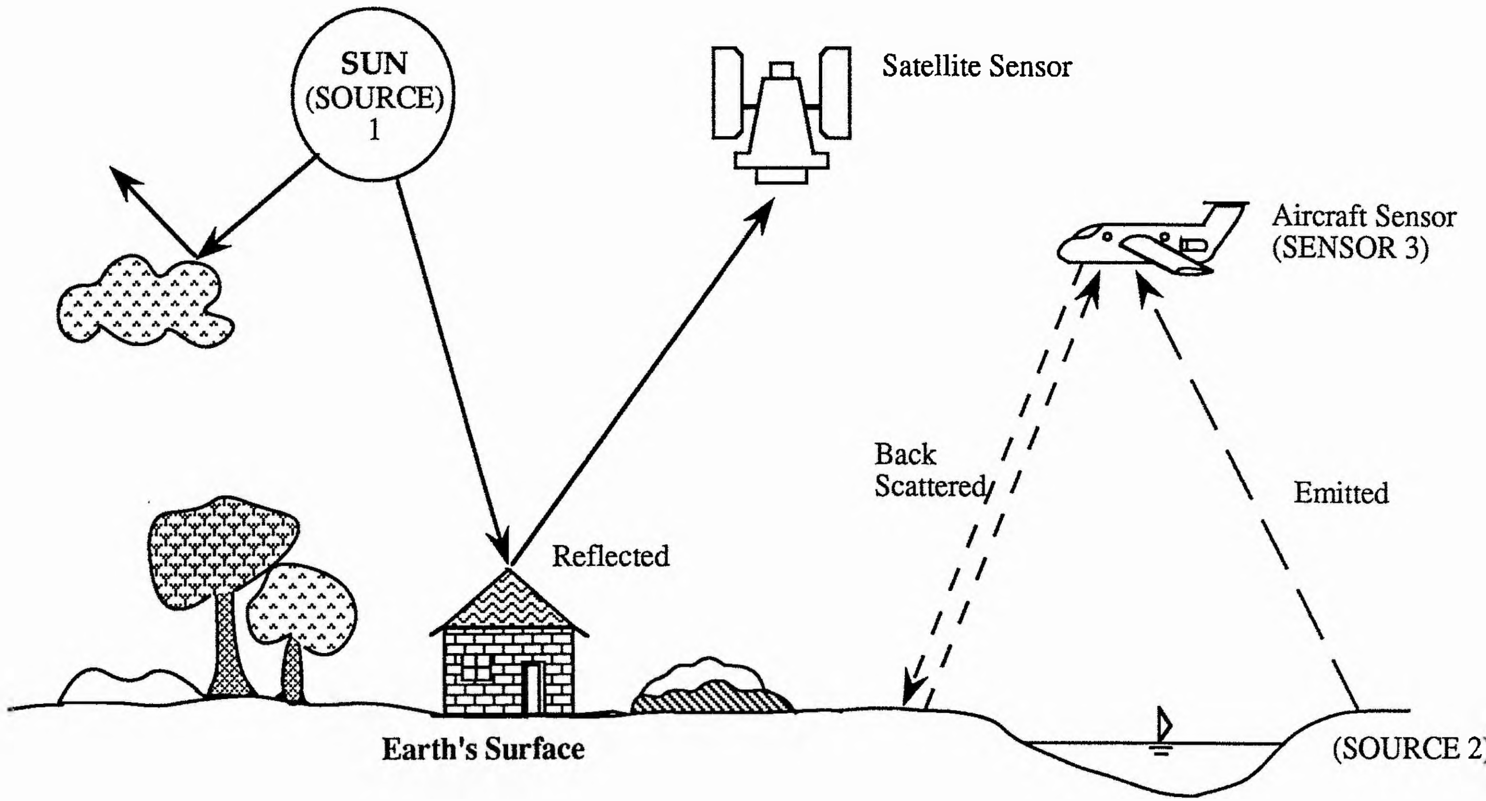


Figure 2.1 A Remote Sensing System and Interaction of Solar Energy. (Modified from Lindgren, 1985).

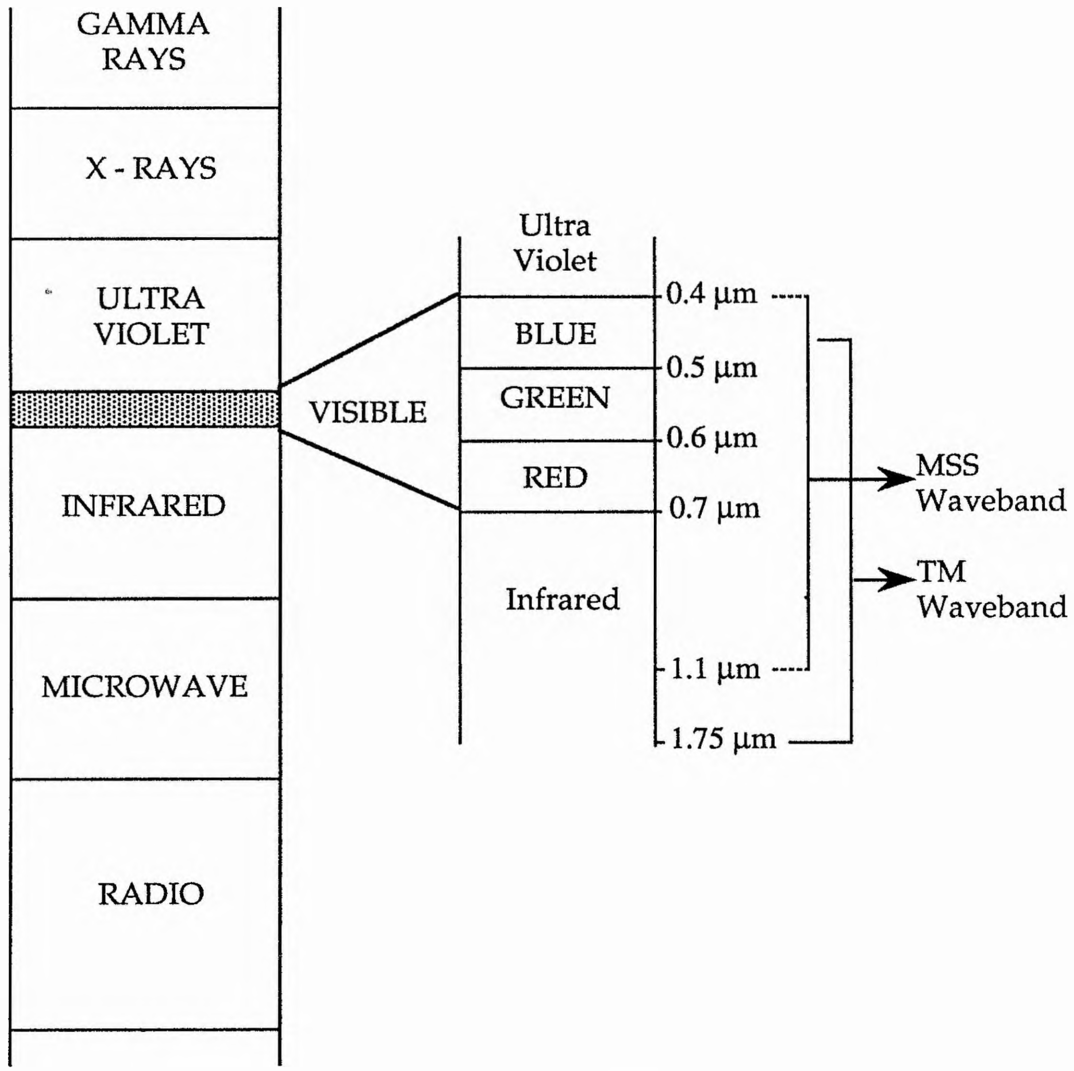


Figure 2.2 The Electromagnetic Spectrum, Landsat MSS and TM Wavebands.
(Modified from King, 1985).

Ozone (O_3), carbon dioxide (CO_2) and water vapour (H_2O) are the main absorbents of electromagnetic energy. Refraction occurs when electromagnetic radiation passes from one medium to another through a stratified atmosphere.

As the electromagnetic radiation interacts with earth surface many factors will affect the energy. It is either reflected, absorbed or transmitted. When electromagnetic energy interacts with vegetation, low reflectance occurs on red and blue wavebands, medium reflectance on the green band and high reflectance on the near infrared band. However, vegetation reflectance is influenced by the effects of soil background, vegetation senescence, solar and sensor elevation, solar and sensor azimuth and the effect of canopy geometry (Curran, 1985). When electromagnetic energy interacts with soil, it will be either reflected or absorbed or transmitted. There are five factors which determine the reflectance properties of soil: its texture, structure, moisture content, organic content and iron oxide content. When interaction of electromagnetic energy with water bodies occurs, the majority of energy is not reflected but either absorbed or transmitted. In visible wavelengths, a little light is absorbed, about 5% is reflected and the majority is transmitted. In near and middle infrared, only a little radiation will be either reflected or transmitted. The majority of this wavelength will be absorbed, and it results in sharp contrasts being observed between water and land boundaries. The three most important factors that affect the reflectance of water bodies, are the depth of the water, the materials content within the water and the surface roughness of the water.

In satellite remote sensing, electromagnetic radiation which is reflected, transmitted, absorbed or emitted by the earth's surface is collected and recorded by some form of sensor on board a satellite platform. The sensor systems employed in satellite remote sensing includes photographic equipment, television camera, scanning radiometers and imaging radar. Many types of photographic cameras have been used since the manned space missions of the US Gemini and Apollo series in 1960s and then in the NASA Space Shuttle program. The first television camera was carried by weather satellite, TIROS 1, launched in 1960. It was continued to be used on weather satellites and then used in the first generation of Landsat satellite (the Return Beam Vidicon camera). Scanning radiometers have been used on a variety of remote sensor satellites including Landsat multispectral scanner (MSS), Landsat Thematic Mapper (TM), the NOAA Advanced Very High Resolution Radiometer (AVHRR) and the Nimbus Coastal Zone Colour Scanner (SZCS) (Harris, 1987).

In summary, it can be stated that remote sensing techniques are based on the fact that different objects on the earth's surface such as water, vegetation, soil, and urban areas will reflect different values within different wavebands. The image data from Landsat Thematic Mapper (TM) sensor has been used in this research; it will be discussed briefly in the following section.

2.2.1 Landsat Thematic Mapper (TM) Sensor.

Landsat (Land Satellite) was originally called Earth Resources Technology Satellite (ERTS), but the name was officially changed to

Landsat in 1974 (Barrett and Curtis, 1982). The ERTS program was established by the United States National Aeronautics and Space Administration (NASA). The Landsat satellite was designed in the 1960s and the first satellite was launched on 23 July 1972. The mission of Landsat is to provide unmanned satellites for repetitive multispectral data acquisition of the earth's surface (Thomas *et al.*, 1987). These data are used for developing various applications of earth resources disciplines such as agriculture and plant science, forestry, geology, geography, hydrology and oceanography. At present, five Landsat satellite series (Landsat 1, 2, 3, 4, and 5) have been successfully operated, but only the last two of those are still in operation (Table 2.1). It should be noted that three different type of sensors have been flown on two different combinations of these missions. These are the Multispectral Scanning System (MSS), Return Beam Vidicon Camera (RBV), and Thematic Mapper (TM).

Landsat has had two generations, the first Landsat generation platform (Landsat 1, 2, and 3) was designed as a modified Nimbus weather satellite which carried two types of sensor (Figure 2.3a), the four wavebands Multispectral Scanning System (MSS) and three television cameras of Return Beam Vidicon (RBV) (Campbell, 1987; Curran, 1985). These Landsat satellites, weighed about 815 kg, were launched to an orbital altitude of approximately 913 km and circled the earth once every 103.3 minutes to achieve 14 orbits per day. This gave an orbit pattern where the same place on the earth's surface is repeatedly covered every 18 days, after 251 completed orbits (Harris, 1987).

The data communication system of Landsat 1, 2 and 3 gave possibilities of direct transmission from satellite to the ground station, particularly

Satellite	Launched	Retired	Sensor (a)	MSS Bands	TM Bands	Orbit
Landsat 1	23 July 1972	1 June 1978	MSS, RBV	4,5,6,7	-	18 days/900 km
Landsat 2	22 January 1975	30 July 1983	MSS, RBV	4,5,6,7	-	18 days/900 km
Landsat 3	5 March 1978	30 September 1983	MSS, RBV	4,5,6,7	-	18 days/900 km
Landsat 4	16 July 1982	(b)	TM, MSS	1,2,3,4	1,2,3,4,5,6,7	16 days/705 km
Landsat 5	1 March 1984	-	TM, MSS	1,2,3,4	1,2,3,4,5,6,7	16 days/705 km

Table 2.1 Characteristics of Landsat Missions.

(Adapted from Campbell, 1987; Curran, 1985; Lillesand and Kiefer, 1987)

(a) "MSS' sensor denotes the multispectral scanner, "RBV" the return beam vidicon, and "TM" the thematic mapper.

(b) Since March 1983, Landsat 4 has been operating at reduced power.

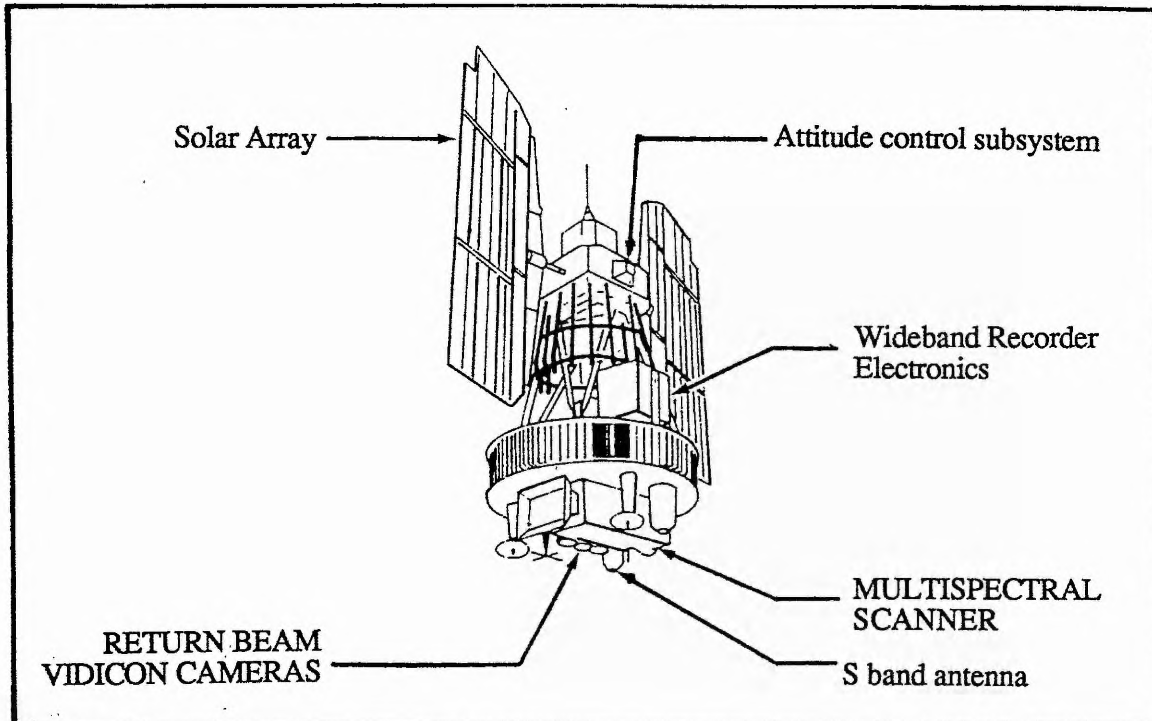


Figure 2. 3 a. The First Generation Landsat Platform,
Landsat 1, 2, and 3.
(adapted from Harris, 1987).

when the satellite had direct line of sight view to the ground station (Kardono, 1988). However, the image of areas outside the receiving range of the station was recorded on the tape recorder on board the satellite. These records were transmitted when the satellite was within range of the ground station.

2.2.1.1 The Second generation of Landsat series.

The second generation of Landsat programmes began with the launch of Landsat 4 on 16 July 1982, and continued with the launch of Landsat 5 on 1 March 1984. Like the previous series, Landsat 4 and 5 were launched into repetitive, circular, sun-synchronous, and near-polar orbit. However, the orbit of these satellites were lowered to 705 KM so that it would be possible to recapture the satellite should repairs be needed using the USA Space Shuttle. As the orbit has been lowered, the repeat cycle of these satellite has also changed to 16 days to achieved 233 orbits, and the total field of view was increased from 11.56^0 (Landsat 1, 2 and 3) to 14.92^0. Because this pattern was different from previous Landsats, Landsat 4 and 5 scenes required a new World-wide Reference System (WRS) system for paths and rows index system. The WRS for the first Landsat generation has 251 paths (corresponding to the number of orbits) and 248 rows, while Landsat 4 and 5 have 233 paths and 248 rows.

The second generation of Landsat platforms was of a completely different design from their predecessors (Figure 2.3b). Both the MSS and the new Thematic Mapper (TM) sensors are carried on an improved platform, that cannot only maintain but improve the

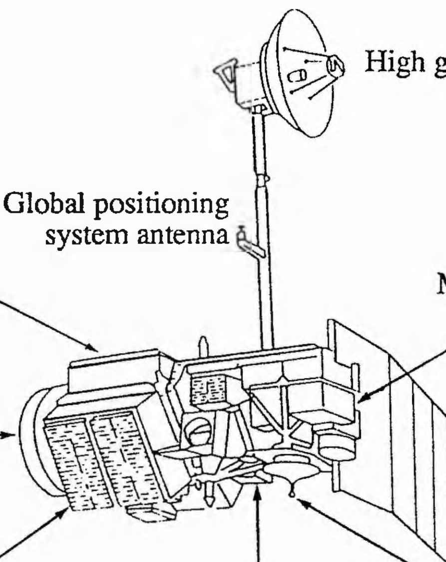


Figure 2.3 b. The Second Generation Landsat Platform,
Landsat 4 and 5.
(adapted from Harris, 1987).

geometric and radiometric qualities of the imagery. However, the RBV cameras have been omitted in this new generation. The MSS on board Landsat 4 and 5 has a similar design to the early Landsats, except the ground pixel size (82 m x 82 m instead of 79 m x 79 m for Landsat 1, 2 and 3), and the band numbering system from 4, 5, 6, 7 to 1, 2, 3, 4. The problems of data collection, particularly outside the range of US ground stations, have been overcome by using the new Tracking and Data Relay Satellite (TDRS). The TDRS satellite is in the same orbits of those Landsat 4 and 5. Therefore, it permits direct transmission to the ground receiving station without being recorded before transmission (Campbell, 1987). The image data acquired from Landsat 4 and 5 are relayed to the TDRS satellite and transmitted to the ground receiving station at White Sand, New Mexico (Figure 2.4). The data are then transmitted via DOMSAT (Domestic Communication Satellite) to NASA Goddard Space Flight Centre in Marryland for subsequent processing.

2.2.1.2 Thematic Mapper.

Thematic Mapper (TM) is a high spatial resolution sensor with an improved radiometric sensitivity (Harris, 1987). It could be considered as an improved MSS, because the design and operation are based upon the same principles as the MSS. It is a mechanical scanner in which a flat mirror scans across the satellite track and reflects each part of the earth's surface through a telescope lens system onto the detectors. The major improvements in the Thematic Mapper are its provision of finer resolution, improved geometric accuracy, greater radiometric detail, and more detail spectral information (Campbell, 1987). Spatial

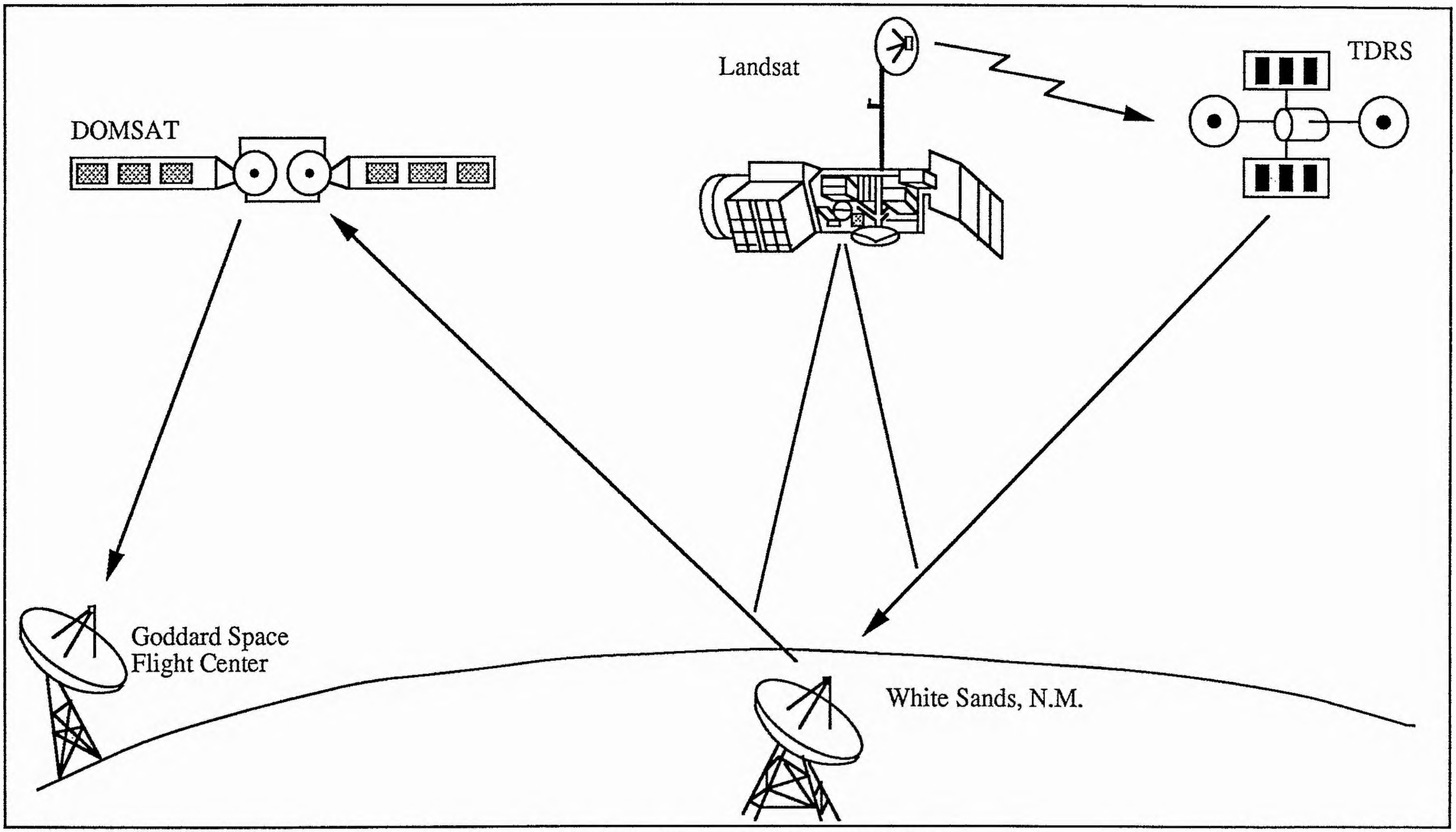


Figure 2.4   Data Flow, Landsats 4 and 5.
(Adapted from Campbell, 1987).

resolution of Landsat TM is about 30 m X 30 m for six bands, and 120 m X 120 m for the thermal infrared band. This finer spatial resolution provides an increasing spatial detail relative to the MSS. Digital values were increased from 64 digital numbers (6 bits) to 254 digital numbers (8 bits). This corresponds to a four times increased in the grey scale range relative to the Landsat MSS. In comparison with MSS images, TM images have much finer spatial and radiometric resolution, therefore, TM imagery shows relatively fine detail in patterns of the earth's surface.

Landsat TM has been finely defined to receive seven spectral bands, compared with only four bands in MSS (Table 2.1). It was particularly chosen to maximize the information context for green vegetation (Tucker, 1978a). The green and red bands of Thematic Mapper are narrower than the green and blue bands of MSS. The near infrared band of TM is also narrower than in MSS and is useful to determine plant vigour, vegetation types and biomass content. The mid-infrared bands (bands 5 and 7) are useful to determine plant water stress, whereas the blue band is useful for plant stress discrimination (Table 2.2) (Lillesand and Kiefer, 1987). In addition to improvements for vegetation discrimination, Landsat TM was also designed to improved use of satellite imagery in other application areas. Among these is the use of bands 5 and 7 for discrimination of rock types, band 1 for bathymetry, bands 4 and 5 for delineation of water bodies, band 5 for differentiating between snow and cloud cover areas, and the addition of band 6 will make TM data particularly useful for thermal mapping (ESA, 1984; Lillesand and Kiefer, 1987).

Band number	Band name	Band width (mm)	Band resolution	Potential application
1	Blue/Green	0.45 - 0.52	30 m	Designed for water body penetration, useful for coastal water mapping. Also useful for soil/vegetation discrimination, forest type mapping, and cultural feature identification.
2	Green	0.52 - 0.60	30 m	Designed to measure green reflectance peaks of vegetation for vigor assessment.
3	Red	0.63 - 0.69	30 m	Designed to sense in a chlorophyll absorbtion region for discrimination of plant species.
4	Near infrared	0.76 - 0.90	30 m	Useful for determining biomass content, vigor, and vegetation type, for deliniation of water bodies, and for soil moisture descrimination.
5	Middle-infrared	1.55 - 1.75	30 m	Useful for measurement of vegetation and soil moisture content. Also useful for differentiation of snow from clouds.
6	Thermal infrared	10.4 - 12.5	120 m	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping.
7	Middle-infrared	2.08 - 2.35	30 m	Useful for discrimination of mineral and rock types, and also useful for hydrothermal mapping.

Table 2.2 Thematic Mapper Spectral Bands and Principal Application.
(Adapted from Lillesand and Kiefer, 1987; Lo, 1986).

The data collection system on board Landsat TM, was also different. The MSS collected data when the mirror scanned from west to east, while the TM scans acquire data as it moves in both east to west and west to east directions. The TM scans through a total field of view of 15.4^0 (about 7.7^0 from nadir), and it completes approximately seven scan cycles per second. The number of detectors used in TM is also different. MSS employs six detectors in each of its four bands (total of 24 detectors), whereas every TM band uses a total of 100 detectors in which each band uses an array of 16 detectors, with the exception of the thermal band (band 6) which uses only 4 detectors (Sabin, 1987).

The imagery of Landsat TM is better than MSS because TM has much finer spatial resolution. With seven rather than four spectral bands and use of a smaller pixel size, within the same area, the TM image contains many more data values than MSS data. The MSS image required about 31,000,000 pixels for all four bands, therefore, the TM image needs about 230,000,000 pixels for all seven bands (Campbell, 1987). Consequently, analysts must determine the appropriate TM bands combination which are expected to provide the required information. Different combinations of TM bands will result in different images which depend upon the purpose of the study, season, geographic region, etc. As any band could be assigned to any colour (blue, green, red) for display, it gives a total of 210 different possible colour presentations of TM composites (Sheffield, 1985). In general, there are two combinations of TM bands which are suitable for general purpose, bands 2, 3 and 4 (in the order blue, green, red) which is similar to the MSS false colour composite, and bands 1, 2 and 3 to form a natural colour composite. A normal colour combination is preferred for mapping of water sediment patterns, while combinations of bands 2, 3 and 4, bands 3, 4 and 7, and bands 3, 4 and 5, are preferred for mapping vegetation types and urban features.

2.2.2 Spectral Characteristics of Soil, Leaves and Vegetation Canopies.

Remote sensing of vegetation is based on difference contrasts in the spectral response of soil and vegetation within visible and near infrared wavelengths (Daves, 1980). As shown in Figure 2.5, soil and vegetation can generally be discriminated on the basis of their contrasting spectral response in visible and near infrared wavelength. In the visible band, the soil reflects more than the vegetation, and in the near infrared, the vegetation reflects much more than the soil. Based in this knowledge, there is a potential to interpret and process the multispectral remote sensing data for vegetation, agriculture and other natural resources (Knipling, 1970). However, the interpretation of spectral data of vegetation has been difficult because of the influences of mixed species, green and senescent vegetation, soil and shadows (Heilman and Boyd, 1986; Huete *et al.*, 1983). Plant leaves depend upon radiant energy to carry on photosynthesis and other physiological processes. The interaction of plants with radiant energy is of interest to ecologists, foresters, geographers, agronomists, botanists, and others, but the perspective will be different as viewed by these various scientists (Gates *et al.*, 1965; Richardson *et al.*, 1975). The radiation incident upon plant leaves can be either reflected, transmitted, or absorbed by the surface (Hoffer, 1978; Tucker and Garrat, 1977). The interrelationship between these energy interactions, as a function of wavelength (λ), can be stated by the energy balance equation as :

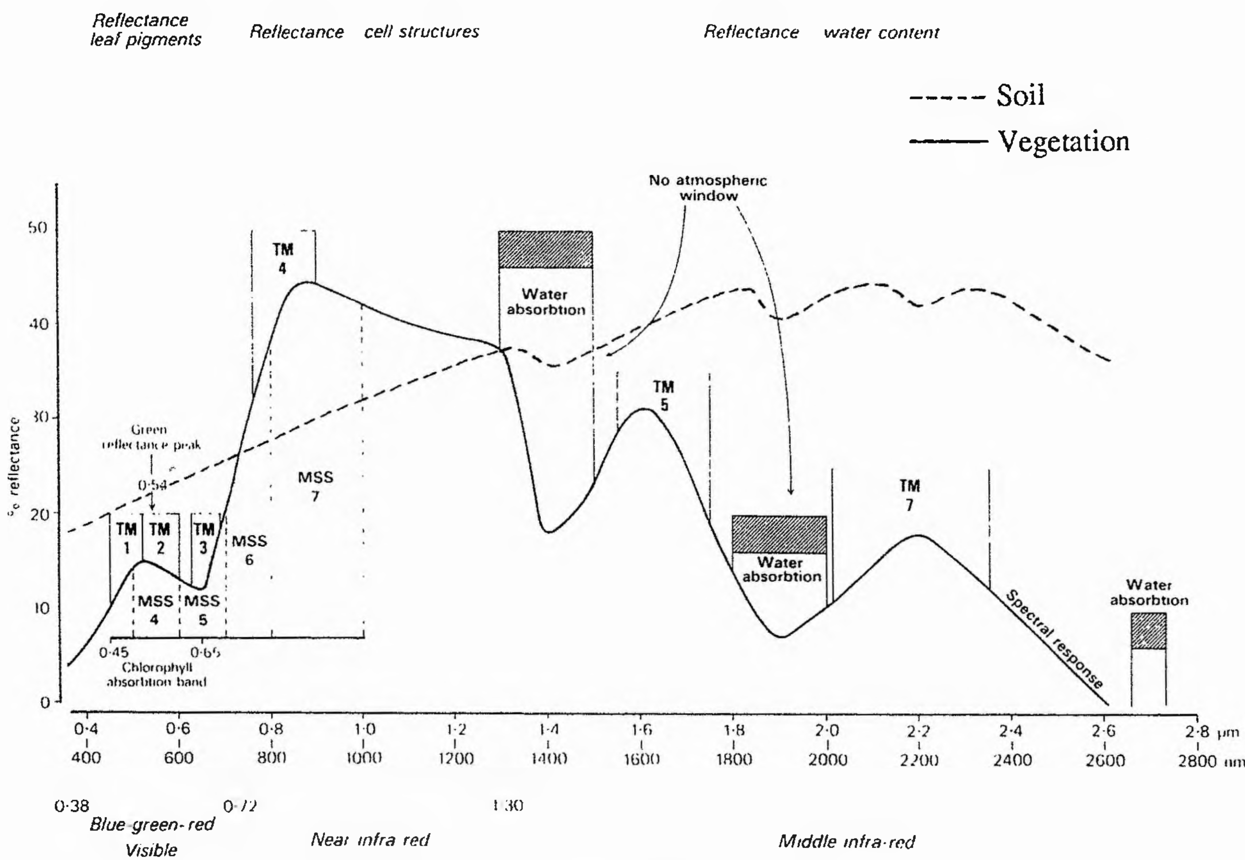


Figure 2.5 Spectral Reflectance Curves of Vegetation and Soil, and the Landsat System.
(Adapted from Soulsby, 1987).

$$I(\lambda) = R(\lambda) + A(\lambda) + T(\lambda) \qquad \text{Equation 1.}$$

where I is the incident energy, R denote the reflected energy, A is the absorbed energy, and T is the transmitted energy (Hoffer, 1978). Since the remote sensing system operates in the 0.3 to 3.0 μm wavelength region in which reflectance energy predominates, the reflectance properties of vegetation are very important. Therefore, it is often useful to think of the energy balance relationship in the form :

$$R(\lambda) = I(\lambda) - [A(\lambda) + T(\lambda)] \qquad \text{Equation 2.}$$

Hence, the reflectance energy is equal to the incident energy reduced by the energy that is either absorbed or transmitted by that feature.

Numerous investigators have studied the spectral response of vegetation canopies which is a function of not only the individual leaves, but also by the amount of soil exposed, soil types, soil colour, soil moisture, surface roughness, percentage vegetation cover, the amount of shadow cast by canopy components and the viewing geometry (Colwell, 1974; Gross *et al.*, 1988; Huete, 1987; Jackson *et al.*, 1979; Richardson and Wiegan, 1977). It should be noted that the response values recorded by multispectral satellites are due to both the reflectance properties of the earth's surface area and characteristics of the environment (McCloy, 1980), therefore, the proportion of energy reflected, transmitted and absorbed will vary for different earth's surface objects, depend upon their materials, type and condition. Accordingly, it should be possible to distinguish different earth's surface objects on an image. Furthermore, the proportions of energy reflected transmitted and absorbed will also vary at different wavelengths. In this case, two different objects may be indistinguishable in one spectral band and be very different in another wavelength band (Figure 2.6). It is therefore important that we should understand the spectral properties of soil, leaves, and vegetation canopies. These will be discussed briefly in the following section.

2.2.2.1 **The spectral response of soils.**

A natural soil surface is a heterogeneous combination of various elements of different composition, size, shape, and spatial distribution (van den Bergh and Bouman, 1986). The combination of these elements can be described as a term of soil properties such as mineralogy composition, textural class, organic matter and moisture content. Bowers and Hanks (1964), Cipra *et al.* (1971) and Condit (1972) found that soil reflectance increased as wavelength increased from blue to red. As the soil itself is a complex mixture of materials with various physical and chemical properties, therefore, it could affect absorption, transmission or reflection characteristics. There are a number of interrelated soil properties which significantly influence the spectral reflectance of soils, such as soil moisture, the relative percentage of clay, silt and sand, the amount of iron oxide, and the amount of organic matter (Coleman and Montgomery, 1987; Condit, 1970; Gerbermann and Neher, 1979; Stoner and Baumgardner, 1981; Venkatachalam and Jeyasingh, 1986). The effects of these soil properties on soil reflectance will be discussed in the following section.

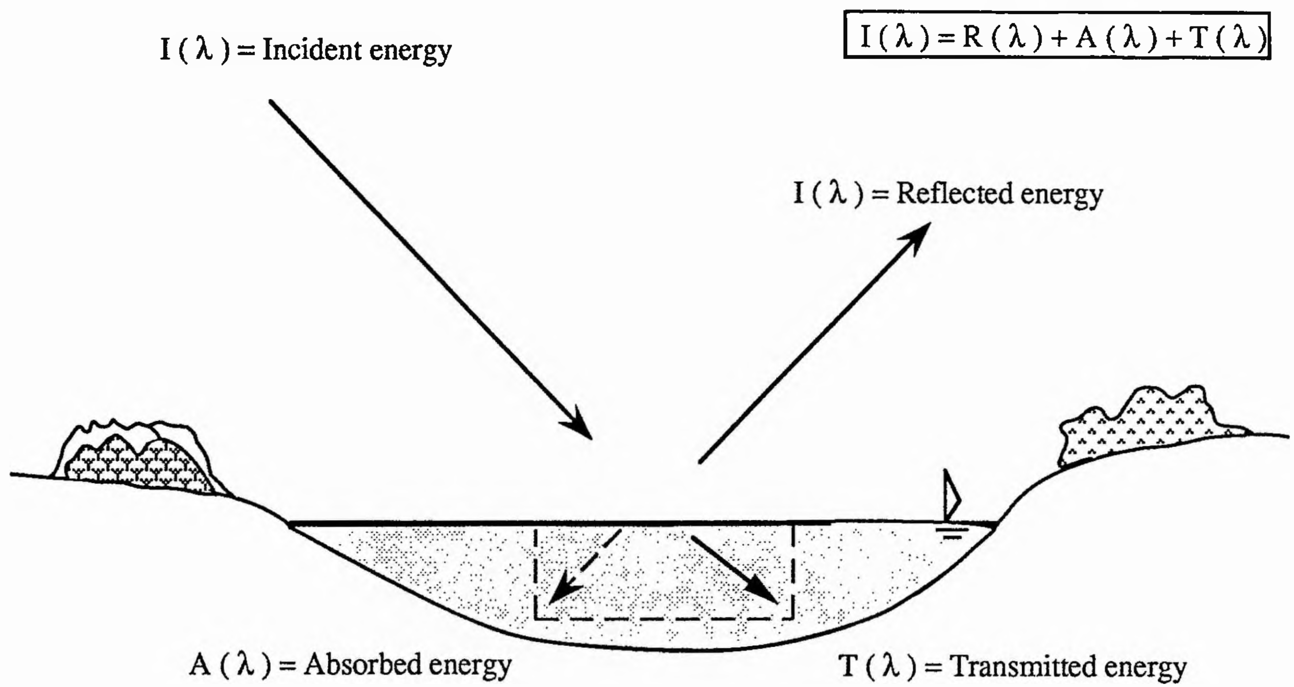


Figure 2.6 Basic Interaction Between Electromagntic Energy and Earth's Surface (Adapted from Lillesand and Kiefer, 1987).

2.2.2.1.1 The effects of soil texture.

Soil texture, the relative proportion of clay, silt and sand particles present in a mass of soil, appears to have an influence on spectral response (Myers, 1975). Soil texture is very variable in size, from less than 0.002 mm in diameter which denotes clay, from 0.002 to 0.06 mm for silt, and with 0.06 to 2 mm in diameter for sand (Carroll and Bendelow, 1981). The relative composition of these different components determines the soil textural classes such as clay loam, silty clay, sandy clay, silt loam, etc. The texture of soil affects the spectral reflectance of soil because of its influence on the moisture-holding capacity and the size of soil particles. Very small particles such as clay will enable those particles to be packed very closely together, leaving only minute spaces between the soil particles. On the other hand, relatively large sand particles will allow larger air spaces between the soil particles, therefore enabling more air or water movements. When soil particle size decreases, the soil surface will be smoother, therefore, more incoming incident energy will be reflected. Gerbermann and Neher (1979) found that soil spectral reflectance increased as sand level increased, and when the wavelength increased, the spectral reflectance increased (Figure 2.7). Cipra *et al.* (1971) suggested that a sandy mollisol had a higher reflectance than silty clay loam mollisol.

As it was described by Bowers and Hanks (1965), the increasing of soil particle size from 0.022 to 2.65 mm will cause an increase of absorption of incoming incident energy of at least 14.6 percent. Using Bentonite and Kaolinite clay samples, it was seen that reflectance from Kaolinite

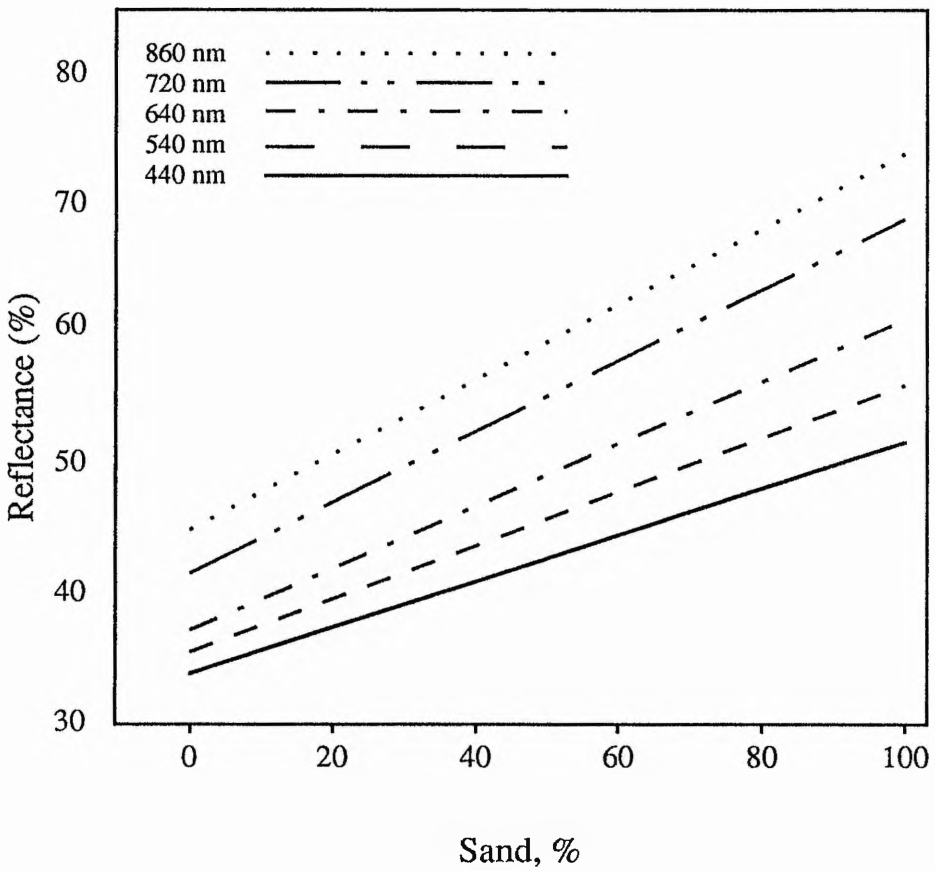


Figure 2.7 Linear Regression Line of Percent Soil Reflectance on Percent Sand Level.
(After Gerbermann and Neher, 1979).

was much greater than from Bentonite, with differences as large as 24 percent. Figures 2.8 a and b shows that increasing the soil particle's diameter will result in a decrease of reflection.

2.2.2.1.2 **The effects of organic matter and iron oxide.**

Organic matter content is another soil property which significantly affects the reflectance characteristics of soil. Organic matter content and iron compounds in the soil have an influence on soil colour, therefore, it will cause a difference in soil spectral reflectance. An increase in organic matter content will give a decrease in soil reflectance (Figure 2.9) (Al-Abbas *et al.*, 1972; Mathews *et al.*, 1973). When the organic matter content of a soil is about 5 percent, the soil will usually appear quite dark brown or black in colour; when the soil has a lower amount of organic matter content, it will appear to be either brown or grey (Hoffer, 1978).

Escadafal *at al.* (1989) have described the relationship between soil colour and spectral reflectance (Figure 2.10). It was illustrated by seven reflectance curves selected from 84 samples. Curves a and g correspond to the darkest and the brightest soil sample. The research by Coleman and Montgomery (1987), and Stoner and Baumgardner (1981), has also suggested that an increase of organic matter will cause a decrease in spectral reflectance in all wavelength bands. It should be noted that soil developed under different climatic conditions might not show the same relationship between colour and organic matter (Hoffer, 1978). Therefore, when considering the relationship between spectral

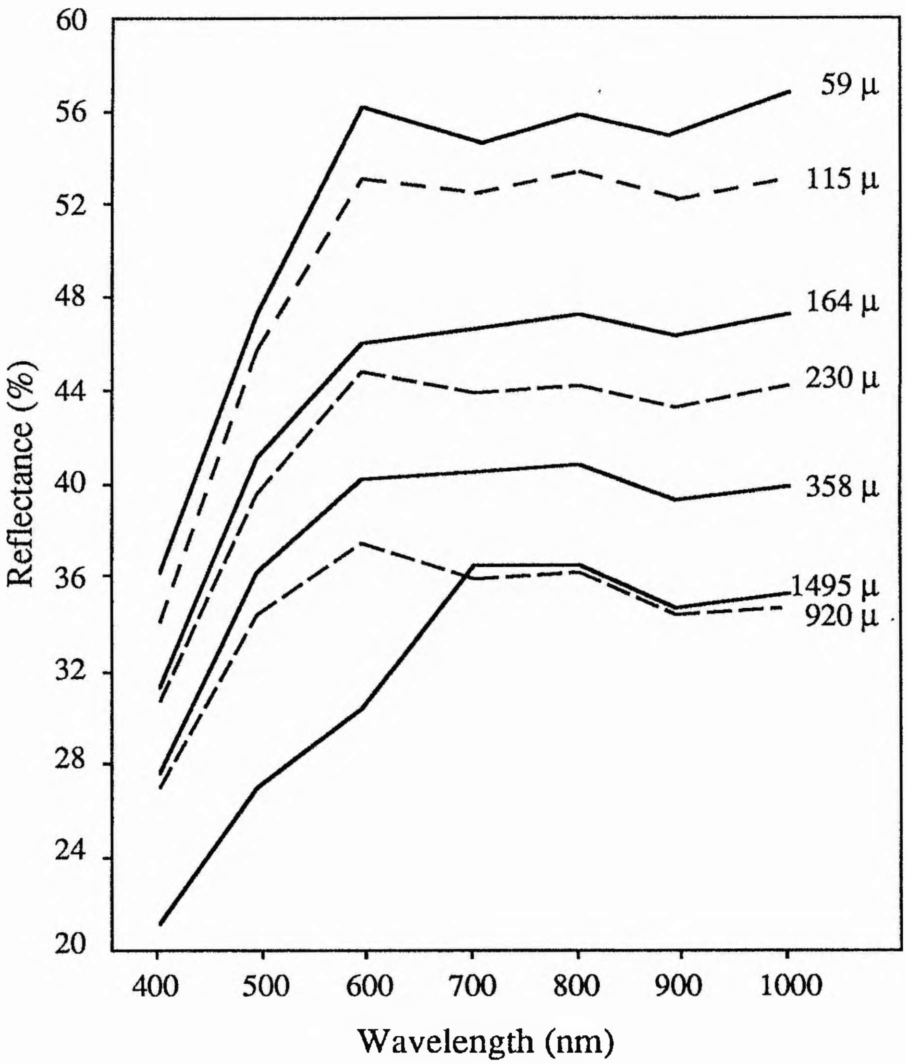
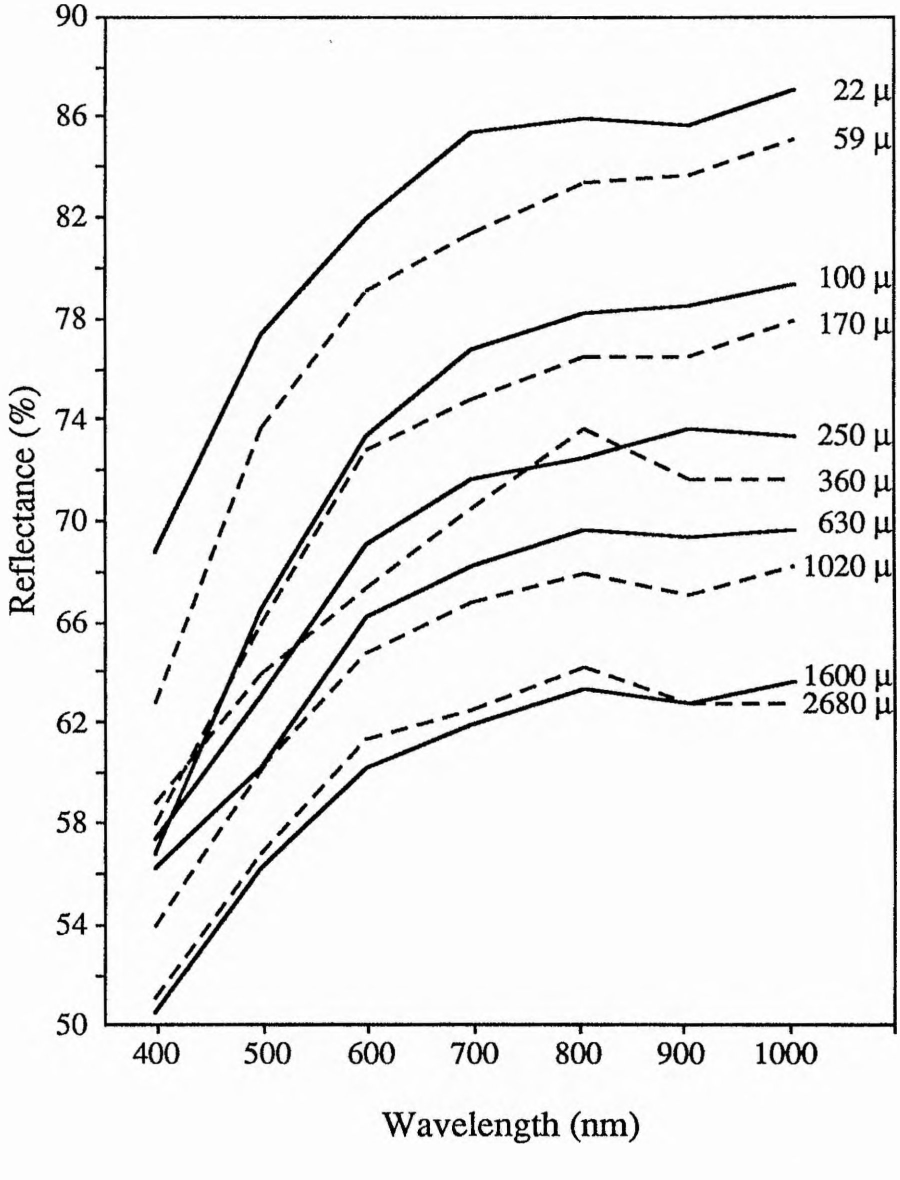


Figure 2.8a Percent Reflectance *vs*. Wavelength of Various Bentonite Particle Sizes. (After Bowers and Hanks, 1965).



Figurre 2.8b Percent Reflectance *vs*. Wavelength of Various Kaolinite Particle Sizes. (After Bowers and Hanks, 1965).

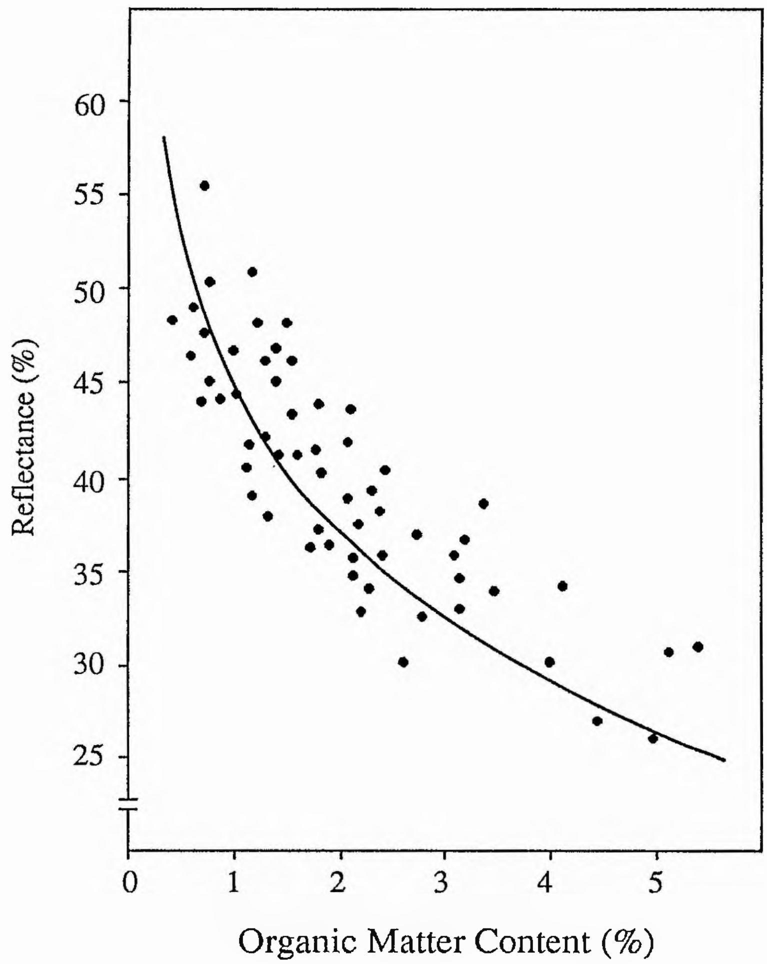


Figure 2.9 Relationship Between Organic Matter Content and Reflectance Within Visible Wavelength. (After Hoffer, 1978).

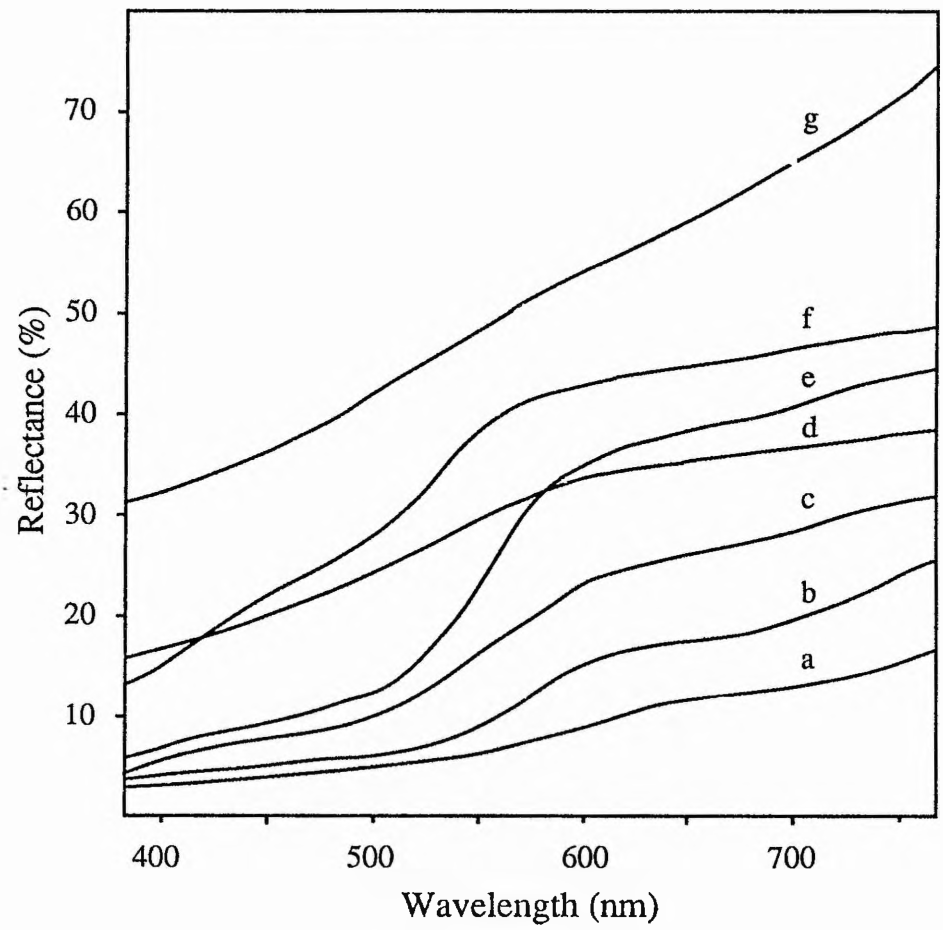


Figure 2.10 Relationships Between Soil Colour Reflectance and Wavelength.
(After Escadafal, 1989).

reflectance and the organic matter of the soil, the climatic region and drainage condition must be take into account.

Spectral response of soil was also affected by the present of iron oxide. The presence of iron oxide in a soil will significantly decrease the soil reflectance, particularly in the visible wavelengths (Hoffer, 1978). Figure 2.11 illustrates the inverse relationship between reflectance within the visible band and the percentage of iron oxide content in the soil. It indicates that increasing iron oxide present in the soil can reduce the reflectance as much as 40 percent. On the other hand, figure 2.12 shows that removal of the iron oxide from a soil will cause in increasing of reflectance throughout the wavelength region of 0.5 μm to 1.1 μm. However, the reflectance above 1.1 μm was not particularly affected. Iron oxide selectively reflects red light in 0.6 - 0.7 μm wavelength region and absorbs green light the in 0.5 - 0.6 μm region (Curran, 1985).

2.2.2.1.3 **The effects of soil moisture.**

Soil moisture content is not constant during the season, and differences in soil moisture content greatly influences soil reflectance (Clevers, 1988). A common visual observation in nature is that most natural surfaces, particularly soil, will appear darker when wet. This is a result of multiple reflections and refractions of incident radiation upon pore water and the films of water around particles, and it also results in the decreased reflectance of incident radiation in the visible region of the wavelength (Evans, 1979; Planet, 1970). Soil moisture or soil water content have strong influence on the amount of reflected and emitted

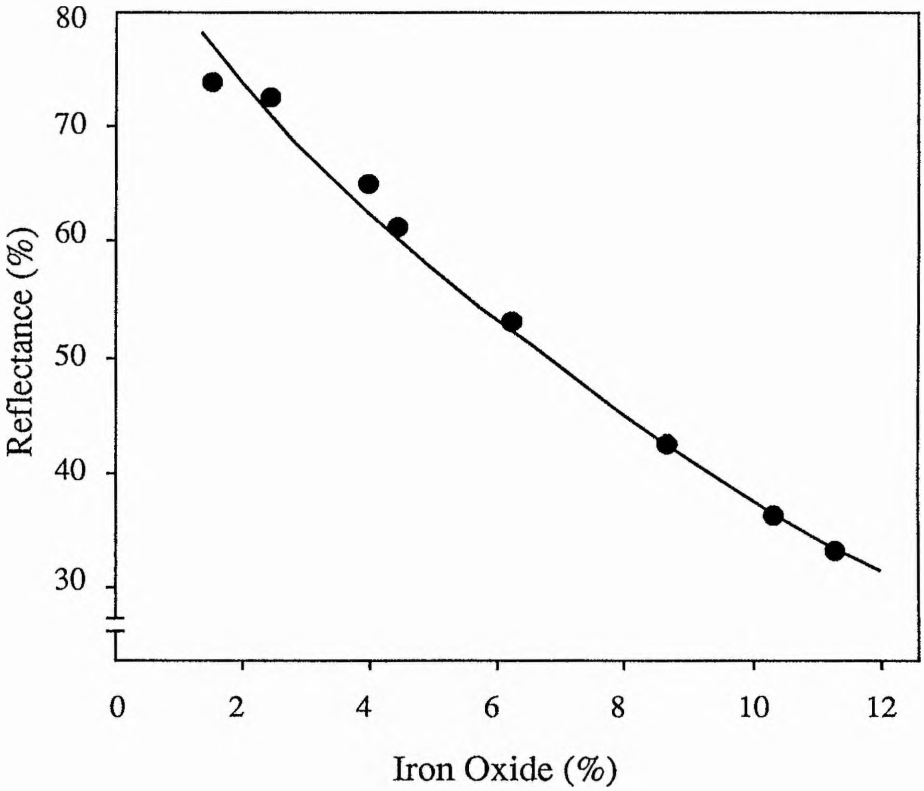


Figure 2.11 Relationship Between Iron Oxide and Soil Reflectance in the 0.50 to 0.64 µm. (After Hoffer, 1978).

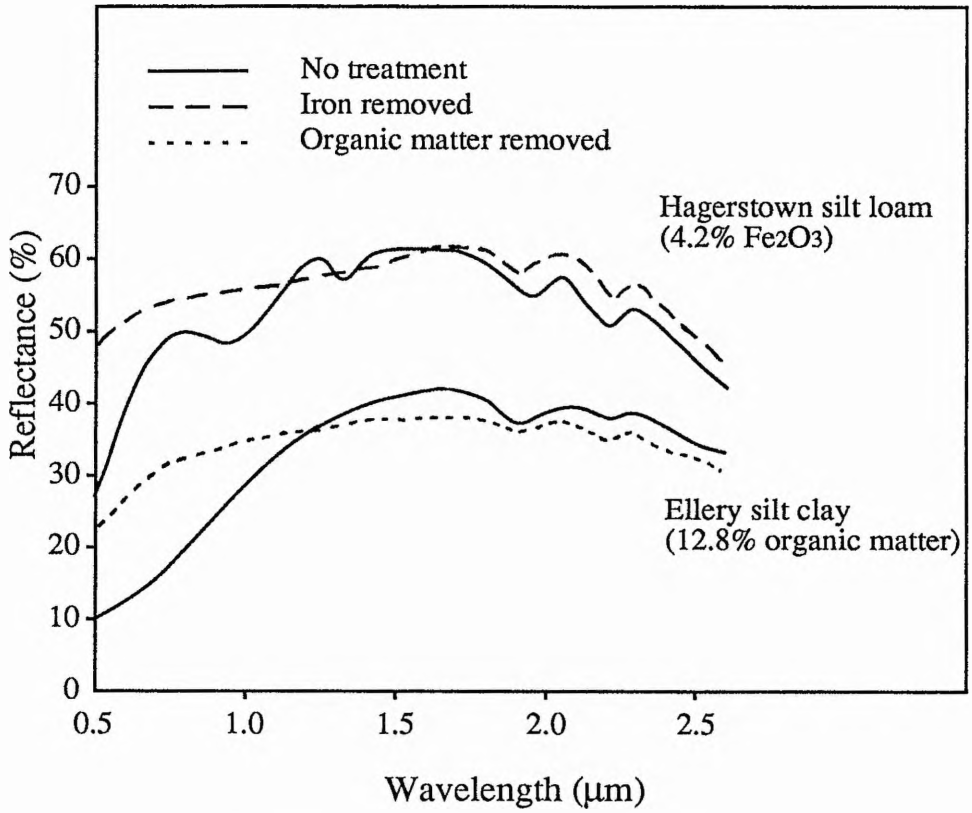


Figure 2.12 The Effect of Iron Oxide and Organic Matter Removal on Spectral Response of Soil. (After Hoffer, 1978).

energy from a soil surface (Huete and Warwick, 1990). When moisture is present in the soil, it means that each soil particle is covered by a very thin layer of water, and this water will also occupy some of the pore space between the soil particles (Curran, 1978; Hoffer, 1978). Extensive studies of the effects of soil moisture on reflectance have been carried out (Bowers and Hanks, 1964; Coleman and Montgomery, 1987; Huete and Warwick, 1990; Musick and Pelletier, 1988; Planet, 1970; Shield *et al.*, 1968).

Bowers and Hanks (1964), working on Newtonia silt loam, stated that the soil reflectance will decrease at all wavelengths as the surface moisture content increases (Figure 2.13). It could be said that increasing the surface moisture content will increasing the absorption radiant energy. However, there are three absorption bands centred at approximately 1.4 μm, 1.9 μm, and 2.2 μm where there is a more intense drop of reflectance. This is caused by the small size of soil particles which enables a significant amount of water to be held by the soil particles even when the soil is in air dried condition. By using three different materials (soil, sand and silt), Condit (1972) indicated that within the same type of soil, there would be differences in spectral reflectance between dry and wet soil conditions (Figure 2.14). A severe lack of soil moisture can also cause crusting, which will affect the soil spectral reflectance. Cipra *et al.* (1971) describe that a higher reflectance was found on dry or crusted soil whereas wet or broken crusted soil have lower reflectance (Figure 2.15).

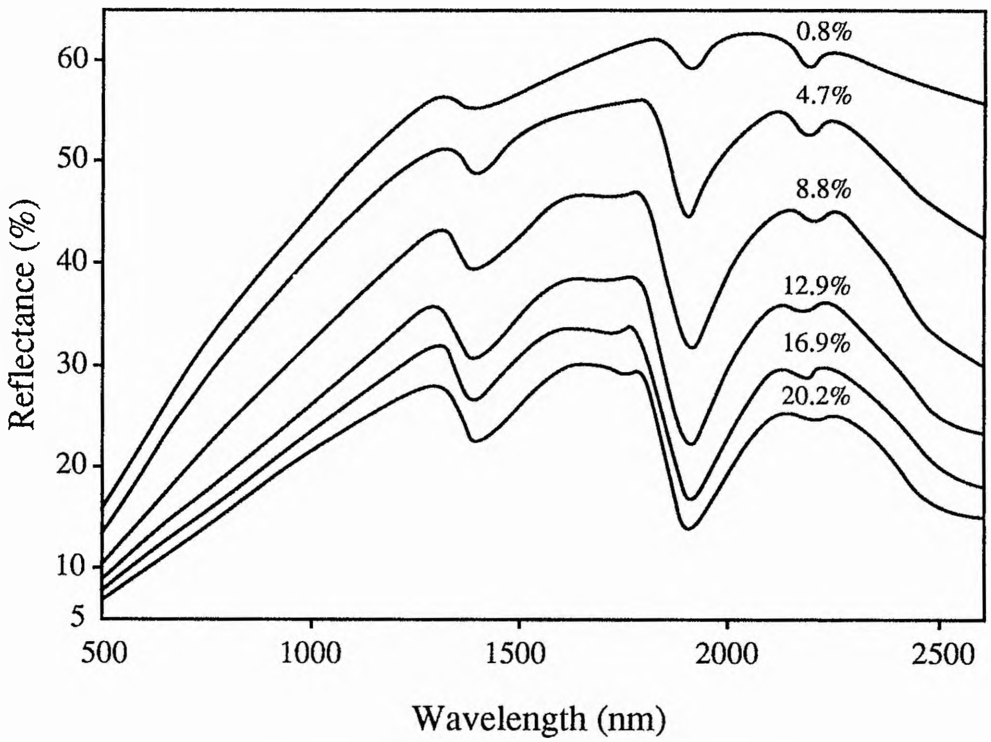


Figure 2.13 Percent Reflectance *vs*. Wavelength at Various Newtonia Silt Loam Moisture Contents. (After Bowers and Hanks, 1965).

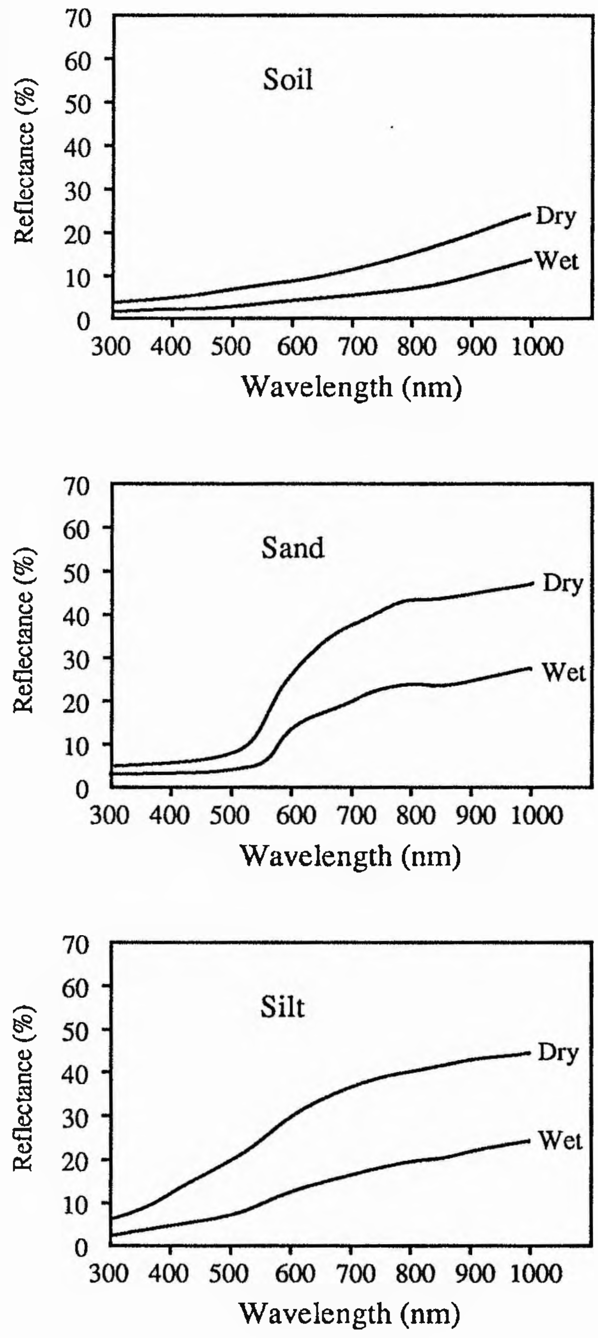


Figure 2.14 The Spectral Reflectance Curve of Dry and Wet Soil, Sand, and Silt.
(Adapted from Condit, 1972).

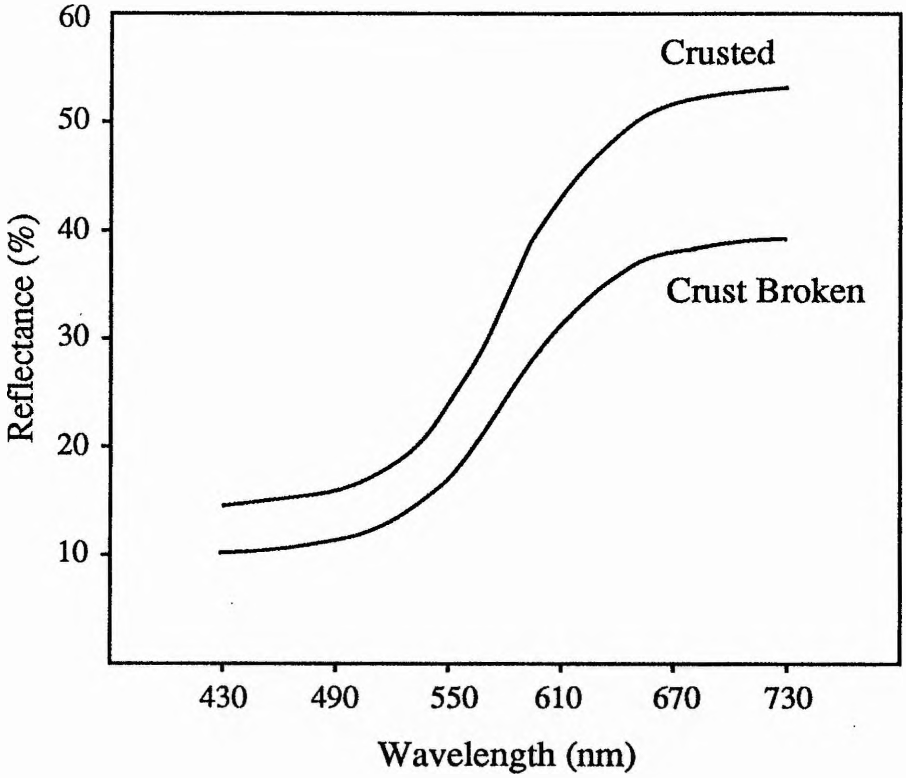


Figure 2.15 Percent Reflectance *vs*. Wavelengths of Light Brown Subsoil in Dry Crusted and Non-crusted Conditions. (After Cipra *et al.*, 1971).

2.2.2.1.4 The interrelationship of soil properties.

It has been found that there is an interrelationship between soil properties. As described above, the texture of the soil will cause an increase in spectral reflectance when particle size decreases; that an increase in organic matter content and iron oxide can cause a decrease in reflectance; and that an increase in soil moisture will cause a decrease in reflectance (Bowers and Hanks, 1965; Coleman and Montgomery, 1987; Hoffer, 1978). However, there are many other factors which are very closely interrelated. For example, soil moisture content is strongly related to the soil texture. Coarse, sandy soils are usually well drained and will have low moisture content; this will cause high spectral reflectance. On the other hand, fine soil particles with poor drainage will be generally dark in colour and therefore have a low spectral response. In particular, the soil colours were generally found to have a relationship with soil moisture content, iron oxide and organic matter, or soil texture. Escadafal *et al.*, (1989), Shields *et al.*, (1968), and Farzee *et al.* (1972) found that light-coloured soils had higher reflectance than dark-colour soils, and Gerbermann *et al* . (1971) showed that soil with high brightness values had a higher reflectance than soils with low brightness values.

2.2.2.2 The Spectral response of leaves.

To understand the factors controlling the spectral response of a vegetation canopy, it is necessary to consider the spectral response of those elements comprising the canopy, such as leaves, stalks, flowers etc. The proportion and location of these components within the canopy depend upon the species and season. However, the particular canopy element which is mostly seen by remote sensing instruments are leaves (Milton and Wardley, 1987). It was suggested above (Section 2.2.2) that the spectral response of an individual leaf to incident radiation will be reflection, absorption or transmission, in which these three components are highly interrelated. Knipling (1970) shows that only a part of the incident energy is reflected while the reminder will be either absorbed or transmitted. Figure 2.16 shows the relationship between reflectance, absorptance and transmittance within range of 0.4 to 2.7 μm spectrum. The reflectance spectrum has the same shape as the transmittance spectrum, and the absorptance spectrum is the opposite of the other two. Absorption is high in the visible wavelength which is caused by chlorophyll, and in the infrared beyond 1.3 μm which is caused by water.

It is known that a leaf is built of structured layers of fibrous organic matter, and comprises pigment within chloroplasts, the cellulose of the cell walls, water-filled cells and air space (Gates, 1965; Gausman, 1984; Kumar and Silva, 1973). However, it is not only these four components which have an effect on the reflectance, absorptance and transmittance of green leaf spectral response, but the illumination and view angle, and the multiple leaf layer also produce effects. These will be briefly discussed in the following section.

2.2.2.2.1 **The effect of leaf pigments on spectral response.**

The reflectance and absorption of leaves in visible wavelength are due to the presence of leaf pigmentation. Most of the absorption in healthy

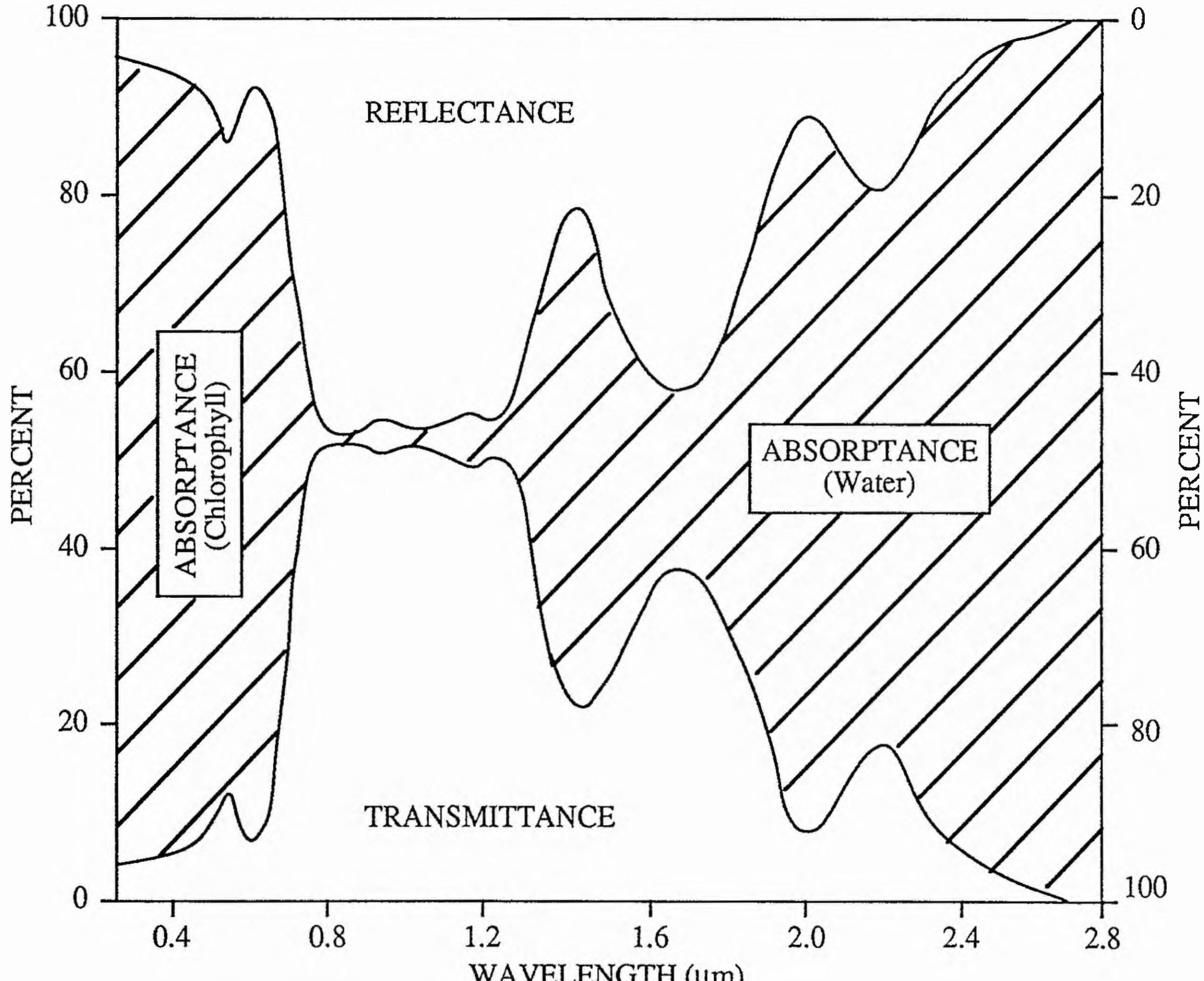


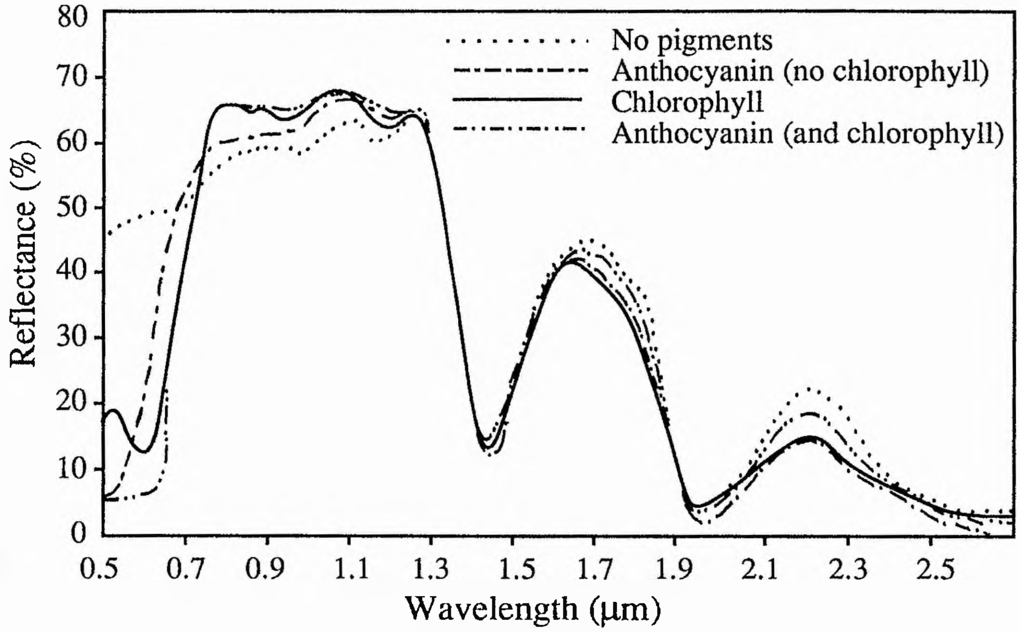
Figure 2.16 Reflectance, Absorptance and Transmittance Spectra of a Plant Leaf.
(After Knipling, 1970).

green leaves is due to the concentration of four primary pigments: chlorophyll a, chlorophyll b, carotenes , and xanthophylls. All of these pigments absorb visible light for photosynthesis (Curran, 1985). The proportion of these pigments found in leaves depends very much upon the species, the age of leaf and the environmental conditions. Gates *et al.* (1965) stated that the percentage of the pigments are 65% of chlorophyll, 6% of carotenes, and 29% of xanthophyll. Chlorophyll was found within the grana, which are long slender strands, and located within chloroplasts. About 50 chloroplasts, within the size of about 5 μ to 8 μ in diameter and about 1 μ in width, are suspended within the parenchyma cellular protoplasm. The grana, which is about 0.5 μm in diameter, may produce a considerable scattering of light within the leaf.

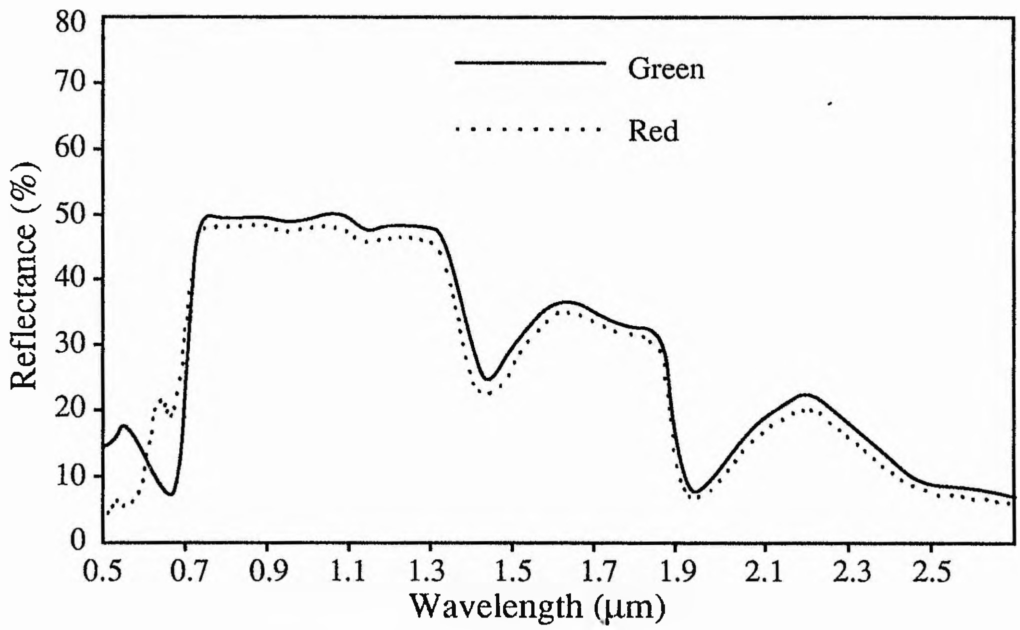
In particular, healthy green leaves strongly absorb electromagnetic energy in the ultraviolet, blue and red regions of the visible wavelength (Tucker and Garratt, 1977). This results from the presence of chlorophyll a and b in the leaf which absorbs most of the incident energy in these wavelength. Chlorophyll a absorbs at about 0.43 μm and 0.66 μm, and chlorophyll b absorbs at about 0.45 and 0.65 μm of the wavelength region (Curran, 1985). A relative lack of absorption in the green wavelength will cause normal healthy leaves to appear green in our eyes. However, when a leaf plant is under stress and chlorophyll production decreases, the reflectance in the near infrared region will decrease and reflectance in the red part of spectrum will increase, therefore, it will appear yellowish (Duggin, 1980). Other pigments of interest which are frequently present in the green leaves are carotenes and xanthophylls, which absorb only in the blue wavelength, at approximately 0.45 μm (Hoffer, 1978). As plants undergo senescence and chlorophyll production decreases, the carotenes and xanthophylls will be dominant. Therefore, it will cause yellow and orange coloration of the leaves particularly in the autumn season. However, in some tree species, when chlorophyll production decreases, the anthocyanin (red pigment) will be dominant and it will gives the leaves a bright red and bronze colour. This therefore indicates that if the proportion of leaf pigments changes, the leaf spectral response will also change accordingly (Figure 2.17). Sanger (1971) showed that the proportion of leaf pigments can alter quite considerably during the growth cycle of plant. However, the concentration of chlorophyll was not only affected by the growth cycle, but also by soil salinity, genetic isoline, decomposition during autumn coloration, and leaf senescence (Gausman *et al.*, 1970; Gausman, 1982; Sanger, 1971). Gausman (1974, 1982) has shown that leaf chlorophyll degradation by stress usually produces a lower reflectance than in non stressed leaves of the same age.

2.2.2.2.2 **The effects of leaf internal structure and water content.**

The internal structure of plant leaves is very complex, and largely controls the incident energy (Figure 2.18). Pigments generally affect the spectral response in visible wavelengths, but the structure and water content of leaves are the main determinants of the near and middle infrared response (Gausman, 1974, 1977). Gausman (1977) described how near infrared wavelengths was scattered or reflected from leaves by refraction index discontinuities. These discontinuities occur between cytoplasm and membranes within the upper half of the leaf, and is most important between individual cells and air spaces of the spongy



(a)



(b)

Figure 2.17 The Effect of Pigmentation on Leaf Reflectance. (a) Coleus Leaf. (b) Maple Leaves. (After Hoffer, 1978).

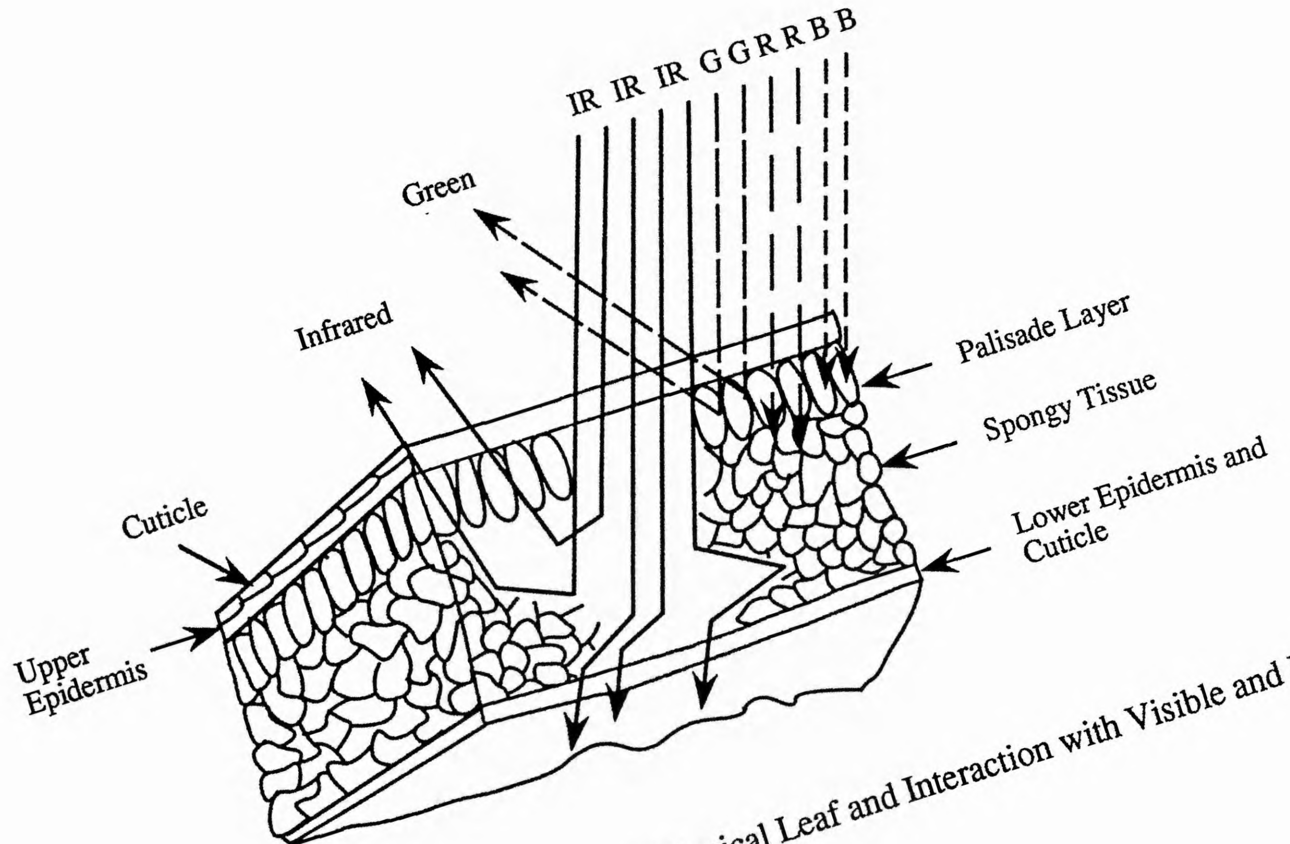


Figure 2.18 Diagram Cross Section of Typical Leaf and Interaction with Visible and Near Infrared Radiation.
(Adapted from Campbell, 1987).

mesophyll within the lower half leaf. However, different plant species will have different internal structures. The major differences in leaf reflectance between species depend upon leaf thickness, which affects the pigment content and the internal structure. Figure 2.19 shows the differences of reflectance curve between corn and soybean, as the internal structure of corn and soybean leaves are very different. Even though only a small difference in reflectance is found in the visible wavelengths, significant differences occur throughout the near and middle infrared wavelength (Hoffer, 1978). Maturity of leaves also affects leaf structure. Gausman (1974) shows how a young leaf is compact with few air spaces in the mesophyll, while an old leaf is spongy and has more air spaces in its mesophyll. Figure 2.20 shows that the spongy mature leaf compared with the compact young leaf, had less reflectance in the visible (0.50 to 0.75 µm) wavelength and about 15% more in the near infrared wavelength (0.75 to 1.35 µm). The pubescence of a leaf also affects the reflectance of both the visible (0.45 to 0.75 µm) and infrared (0.75 to 2.45 µm) wavelengths (Billings and Morris, 1951; Everrit and Richardson, 1987; Gates and Tantraporn, 1952). It was reported that pubescent leaves had higher visible reflectance than glabrous leaves. This is caused by white hairs which increase the scattering of incident energy.

The water content of leaves has its main effects in middle infrared wavelengths, in which major absorption bands occur at 1.45 µm, 1.95 µm and 2.7 µm (Figure 2.21) (Curran, 1985; Hoffer, 1978). However, severe dehydration as a result of plant disease or senescence, could increase the total air-cell interface within the cell. This will increase the internal reflections and enhance the near infrared reflectance

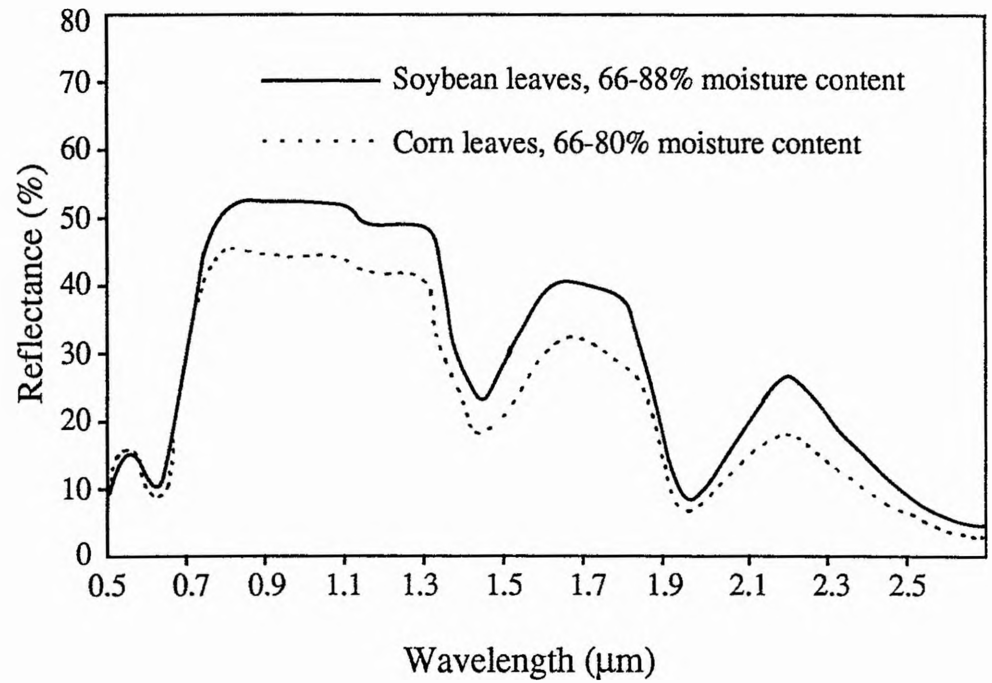


Figure 2.19 Reflectance Curves for Corn and Soybean Leaves. (After Hoffer, 1978).

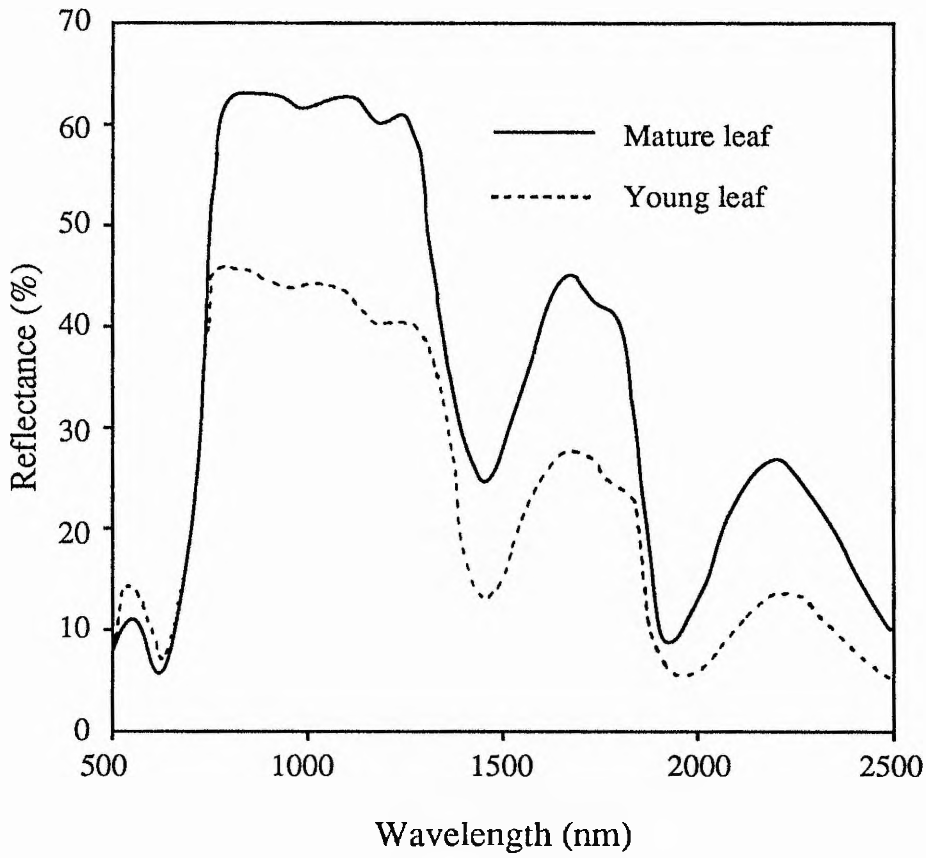


Figure 2.20 Reflectance of Young and Mature Citrus Leaves. (After Gausman, 1974).

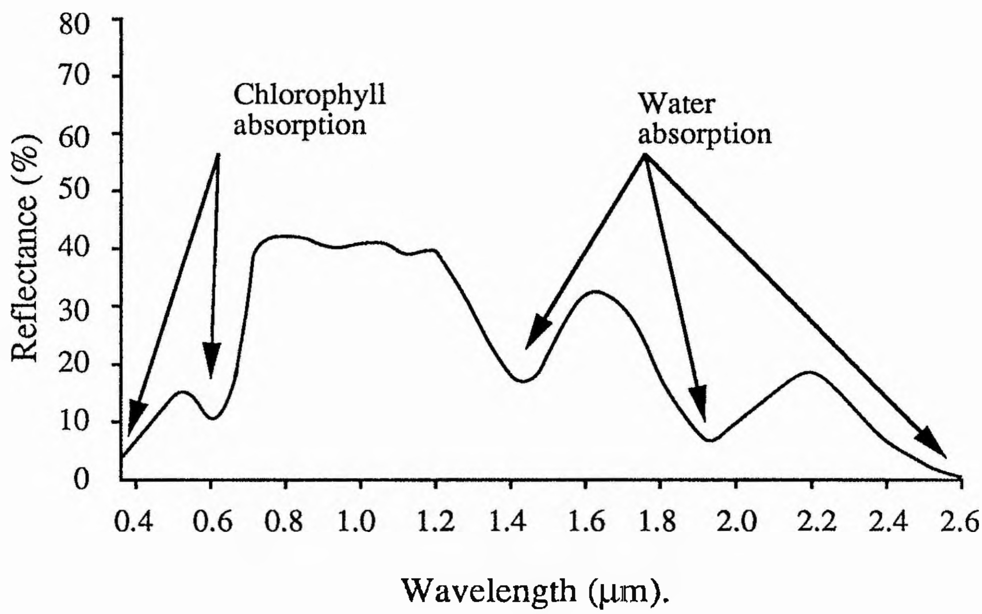


Figure 2.21 Significant Spectral Response Caracteristics of Green Vegetation.
(Adapted from Hoffer, 1978).

(Gausman, 1974; Wooley, 1971). As was explained above, there is a different spectral response between young and mature leaves. Myers (1975) describes how young leaves contain less water than mature leaves. This is because of immature cells in young leaves which are primarily protoplasmic with only little vacuolate water storage. Figure 2.22 shows the effects of progressive cotton leaf drying at four different dates within 0.5 to 2.5 μm wavelength. The lower solid line represents fresh leaves while the upper, broken line, represents dehydrated leaves on the fourth date of measurements. It is evident that dehydration increased the leaf reflectance response. As the leaves were progressively dried, the infrared reflectance increased because the leaf structure altered. Tucker (1980) emphasized that the spectral reflectance of different leaf water contents within the region of 0.7 to 2.5 μm wavelength, will result in different reflectance responses. Myers (1975) described the close relationship between water absorption and reflectance of healthy green leaves (Figure 2.23). In the spectral region where the water absorption is high, the leaf reflectance is low. This is particularly true in the water absorption bands centred at 1.45 and 1.95 μm.

2.2.2.2.3 **The effects of illumination and viewing angles.**

Most of the information relating to the spectral response of leaves has been obtained from measurements taken normal to the leaf surfaces. In addition, research has also been carried out to determine whether leaves reflect incident energy equally in all directions irrespective of angles of illumination and view. However, much work has been concerned with the effect of these angular changes upon the spectral

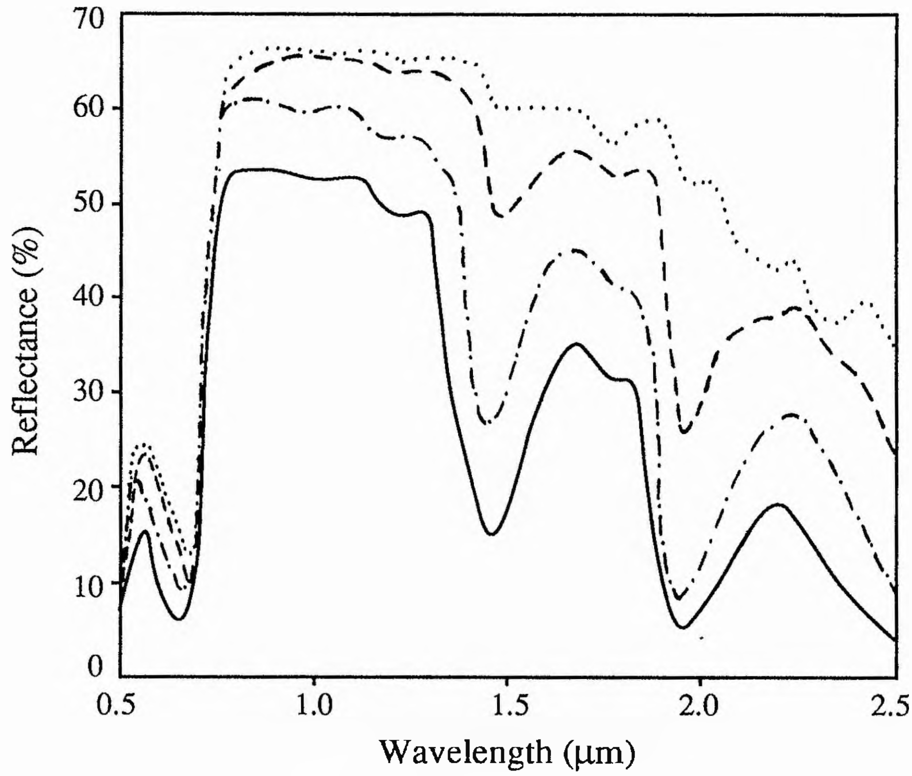


Figure 2.22 Effect of Dehidration on the Reflectance of Cotton Leaves.
(After Myers, 1975).

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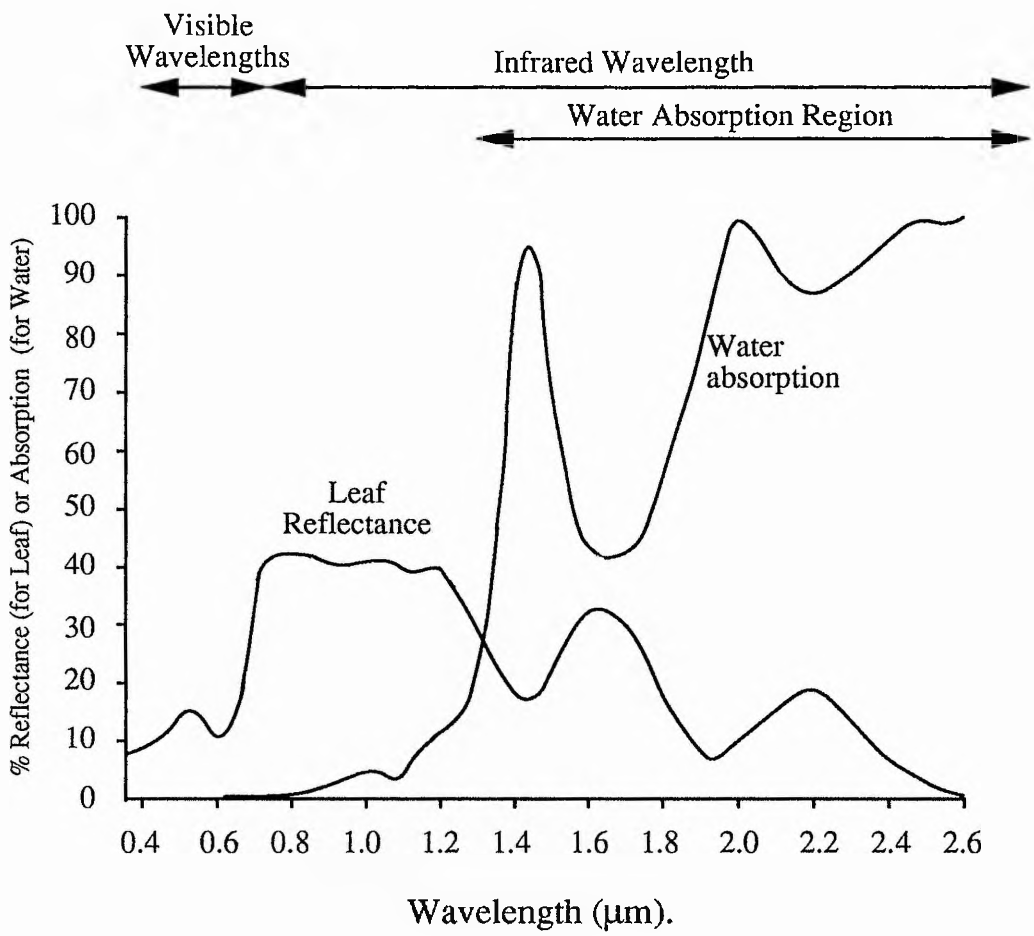


Figure 2.23 Relationship Between Leaf Reflectance and Water Absorption.
(After Myers, 1975).

reflectance of vegetation canopies and only a little has been carried out on individual leaves. Therefore, it is necessary to briefly review work done by Breece and Holmes (1971), Salisbury *et al.* (1987) and Wooley (!971). In particular, they present evidence that leaves are not diffuse reflectors in visible and near infrared wavelengths, and from single leaves, the anisotropy (ratio of the highest to the lowest reflectance value; Kriebel, 1978) in the reflectance of red light was larger than near infrared light. This was described on the basis of the number of layers within leaves encountered by incident radiation. This large number of discontinuities is caused by the presence of chloroplast in the upper part of the leaf which increased specularity of red reflectance. Grant (1987) described that the primary mechanism determining the specular component is reflection from surfaces comprising the undulating leaf surface which are large compared with the wavelength of the incident radiation. The author also noted that reflectance of leaves is neither purely diffuse (*i.e.* Lambertian) nor purely specular.

Milton and Wardly (1987) stated that there was a specular component in the reflected light at all angles. Salisbury *et al.* (1987) noted that the geometric partition of reflected radiation from leaves will be different in red and infrared wavelengths. When the illumination angle and geometry of observation changes, the distribution of energy reflectance within different spectrum may also change. Figure 2.24 shows that change in the angle of illumination will affect the ratio of energy reflected in each of two spectral regions.

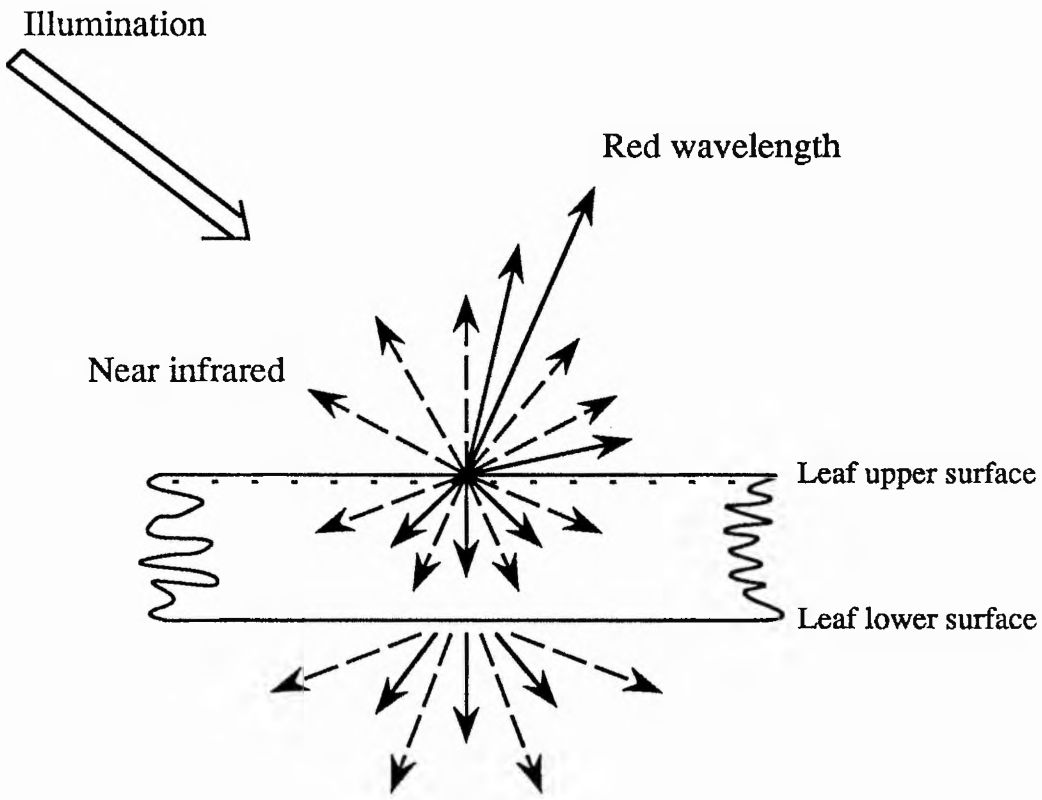


Figure 2.24 Incident Flux is Reflected from a Leaf Surface According to Wavelength. (Modified from Milton and Wardley, 1987).

2.2.2.3 The spectral response of vegetation canopy.

In the previous section it was shown that the spectral response from individual leaves can be seen to vary with their internal composition and structure, as a result of the amount of vegetation seen by the remote sensing instrument, and in response to a change in the angles of illumination and view. Nevertheless, the reflectance of individual leaf or leaves alone is not sufficient to describe the remotely sensed reflectance of a vegetation canopy (Curran, 1985; Curran and Milton, 1983; Simonet, 1976). This is because a vegetation canopy is not a large leaf but it is composed of a mosaic of leaves, other plant structures (stems, fruits and flowers), soil or rock background and shadow (Curran, 1985). Therefore, the spectral response of a vegetation canopy is mainly related to the area of leaves within the canopy rather then the reflectance of the component of leaves (Colwell, 1974). It has been shown by many researchers that the spectral response of a vegetation canopy is related to the amount of vegetation seen by the sensor. However, there is a negative relationship between vegetation amount and red reflectance. Colwell (1974) using simulated grass canopies showed that decrease in leaf area index (horizontal area of leaves per unit area of ground; Curran, 1983a) caused canopy reflectance to increase in the red reflectance and increase in the near infrared. Tucker *et al.* (1975), Tucker (1977a; 1977b; 1979), and Tucker and Maxwell (1976), using a hand held radiometer measuring reflectance in the red and near infrared wavelengths, showed that changes in these spectral regions are causally related to vegetation amount, leaf water content and chlorophyll content of blue grama grass.

In a laboratory experiment, Curran and Milton (1983) described how there is a negative relationship between red reflectance (0.615 - 0.690 μm) and vegetation amount and positive relationship between near infrared reflectance (0.780 - 0.995 μm) and vegetation amount of curled cress (*Lepedium sativum*). Kimes *et al.* (1981) found that there is a high correlation between leaf area index, green biomass and red reflectance of Landsat TM (band 3: 0,63 - 0.69 μm) and near infrared (band 4: 0.76 - 0.90 μm). In general, therefore, it can be seen that there is a fairly consistent relationship between the amount of green vegetation and red and near infrared reflectance over a variety of vegetation types. Nevertheless, Curran (1983) stated that this relationship may be altered due to a variation of the environment factor such as soil background, senescent vegetation, scene and sensor geometry. Therefore, it is possible for the reflectance of a canopy to change, often with no change in the hemispherical reflectance of the individual leaves as a result of specific factors in the vegetation canopy and viewing geometry.

Linked to the problem of senescent vegetation is that of vegetation phenology. As a canopy proceeds through the growing season, different canopy elements are presented to the sensor. These elements, such as fruit heads, flowers, or seeds may have reflectance which is different to that of leaves, therefore the reflectance of the canopy could alter. It is also possible for some episodic event such as drought or disease to affect the vegetation. This may result in physiological change in the vegetation, possibly causing a change in the hemispherical reflectance of the individual element, or it may cause wilting, giving rise to decrease in the area of leaves seen by the sensor, and an increase in the effect of background upon which the canopy is growing. The background effect is also a problem in the canopy reflectance, the variability in soil reflectance will cause the response from the two canopies to be different.

Vegetation canopy specific factors are related to those factors which have been shown to cause a change in canopy reflectance without any change in the viewing geometry. For example, a canopy can be composed of various amounts of live green and senescent brown vegetation. Therefore, there is the possibility that the proportions of two different canopies component types will produced differences in canopy reflectance, while the total amount of biomass of these two canopies may be same.

Viewing geometry specific factors relate to those factors which have been shown to cause a change of vegetation canopy reflectance as a result of changes in the sensor look angle, changes in the solar elevation angle, and the azimuth angle between the plane illumination, and changes in the plane of view. The relationship between these three angles are shown in figure 2.25. In the following section, the relationships between vegetation canopy reflectance and vegetation canopy specifics and the viewing geometric factors will be described.

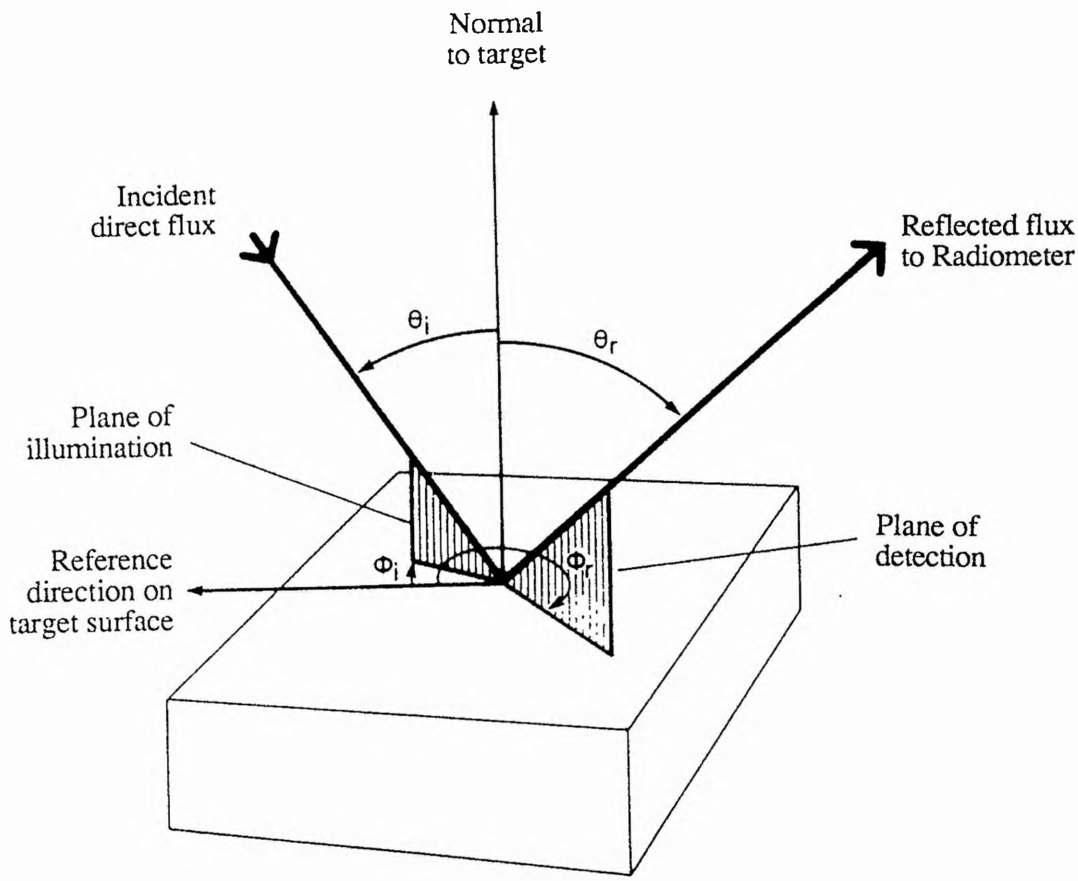


Figure 2.25 Geometric Definition of Angles Important in Remote Sensing.
(After Milton and Wardley, 1987).

2.2.2.3.1 **Vegetation canopy specific factors.**

2.2.2.3.1.1 <u>The effect of the soil background</u>

Soil background is a major factor influencing the spectral reflectance of vegetation canopies, and therefore canopy reflectance varies with different soil reflectance and amount of soil exposed (Bauer, 1985). In certain situations where the reflectance of a vegetation canopy is examined, the soil, or soil and leaf litter background contributes to the composites reflectance of the scene (Colwell, 1974; Richardson and Wiegand, 1977; Tucker and Milton, 1977). The contribution will be minimal if the vegetation canopy is complete, because the spectral response will be dominated by the response of vegetated components. Nevertheless, the reflectance of the soil background could contribute significantly to the canopy spectral response if the vegetation canopy decreases or is thin (Frank, 1985). Soil influences on incomplete spectra are partly due to a dependency of the soil background signal on the optical properties of the overlying canopy (Huete, 1988; Lillesaeter, 1982).

In general, the effect of soil background is summarized in figure 2.26 a and b, which plots red and near infrared reflectance against the leaf area per unit of ground (Leaf Area Index or LAI). In Figure 2.26a, vegetation is growing upon a light coloured soil with high infrared reflectance. The contrast between the high reflecting soil and the low reflecting vegetation in the red wavelength causes a large decrease in reflectance with increasing vegetation amount due to red light absorption. In Figure 2.26b, vegetation is growing on a dark soil with a low red

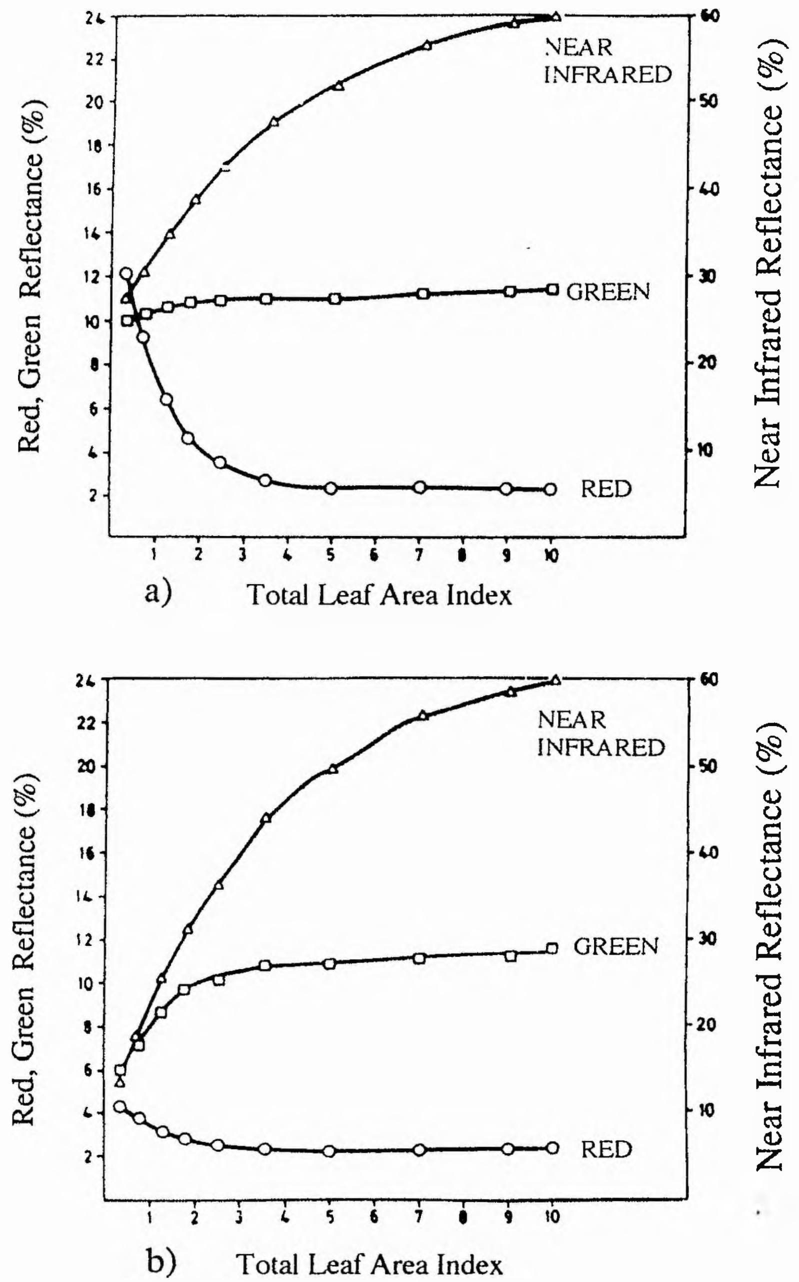


Figure 2.26 The Reflectance of Simulated Vegetation Canopies on a) a Light and b) a Dark Soil in Green, Red, and Infrared Wavebands. (Adapted from Curran, 1980).

reflectance. Therefore, there is a little contrast between the spectral response of the soil and that of vegetation in red wavelength with increasing amounts of vegetation due to the low reflecting soil, which is covered by low reflecting vegetation. The contrary occurs in the near infrared where the low reflecting soil is covered by increasing amounts of highly reflecting vegetation, therefore, more contrast occurs between the soil and vegetation. In particular, the effect of the soil background depends upon the contrast ratio between the soil and vegetation growing upon it and this in turn will also depend upon wavelength and solar / sensor geometry.

The effect of the soil background is most pronounced for agricultural crops where cover increases from 0% at early in the growing season to 100% at the end of season (Rao *et al.*, 1979). Cultural practices in corn and soybean cultivation such as row width, irrigation treatments, and planting date can give a different contribution to the soil effect at different time of the growing season (Crist, 1984; Gardner and Blad, 1986). Tucker and Miller (1977) used a regression approach to estimate the soil spectra from the composite reflectance of blue grama grass. Theoretical considerations indicated that the soil or background spectra could be extracted after regressing canopy spectral reflectance against some biophysical characteristics of the canopy such as total biomass, green biomass, brown biomass, leaf water or chlorophyll. Using Landsat MSS data, Westin and Lemme (1978) described that even though soil associations could not consistently be separated within the data of a single vegetative type, it was seen that soil did influence all vegetative spectral reflectance to some degree. Ezra *et al.* (1984), and Heilman and Boyd (1986) using Landsat MSS data showed that in most cases the greenness indices were affected by soil background reflectance. As explained by Elvidge and Lyon (1985) variation in rock and soil brightness have a strong influences on the ratio-based vegetation indices.

2.2.2.3.1.2 The effect of senescent vegetation.

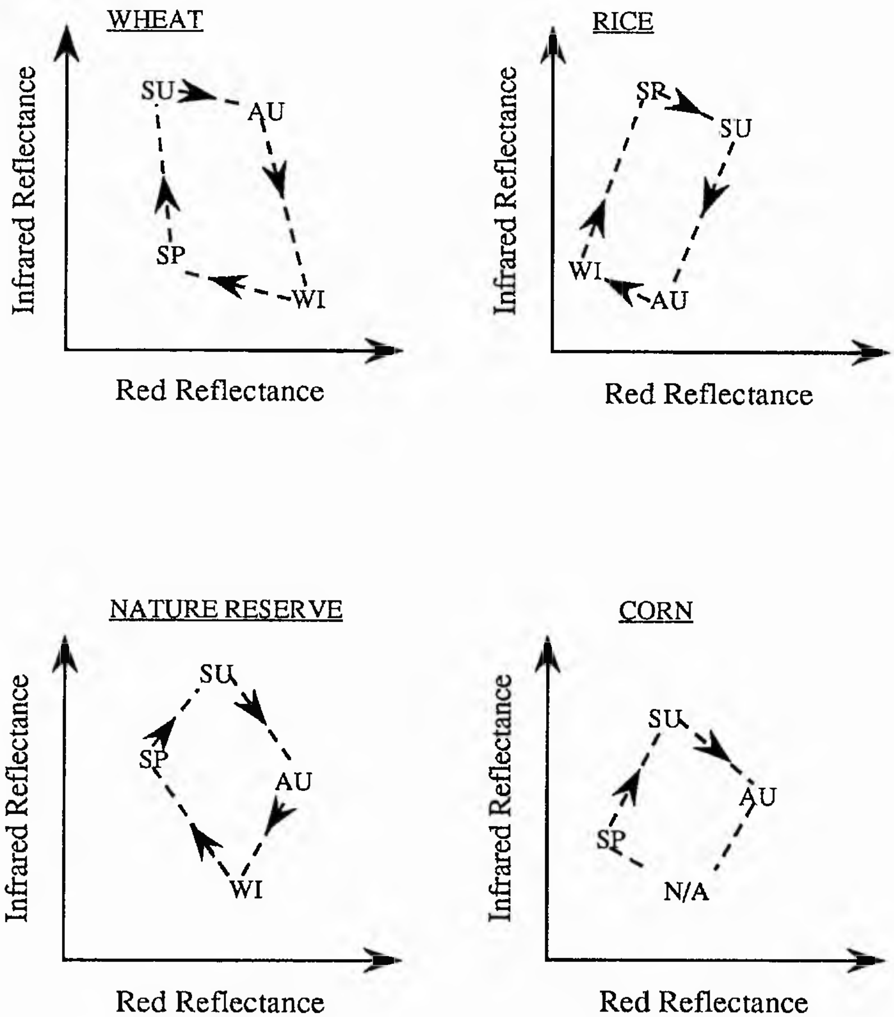
It was explained in section 2.2.2.2.1 that as plant leaves senesce, the proportion of carotenoid pigments to chlorophyll pigments will increase giving rise to an increase in the reflectance of red wavelength. However, there is little information available concerning the effect of senescent on canopy spectral response. To understand the effect of senescence vegetation, it is necessary to be able to describe the amount and position of this vegetation within the canopy (Milton and Wardley, 1987). Even though this has not been rigourously attempted, some research has clarified general relationships between the presence of senescent vegetation and reflectance. Colwell (1974) measured the effect on green, red and near infrared reflectance of oats canopy with approximately 60% cover, with varying amounts of live and dead vegetation. It was found that the reflectance of an all-live canopy in green and red wavelength were considerably different to those values obtained from the half live and all-dead canopies. The green and red reflectance increased from 8% and 4% respectively for all-live canopy to 22% and 37% for the all-dead canopy. On the other hand, the near-infrared reflectance ranged from 37% for all-live canopy to 41% for the all-dead canopy. The main reason for these effects are due to major differences in the hemispherical reflectance and transmittance between live and dead vegetation in the red wavelength, and the small difference in the near infrared. Tucker (1978b) evaluated the relationships between reflectance in the 0.50 - 0.80 μm region and senescent grass canopy biomass. It showed that there was a relationship existed between canopy spectral reflectance and total wet and total dry biomass.

2.2.2.3.1.3 The effect of phenology

The spectral response of cover types is strongly influenced by changes over time in vegetation, the atmospheric and hydrological conditions, and the illumination sources (Estes *et al.*, 1983). One of the most important changes affecting vegetation reflectance is phenology, or the seasonal growth changes of plants. The spectral reflectance of many vegetation species are in an almost constant condition of change throughout of the year, as plants pass through the stages of leaf growth, budding, flowering, fruiting, senescence and dormancy (Hoffer, 1978). These stages have associated changes in plant morphology, pigmentation and internal structure which affect the spectral response pattern (Sanger, 1971). The utility of remotely sensed data for monitoring vegetation development has been reviewed by Steiner (1970). Ashley and Rea (1975) used Landsat MSS data to describe phenological change. Information regarding the temporal spectral nature of vegetation development has also been obtained using hand-held instruments. Kanemasu (1974) reported one of the first ground based attempts to monitor seasonal changes in wheat, soybeans and sorghum. A number of workers also reported on the temporal spectral profiles of a series of vegetation types. Tucker *et al.* (1979a and b) monitored the red and near infrared reflectance of corn and soybean canopies over a growing season. Kimes *et al.* (1981) and Markham *et al.* (1981) examined the temporal spectral response of corn canopy in TM band 3, band 4 and band 5. It found that there was potential for providing corn yield information from visible and near infrared wavelengths. Collins (1978) using a high resolution airborne spectroradiometer stated that the position of absorption edge in the red wavelength shifts towards the longer wavelength during the crop growth cycle and reaches a maximum in the fully headed or pre-ripening stages. The potential utility of the red edge of reflectance for examining phenological change has also been noted by Horler *et al.* (1983). However, the form of the temporal spectral profile of semi natural and natural vegetation has not been so widely examined. Curran (1983b) summarized the relationship between red and near infrared bidirectional reflectance as a hysteresis loop for a nature reserve in Britain, rice, corn and wheat (Figure 2.27), whilst Hardisky *et al.* (1984) using Landsat TM band 3, 4, and 5 examined seasonal exchanges in a salt marsh environment.

2.2.2.3.2 **Viewing geometry specific factors.**

A vegetation canopy is not a perfectly diffuse reflector (a Lambertian reflector) so the bidirectional reflectance factor changes as the view and solar angles, and canopy characteristics change (Shibayama and Wiegand, 1985). In the following section, the three main factors, solar zenith angle, sensor look angle and relative solar azimuth angle will be considered.



Key

SP Spring
SU Summer
AU Autumn
WI Winter
N/A Not Available

Figure 2.27 Four Hysteresis Loops of the Seasonal Development of Vegetation Amount.
(Adapted from Curran, 1980).

2.2.2.3.2.1 The effect of the solar zenith angle.

An understanding of variations in canopy reflectance as a function of solar zenith angle is important for several remote sensing applications. Many workers report that the effects of changing solar zenith angle on canopy spectral response show a great deal of variability in different reflectance trends (Kimes *et al.*, 1980). For example, Duggin (1977) has shown that reflectance differed quite significantly among seven wheat varieties at the same growth stage. Similarly, Jackson *et al.* (1979) and Kollenkark *et al.* (1982) reported that the effects of solar zenith angle on spectral reflectance were quite different for various crop configurations (row spacing, row orientation, canopy cover, plant height etc.). The main reason for this variability is that changes in the amount of canopy shadowing, particularly in visible wavelengths, are highly dependent upon solar zenith angle. Ranson *et al.* (1986) observed that the effect of sun angle and view angle on the multispectral response of small Balsam Fir trees are quite significant. The author also noted that changes in the solar zenith angle produced different shadowing effects. As the sun angle increases, the denser shadows produced will cause an overall darkening of the scene. Ranson *et al.* (1985) showed that there was a strong effect of solar zenith angle on the reflectance in all spectral bands for corn canopies with low leaf area index. A decrease in contrast between soil background and vegetation due to shadows as solar zenith angle increased appeared to be the major contributor to this change in reflectance. Eaton and Dirmhirn (1979) reported that substantial changes in the spectral response of a variety of surfaces with solar angle change was a result of vertical structures in the features under study. For certain surfaces, such as snow, alkali and salt flats, forward scattering predominated but for ploughed fields and vegetated surfaces, back scattering was the dominant effect. Huete (1987) has shown how the nadir reflectance of an incomplete cotton canopy can either increase, decrease or remain stable, with the changes in solar angle depending upon the type of soil beneath. Most of the above studies have examined the effects of solar zenith angle on crop canopy reflectance which may have a preferential orientation of vegetation in rows. However, measurements and simulation have been carried out for some semi-natural sites such as grassland. Kimes *et al.* (1980) reported that in general, the reflectance in red and near infrared wavelength was relatively unaffected by changing solar zenith. This is due to the small change in the amount of shadow occurring in fairly dense canopies. However, it is not just the amount of shadow occurring but also the quality of the shadow. For example, the same amount of observable shadow area in a coniferous canopy and a hard wood canopy would have a greater effect on the near infrared reflectance in the coniferous canopy. This is because of the near infrared shadow in conifers which is relatively much darker due to the low transmittance of coniferous vegetation compared to hard woods.

2.2.2.3.2.2 The effect of sensor look angle.

In general, an increase in the angle in which a sensor views a vegetation canopy will reduces the amount of soil and shadow seen, therefore, it will increase the amount of vegetation seen by the sensor (Curran, 1983a). The effect of solar elevation has been shown to be of particular importance for a sensor elevation within a few degrees of vertical. Figure 2.28 indicates how the effective plant cover changes for

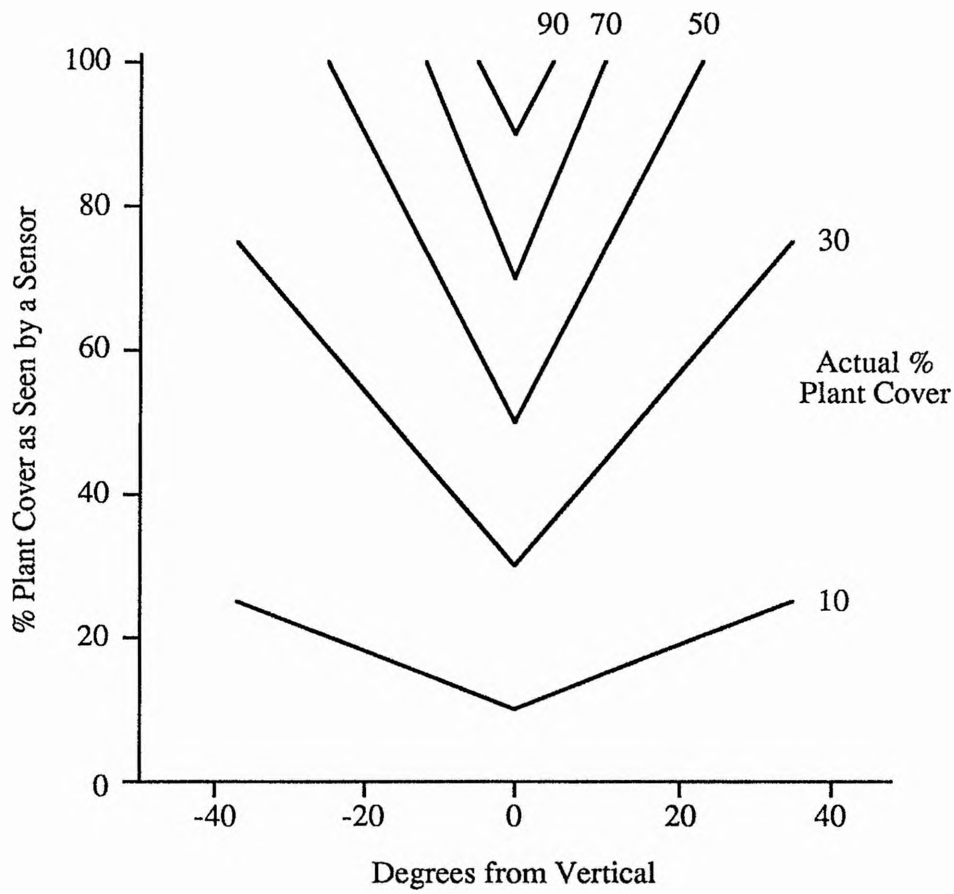


Figure 2.28 Fraction of a Plant Cover as a Function of Degrees from Nadir. (Adapted from Curran, 1983).

various actual cover values with increasing look angle. Thus a canopy with a 90% cover, for example, located only 3.5^0 from the vertical (56 km from the centre of a Landsat MSS frame) would appear to have 100% plant cover. Among the first to report upon the effects of look angle for grass and asphalt surface were Egbert and Ulaby (1972). It was shown that grass canopy reflectance contained little variability at large solar elevation angles, and also that red reflectance at 0.70 μm was highly responsive to angular variations. Since then the effect of off-nadir viewing have been reported for a range of surfaces, sensors and altitudes. Kirchner *et al.* (1982) studied the reflectance changes in a developing alfalfa crop with a 3 band ground based radiometer. The authors noted that the sensor view angle had less impact on perceived reflectance as the alfalfa progressed from a canopy with leaves oriented predominantly horizontally at maturity to a predominantly erect canopy of stem after harvest. Wardley (1984) investigated the effect of look angle on vegetation indices measured from a grass canopy under laboratory conditions. The author found that ratioed indices were least affected in viewing geometry and that most effect occurred at off-nadir angles looking into the sun at low solar elevation angles. Danson (1985) reported that canopy reflectance was influenced by off-nadir viewing angles, and this effect was greater in the red waveband than in the near infrared waveband. Kirchner *et al.* (1981) also reported that off-nadir viewing effects are more pronounced in the red than in the near infrared waveband. Other studies such as those by Barnsley (1984), Bartlett *et al.* (1986), and Salomonson and Marlatt (1977), found considerable view angle effects using airborne MSS data.

The influence of viewing angle on the reflectance of bare soils has also been studied by several workers, including Eaton and Dirmhirn (1979), Kimes (1983), and Milton and Webb (1987). All these studies have found a large peak in reflectance in the back scatter direction (*i.e.* looking down-sun) which is attributed to enhanced reflection from facets of the soil surface sloping towards the sensor. In contrast, a sensor looking up-sun receives less energy from illuminated facets and also sees a larger proportion of shadowed soil. This situation is shown in Figure 2.29.

2.2.2.3.2.3 <u>The effect of the relative solar azimuth angle.</u>

When considering the effect of the viewing geometry on the bidirectional reflectance of a vegetation canopy, it has been shown that the relative solar azimuth angle between the plane of illumination and the plane of view can be a very important determinant of the off-nadir viewing effect (Milton and Wardley, 1987). This convention was adopted by Suits (1971) that when the sun is behind the sensor and the sensor is viewing directly away from the plane of illumination, then the relative solar azimuth angle is 0^0. When the sensor views toward the sun, then the relative solar azimuth angle between the plane of illumination and view is 180^0. A similar approach was also adopted by Egbert and Ulaby (1972). The effect of the relative solar azimuth angle is highly dependent upon the surface condition such as rough or smooth, vegetated or unvegetated. Kirchner *et al.* (1981) used another convention that 0^0 relative solar azimuth is when the sensor views towards the sun and 180^0 when the sensor views away from the sun.

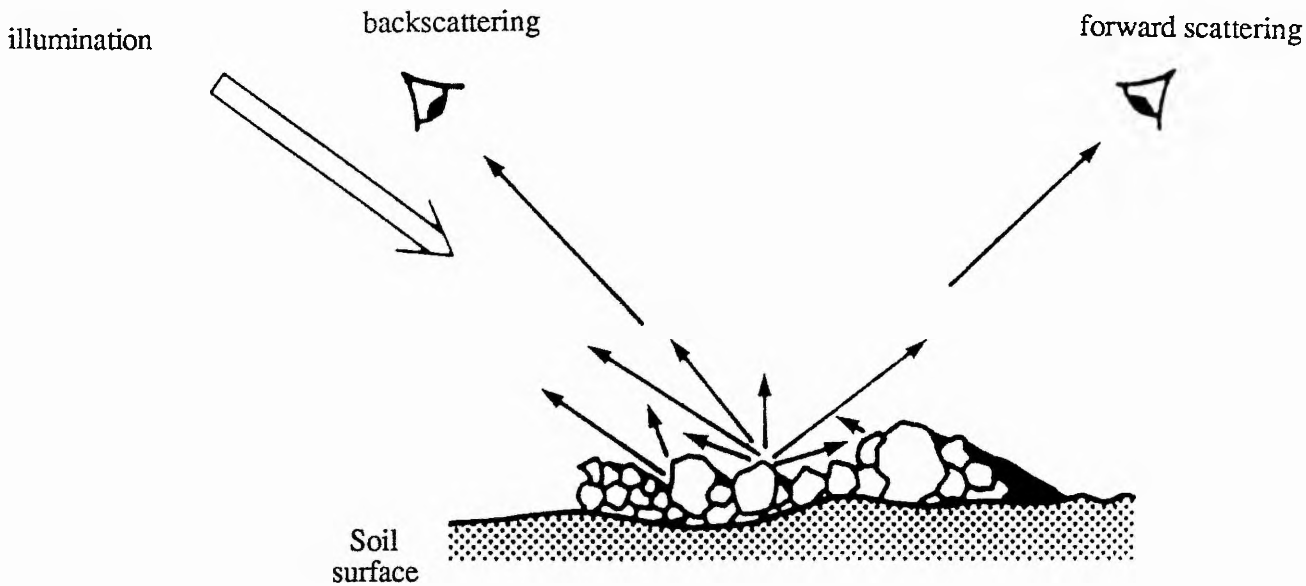


Figure 2.29 Back Scatering and Forward Scattering From a Soil Surface.
(Modified from Milton and Wardley, 1987).

The most significant differences in surface bidirectional reflectance as a function of relative solar azimuth angle appear to occur either when the sensor views into or away from the sun as opposed to viewing at intermediate azimuth angles (Eaton and Dirmhirn, 1979; Kimes, 1983). Suits (1972) showed that when a sensor views into the Sun, only transmitted light is received by the sensor. However, when the sensor views with the sun behind it, only reflected light is received. Kimes (1983) indicated that for complete and homogeneous canopies, the directional reflectance increases as the off-nadir view angle increases for all azimuth angles.

2.2.2.3.2.4 <u>The effect of topography and the atmosphere.</u>

Remote sensing of vegetation is also influenced by two factors, the effect of topography (Hall-Könives, 1987; Justice *et al.*, 1981; Sthor and West, 1985) and the effect of atmosphere (Gerstl and Zardecki, 1985; Otterman and Robinove, 1981; Sjoberg and Horn, 1983), which can greatly affect the spectral response of vegetation canopies. The topographic effect is defined as the variation in response from inclined surfaces compared to the response from horizontal surfaces as a function of the orientation of the surface relative to the light source and sensor position (Holben and Justice, 1981; Justice, 1981). The receipt of solar irradiance varies greatly with the elevation and azimuth of surface slope. A sloping surface either towards or away from the sensor will cause an effect very similar to that of moving the sensor away from the vertical. However, when a surface slopes facing toward the sun, it will receive more irradiance and will therefore have a higher radiance. In contrast, a slope facing away from the sun will receive less irradiance and hence will have a lower radiance. In Britain, for example, irradiance is high on south facing slopes and is low on north facing slopes (Curran, 1983a). A situation can thus be envisaged where slopes having the same amounts of vegetation, could have different spectral responses due to the topographic effect. The topographic effect on Landsat MSS data was examined by Holben and Justice (1980) who reported that one cover type at a solar elevation of 40 degrees had a range of 52 DN (Digital Number) difference in the red wavelength, as a result of variation in surface topography. Using Landsat 5 Thematic Mapper data of upland North Wales, Thomson and Jones (1990) reported that terrain orientation has important effects on the radiance level detected from semi-natural upland vegetation. However, these effects are different for the three vegetation types (*Agrostis* grassland, *Nardus* grassland and *Calluna* heathland) examined. Research was also undertaken by Pinter *et al.* (1987) using a ground based radiometer to determine the effect of topography and sensor view angle on the diurnal behaviour of two spectral vegetation indices.

Solar radiation flux is partially absorbed or scattered as it passes through the atmosphere to the earth's surface (Slater and Jackson, 1982). This atmospheric effect is found when atmospheric particles such as dust, water vapour etc. scatter both incident flux from the sensor back into the sky and into the sensor, and the reflected surface flux in all directions. Gerstl and Zardecki (1985) showed that atmospheric effects are major contributions to Landsat MSS visible bands (band 1 and band 2), and only a minor contribution in MSS near- infrared waveband (band 3 and band 4) for remotely sensed images of vegetative surfaces. Tanre *et al.* (1979) stated that the main mechanisms by which the terrestrial atmosphere disturbs the measurements of ground reflectance from space are aerosol and molecular backscattering both of which change the measured target reflectance.

2.3. The Potentials of Remote Sensing Technique for Upland Vegetation Mapping.

Many vegetation maps or plant inventories are dependent on detailed ground observation which will give useful information on plant distribution and amount, density and percentage cover. Although ground based survey techniques offer a fairly detailed source of information, they also suffer from a number of disadvantages. They are mostly time consuming, because of the long time needed to collect data in the field and travelling to the survey areas. Even though field survey can be expedited by increasing the number of surveyors, this will make the survey very expensive, and may introduce variation between surveyors.

As concern increases over the need for upland vegetation mapping to assist land use management, remote sensing techniques seem to be one of the most suitable choices to provide these data. However, when using remote sensing, particularly multispectral scanners, the spectral, temporal and spatial resolution should be considered as these factors are important in image analysis. These will be examined briefly in the following section.

2.3.1 The effect of temporal characteristics.

Temporal changes can strongly affected the spectral characteristics of the earth's surface. These temporal changes can be either natural, such as seasonal changes in vegetation, or vegetation phenology, or man-made changes such as when farmers plough their fields, planting, and harvest (Hoffer, 1978). These changes mean that a major consideration should be the selection of imagery at the best time of the year to optimise the differences of spectral response between classes and the homogeneity within classes. Simonet (1983) stated that there are optimum time periods for many land surface types when they may be observed and contrasted with surrounding areas. The vegetated surface will alter throughout the year because of the different growth stages, and hence a particular time of year will possibly provide the optimum separation between classes. Myers (1983) reported that there may be a difference in spectral response pattern between two stages of growth in one species. Therefore, it is necessary to recognize the best time, or temporal resolution, for separating cover types. However, there are considerable problems with this approach. In practice, it is difficult to optimise because images are composed of various mixes of vegetation cover at different growth stages, and it is impossible to optimise all cover types at one point of time. Nevertheless, when a certain cover type has a greater importance in one scene, there is a possibility to emphasise this feature in comparison with other cover types.

2.3.1.1 Temporal characteristics of moorland vegetation.

Two major types of temporal alteration in the moorland species are the plant's phenology and the stage of development. The seasonal changes and growth phase of *Pteridium aquilinum,* and *Calluna vulgaris,* both of which are very important components of the North York Moors vegetation complex, and other important upland vegetation types will be described briefly in this section.

2.3.1.1.1 Temporal alterations in Bracken (*Pteridium aqulinum*).

There are three main annual growing stages of *Pteridium aqulinum* (Bracken), growth, senescent and decay (Nicholson and Paterson, 1976). However, the timing of growth stages is dependent upon the weather, temperature, moisture, soil aeration, water supply, soil pH and nutrients (Nicholson and Paterson, 1976; Watt, 1976). Most of the fronds emerge in May or June and from the beginning of June to the middle of July the fronds gradually unfurl and grows up to 30 cm high (Figure 2.30). The plant continues to grow until fronds have five pairs of fully expanded pinnae (Williams and Foley, 1976). The peak of growth is from the end of July until the end of August when the plant can reach more than one meter in height. During September, fronds gradually become senescent and by the end of the month many fronds are dead. This stage is quickened by the wind or early frost. By the beginning of October, the fronds are yellow and brown and starting to snap and fall over around the plant, forming a litter layer. In addition, during the growth stages, the individual plants will change in form and growth characteristics.

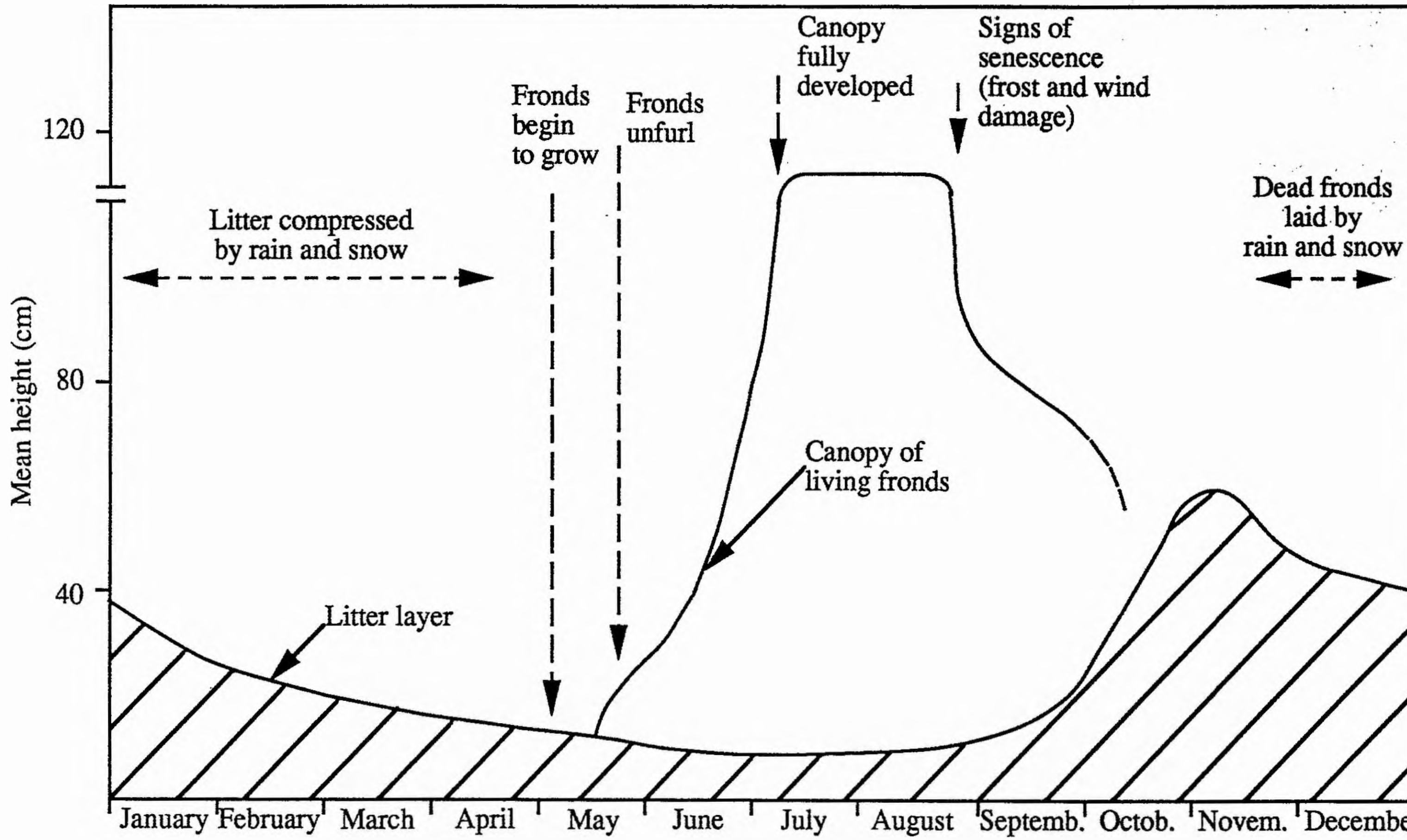


Figure 2.30 The Seasonal Growth Pattern of Bracken (*Pteridium Aquilinum*). (Adapted from Nicholson and Paterson, 1976).

Watt (1947, 1976) described five main life-cycle phases of bracken. However, the ages in every growth stage are an approximation and dependent upon local conditions.

a). **Grass heath.**

No fronds are obviously above the surface, but the rhizomes of the plant grow underground.

b). **Pioneer** (0 - 10 years).

In this stage, the fronds are generally small (less than 40 cm high) and sparse. The litter will quickly decay in the spring.

c). **Building** (10 - 25 years).

The fronds become much more dense and taller (between 50 cm and 1 meter).They produce more litter and decay more slowly.

d). **Mature** (25 - 65 years).

The fronds grows densely in this stage, and according to Watt (1947), has a density of about 70 fronds per square meter. The canopy cover is complete and the plant can grows to over 1,5 m. More litter is produced which cannot decompose before new litter is added in the following year, and therefore a continuous litter layer is established.

e). **Degenerate** (65 - 80) years).

Only a few fronds are produced in this stage, and the plant is smaller in height (less than 1 m). The litter becomes less abundant, and part of the previous season's litter is decomposed. In particular, the plant dies and the litter gradually disappears, even though it may remain for some time after the disappearance of the plant.

2.3.1.1.2 **Temporal alterations in *Calluna vulgaris*.**

Whilst *Pteridium aquilinum* is seasonally green, *Calluna vulgaris* is evergreen with minute leaves (Gimingham, 1960; Watt, 1955). In Britain, *Calluna* seldom growing exceeds 1.25 m in height but is generally less than 80 cm. With good drainage, *Calluna* can make a dense uniform growth of 60 - 90 cm in height (Tansley, 1965). *Calluna* has long and short shoots, in which the long shoots have widely spaced leaves (about 3 - 4 mm in length), while short shoots have more closely spaced leaves at about 1 - 2 mm (Figure 2.31). Flowers are produced singly an short stalks and mostly arise from leaf axiles on the long shoot (Gimingham, 1960). The annual growth stages start in April or May when new short shoots begin to appear and over-wintered shoots grow into long shoots. The main flowering period may begin individually in late June, but in Britain mass flowering starts in the middle of August and continues until late September (Gimingham, 1960). Dispersal of seed begins in September, and during October and November most of the seeds are shed. No litter is produced until the first flowering season is over (Cormack and Gimingham, 1964).

The life cycle of *Calluna vulgaris* has been divided into four phases in its life span of more than 30 years (Figure 2.32) (Barclay - Estrup, 1970, 1971; Barclay - Estrup and Gimingham, 1969; Cormack and Gimingham, 1964; Gimingham, 1960, 1972, 1975; Watt, 1955). The ages quoted are approximations.

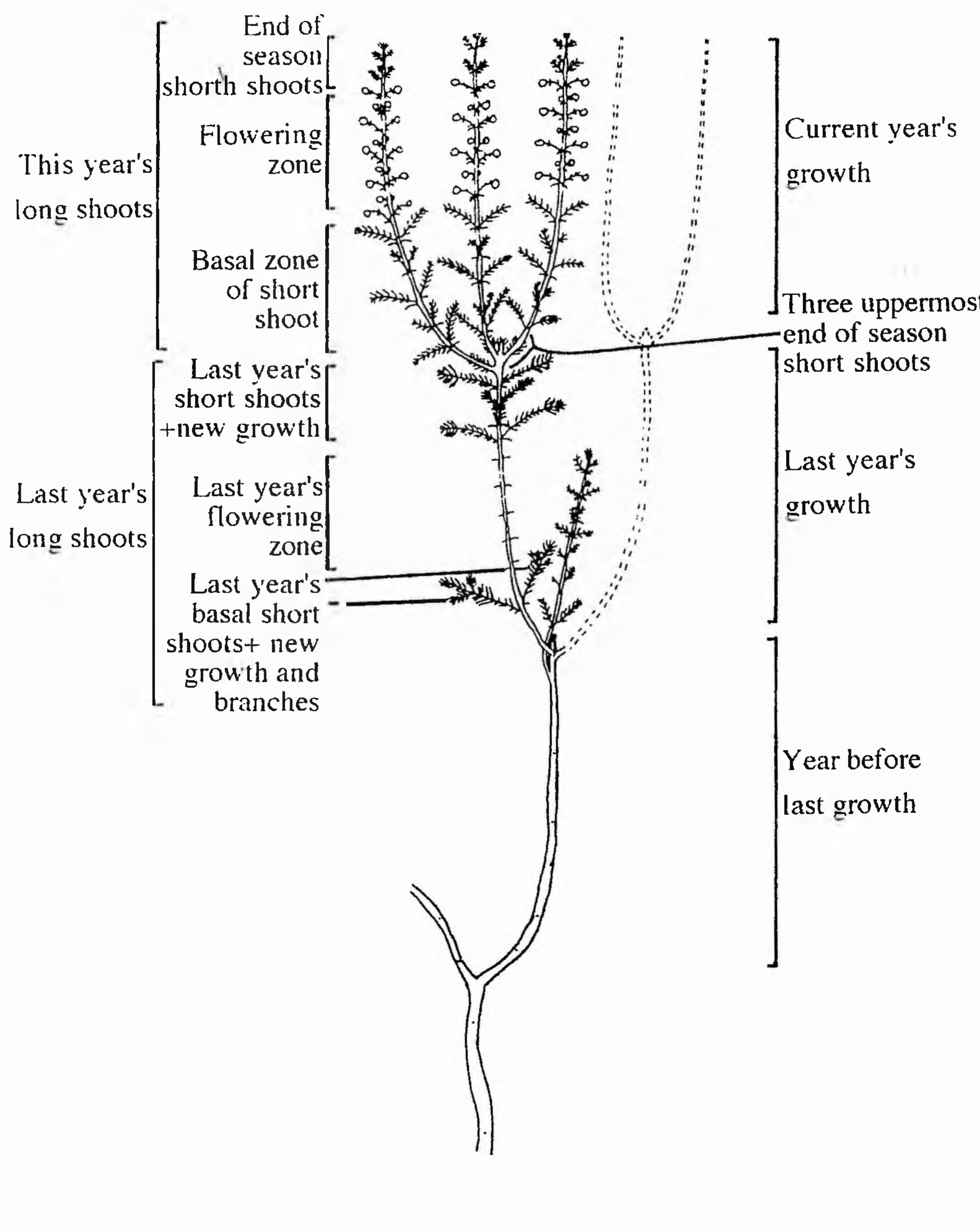


Figure 2.31 Diagram Showing the Form and Growth Zones of *Calluna Vulgaris*.
(Adapted from Gimingham, 1975).

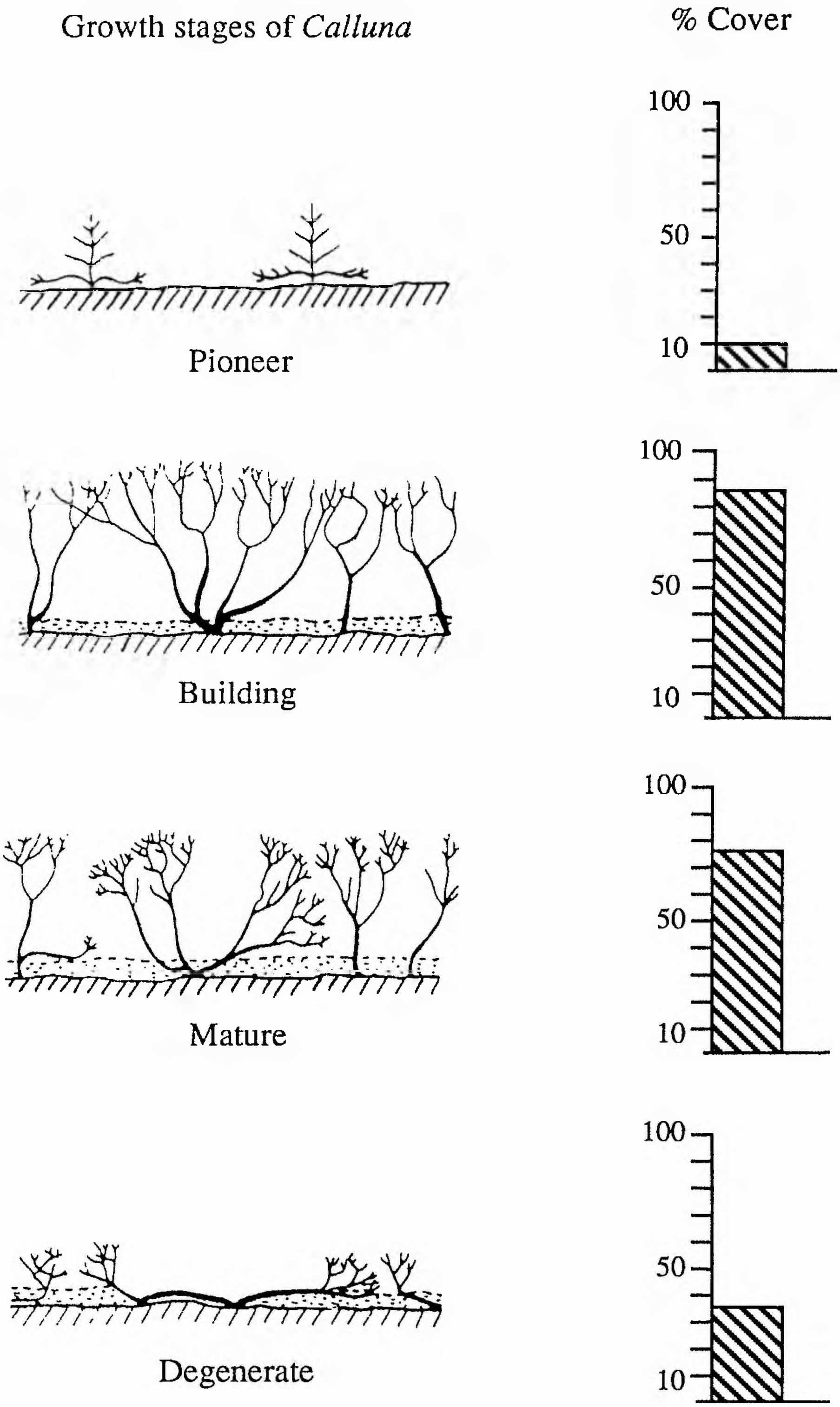


Figure 2.32 The Growth Stages of *Calluna Vulgaris*. (Adapted from Gimingham, 1975).

a). **Pioneer** (0 - 6 years).

This is the phase of early growth and establishment. The original leading shoots are replaced after two years. These leading shoots contribute about 10% of the total storey cover. The plant reaches 10 - 30 cm in height, producing a pyramid shape, whilst flowering is sparse. A fully developed bush is formed by the end of this phase.

b). **Building** (6 - 15 years).

In this stage the form of the bush becomes more hemispherical. Shoot production is at a maximum, flowering is vigorous and the plant can become 30 - 60 cm high. Canopy cover is at maximum and well established, this contributing more than 85% of total over storey cover.

c). **Mature** (15 - 25 years).

In the mature phase, net production of young shoots gradually becomes less vigorous. The outer most shoots becomes darker and smaller. Toward the end of this stage, a gap begins to form in the canopy and centre frame branches are gradually exposed, giving about 75% over storey cover.

d). **Degenerate** (25 years and over).

In this phase, the gap in the canopy become larger as the majority of the central branches collapse sideways and die. The plant dies from the centre outwards, gradually increases the amount of bare ground in the middle of each plant, and contributes only 35% of over storey cover.

In addition of the *Calluna* growth stages, there is a burning stage at regular interval of 7 to 15 years which has been used in the management of moorland (Pearsall, 1971). This is mainly in order to regenerate the growth of short shoots for grazing animals (sheep or grouse). The rotation of burning stages usually take place in small areas before *Calluna* exceeds 15 years of age, or before it passes the building phase (Gimmingham, 1975). This will result in a different spectral response within *Calluna* areas.

2.3.1.1.3 Temporal alterations of other moorland vegetation cover type.

Many vegetation communities exist in the North York Moors, only the most important species will be described in this section.

1. *Erica tetralix* (cross-leaved heath). It is a small evergreen shrub, growing to about 60 cm, and mainly found in bogs or wet moors (Webb, 1986). The main growth season begins in late March or the beginning of April, whereas rose-pink flowers are produced between June and October. Mature seed can be found from September to October but it is largely shed by December (Bannister, 1966).
2. *Erica cinerea* (bell-heather). It is an evergreen shrub, usually found in the drier areas and quite often associated with *Calluna*. The main growth season begins in late March or the beginning of April and crimson-purple flowers grow before *Calluna*'s main flowering period, commencing in July and continuing until early August. Early flowers appear at the end of May and late ones can still be found in November (Bannister, 1965). Most of the mature seed is shed in October and November (Webb, 1986).

3. *Eriophorum vaginatum* (cotton-grass). It is a perennial sedge with growth initiated in March. It flowers from June onwards, and produces a maximum of leaves at the end of June (Cheatle, 1976).
4. *Juncus squarosus* (heath-rush). It is a perennial herb which consists of rosette leaves with long flower-stalk bearing a group of brownish flowers on the upper part. Flowering is completed between June and September (Pearsall, 1971).
5. *Nardus stricta* (matt-grass). It is a perennial grass, about 40 - 60 cm in height, with vegetative shoots closely compacted on a short rhizome. The main growth season begins in February and reaches a maximum in April. It produces dark chesnut-brown flowers from the end of May to August (Chadwick, 1960).
6. *Molinia caerulea* (purple moor-grass). It is a densely and compactly tufted perennial grass, and produces purple flowers between July and September (Cheatle, 1976).

2.3.1.1.4 The analysis of the temporal characteristics of the acquired Landsat TM data.

As was described in section 2.3.1.1, the seasonal changes in vegetation are different for each type of moorland vegetation community. Flowering, the production of new green shoots, or the die back of green vegetation will all have a visible effect on the canopy surface. Therefore, it is not an easy matter to chose the correct time for imaging upland vegetation, especially moorland, as the land is covered by many different vegetation type which have different growth cycles. Nevertheless, because of limited data acquisition, only one date of

Landsat TM data has been used in this research (section 3.3). The Landsat data acquisition programme gives a potential data set of 24 scenes each year. However, cloud cover reduces this potential to an actual acquisition of 3 or 4 scenes in any one year. Such scenes may not coincide with the growth stages required for analysis (Soulsby, 1991). This image was taken in the spring when moorland vegetation has generally similar conditions as in the winter season.

In particular, there are advantages and disadvantages of using satellite remote sensing data, which acquired at or near the end of spring time, for upland vegetation mapping. It is a good time to separate bracken (*Pteridium aquilinum*) and other moorland species because of the contrast between brown bracken litter and other evergreen vegetation such as ling (*Calluna vulgaris*), cross-leaved heath (*Erica tetralix*), and bell-heather (*Erica cinerea*). In the Landsat TM colour composite bands 2, 3 and 4, the spectral reflectance of bracken looks brighter than other moorland species. However, in spite of possibilities to distinguish bracken from other moorland vegetation types, there are also some problems of using image data acquired in spring. The most obvious problem occurs between bracken and open land (bare ground) such as in the agricultural fields, urban areas, roads, and car parks. There is also a problem of distinguishing *Calluna* at the building phase from deciduous woodland at this time. During the spring, *Calluna* develops woody branches in the building phase. At the mature stage the centre of the bush become rapidly exposed and degenerates. This gives possibilities of confusion with deciduous woodland in the early part of the year when the lack of leaves causes the tree's woody elements to be exposed.

2.3.2 The effect of spectral characteristics.

The vegetation cover of the earth's surface is often the first surface encountered by the solar energy used in remote sensing. Therefore, most of the remote sensing imagery records the character of vegetation of the earth's land area. A basic assumption of multispectral analysis is that the earth's surface features are spectrally separable, and accordingly can be individually identified and mapped. However, in many cases, some surface features cannot be spectrally separated and identified. Consequently, successful efforts of multispectral analysis should be based on entire recognition and understanding of the spectral characteristics of the different earth's surface features, and the factors which can influence these spectral characteristics (Hoffer, 1978).

As was described in section 2.2, most remote sensing data-acquisition systems only record the energy reflected or emitted by the earth's surface objects in selected wavelength bands. However, many factors cause differences in the spectral response received by the sensor. The properties of the earth's surface, environmental conditions, solar illumination, and atmospheric conditions are the most common factors affecting the spectral reflectance of the earth's surface (Hall-Köynes, 1987; Hutchinson, 1982; McMorrow and Hume, 1986; Stohr and West, 1985) (section 2.2.2).

2.3.3 The effect of spatial characteristics.

Agricultural fields in Britain are usually characterized by large homogeneous areas with single crops and are well defined from other field crops by field boundaries. Even though the spectral reflectance of crops are generally similar, they can be discriminated field by field using multitemporal imagery (Odenweller and Johnson, 1984). However, semi-natural vegetation communities such as in the North York Moors are more difficult to inventory and map. This is due to the extreme spatial diversity and various species composition of vegetation communities encountered (Jones and Wyatt, 1984). Furthermore, the boundaries between these communities are diffuse and the land cover is spatially variable. The high spatial variance of upland vegetation communities make for difficulties of classification. For example, in a bracken or heather moorland, these communities will contain several other species. Therefore, the land cover classes will represent composites of different objects rather than a compound of similar objects as in agricultural crops. Because most plants are gregarious, and grow together in a groups of various sizes and species, the upland vegetation communities are also integrated with other communities over wide areas (Pears, 1977). The vegetation of almost any area is very complex, and the boundaries between different vegetation communities tend to be gradual and are quite often difficult to determine by using either field work or even remote sensing techniques (Küchler, 1967).

2.4 Upland Vegetation Mapping Studies Using Remote Sensing.

A number of studies using Landsat MSS, Landsat TM and SPOT data for monitoring and mapping upland vegetation in Britain will be outlined briefly in this section. However, it should be noted that these researches have been preceded by, and are often simultaneous with, other moorland research employing imagery.

Despite the availability of Landsat MSS data since 1972, Morton (1986) reported that the data and derived imagery have been little used in the United Kingdom for ecological research. The low availability of image analysis facilities in the 1970s and the relatively coarse spatial resolution of MSS (79 m X 79 m) are the reasons for relative little research having been done using this data source. Many difficulties were also encountered when remote sensing techniques were used in the varied landscape of upland areas, because the pixel size will contain many different species (Southgate, 1986). Therefore, most remote sensing in conjunction with vegetation research in the past has been concerned with agricultural crops (Bauer, 1985; Curran and Williamson, 1985; Odenweller and Johnson, 1984). In spite of this, when remote sensing techniques have been applied in the study of semi-natural vegetation, much research has been directed towards biomass estimation (Curran, 1983; Tucker, 1977a), and relatively little for the classification of semi-natural plant communities.

Weaver (1984) is one researcher who has appraised Landsat MSS data for studying heather moorland in relation to management problems. Working on Danby High Moor in the North York Moors National Park, she found that using Landsat MSS data and maximum likelihood classification, seven major different moorland plant communities could be detected. However, the finer units were not separable due to the small scale variation within the communities. Nevertheless, using air borne MSS data with 5 m of ground resolution and a ground based radiometer, some of the finer sub-class plant communities were identified. Morton (1986) also used Landsat MSS data to discriminate the extent of moorland plant communities in the Plynlimon area of Wales. It was concluded that *Calluna* dominated heather communities, was spectrally distinct while *Molinia-Eriophorum* mire was fairly distinct. *Nardus* grassland was poorly discriminated due to its distribution on different slopes with different aspects.

In recent developments, now that image processing analysis facilities are more widely available and given the availability of Landsat TM data with better resolution (30 m X 30 m), much of the current and future research will focuses on this higher resolution data. Williams (1987) has used Landsat-5 TM data for mapping upland vegetation in the Glyderau mountains of Wales. Using geometrically corrected TM data of scene 204/24, taken on 22 July 1984, and the Nature Conservancy Council Vegetation Map at 1:10,000 scale, he produced a maximum likelihood classmap. Using Ratcliffe and Birks's classification of upland vegetation types (1980) and a fast maximum likelihood classifier, sixteen TM classmaps have been found, including *Agrostis-Festuca, Nardus-Juncus* and *Molinia* grassland; *Calluna, Vaccinium* and *Rhacomitrium* heaths; *Pteridium acquilinum* (bracken); soligeneous flushes; blanket bog; crags; and scree. The combination of four pre-classification and four post-classification filters were produced for comparison with the ground data of National Conservancy Council vegetation map. It was reported that there were improvements in correspondence at about 32% for all vegetation types, compared with unfiltered TM class maps. Bracken and *Calluna* heath were clearly distinct from other classes, while grassland communities were fairly distinct. However, for bracken, even when relatively spectrally distinct, only small increases in correspondence were produced after filtrations. Greater correspondence was found in large areas of homogeneous vegetation such as *Molinia*, *Nardus-Juncus* and *Agrostis-Festuca* grassland, and *Calluna* heath. The best overall correspondence with ground survey have been achieved after use of 7 X 7 filtrations (Wiliams, 1988). Therefore, even though Landsat TM data has a finer resolution, it was suggested that, using this technique, Landsat MSS data could be quite sufficient for the mapping of general upland vegetation communities.

O'Hare (1987a) has used Landsat TM data for upland land cover mapping in the Peak District, Derbyshire. Using Landsat-5 TM data, taken on 26 April 1984, and a maximum likelihood classifier, ten land cover types were identified. These comprised water, coniferous forest, improved pastures, rough pastures with *Molinia* and fescue grassland, acid grassland with *Nardus* and *Eriophorum*, heather moorland, mixed moorland (heather and acid grassland), peat and bog, urban areas, and finally burnt/unclassified area. It was reported that there is relatively little confusion between *Nardus* and *Molinia* dominated grasslands. This result was much better than using Landsat MSS in which grassland has not previously been easily identifiable, particularly in the high relief areas (Morton, 1986). *Calluna* (heather moorland) was fairly distinct even though confusion still occurred, mostly with bog vegetation. Bracken communities were confused with a number of other vegetation types, notably with *Nardus* and bog vegetation (O'Hare, 1987b). There were also some problems caused by relief and aspect. For example, heather and grass moorland on north facing slopes are often confused with coniferous forest on other landform types.

Stuart and Hogg (1987) have also analysed upland vegetation in the Peak District using Landsat TM data and the NRSC Maximum likelihood classmap. Ten upland vegetation classes have been produced using TM data, acquired on 26 April 1984. Each vegetation class was read into a pilot geographical information system (GIS) and held in the system as quadtree images. The facilities of the GIS were used to manipulate these images in different ways, such as editing, separating, combining or generalising the images. It was reported that encoding classified Landsat TM as a linear quadtrees is an efficient technique especially suitable for representing extensive homogeneous regions such as extensive areas of grassland. However, to date studies by Stuart and Hogg have focused particularly on resource analysis and Geographical Information Systems rather than on interpretation of Landsat TM for upland vegetation mapping (Hogg *et al.*, 1989; Stuart and Hogg, 1987). In addition, Foody and Wood (1987) also used Landsat TM data and GIS for environmental monitoring, notably for the semi-natural habitats of lowlands heaths of Surrey.

In the Ash Ranges heathland, northwest Surrey, Wood and Foody (1989) also explored the potential of Landsat TM data for mapping lowland heath vegetation communities. Landsat TM data, scene 204/24, recorded in October 1984 and a supervised multivariate discriminant analysis were used to classify six major land cover classes, namely coniferous woodland, deciduous woodland, pioneer and burned heath, bracken, dry *Calluna vulgaris* heath and wet *Calluna vulgaris* heath with bog. It was reported that 87% classification accuracy had been achieved. Bracken, however, was poorly classified.

As satellite multispectral imageries have been used by many researchers for upland vegetation mapping, McMorrow and Hume (1986) have used Airborne Thematic Mapper (ATM) data for vegetation mapping in central Wales. The data was acquired on 21 August 1984, bands 3, 4 + 5 and 7 were used to represent SPOT data bands XS1, XS2 and XS3 which produced a pixel size of approximately 8.5 m X 6.0 m. An unsupervised classification was applied, prior to the maximum likelihood supervised classification, producing sixteen classes to represent eleven land cover groups including water, unvegetated, conifers, bracken, improved grassland A and B, *Molinia* grassland, *Nardus* grassland south and north facing slope, *Calluna* mires and dwarf shrub heath. It was reported that an average accuracy of 80% was achieved, with *Molinia* among the highest accuracy (89.5%) and bracken the lowest (40.6%). However, topographically-induced illumination effects, choice of ecological criteria, and selection of training data are the most significant problems when considering the classification result. Using the same ATM data and aerial photographs of the same study area, Hume, *at al.* (1986) compared those data with the field maps. It was reported that *Molinia caerulea* and *Nardus stricta* are easily distinguished on both data sets. The area of *Vaccinium* could only be discriminated on the image. However, it was not detectable on textural grounds at the same scale on aerial photographs. For the

Nardus class, aspect effects are the main problem for the image, but less so for the photographs. The problems of topographical environments occurred on the image which caused variations in spectral reflectance, particularly in near infrared wavelengths. However, vegetation communities are more easily and accurately discriminated on multispectral imagery than on panchromatic photographs.

Wardly *et al.*, (1987) have studied spectral characteristics of heathland vegetation types using ATM and ground radiometer data. Eleven study sites were selected in the New Forest, southwest of Southampton. Two different dates of ATM data collected on 6 June and 15 September 1984 were used to determine ten vegetation types, including *Pteridium*, mature *Calluna* with bracken, wet heath, degenerate *Calluna*, burnt *Calluna*, grassland (lawn), the building phase of *Calluna*, pioneer *Calluna*, valley bog, and mature *Calluna*.. The ground data showed that there is little spectral separability in the red band due to the generally low contrast between *Calluna* and the soil background and shadow. However, the near infrared and middle infrared bands have much better spectral separability, particularly for mature *Calluna*. The ATM data of June showed that there is greater spectral separability than the ground data, especially for *Pteridium*, burnt Calluna and lawns, However, confusion still occurred between *Calluna* at various growth stage, even though *Calluna* with *Pteridium* is fairly distinct. For the September ATM data, spectral separability was high among the *Pteridium*, pioneer *Calluna*, burnt *Calluna* and lawn. This is due to the alterations of the canopy caused by phenological changes. The investigation of heathland canopy reflectance using ground radiometer and ATM data was also done by Milton and Rollin (1987). Three different ground radiometers were used to collect spectral data of heathland in the New Forest, southwest of Southampton, during the 1984 - 1987 seasons. The ATM data at nominal ground resolution of 2.5 m and 7 m were acquired on six different dates during 1984, 1985 and 1986. Three ATM bands, bands 5 (red), 7 (near infrared) and 9 (shortwave-infrared), were used to classify seven vegetation types, namely post-burn *Calluna* / pioneer *Calluna*, the building *Calluna* phase, mature *Calluna,* degenerate *Calluna,* grazed lawn, burnt areas and bog areas. Grazed land (lawn) was identifiable by its high reflectance in near infrared and shortwave-infrared bands, while burnt heather was distinct from live heather as it had a higher reflectance in shortwave-infrared. The building and mature heather phases were generally found to have lower spectral responses in all ATM bands than pioneer/post-burnt and degenerate phases. However, there is a big difference between building and mature heather, and the pioneer/post burn and degenerate phases in red wavebands, particularly in May and June. The angular response of heather canopies was also measured using ground radiometers and ATM data. All of these data were used to produce an empirical model of heathland canopy reflectance.

The study of classification of moorland vegetation types in the North York Moors, using ATM data has been performed by Weaver (1987a). The ATM data were acquired on 7 September 1983 at a resolution of about 1.4 m X 1.3 m, and recorded into seven different wavebands. The transform divergence (TD) was calculated for all combination of wavebands to identify the response characteristics of each vegetation type. It was reported that the lowest spectral separability occurred between a mature/over-age heather canopy and a similar cover interspersed with *Eriophorum* species over deep peat area. However, the mature /over-age heather was clearly separable from an older stand with higher biomass and an open canopy. The boundary between mature/over-age heather canopy and the peat surface was visible in the image but these two classes were not statistically separable. It also showed that there are clear distinctions which can be recognised between heather stands at various growth stages, from approximately 60 percent cover to a full pioneer cover, and one of more condensed growth .

The study of spectral discrimination of moorland vegetation in a complex semi-natural vegetated area of the North York Moors has been taken by Alam and Southgate (1987) using ground radiometers. The data were collected in June 1986 using two slightly different radiometers. The first radiometer had four wavebands to represent the Landsat MSS bands 4, 5, 6 and 7, and this radiometer was used in the Glaisdale Moor study area. The other radiometer had four bands representing the Landsat TM bands 2, 3, 4 and 5, which was used in the Blakey Ridge study area. The bidirectional reflectance of the three land cover types in Glaisdale (bare soils, vegetation and peat) and four vegetation types on Blakey Ridge were calculated in each band. It was reported that the peat area showed the lowest reflectance in all wavebands due to its high moisture and organic matter content. The vegetation showed low reflectance in the visible bands and higher values in the near infrared. Because of the low moisture and organic matter content, bare soil showed the highest reflectance in all bands. The spectral response for the four vegetation types showed a similar pattern, with low reflectance in visible bands and high reflectance in the near infrared wavebands. However, *Calluna* and *Erica* were spectrally distinct because *Erica* has a higher moisture content than *Calluna*. *Erica* and *Calluna* were separable from both *Vaccinium* and *Pteridium,* especially in the near infrared wavebands. Nevertheless, the spectral reflectance of *Pteridium* and *Vaccinium* are very similar because *Vaccinium* is often an understorey of *Pteridium* early in the growing season. More than 90% overall classification accuracy was achieved, with greatest success (100%) in the bare soil class.

An alternative technique for classification of upland vegetation has been performed by Wyatt *et al.,* (1988). Using multispectral imagery from Landsat-5 (TM) and SPOT-1 (HRV) of the Snowdonia National Park, various classification approaches have been applied. The uncorrected imagery and the radiometrically corrected imagery have been classified into ten groups using a maximum likelihood classifier. Overall accuracy results of 60% for uncorrected imagery and 73% for radiometrically corrected imagery were achieved. Even though classification accuracy was improved, as a result of radiometric normalization, the overall classification accuracy remains unacceptably low. Two methods of spectral mixture modelling have been applied to Landsat TM. The first method uses the SPAM software system and the second method uses maximum likelihood, resulting in six cover types (namely shadow, coniferous forest, clear felling, moorland, improved grassland and acid montane grassland) being identified. However, the accuracy of classification results of both methods was similar. From visual analysis of the images it was seen that acid grassland, improved pasture, and areas of clear felling produced a result close to the ground reference data. Although there is confusion with shadow, coniferous forests were also well discriminated.

Jones and Wyatt (1988) have studied the potential of SPOT HRV multispectral imagery and digital elevation models (DEM) for upland vegetation mapping. The SPOT-1 HRV image scene K/J 22 - 244 taken on 17 October 1986 covered a 10 X 10 km study area of Snowdonia, North Wales. A DEM of the study area was produced by automatically scanning the contour pattern at 30 m intervals at a scale of 1:250,000. However, this image had low contrast and resulted in poor false colour composites and also in poor principle component analysis. By using simple image enhancement, coniferous forest, areas of clear felling, moorland, improved and unimproved grassland were easily identifiable. Nevertheless, problems still occurred for homogeneous vegetation on different slopes of differing aspect. To minimize the effect of topography, a DEM was applied to develop procedures for radiometrically preprocessing the mutispectral data, to produced Lambertian and non-Lambertian corrected data. Two different classifications, supervised and unsupervised, were applied to the data, resulting in overall accuracies of 60%, 52% and 67% for raw, Lambertian and non-Lambertian data sets. However, the addition of the elevation data produced an improvement in the discrimination of land cover types, with the separation of high-altitude mountain grasses, improved pasture and lowlands grasses being very pronounced.

Many remote sensing researches for vegetation mapping have been undertaken in the North York Moors, and most of these research use of Landsat TM as a data source. Weaver (1987b) has been use three different remote sensing systems for monitoring bracken encroachment. Landsat MSS acquired on 27 May 1977, Airborne SPOT simulation acquired on 14 May 1984 and 7 July 1984, and Airborne Thematic Mapper simulation acquired on 9 September 1983 were used in her research. In the analysis result of Landsat MSS, which aimed to distinguish between moorland and bracken, it was reported that the bracken class can be separated from heather moorland and these two vegetation communities can be clearly mapped. Using SPOT simulation data of July 1984, which have 20 m X 20 m resolution, no clear separation of moorland and bracken signature has been found. Therefore, the areas of bracken will be confused with areas of regenerating heather, bareground or *Eriophorum* within the *Calluna* moorland. The May data produced a result which showed that bracken was more clearly separable from the moorland signatures. Nevertheless, it was concluded that using imagery at the correct temporal acquisition, bracken can be delimited and its overall signature can be sub-divided into components representing different stages of regeneration. The result of simulation TM data showed that the remote sensing technique has potential for monitoring moorland vegetation. From a consideration of these three different imageries, it can be concluded that the best result will come from using detailed spectral and spatial information of SPOT or TM data taken in summer. A study of moorland and bracken change using remote sensing techniques was also done by Southgate (1986). Four different remotely sensed data, Landsat TM, SPOT simulation, ATM and aerial photographs, were used in this research.

Jewell and Brown (1987) also used Landsat TM data for vegetation mapping in the North York Moors National Park. Multitemporal TM data of scene path 203 / row 20, acquired on 26 April 1984, 31 May 1985 and 2 May 1986 were used in this research. The visual analysis of false colour composite bands TM3, TM4 and TM5 showed that established heather stands can be distinguished from regenerating heather after fire and from the bracken stands. The peat surface as a result of recent heather burning was clearly distinct in the near-infra red band. Using a box classification, three different classes namely established heather, heather/peat surface and bracken, have been use to classify the whole study area. However, formal estimation of classification accuracy cannot be given, but from the visual analysis it is suggested that the accuracy will be high enough for management purposes.

Studies of monitoring heather burning management in the North York Moors using multitemporal Landsat TM data have been taken by Ward *et al.*, (1987, 1989). Using the near infrared band of TM data, acquired in May 1984 and May 1985, the newly burnt areas of heather were clearly distinct as dark colours on the image of May 1984. However, their separability from the surrounding heather and regenerating stands was reduced as the peat surface has been weathered and a carpet of mosses and lichens were re-established. The discrimination between elements of the moorland mosaics was possible in the visible and the near infrared bands.

The National Remote Sensing Centre (NRSC) have used Landsat TM for vegetation mapping in the North York Moors National Park. Using box classification and smoothed image data bands TM 3, TM 4, TM 5 and TM 7 acquired on 31 May 1985, the heather degenerate phase and heather building phase maps have been produced. In general, the classification result of heather was successful. However, the heather classification using single image data acquired in the Spring time was even more successful.

CHAPTER 3

THE STUDY AREA AND DATA ACQUISITION

3.1 Introduction.

The objective of this chapter is to introduce the study area and to describe the management problems in the North York Moors National Park. Data acquisition will also be considered, including Landsat TM data, ground information sources and ground radiometer data.

3.2 Description of the Study Area.

This section will describe briefly the location of the study area, physiography, geology, soil, climate, and land use and management problems in the North York Moors.

3.2.1 Location of the Study Area.

The North York Moors consist of a dissected upland plateau in the north east of England (Figure 3.1). It is located between 54^0 10' 1" and 54^0 34' North Latitude, and 0^0 25' 30" and 1^0 20' West Longitude. The moorland rises sharply to a height of over 400 m above the surrounding plains, with the exception of the seaward boundary. It extends from east to west for about 55 km inland and from north to south for about 25 km; from the North Sea coast in the east to the steep escarpments of the Hambleton Hills in the west, facing to the Vale of

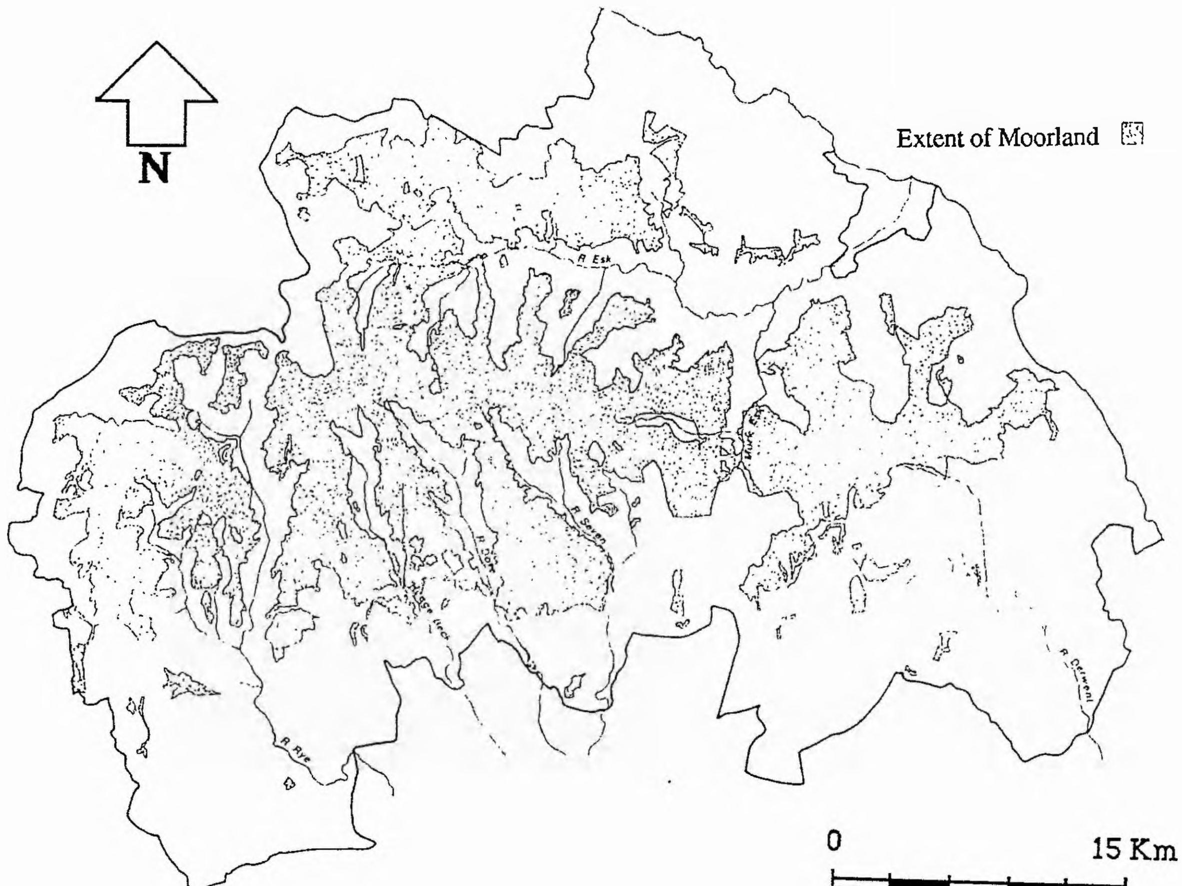


Figure 3.1 The North York Moors National Park Study Area.
(After North York Moors National Park, 1991).

Mowbray (Carroll and Bendelow, 1981). The northern boundary consist of another great series of escarpments, the Cleveland Hills, which over look the plain of the River Tees basin. The area is bounded in the south by the Vale of Pickering. The eastern boundary is marked by the sea-cliffs which extend between Saltburn and Scarborough for about 40 km.

3.2.2 **Physiography.**

It was stated by Carroll and Bendelow (1981) that the main topographical feature in the North York Moors are caused by stream erosion in the early Tertiary.

The main moorland areas on the central watershed, trend from west to east, falling from a height of 454 m on Urra Moor in the west to the lowland near the North Sea coast in the east. The moor is broken in the east by the through valley of the Murk Esk and Newton Dale. Valleys up to 250 m deep have been formed (such as the valleys of Westerdale, Danby Dale, the Fryup Dales, Glaisdale, and Wheeldale), which drain to the sea through the River Esk. The larger and broader valleys of Ryedale, Bilsdale, Bransdale, Farndale and Rosedale drain southwards to the Humber through the River Derwent, whilst Harwood Dale and Flyingdales drain to the east (Carroll and Bendelow, 1981).

The Tabular Hills are bounded by a north facing scarp which rise up to the height of 60 m above the moorlands which lie immediately to the north. This plateau gently dips to the south, towards the Vale of Pickering. The Hambleton Hills in the west, rise to 398 m at Black Hambleton and end in a great scarp, falling to about 180 m to the vale below (Carroll and Bendelow, 1981).

3.2.3 Geology.

The North York Moors are underlain by rocks of the Jurassic period. Deposition of the Jurassic sediments began 213 million years ago and continued for about 63 million years (North York Moors National Park, 1990). The youngest rocks in the North York Moors are 150 million years old with the exception of Cleveland Dyke, a stream of molten lava injected into the rocks of the high moors (Figure 3.2).

The sedimentary rocks in the North York Moors have been classified into four groups, including Kimmeridge Clay Group (the youngest), Middle Oolite Group, Ravenscar Group, and Lias Group (the oldest). In particular, the Jurassic rocks are subdivided into Lower, Middle and Upper.

a). Lower Jurassic.

The lower Jurassic system is termed the Lias (flat stone) which divides into Lower, Middle and Upper. The Lias Rocks can be clearly identified as they are relatively soft and form the bottom and sides of the dales (Cundill, 1971). The Lower Lias rocks are mainly argillaceous, ranging from dark grey clay shales to soft sandy shales. They can be calcareous, siliceous, siderite mudstone concretions, and can be found in the floors of the valleys incised into the moorland (Carroll and Bendelow, 1981).

The Middle Lias rocks consist of fine to medium -grained micaceous sand stones and ironstone, often cemented by carbonate, overlain by ferruginous mudstones and shales. The ironstone deposit, or Dogger, has been extensively worked causing surface disturbance, particularly

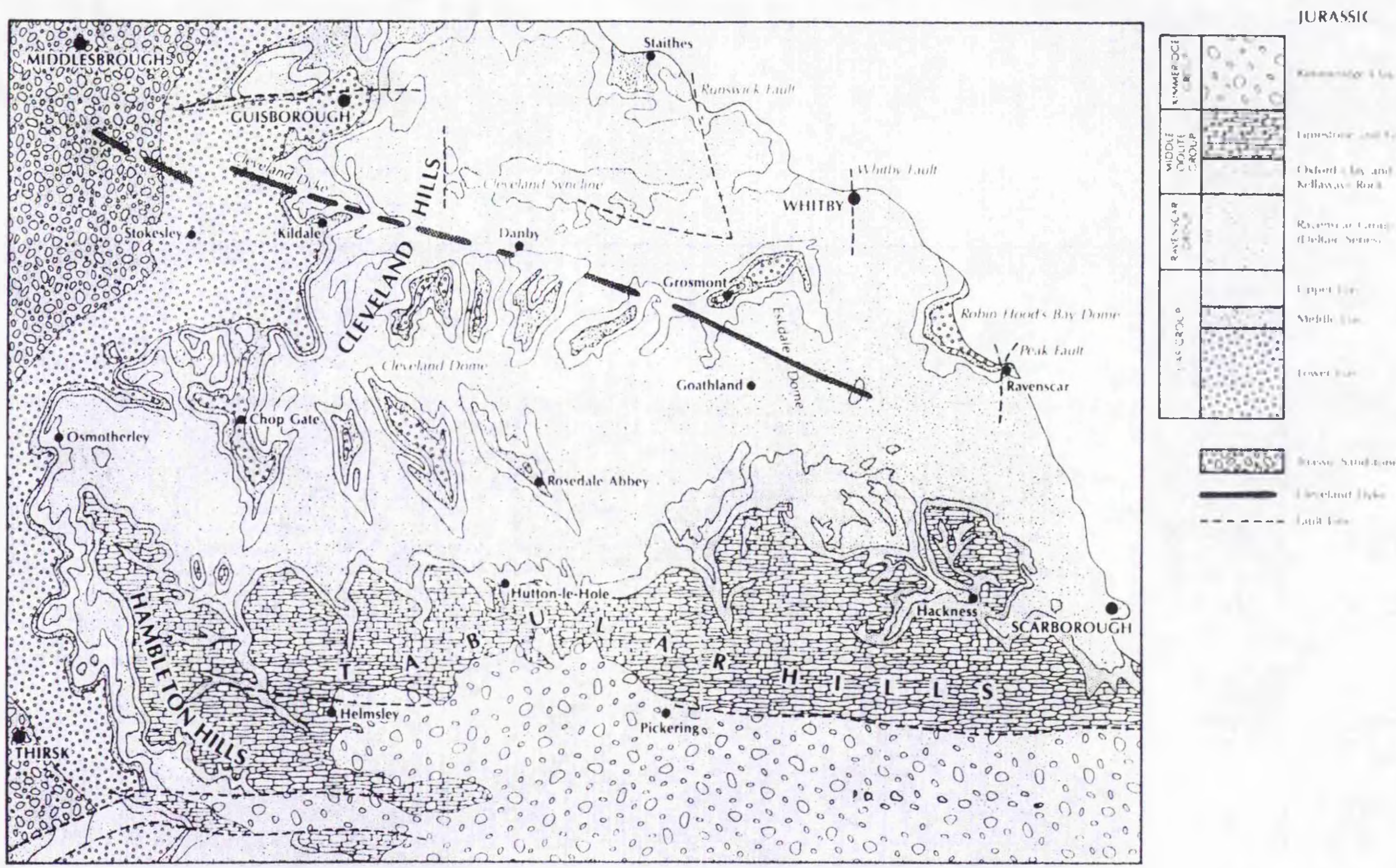


Figure 3.2 The Geological Map of the North York Moors.
(After North York Moors National Park, 1990).

in Rosedale and Cleveland Hills (North York Moors National Park, 1990).

The Upper Lias rocks mainly contain argillaceous, pale grey soft silty shales, often with calcareous inclusions, and also include denser, finely laminated dark brown bituminous shales with jet rocks, which form steeper valley sides (Carroll and Bendelow, 1981).

b) Middle Jurassic.

The moorland area from Ravenscar to Black Hambleton is mainly composed of Middle Jurassic rocks, whereas the greatest thickness of these rocks is the Estuarine Series or the Deltaic Series. These consist of clay or clay shales, sandstones, siltstones, coals, ironstones, sometimes capped by Moor Grit, a hard quartzitic sandstone (Carroll and Bendelow, 1981). The Middle Jurassic rocks mostly consist of clay or clay shales, which usually form an undulating moorland covered by clays with a peaty surface.

c) Upper Jurassic.

In particular, there are two types of the Upper Jurassic rocks, the Oxford Clay and the Corrallian rocks. The Oxford clay is a grey, slightly calcareous and silty clay or clay shale, which occurs at the base of Tabular Hills scarp. The Corrallian rocks mostly consist of calcareous grit, limestones, and hard siliceous sandstone. These form the plateaux of the Tabular, Hackness and Hambleton Hills. The oolitic limestone of the Corallian caps the Tabular Hills and helps to form the distinctive scarp.

It was stated by the North York Moors National Park (1990) that all the rocks forming the North York Moors belong to the sedimentary class. Even though there are many different types of sedimentary rocks in this area, they may be divided into four groups namely Kimmeridge Clay Group, Middle Oolite Group, Ravenscar Group (Deltaic Series) and Lias Group (Figure 3.2). The Kimmeridge Clay Group form the low ground of the Vale Pickering, while the Middle Oolite groups (consisting of Kellaways sandstones, Oxford clay, Lower Calcareous Grit, Coralline Oolite and Upper Calcareous Grit) form the Tabular Hills and Hambleton Hills.

3.2.4 **Soil.**

Soils are composed of mineral material derived from the parent rock, whether drift or solid, in the form of particles in one or more grades such as sand, silt or clay to which organic matter is added and incorporated (Cheatle, 1976). In general, there are five types of environmental factors which control the development of a soil: parent material, climate, relief, time-factor, and vegetation (Pearsall, 1971). It was known that the soils in the North York Moors have a strong relationship with the geological parent material (Carroll and Bendelow, 1981; Cundill, 1971; Dimbleby, 1952b; Jacks, *et al.*, 1984), and are generally very poor and mainly acid soils.

In particular, there are six main soils types, which divided into twelve groups: Lithomorphic soils which include the Rankers and Rendzinas groups, Pelosols (Non-calcareous pelosols), Brown soils (Brown earths, Argillic brown earths and Paleo-argillic brown earths), Podzolic soils

(Podzols, Gley-podzols and Stagnopodzols), Surface-water gley soils (Stagnogley soils and Stagnohumic gley soils), and Organic peat soils which include raw peat soils (Carroll and Bendelow, 1981). However, only podzols, gleys and organic peat soils are represented on the upland central watershed (Cundill, 1971).

Cundill (1971) showed that the soils of the central watershed were formed by heavy rainfall which removes the upper soil nutrients by leaching (Figure 3.3). In the wet uplands, intense leaching will produced strongly acid soils, while intense leaching and clay translocation (Figure 3.3) can lead to podzolisation (Figure 3.3) (Jarvis *et al.*, 1984). Podzolisation influence the drainage of soils, as leaching increases with altitude the acid brown earths will change to brown podzolic soils (Jarvis *et al.*, 1984), and may be succeeded by podzols on steep slopes which are relatively well drained.

It was stated by Jarvis *et al.* (1984) that man has influenced the soil by modifying the native vegetation particularly through agricultural practices. Dimbleby (1952b) described a deciduous forest growth on a brown forest soil until Bronze Age times, whereas heathland is the result of man's influence from that time onward accompanied by the development of advanced podzols. Deforestation will altered the micro climate and break the sequence of nutrient recycling which is favourable to brown earth formation. This will lead to acidification, podzolisation and the invasion of heather. Moreover, heather will cause acid humus to develop and form thin peat in wetter sites (Jarvis *et al.*, 1984).

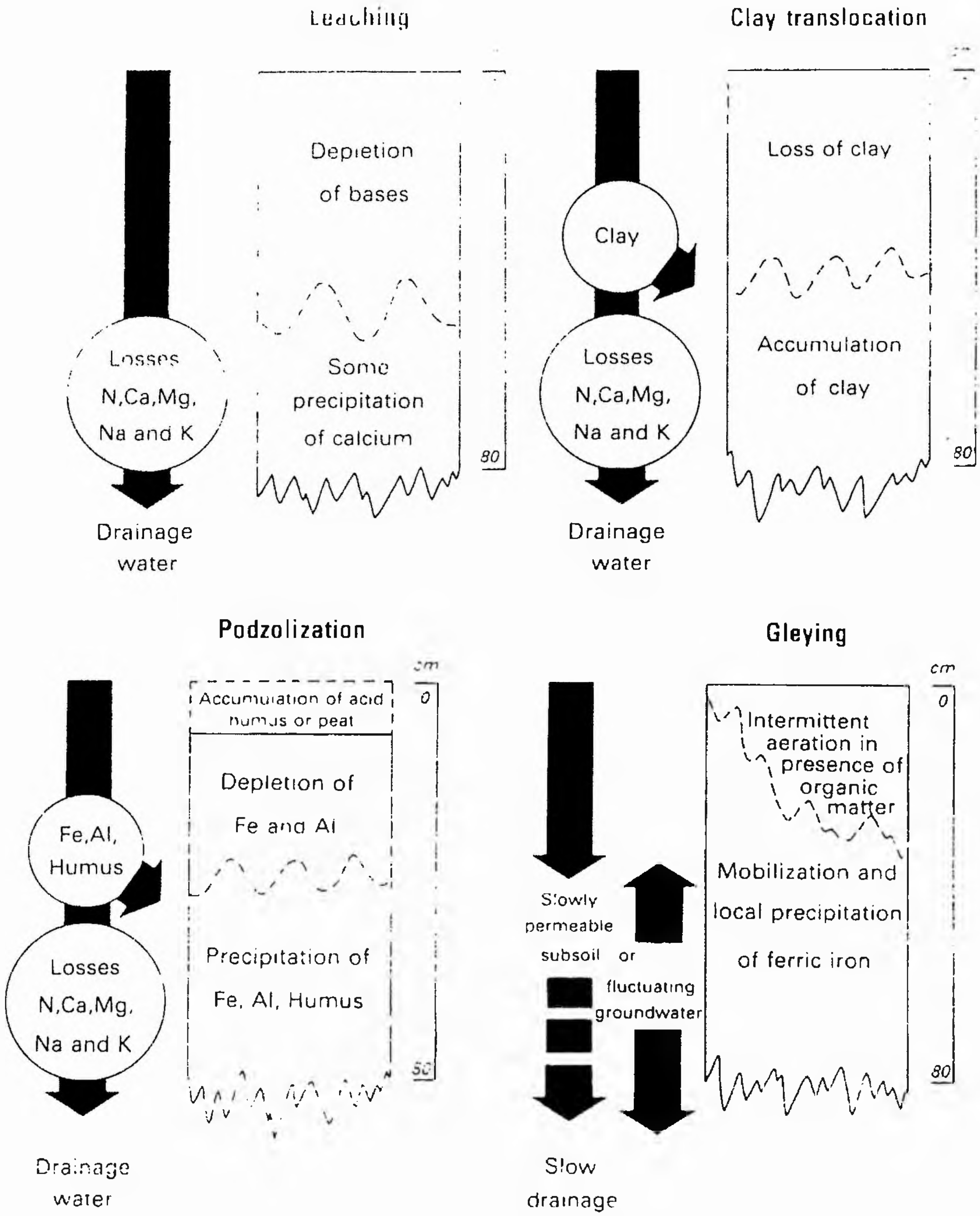


Figure 3.3 Soil Forming Process (Leaching, Clay translocation, Podzolization, and Gleying), and the Movement of Soil water.
(After Jarvis, *et al.*, 1984).

There are two main types of organic soil on the watershed, namely basin peat and blanket or hill peat , which at least have 40 cm depth of organic material (Carroll and Bendelow, 1981). The peat subsurface horizons, between 30 and 90 cm thickness, are derived from oligotrophic plant communities and are mostly composed of semifibrous or amorphous material (Carroll and Bendelow, 1981). Basin peats usually occur in natural depressions and on flat land with poor drainage. The majority of peats on the central watershed occur in the basin areas. Nevertheless, the peat has not spread from these basins due to the low rainfall in the North York Moors (Cundill, 1971). Most of the hill or blanket peat on the watershed has spread over grit on Egton High Moor and on the moors above Rosedale and Farndale. There are various depths of the hill peat on the central watershed. Cundill (1971) found that the maximum depth at Bluewath Beck was is just over three metres. However, Simmons (1969) found that the maximum depth is about six metres on Egton High Moor.

3.2.5 **Climate.**

The range of weather condition in the North York Moors is wide (North York Moors National Park, 1977). However, as described by Cundill (1971), the information about climate is very limited. Most of detailed information was provided by the meteorological stations in the surrounding lowland area.

The average annual rainfall in the North York Moors is relatively low, it is about 1015 mm in the high ground and about 762 mm in the low ground (North York Moors National Park, 1977). Cundill (1971) showed

3.2.6 Land use and management problems

There are four major land use in the North York Moors National Park (North York Moors National Park, 1977), in which farm land is the largest category covering about 570 square kilometres or about 40% of the area. The moorland area covers about 500 square kilometres or about 35%. Forested areas cover approximately 344 square kilometres or about 25%, where about 20% is coniferous woodland, and only 5% is deciduous woodland. There are also small areas of settlement and industry.

Carroll and Bendelow (1981) showed that agriculture is the biggest land use area which mostly consists of arable cropping and permanent grassland. Most arable crops spread from the west (Hambleton Hills) to the east coast, while grassland is mainly on the dipslope to the west of Pickering. In the central watershed, most of the permanent grassland and arable cropping are limited in the valleys, while most of agriculture land in the north of the North York Moors is used for grass and arable crops. Sheep farming is very common and most are grazed on the moorland. However, dairying is important in the central moorland and in the Cleveland area mainly to supply the industrial towns of Teeside and the coast.

About 500 square kilometres of the North York Moors is covered by moorland which is mainly used for sheep grazing and rearing of grouse (North York Moors National Park, 1991). The moorland is dominated by Ling (*Calluna Vulgaris*) in which the young shoots of the *Calluna* are needed to feed the sheep and grouse. It is necessary to manage this resource by burning the heather in small strips on a cycle of approximately 10 to 15 years. This will result in a patchwork of *Calluna* at various growth stages. The old *Calluna* is less productive; it also has high calorific values, and creates a fire hazard. It will burnt intensely and may damage or destroy the underlying soil, particularly medium depths of peat (North York Moors National Park, 1986).

Forestry is one of the major land uses of the North York Moors and occupies about 20% of the area. This forest land was designated primarily for timber production. About 23.690 ha forest in the North York Moors is owned by the Forestry Commission, and about 5.126 ha is owned by private sector (MacEwen and MacEwen, 1982; North York Moors National Park, 1977). The forest plantation is dominated by conifers which have been planted since 1921. Most of the species are Scots pine (*Pinus sylvetris*), and there is also a large area of Japanese larch (*Larix kaempferi*) and Sitka spruce (*Picea sitchensis*), and a small area of Lodgepole pine (*Pinus contorta*), Norway spruce (*Picea abies*), and European larch (*Larix decidua*) (Carroll and Bendelow, 1981).

Considerable areas of the North York Moors have been reclaimed in recent years. In particular, one policy of the National Park Committee is to discourage the conversion of moorland to agricultural land. It was reported that since 1853, over 200 square kilometres of the National Park's moorland has been changed to agriculture or forestry (North York Moors National Park, 1991). Between 1950 and 1975, about 38.8 square kilometres of the 1950 moorland area has been converted to agricultural land (Table 3.1) (North York Moors National Park, 1977), while between 1950 and 1984 the conversion of moorland area to agricultural land is about 50.1 square kilometres or about 7.4% of the 1950 moorland areas. However, despite moorland conversion to

	Area (Square km)	% of 1950 Total Area
Moorland area:		
in 1950	678.7	100.00
in 1975	528.6	77.88
in 1984	502.7	74.06
Change between:		
1. 1950 - 1975:		
to Agriculture	38.8	5.7
to Forestry	111.4	16.4
2. 1950 - 1984:		
to Agriculture	50.1	7.4
to Forestry	124.3	18.3

Table 3.1 Conversion of Moorland and Rough Pasture in the North York Moors, 1950 - 1975, 1950 - 1984. (After North York Moors National Park, 1977; 1986).

agricultural land, Parry *et al.* (1986) showed that between 1853 and 1979 about 20.6% of improved farmland has been converted to forest cover.

There is a policy in the National Park to encourage regular moorland burning, at least every 15 years to avoid fire risk and reducing productivity. It was reported that in the dry summer of 1976, a series of moorland fires destroyed a large area of moorland in the Rosedale Head, Glaisdale Moor and Wheeldale Moor (North York Moors National Park, 1977). Such fire will caused the destruction of the peat and to the total loss of moorland vegetation (Barber, 1986).

The pressure facing the moorland areas also occurs as this land use is being converted to agriculture or forestry. Table 3.2 shows the areas of moorland suitable for conversion to agricultural land or to forestry. About 22% of the 1950 moorland area has been converted to agriculture and forestry between 1950 and 1975 and this figure was increased by a further 4% between 1975 and 1984, and conversion is still continuing today (Table 3.1) (North York Moor National Park, 1977; North York Moors National Park, 1986; and Rees, 1991).

Another loss of moorland area occurs with bracken encroachment. In 1988, about 28% of the total moorland area was encroached upon by bracken, and it was spreading at the rate of over 120 ha annually (North York Moors National Park, 1986; North York Moors National Park, 1991). Bracken is mostly found on the steep and better drained slopes surrounding the moors. Once bracken becomes established, it modifies the soil, reducing acidity and creating a nutrient rich litter layer. This reduces the heather seed germination and regeneration of heather stand (North York Moors National Park, 1986).

	Area (Square km)	% of Open Moorland
1. Land suitable for afforestation.	437.8	85.0
2. Land suitable for agriculture and conversion.	169.9	33.0
3. Land suitable for agricultural conversion but not afforestation.	17.0	3.3
Total area suitable for conversion	454.8	88.3

Table 3.2 Areas of Open Moorland Suitable for conversion to Agricultural and Forestry.
(After North York Moors National Park, 1986).

A further problem producing moorland comes from erosion which leads to soil loss. This can be caused by unstable surface areas resulting from fires, old mining operations, laying of pipe lines, old peat working and trampling; poorly-managed heather; visitor pressures; and poor vegetation management (North York Moors National Park, 1986). However, the biggest single threat comes from over-aged highly-lignified heather producing a potential fire hazard. The main moors under erosion threat are Rosedale, Glaisdale, Wheeldale and Danby High. About 97.8 square kilometres of the moorland areas is classified as eroding, eroded or liable to degradation (Table 3.3) (North York Moors, 1986).

3.3 **Landsat Thematic Mapper (TM) of the study area.**

A brief description of the Landsat Thematic Mapper (TM) used in this research and the choice of study extracts will be presented in this section.

3.3.1 **The image of the study area.**

The image which used in this research in this research was produced using Landsat 5 TM data from path 203 / row 22, recorded on 31^{st} May 1985. To reduce pixel confusion during classification, this Northern England scene was extracted into smaller areas. The subscene was 701 by 967 pixels in size and covered only the central watershed of the moorland. It was located between North Latitude $54^{0}17'10''$ and $54^{0}28'30''$, and East Longitude $0^{0}38'17''$ and $10^{0}5'15''$.

	Area (Square km)	% of Open Moorland
1. Area subject to erosion and degradation.	97.8	19.0
2. Area subject to erosion also suitable for agriculture and afforestation.	62.3	12.0
3. Area subject to erosion outside land suitable for agriculture and afforestation	35.5	7.5
Total area subject to erosion	195.6	38.5

Table 3.3 Areas of Open Moorland Subject to Erosion.
(After North York Moors National Park, 1986).

The Landsat TM image of the study area was geometrically corrected by using Nearest Neighbour analysis, with estimated error is <0,85 of a pixel. The sun azimuth is 45^0 and the sun elevation is 54^0.

This image was chosen because of good quality and there is no line banding. A small amount of cloud cover is found in the bottom left corner of the subscene. As this image was taken in the early summer, it is particularly good to distinguish between heather and bracken.

3.3.2 The choice of study extracts.

In an extensive area with a variety of land forms and vegetation cover, it is possible to have classification problems, particularly in spectral pattern recognition. To use full image resolution and to reduce misclassification risk during the interpretation process, it was necessary to define some study extracts within the subscene of the study area. In this research, the study extracts have been selected using the National Grid system at a scale of 1:10.000, to facilitate image interpretation and field checks, and also to assist in accuracy assessment. Every study extract covers an area of 5 km by 5 km.

Five study extracts have been chosen to represent all vegetation communities in the North York Moors, namely Blakey, Egton, Farndale, Glaisdale and Whitby. The first study extract area is Blakey which covers an area of sheet SE 69 NE. Include in this area are Blakey Ridge, High Blakey Moor and Horn Ridge in Farndale west. Most of this study area is covered by farmland dominated by improved grassland. Bracken is found mostly surrounding Horn Ridge, on the east and west slope of Blakey Ridge and on High Blakey Moor. The second study extract is Egton which covers an area of sheet NZ 70 SE which includes Egton High Moor, a part of Glaisdale Moor, Glaisdale Side and Egton Grange. This area is dominated by heather with only a small area of bracken. Plantations of coniferous woodland (PCW), improve grassland and arable land are also found. Farndale is the third study extract which covers an area of sheet NZ 60 SW. Included in this study area are Baysdale Moor, Stockdale Moor, a part of Westerdale Moor, Cockayne Ridge, Greenhow Moor and Ingleby Moor. Most of this area is covered by heather, with most of the bracken being found in Middle Head, Greenhow Bank and Baysdale Moor. The fourth study extract is Glaisdale which covers part of sheet of NZ 70 SW. The Cock Head of Glaisdale Moor, High Moor, Glaisdale Rigg, a part of Danby High Moor and Danby Rigg are included in this study extract. Heather is the dominant vegetation with improved grassland as the second major vegetation. Acid Flush (AF) is found in Westhill Head and in Middle Head with *Juncus* and *Sphagnum* dominant. The last study extract is Whitby which mostly covered sheet NZ 80 SE and a part of sheet NZ 80 SW. This study area was chosen to include Sleights Moor, Low Moor and Sneaton High Moor. Heather is the dominant vegetation while plantations of coniferous woodland, bracken and improved grassland are also found in this study area. The location of the study extracts is shown on Figure 3.4.

3.4 Ground Information Sources.

Ground ancillary data was important to support image classification, particularly for defining the training areas. Most importantly, the

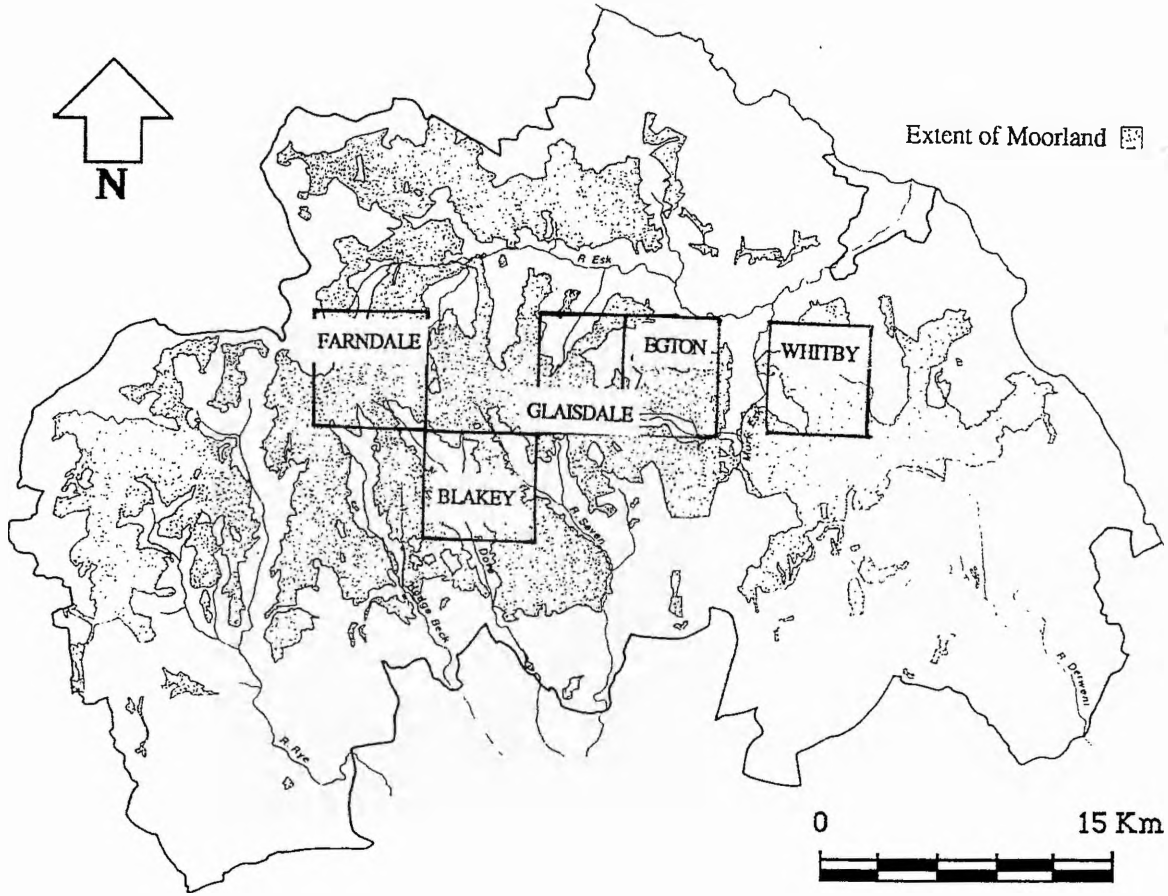


Figure 3.4 The Location of the Study Extracts.

quality of the training process determines the success of the image classification, therefore better training classes will give a better interpretation result. To achieve an acceptable classification result, training data must be representative, homogeneous or uniform, and at an accurate location. Consequently, ground information data are needed, such as topographical maps, aerial photographs, vegetation maps, land use / land cover maps, and other ground truth data (*e.g.* field checks, quadrats and ground radiometers readings), as a guide to the delineation of training area boundaries.

In this study, some useful ground truth data have been obtained: including Habitat maps, aerial photographs, topographical data, and ground radiometer values. All these ancillary data will be described briefly in this section while the ground radiometer data will be described in the next section (Section 3.4).

The main supplementary data source for vegetation communities distribution was the Habitat Map at a scale of 1:10.000. This is the best information data, and has been compiled from airphoto interpretation and field studies. This map is a Phase 1 map of sites of high conservation values, published by North York Moors National Park in 1988 / 1989. It is quite useful in indicating details of vegetation communities and also very helpful for guidance in the determination of training area boundaries. The description of Habitat Map categories has been given by the Nature Conservancy Council (1990).

Another excellent ground information source for this research is the new colour aerial photographs taken on 21st October 1991, at a scale of 1:10.000. However, these aerial photographs are only available for part of the study area. The samples of these aerial photographs are briefly described as follows:

1) **Print No.:** 91 - 38 - 9 **Location:** Glaisdale Rigg

G.R. Centre: NZ 740 040

Description: Glaisdale to East, Great Fryup Dale to West. Some cloud cover at the centre left and top right corner of the print. *Nardus* bog in centre of northern edges of print. Bracken sprayed in 1990 shows as patchy grey areas on either side of the road. Russet tones of unsprayed bracken above improved land in Glaisdale Dale.

(2) **Print No.:** 91 - 38 - 3 **Location:** Head of Northdale

G.R. Centre: NZ 718 002

Description: Dead woodland with sprayed bracken on North East slope. Burning of various ages with flush at head of valley feeding in to Northdale. Cotton grass (brownish tone) in extreme North East corner of print.

(3) **Print No.:** 91 - 40 - 53 to 91 - 40 - 56 inclusive.

Location: Glaisdale Head to Northdale Head

G.R. Centre: NZ 745 015 to SE 728 997

Descriptions:

a) Print No. 91 - 40 - 53
Bracken clearly visible, including patches in moor where untreated.

b) Print No. 91 - 40 - 54 (see Plate B).
Experimental plots to South of road shows up as light areas.
Cotton grass moor.

c) Print No. 91 - 40 - 55
As for (b), print is of better quality. Variations stands out much more clearly. Includes treated bracken at head of Northdale.

d) Print No. 91 - 40 - 56 (see Plate A)
Much treated bracken, heaths more various stages of grown, + Lyke Wake walk.

Two topographic maps have been used for this research. The Ordnance Survey outdoor leisure map of the North York Moors at a scale 1:25.000 was compiled from 1:10.000 scale maps and published by the Ordnance Survey in 1982. Another topographic map is the Ordnance Survey tourist map at a scale of 1: 63.360 (one inch to one mile), published in 1966 by the Director General of the Ordnance Survey. These maps were useful to locate the training areas, as topography has a marked influence on the vegetation reflectance (section 2.2.2.3.2.4).

3.5 **Ground Radiometer Measurements.**

Techniques for the measurement of the spectral response of objects under field conditions was introduced at the beginning of this century, particularly for use in the study of human vision. As the use of airborne remote sensing in the USA increased in the late 1960's, ground instruments were developed, particularly to calibrate the new sensors and to investigate the interactions at ground level (Milton, 1987). Since the development of satellite remote sensing, many types of radiometer have been designed for used in the remote sensing field.

Plate A 1 : 10,000 Aerial Photograph (1991) of Glaisdale Study Extract (reduce to 1 : 16,000 for illustration).
See Plate C for location on TM image.

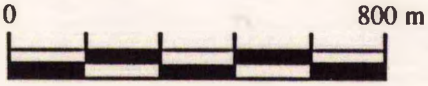


Plate B 1 : 10,000 Aerial Photograph (1991) of Glaisdale Study Extract (reduce to 1 : 16,000 for illustration).
See Plate C for location on TM image.

0 800 m

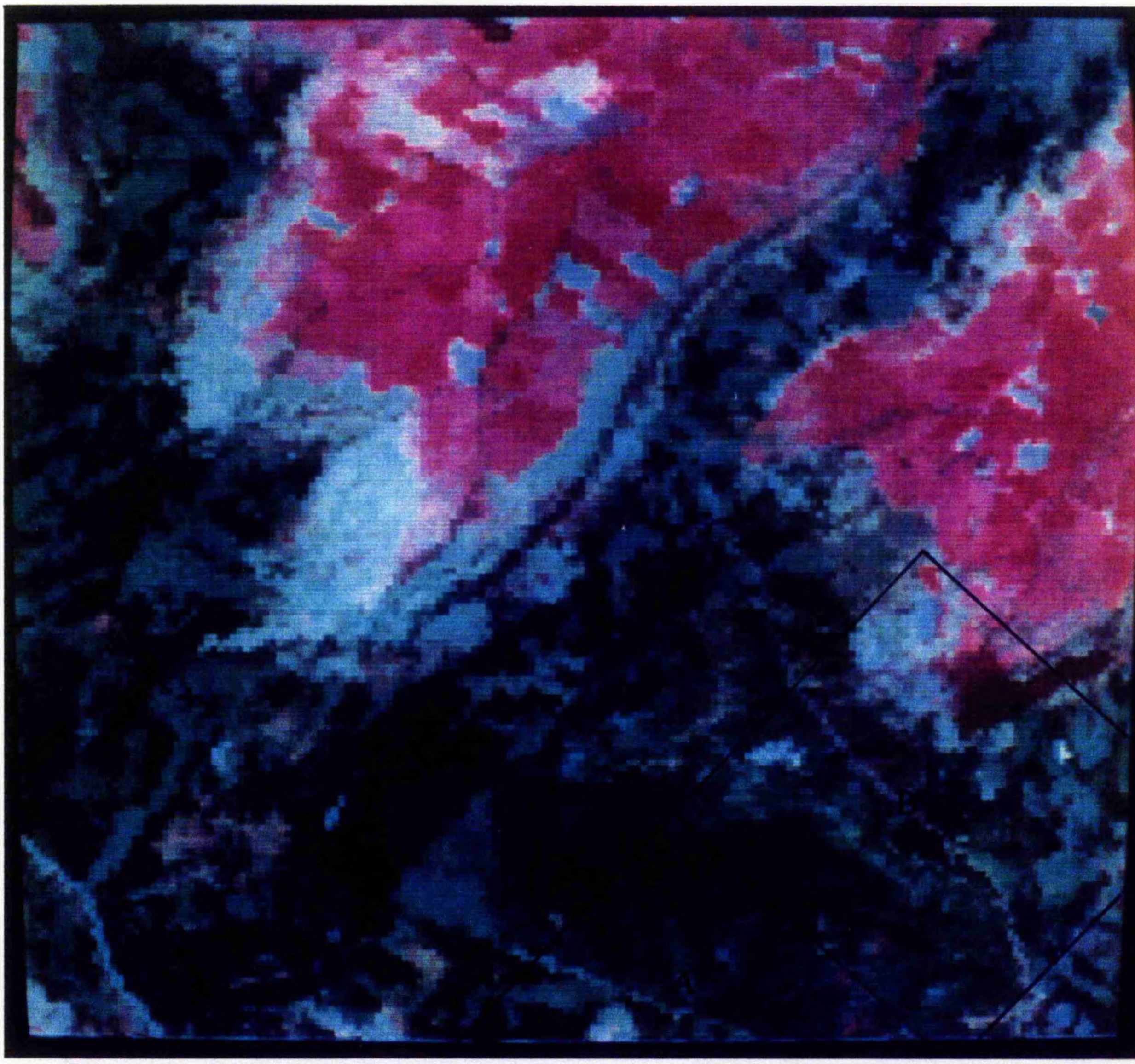
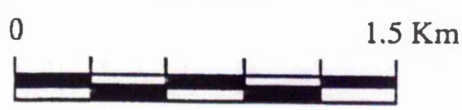


Plate C Location of 1 : 10,000 Aerial Photographs (Plate A & B).



To date, collecting ground radiometer data has apparently become an essential part of remote sensing work. The measurements of field spectral reflectance within remote sensing have several terms, including "hand-held radiometer", "field radiometry", "reflectance spectrometry", "field spectroradiometry" and "ground radiometry" (Milton, 1987). Longshaw (1974) introduced the term of field spectroscopy as the study of the relationships between the spectral response of objects and their biophysical attributes in the field environment. The spectral characteristics can be measured using spectro radiometers or spectrometers which can sense over a wide range of wavelength in a continuous manner, or using radiometers which sense only in a limited number of preset spectral bands (Milton, 1987).

3.5.1 The use of field spectroscopy in remote sensing.

Milton (1987) showed that ground spectroscopy measurement has an important role at least in three main areas of remote sensing : calibration, prediction, and modelling.

One of the most difficult problems of remote sensing concerns the intercalibrations of data from different platforms and sensors, or from the same sensor at different times (Milton and Webb, 1987). Even though in-flight calibration is common, the calibration airborne and satellite sensors using ground site data, where reflectivity is well known, will be more effective. Therefore, it is necessary for the radiometer or spectroradiometer to have an identical wavebands to the remote sensors, and also it must be highly linear and stable with respect to environmental changes (Milton, 1987).

The field spectroscopy has also been used for prediction, in which radiometer data may be used to predict the optimum band (Tucker, 1978), the optimum geometric configuration of source and sensor (for example look angle, time of day, etc.), and the optimum season of the year, for a specific project. (Milton, 1987).

Field spectroscopy also provide data for the development and testing of models in relation to biophysical and remotely sensed attributes (Milton, 1987). Budd and Milton (1982) showed the correlation models such as relationship between green leaf area index (GLAI) and the infrared/red ratio, while Suits (1972), and Chance and LeMaster (1977) described analytical models such as the various canopy reflectance models.

In spite of the potential of field spectroscopy, there are several factors which must be considered before it used in research.

The spatial and spectral resolution of radiometers differs from that of remote sensing sensors. The spatial resolution of satellite sensors range from 1000 m for the NOAA/AVHRR, 79 m for Landsat MSS, 30 m for Landsat TM, 20 m for SPOT or 10 m for SPOT panchromatic (Lillesand and Kiefer, 1987), while a radiometer with approximately 15^0 field of view and mounted at a height of about 3 m will have a resolution of approximately 1.3 m in diameter (Macaulay Institute, 1986). The spectral resolution of the satellite sensor and the radiometer are also different. The Macaulay radiometer used in this research has only two bands, red and near infrared (section 3.5.2) which is roughly correspondent to the Landsat TM band 3 and 4 (section 2.2.1.2, table 2.2). In addition, Duggin and Phillipson (1985) showed that there is a distortion in the reflectance which is detected by satellite sensor. The principal cause of this distortion is atmospheric attenuation and forward scattering. This would therefore affect the result of radiometer measurements. Milton (1987) showed that even though the path length of a reflected beam through the atmosphere was not as long as that of an incident beam, given the contribution of sky light to the incident beam and changes in atmospheric properties, a significant atmospheric effect is produced on the field reflectance measurements. Another problem which may be expected to occur during data collection is caused by the presence of nearby objects. Kimes *et al.* (1983) showed that the presence of the researcher's body during radiometer data collection has two erroneous effects on the radiance measurements. First, the body could block a portion of the diffuse solar flux to the target point. And second, the body could reflects the direct solar flux, incoming diffuse solar flux and reflected ground flux to the target point.

However, in spite of these problems, ground reflectance data would help in estimating the similarity response from satellite sensors.

3.5.2 **The Macaulay portable radiometer.**

A radiometer is an instrument for monitoring and recording the electromagnetic radiation at a number of spectral regions, reflected from a target scene (Adams, *et al.*, 1985; Macaulay Institute, 1986). For regular field use, therefore, this instrument should be portable, lightweight, fast and easy to operate (Milton, 1981). The spectral range which can be recorded are set by placing a filter in the path of each detector (Tucker, *et al.*, 1981).The radiometer can be hand-held, mounted on the mast or tripod, or attached to and mounted on a vehicle.

Field measurements with portable radiometers are now commonly used in different field studies within remote sensing. They have been used extensively in agricultural study to determined the crop condition and yield estimation in remotely sensed data (for example Aase *et al.*, 1984; Aase and Siddoway, 1981; Everitt *et al.*, 1985 a and b; Gross *et al.*, 1988; Jackson and Robinson, 1985; Kimes *et al.*, 1984; Markham *et al.*, 1981; Pinter, 1986; Richardson *et al.*, 1983; and Tucker *et al.*, 1979). It has also been used for agricultural and grassland studies (*e.g.* Bartlett and Klemas, 1981; Curran and Williamson, 1985; Majoram *et al.*, 1985; Miller *et al.*, 1976; Milton, 1980; Richardson and Everitt, 1987; Richardson *et al.*, 1983; and Ripple, 1985 a and b). The study of vegetation, leaf area index and biomass using radiometers have also been carried out by Budd and Milton (1982), Curran and Williamson (1987), Hardisky *et al.* (1983), Holben *et al.* (1980), Pearson *et al.* (1976), Richardson and Everitt (1987), Wardley and Curran (1984), Wiesen *et al.* (1986), and Williamson (1987). Radiometers were also used to study the spectral reflectance of heath and moorland communities, including a study in New Forest on *Calluna Vulgaris* by Milton and Rollin (1988), and Wardley *et al.* (1987), and in the North York Moors by Alam (1985), Alam and Harris (1987), Alam and Southgate (1987), and Southgate (1986).

The Macaulay portable radiometer used in this study is a relatively cheap, lightweight (<1 kg total) instrument, easy to carry and capable of being operated in the field by one person. The full description of the radiometer can be found in Macaulay Institute (1986) and Adams *et al.*, (1985). This radiometer was a single-beam with two channels, and consist of two units: an optical reading head, and a display and control box. The working principle of the radiometer is that radiation from the target scene is monitored through a single lens and beamsplitter arrangement, at red and near infrared wavelength using filters and photodetectors. The recorded reflectance values are displayed on a digital panel at the display and control box.

The optical reading head contains two detectors with two different filters, a single concave lens, beamsplitting mirror, and two Pre Amplifiers (Figure 3.5). Radiation reflected from the object enters the optical reading head through the single concave lens, and passes to the detector via a 50/50 beam-splitting mirror which is set at 45^0. Each detector unit consists of an optical filter which has a different channel (band width). The red channel has a peak spectral response of 600 nm, whilst the near infrared channel has a peak spectral response of 880 nm. These filters can be changed to other combinations which simulate Landsat MSS, TM, SPOT, etc.

The display control unit contains the power supply, electronic assemblies and display unit seen in the schematic diagram in Figure 3.6. The signal from each detector is amplified, and sent through a sample and hold circuit to the multi-range display meter. The channel display is selected by a single channel push button switch, and the signal can be held with the read button to provide simultaneous red and near infrared reflectance reading. This radiometer can monitor not

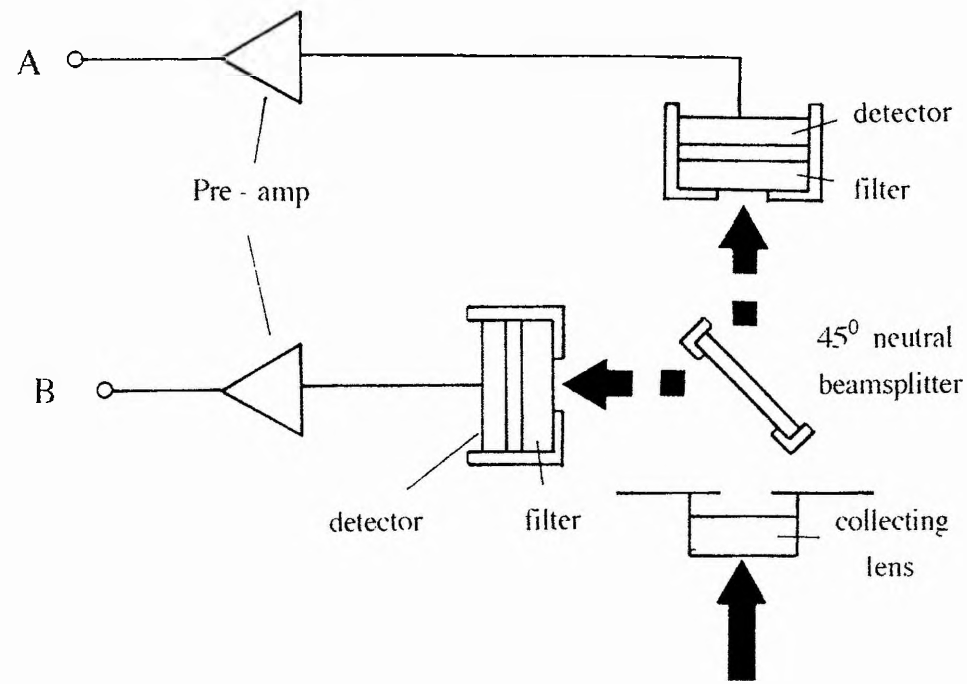


Figure 3.5 The Basic Arrangement of the Two-band Radiometer.
(After Adam *et al.*, 1985).

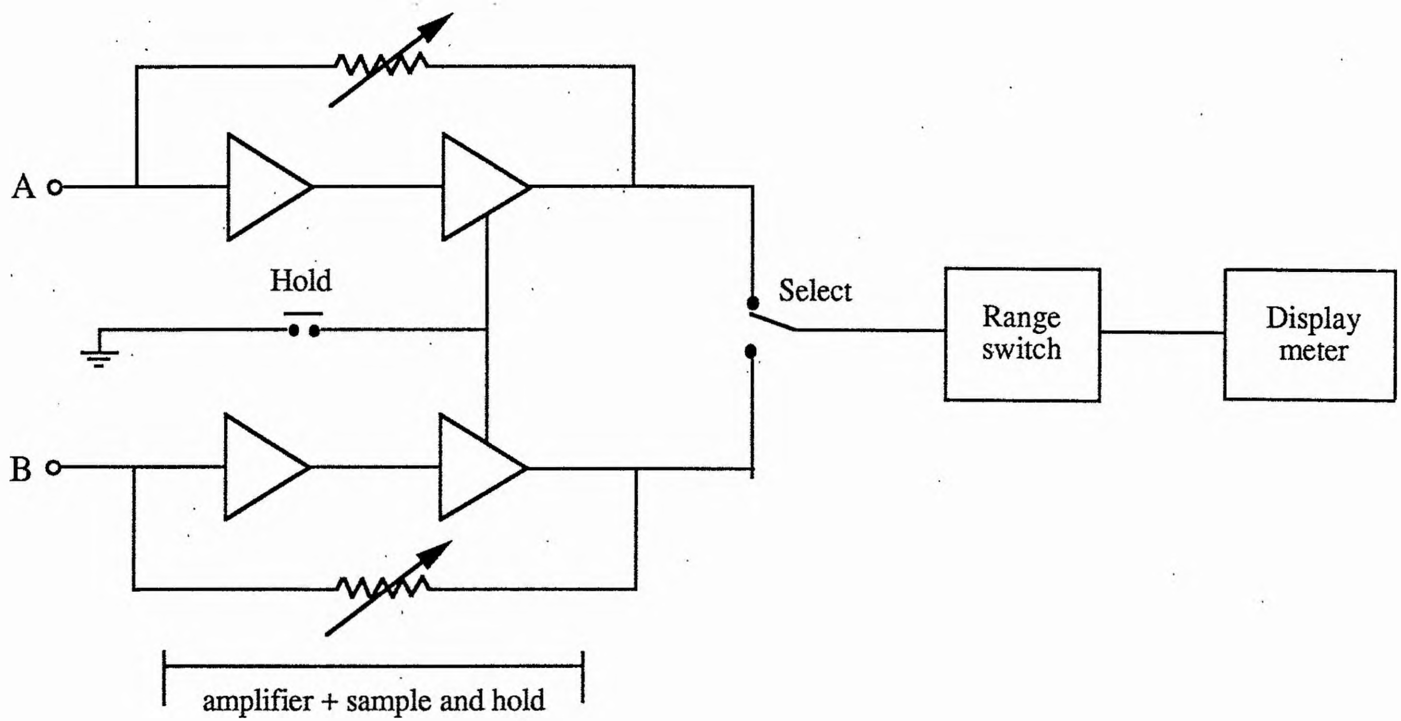


Figure 3.6 A Schematic Diagram of the Units within Control Box of the Radiometer. (After Adam *et al.*, 1985).

only the reflected light from the object but also the intensity of incident radiation at the red and near infrared wavelengths.

The Macaulay radiometer has been used in several field researches to provide information on the growth and development of vegetative canopies such as grass, winter barley, oil-seed rape and potato crops.

3.6 The Result of Radiometer Measurements.

The previous discussion has highlighted the importance of understanding the spectral characteristics of the earth's surface features before multispectral analysis are performed, as different land covers will have different spectral characteristics. Field radiometer measurements may be used to characterize various cover types, and it is therefore necessary to collect radiometer data of the major moorland communities in order to consider their spectral response in Landsat TM data.

Ground radiometer data for 13 different land covers were acquired in late March 1992 on Egton and Glaisdale Moors. In order to remove anomalies for different illumination conditions at the time of readings, the IR/R band ratio has been used in an attempt to produce spectral separation. The result are shown in Table 3.4.

The values recorded in Table 3.4 are in general accordance with what is known of the biomass of moorland communities with the highest biomass (indicated by the IR/R ratio) for the plants which are either evergreen *e.g. Vaccinium* or growing strongly *e.g.* mature and degenerate heather.

No.	COMMUNITY/LAND COVER	IR/R ratio
	***Calluna* Communities**	
1.	16 years old degenerate heather	5.26
2.	Mature heather 8 - 10 years old, 100% cover	4.67
3.	Heather 3 years old 100% cover. Site 1	3.32
4.	Heather 3 years old 100% cover. Site 2	3.18
5.	Thin burned heather cover with bare ground	2.20
6.	Newly burned degenerate heather	1.95
	Other Community	
1.	Grazed *Vaccinium myrtillus*	2.96
2.	*Juncus* acid flush	2.60
3.	Hypnum cupressiforme moss community	2.20
4.	Senescent bracken 100% cover	1.53
	Mixed Land Covers	
1.	*Vaccinium* + 10% senescent bracken	3.14
2.	*Nardus/Calluna* mix with *Erica tetralix*	1.72
3.	Bare Peat	1.51

Table 3.4 Ground Radiometer Data.

Note. All radiometer readings taken on 30-03-1992, 3 samples for each community/land cover under a range of lighting conditions from bright sun to hazy sun and cloud.

Of the *Calluna* communities, the IR/R ratio varies with the date of burning and hence the maturity of the community. It would also appear to be significant that similar ages of *Calluna* and separate moors (Sites 1 and 2, 3 years old *Calluna*, 100% cover) show remarkably similar values. As the amount of bare ground increases with newly burned patches, the IR/R ratio value decreases.

The other pure communities may again be ranked, but it should be noted that spectral confusion can be expected between thinly burned heather cover as both have a value of 2.20 for the IR/R ratio. Dead bracken with 100% cover can also be confused with bare peat at values of 1.53 and 1.51 respectively.

Mixed land covers show the greatest variation, as might be expected. As Plate 8 (Appendix 1) shows the intimate mixture of *Nardus* and *Calluna* might not be expected to produce a similar spectral response on any occasion, yet the IR/R values for three different sites within this land cover shown remarkable similarity at 1.74, 1.71 and 1.70 (average 1.72). This may suggest that band ratio values can be used to separate communities, but many more ground radiometer readings must be made, with filters designed to match the particular wavelengths for Landsat TM bands. The variability in the spectrum of moorland vegetation, different slope and light values and seasonal changes will all need to be standardized.

CHAPTER 4

DISCRIMINATION OF UPLAND VEGETATION USING LANDSAT TM DATA

4.1 Introduction.

The aim of this chapter is to describe briefly the digital image processing systems used, including the R-CHIPS image processing software, and the image classification techniques including box and maximum likelihood classifiers. The upland vegetation classification result of each five study areas and the analysis of the classification result will be described in the following section.

4.2. Image Processing.

The term of image in remote sensing refers to a continuous or discrete record of a two dimensional view (Curran, 1985). In a continuous image such as aerial photograph, the detail is displayed in a continuous signal so that can be seen and interpreted. In the other hand, the detail in the discrete image such as Landsat MSS/TM is formed in discrete digital units which can only be handled qualitatively. The discrete image comprises a number of of individual pixels (picture element), and has an intensity value which is recorded by a digital number (DN) at an intensity range between 0 (low radiance) to 255 (high radiance).

The processing of discrete images, which are stored on computer compatible tapes (CCTs), therefore need an aid of a computer. It can be a main frame computer, special built digital image processor, a micro-computer with graphics, or even a personal computer (PC). The CCTs are then read into a computer and stored the result in the form of a new digital image which may be manipulated and displayed.

In general, there are three main types of image manipulation: image restoration and rectification, image enhancement, and image classification (Curran, 1985; Lillesand and Kiefer, 1987).

1) Image restoration and rectification.

These processes are the first stage in the image processing routine to correct distorted or degraded image data to achieve a better representation of the original scene. This operation, usually called preprocessing, includes geometric correction (to correct geometric distortion), radiometric correction (to calibrate the data radiometrically) and noise removal (to eliminate noise which is present in the raw data).

2) Image enhancement.

The aim of this operation is to create a new image from the original data, to improved the quality of image, so that more information can be collected by visual interpretation. Lillesand and Kiefer (1987) suggested that this technique can be categorized as a) Contrast manipulation, including gray-level thresholding, density slicing and contrast stretching, b) Spatial feature manipulation including spatial filtering (convolution), edge enhancement and Fourier analysis, c) Multi-image manipulation including band ratioing and differencing, principal components analysis, vegetation components (Vegetation Index) and intensity-hue-saturation (IHS) colour space transformation.

3) Image classification.

The aim of this process is to classify automatically all pixels of the digital image into a specific identity describing the earth's surface objects. Usually this process involves the analysis of multispectral image data and the application of statistically based decision rules such as minimum distance means classifier, parallelepiped (box) and maximum likelihood classifiers. The box and the maximum likelihood classification techniques which are used in this research will be discussed in section 4.3.

4.2.1 R-CHIPS image processing system.

It was mentioned in a previous section that the computer was the main device to process the digital remotely sensed raw data. The computer will store and manipulate data based on the computer program (Mather, 1987). Nevertheless, the capability of computer to store a large number of data items and the facilities of computer programs (software system) depend upon the type of the computer.

Up to now, a variety of image processing systems have been developed which can improved the quality, quantity and speed of acquisition of information from remotely sensed data. Computers for processing Landsat MSS, Landsat TM, SPOT and other images have been developed by a number of institutions and commercial companies. As the cost of main frame computers was relatively high, more software systems have been developed for use in less costly microcomputer-based systems (Jensen, 1986; Ritchie *et al.* 1988) or even personal computers (PCs). However, small PCs cannot handle all of the necessary operational processing tasks (Szekielda, 1988).

One of the software systems which is compatible to the IBM PC is R-CHIPS. It was originally called "CHIPS" image processing system written by the Geography Department of the University of Copenhagen in relation with vegetation monitoring in Senegal (R-CHIPS manual, 1988). The R-CHIPS image processing system was written for educational purposes in the Geography Department, University of Reading and is now copyrighted by I.S. Limited company. The R-CHIPS version 3 has been used in the Department of Geography and Geology, University of St. Andrews since 1991, and this version has been superceded by the new version (version 4) in January 1992. This software system has been designed to combine excellent graphics display with a user friendly menu system. Therefore, users with limited understanding of image processing or computer literacy could use the system effectively.

Two user interface have been provided by R-CHIPS: the menu interface and the direct access interface. In the menu interface, the list of program options, which is called a "menu", will be displayed by the computer on the operator console. The menu interface is structured so that programs with similar functions are grouped into thematic menus. These are accessed from the main menu which allows the user to enter or exit the system, or change the interface. Therefore, once the menu option has chosen, it will be followed by a subprogram, or execute the function to continues the process. In addition, each menu has a "help" option and is also provided with "display inspection" submenu, which contains a set of routines such as zoom, data values, histogram, etc. The user can select items from the menu by using the arrow keys on the keyboard or using the mouse, to highlight the menu option required.

The direct access interface is an option that is included on the main menu. All the functions which are available in the menus are also available in the direct access. However, as this interface is placed in a disk operating system (DOS) environment, the user must know the name of the program to be run. Even though this command line interface is much faster and more flexible, it is potentially difficult for inexperienced users.

In general, R-CHIPS has both speed and functionality as it was written around a piece of graphic hardware, produced by the Number Nine Company (USA). This graphic card, called the 512 X 32, is capable of delivering a 512 pixels by 512 lines picture with 32 bits depth which allows 16 million possible colours. It also has a hardware zoom and roam with 16 look up tables for contrast and colour manipulation.

The most recent version of the R-CHIPS (version 4) have been provided with minimum distance, box (parallelepiped), and maximum likelihood classifiers. Using box classification, only up to eight classes can be selected while using minimum distance and maximum likelihood classifiers, a maximum of 20 classes can be chosen. However, due to technical problems, only up to 12 classes can be used for the maximum likelihood classifier. Another advantage of using this system is that once training areas have been selected, they can be used for both box and maximum likelihood classification techniques. However, this technique can only use up to 8 classes. Thus, the result of the box classification can be compared directly with the maximum likelihood classification.

4.3 Image Classification.

A Landsat TM images is composed of 5700 scan lines of 6900 pixels in each of seven bands, or about 39 million pixels per channel (Mather, 1987). As the spectral reflectance is recorded in seven different wavelength bands, therefore, every single pixel will be characterized by its spectral signature within different bands. As was previously discussed every single pixel has an intensity value which is recorded as a digital number (DN) within the range of 0 to 155. The different feature types will manifest different combinations of DNs, this will depend upon their inherent spectral reflectance and emittance properties (Lillesand and Kiefer, 1987).

In the automatic classification process, every pixel will be classified on the basis of comparison with the spectral signature (spectral reflectance characteristics) of the known earth's surface objects such as water, vegetation, soil, etc. (Mather, 1987). Therefore, it is possible to compose groups of similar pixels into classes by comparing the known identity of pixels with others. The most common method used in information extraction is multispectral classification. The process of multispectral classification can be performed by using unsupervised or supervised methods (Jensen, 1986).

Unsupervised classification is the identification, labelling, and mapping of natural groups or structures within multispectral data (Campbell, 1987). This process requires only a minimal amount of initial input from the analyst, without utilizing training data, as the basis for classification. The unknown pixels in an image will be collected into a number of classes based on the natural groupings or cluster of the image values. The pixels of the whole image which have similarity in each group will then be automatically classified. The classes which result from unsupervised classification are spectral classes. This is because the classification is based solely on the natural groups in the image values, without known class identity (Lillesand and Kiefer, 1987). The analyst must identity the classes by comparing the classified data with the reference data. Therefore, this method is useful if there is only limited ground data available or if the analyst is unfamiliar with imagery of a new geographical area. However, there are also some disadvantages of unsupervised classification a) The unsupervised identifies spectrally homogeneous classes within the data which do not necessarily correspond to the information that is of interest to the analyst. This will caused a problem for the analyst in matching classified data and the information provided, b) The analyst has very limited access in the process, c) The spectral properties of the classes will change on a seasonal basis, therefore, classes are not constant.

Supervised classification is the process of using samples of known identity to assigned unclassified pixels to one of several information classes (Campbell, 1987). The samples of known identity are those pixels which are located within training areas or training fields. The analyst defines training areas by identifying regions within the image which can be clearly matched to areas of known identity in the ground truth data. The training data is then used to categorized the remaining pixels in the image data set.

Lillesand and Kiefer (1987) showed that there are three basic steps in supervised classification procedures: training stage, classification stage, and output stage.

a) In the training stage, the analyst defines representative training areas and develops a numerical description of the spectral characteristics of each land cover type.
b) In the classification stage, each pixel in the image data set is assigned into a land cover class using classification strategies such as minimum distance means classifier, parallelepiped (box), and maximum likelihood classifiers. Based on the training data, which are used as interpretation keys, the classification strategies will categorize the unknown pixels into their appropriate class. The classified pixels will be recorded as an interpreted data set or an output image. However, any pixels which are insufficiently similar to the training data set will be recorded as unclassified. Therefore, the result of supervised classification accuracy depends upon the selection of suitable training areas with an appropriate choice of wavebands (Priyadi, 1992).
c) In the output stage, the result of the classification stage may be in the forms of thematic maps, tables of area statistics for the various land cover classes, or in the digital data files which could be used as a geographic information system input.

4.4 The Training Stage.

The aim of training is to obtain sets of spectral data that can be used to determine decision rules for the classification of each pixel in the whole image data set (Curran, 1985).

It was mentioned in the previous section that supervised classification methods are based upon prior knowledge of the number of spectral classes. Details of the statistical attributes of these classes are defined at the training stage. Therefore, the quality of training data determines the success of the classification stages (Lillesand and Kiefer, 1987). To achieved better training data, the choice of training areas should consider that a) training data for each class must be representative of all data for that class, b) the training data should ideally have a multivariate normal distribution, c) the location of the training area pixels should be chosen using some form of random sampling and positioned throughout the image, d) training areas should be placed within the image to permit convenient and accurate location with respect to a distinctive feature or between distinctive features on the image. This will reduce the mixed pixels at the edge of the different classes included within the training areas (Campbell, 1987; Curran, 1985; Harris, 1987). To achieve all those requirements, therefore, it is necessary to use map interpretation, aerial photographs or field work data as a guide. Following the selection of the training areas, the computer will then calculate the statistical data such as minimum, maximum, mean and standard deviation. These data will be used to classify the remaining pixels either by using supervised or unsupervised classification techniques.

In this research, only 8 training classes have been selected for all of five study extracts which are then used for both box and maximum likelihood classification. Training classes have been selected based on the dominant species within the study extracts. Therefore, a generalisation technique has been used in the grouping of training classes. The species which cover only a small area and which are difficult to identify on the image will be eliminated and other land covers such as urban and water bodies are also ignored. On the other hand, dominant species such as *Calluna vulgaris* or bracken may be grouped into two or more different classes based upon different ages or because of mixing with another vegetation species.

In this research, training classes for five different study extracts have been defined based on these criteria with the assumption that using these categories better training areas could be achieved. However, it is necessary to understand the pseudocolour of image colour composites for each of the vegetation communities in order to locate the training areas in the correct place. In particular, there are no actual differences of pseudocolour for any of the study extracts. However, owing to hard copy processing problems, one image may appear to be different from the others.

Eight training classes have been selected for the Blakey study extract (Plate 1), and represent six vegetation communities namely bracken; *Calluna*; improved grassland; semi-improved acid grassland; acid flush; and broadleaved semi-natural woodland. More than two different

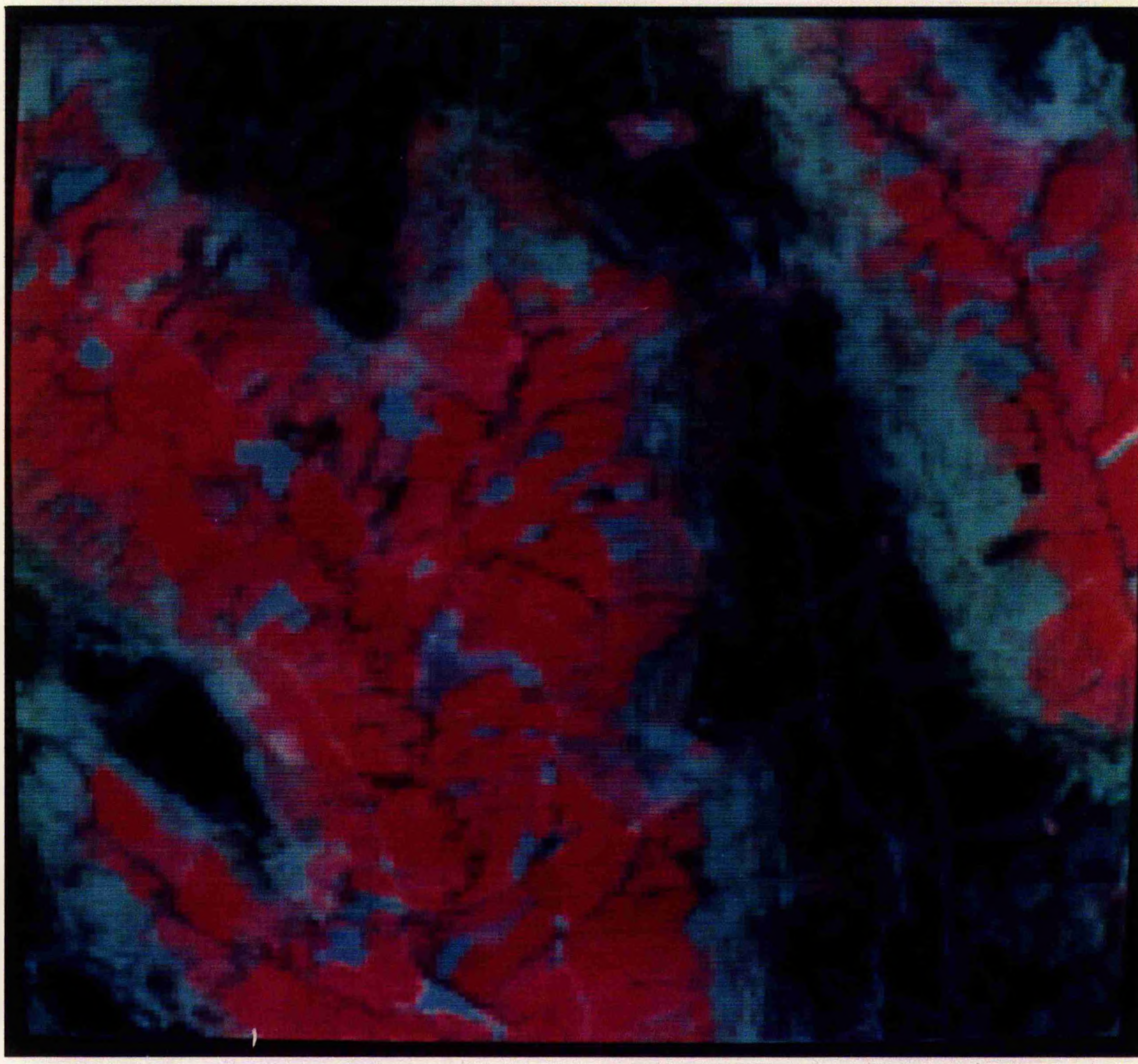


Plate 1 Landsat TM Colour Composites Band 2, 3, and 4 of Blakey Study Extract (after enhancement).

Calluna spectral classes can be recognized, however, due to different growth stages in the *Calluna* community. These have been generalized into two classes (mature and young/building phase) in order to retain space in the classification for other vegetation types. Bracken communities have also been divided into two classes to include bracken mixed with *Calluna* or acid grassland. On the colour composite imagery, bracken has light blue/cyan to white colours. The differences of the colour is possibly caused by different facing slopes. Bracken on the slopes facing to the west will have darker colours whilst bracken on the east slopes looks brighter. A similar colour (light blue/cyan) also represents farmland or urban areas and also bare ground. However, this colouration is usually located in the improved grassland and arable crop areas. Bracken mixtures have mottled tones of green/dark green, usually appearing at the edges of bracken encroachment on to the *Calluna*. *Calluna vulgaris* is represented by mottled tones of various colours: dark purple/dark blue, dark green and green. These differences represent different growth stages caused by the burning cycle. Mature *Calluna* is shown in dark purple/dark blue and is difficult to separate from the degenerate *Calluna*. The young/building *Calluna* appears as a dark green colour and also in different tones. The easiest cover type to identify is improved grassland as this is represented by bright pink colours. Semi-improved grassland is represented by a light pink colour. Acid grassland has pink/ red colours and is usually located within the heathland. The broadleaved woodland shows as a dark red colour and it usually scattered among the improved grassland or arable crops. The result of training area statistics can be seen in Table 4.1.

		Class Number							
		1	2	3	4	5	6	7	8
TM Band 4	Mean	69	39	37	63	135	91	73	67
	Maximum	85	58	51	71	154	114	85	110
	Minimum	61	33	30	53	111	78	63	43
	No. Pixels	1049	2179	1068	644	1227	394	130	443
	Std. dev	4.17	4.10	4.38	3.78	9.58	7.88	6.06	11.69
TM Band 3	Mean	46	19	27	37	18	25	22	20
	Maximum	53	25	30	45	23	31	25	25
	Minimum	39	17	23	30	16	19	20	18
	No. Pixels	1049	2179	1068	644	1227	394	130	443
	Sdt. dev	2.90	1.50	1.50	2.75	1.37	2.31	1.27	1.93
TM Band 2	Mean	35	21	26	32	26	29	26	25
	Maximum	39	26	29	35	30	34	29	29
	Minimum	32	19	23	29	24	25	24	22
	No. Pixels	1049	2179	1068	644	1227	394	130	443
	Std.dev	1.66	1.25	1.15	1.40	1.14	1.90	1.10	1.82

Table 4.1 Training Area Statistics of Blakey Study Extract.
Note:
1 = Bracken; 2 = *Calluna* Mature; 3 = *Calluna* Young/Building; 4 = Bracken Mixed;
5 = Improved Grassland; 6 = Semi-improved Acid Grassland; 7 = Acid Flush; 8 = Broadleaved Woodland.

In the Egton study extract (Plate 2), six vegetation communities have been recognised representing bracken; *Calluna*, improved grassland; arable cultivated land; plantation coniferous forest; and broadleaved semi-natural woodland. Two different training classes have been selected for bracken: pure bracken and bracken mixed with dry dwarf shrub heath *Calluna vulgaris* and Vaccinium *mirtillus*. *Calluna vulgaris* was also divided into two classes to represent mature and young (building phase) *Calluna*, whilst four other training classes were used to determine the remaining classes. It shows that pure bracken has bright light blue/green colours whilst mixed bracken has mottled colours of green and dark green. There are three different colours of coniferous plantation woodland: red, dark red and dark blue, however, these have been combined into one class. Broadleaved woodland is displayed as a dark pink/blue colour, whilst arable cropland is a bright pink colour. The training area statistical data are shown in Table 4.2.

For the Farndale study extract (Plate 3), eight training classes have been selected representing six vegetation communities, namely bracken; *Calluna* (3 classes); improved grassland; acid flush which consists of *Juncus* and *Sphagnum*; acid grassland which is mixed with scattered bracken; and plantation coniferous woodland. In this study extract, *Calluna vulgaris* has been divided into three separate classes based upon three different growth stages to represent mature, young/building and pioneer phases. In this study extract, various colours appear for *Calluna vulgaris*. These will be divided into three different class as follows: dark blue/purple for mature *Calluna*, light blue for young/building *Calluna*, and green for pioneer *Calluna* . Training area statistics for this study area are shown in Table 4.3.

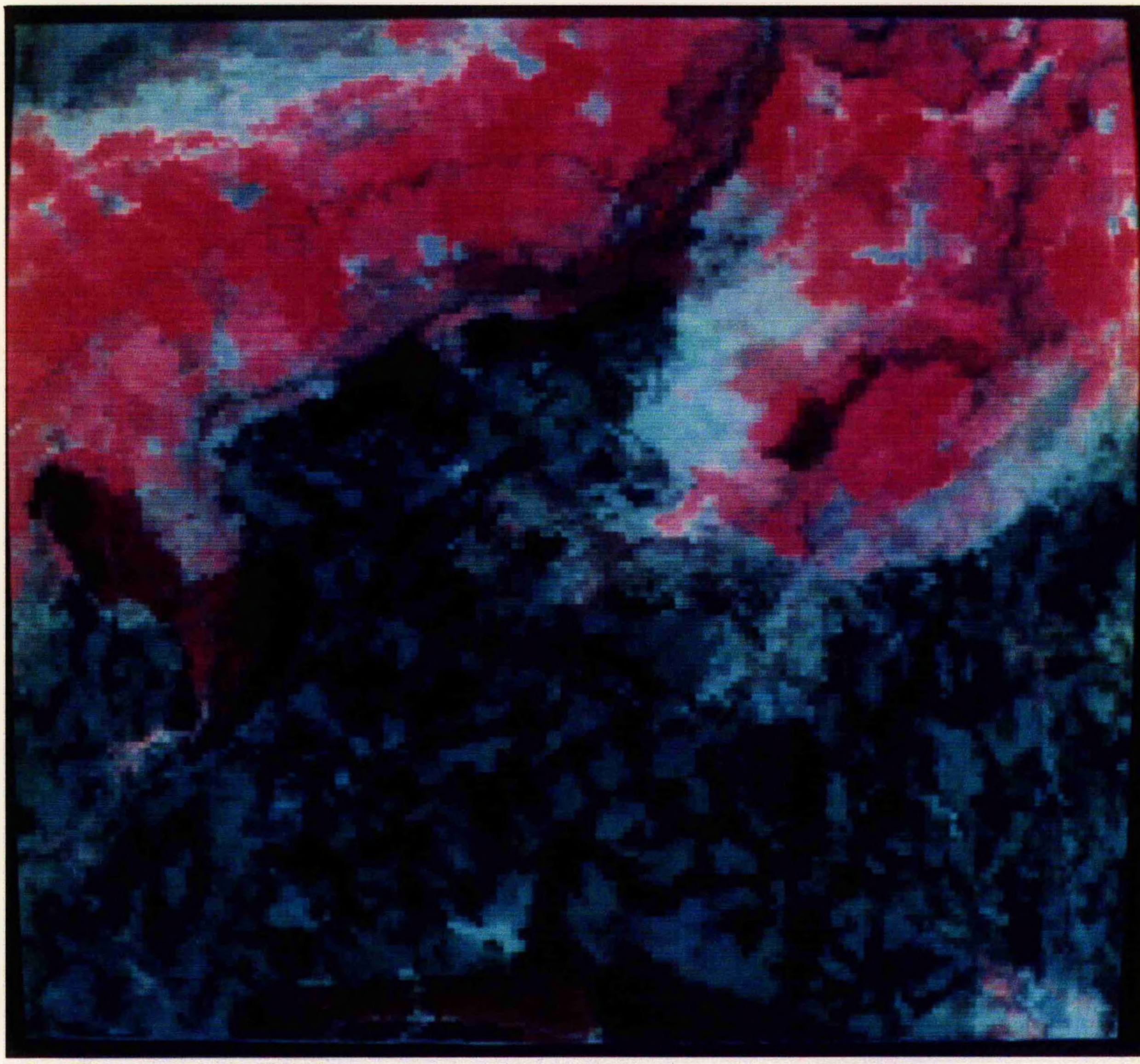


Plate 2 Landsat TM Colour Composites Band 2, 3, and 4 of Egton Study Extract (after enhancement).

		Class Number							
		1	2	3	4	5	6	7	8
TM Band 4	Mean	71	53	35	37	99	136	50	69
	Maximum	84	86	42	55	115	172	65	96
	Minimum	52	40	29	30	74	117	37	54
	No. Pixels	676	436	694	903	987	1200	1058	406
	Std. dev	6.09	7.81	2.57	6.83	9.74	10.17	7.64	9.31
TM Band 3	Mean	44	35	17	27	23	18	17	19
	Maximum	54	45	20	31	27	22	21	21
	Minimum	36	29	16	24	21	17	15	17
	No. Pixels	676	436	694	903	987	1200	1058	406
	Sdt. dev	3.38	3.44	1.13	1.68	1.56	1.15	0.80	1.08
TM Band 2	Mean	36	29	20	26	30	26	21	25
	Maximum	42	36	22	30	33	30	25	28
	Minimum	34	25	19	24	27	24	20	23
	No. Pixels	676	436	694	903	987	1200	1058	406
	Std.dev	1.57	2.43	0.86	1.35	1.34	1.26	1.30	1.33

Table 4.2 Training Area Statistics of Egton Study Extract.
Note:
1 = Bracken Pure; 2= Bracken Mixed; 3 = *Calluna* Mature; 4 = *Calluna* Young/Building;
5 = Improved Grassland; 6 = Arable; 7 = Plantation Coniferous Woodland; 8 = Broadleaved Woodland.

		Class Number							
		1	2	3	4	5	6	7	8
TM Band 4	Mean	65	36	41	32	15	61	63	64
	Maximum	76	42	51	39	143	73	75	78
	Minimum	46	32	34	28	85	49	57	45
	No. Pixels	955	1836	789	830	930	238	264	1271
	Std. dev	6.02	2.13	4.00	2.50	12.37	5.94	5.06	6.04
TM Band 3	Mean	44	18	26	26	23	27	28	18
	Maximum	51	22	30	30	30	33	34	26
	Minimum	35	16	23	24	18	22	22	16
	No. Pixels	955	1836	789	830	930	238	264	1271
	Sdt. dev	3.03	1.26	2.01	1.47	2.68	3.30	2.91	1.98
TM Band 2	Mean	35	20	25	24	30	27	28	23
	Maximum	38	23	29	27	35	31	33	27
	Minimum	29	18	23	22	27	25	26	21
	No. Pixels	955	1836	789	830	930	238	264	1271
	Std.dev	1.69	0.96	1.36	1.05	1.71	1.91	2.00	1.64

Table 4.3 Training Area Statistics of Farndale Study Extract.

Note:

1 = Bracken; 2 = *Calluna* Mature; 3 = *Calluna* Young/Building; 4 = *Calluna* Pioneer;
5 = Improved Grassland; 6 = Acid Flush; 7 = Acid Grassland; 8 = Plantation Coniferous Woodland.

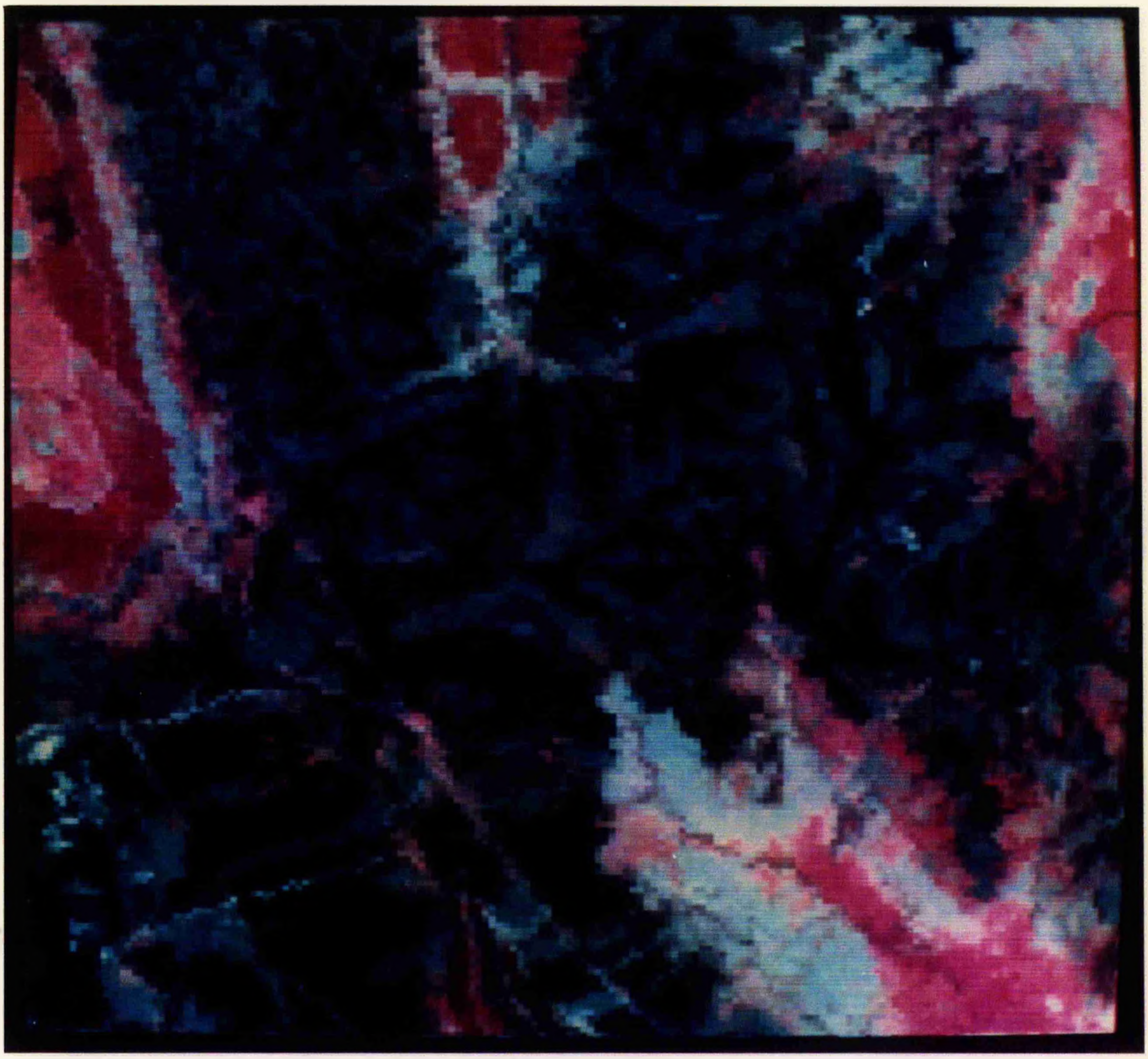


Plate 3 Landsat TM Colour Composites Band 2, 3, and 4 of Farndale Study Extract (after enhancement).

In the Glaisdale study extract (Plate 4), seven vegetation communities have been selected, namely bracken; *Calluna*; semi-improved natural grassland; improved grassland; bryophytes mixed with *Eriophorum angustifolium* and *Calluna vulgaris*; wet heath/acid grassland mosaic which consist of mixed *Erica tetralix, Nardus stricta,* and *Empetrum nigrum*; and plantation coniferous woodland. In this study area, *Calluna vulgaris* was divided into two classes to represent mature (dark blue/purple) and the young/building phase which has green/light green colours. Bryophytes which are mixed with *Calluna* in some areas, have dark blue/dark red colours. The training area statistical data are shown in Table 4.4.

Eight training classes have been chosen for the Whitby study extract (Plate 5) to represent eight vegetation communities including bracken; *Calluna vulgaris*; wet dwarf shrub heath which consists of mixed *Erica tetralix, Calluna vulgaris,* and *Molinia caerulea*; improved grassland; arable cropland; recently-felled coniferous woodland; broadleaved semi-natural woodland; and plantation coniferous woodland. Felled coniferous woodland has a dark red colour and appears on the image to be similar to mature *Calluna*. The training area statistics can be seen in Table 4.5.

As mentioned above, the more carefully selected training area will produced better classification results. Therefore, it is necessary to evaluate the spectral separation between training classes by using some form of coincident spectral plots, based upon the training data statistics. These plots illustrate the mean response of each of the classes and the variance of the distribution (± 1 standard deviation) within Landsat TM

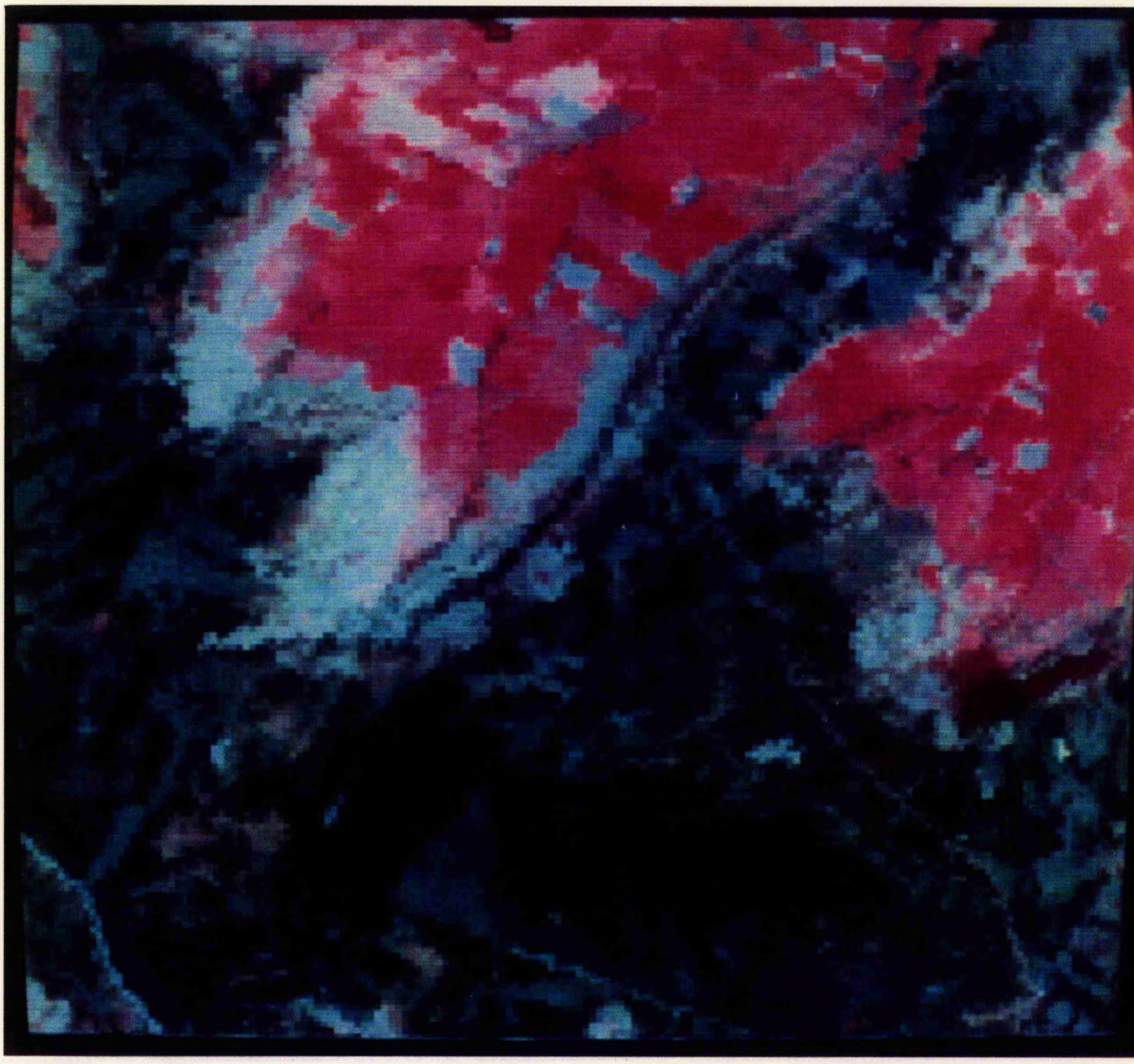


Plate 4 Landsat TM Colour Composites Band 2, 3, and 4 of Glaisdale Study Extract (after enhancement).

0 1.5 Km

		Class Number							
		1	2	3	4	5	6	7	8
TM Band 4	Mean	69	36	36	99	143	25	48	55
	Maximum	86	50	55	111	175	33	56	72
	Minimum	55	32	30	88	114	22	34	43
	No. Pixels	1036	1598	1018	618	868	1042	346	446
	Std. dev	5.02	3.17	4.26	5.07	14.13	2.37	5.75	7.41
TM Band 3	Mean	45	18	27	24	19	19	29	17
	Maximum	56	23	32	30	23	22	33	21
	Minimum	40	16	25	21	17	18	27	16
	No. Pixels	1036	1598	1018	618	868	1042	346	446
	Sdt. dev	3.16	1.25	1.81	1.90	1.80	1.42	1.32	0.97
TM Band 2	Mean	36	20	25	30	27	20	28	22
	Maximum	45	25	30	34	32	23	31	26
	Minimum	33	19	23	27	24	19	25	20
	No. Pixels	1036	1598	1018	618	868	1042	346	446
	Std.dev	2.11	1.20	1.40	1.69	2.17	1.42	1.26	1.30

Table 4.4 Training Area Statistics of Glaisdale Study Extract.

Note:

1 = Bracken; 2 = *Calluna* Mature; 3 = *Calluna* Young/Building; 4 = Semi-improved Neutral Grassland;
5 = Improved Grassland; 6 = Bryophytes; 7 = Wet Heath/Acid Grassland; 8 = Plantation Coniferous Woodland

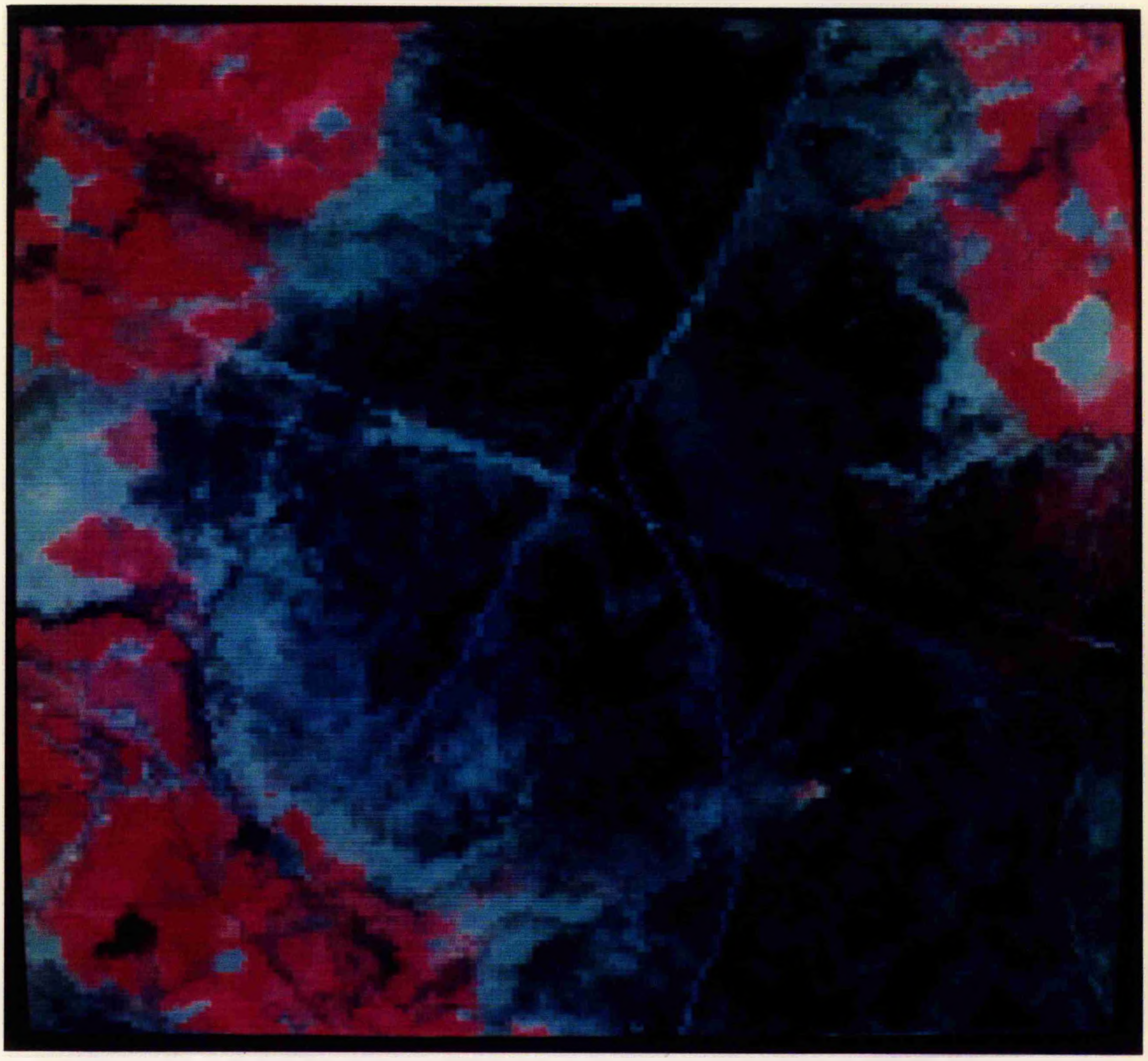
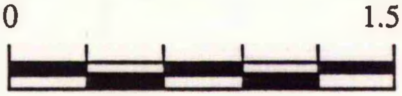


Plate 5 Landsat TM Colour Composites Band 2, 3, and 4 of Whitby Study Extract (after enhancement).



		Class Number							
		1	2	3	4	5	6	7	8
TM Band 4	Mean	66	33	47	70	124	46	69	53
	Maximum	84	43	62	131	163	59	90	65
	Minimum	57	27	37	42	96	40	46	47
	No. Pixels	901	1041	680	415	719	192	471	526
	Std. dev	5.67	3.12	6.61	33.54	10.20	4.73	7.86	4.14
TM Band 3	Mean	45	18	30	27	19	18	20	18
	Maximum	53	22	39	36	22	22	27	20
	Minimum	41	16	26	21	17	16	17	17
	No. Pixels	901	1041	680	415	719	192	471	526
	Sdt. dev	2.91	1.50	3.18	4.41	1.32	1.66	1.98	0.67
TM Band 2	Mean	36	20	29	28	26	22	26	22
	Maximum	41	24	34	32	32	26	30	24
	Minimum	33	19	26	25	25	20	22	21
	No. Pixels	901	1041	680	415	719	192	471	526
	Std.dev	1.73	1.29	2.21	1.71	1.33	1.68	1.53	0.70

Table 4.5 Training Area Statistics of Whitby Study Extract.

Note:

1 = Bracken; 2 = *Calluna* Mature; 3 = Wet Heath; 4 = Improved Grassland;
5 = Arable Cropland; 6 = Felled Coniferous Woodland; 7 = Broadleaved Woodland; 8 = Plantation Coniferous Woodland.

bands 2, 3 and 4. It shows that the longer the line, the greater the variance of the data. In contrast, cover types with little variance will be shown as relatively short lines. The cover types are shown as entirely separable if their distribution are non-overlapping in one or more bands. However, if any cover types overlap in one or two spectral bands, this does not preclude successful classification when two or more bands are analysed (Lillesand and Kiefer, 1987).

The result of coincident spectral plots for the five study extracts are presented in Figures 4.1 to 4.5. From these Figures, it can be summarized that the spectral response of bracken is separable within two or three bands in all study areas. Therefore, bracken can be expected to be successfully classified and separated from other vegetation communities. *Calluna* at the mature and young/building phases were also separable at least in one band of all study extracts. Improved grasslands which occurs in all study areas, mostly have greatest variance in band 4.

In the Blakey study area (Figure 4.1), bracken mixed (class 4) was separable in band 3. Improved grassland (class 5) was separable in band 3 and 4, and semi-improved grassland (class 6) was separable from other vegetation types in band 4. *Calluna* young/building (class 3), acid flush (class 7) and broadleaved woodland (class 8) were overlapping in all bands. *Calluna* mature (class 2) was separable in band 2 whilst bracken mixed (class 4) was separable in band 3.

In the Egton study extract (Figure 4.2), improved grassland (class 5) was separable from the other cover types in band 3 and 4 whilst arable cropland (class 6) was separable only in band 4. Most of the cover types

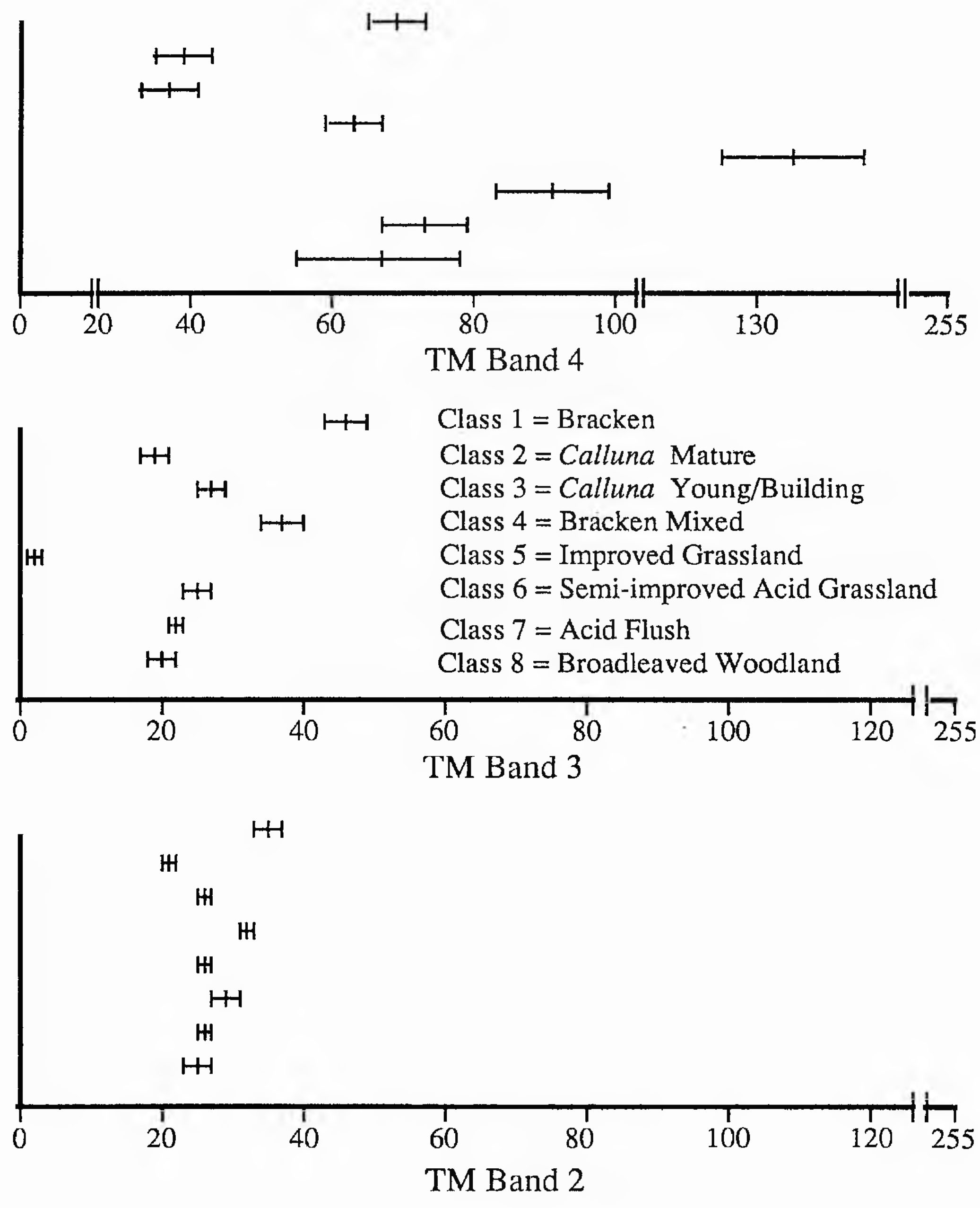


Figure 4.1 Coincident Spectral Plots of Blakey Training Data.
(The Mean +/- 1 Standard Deviation).

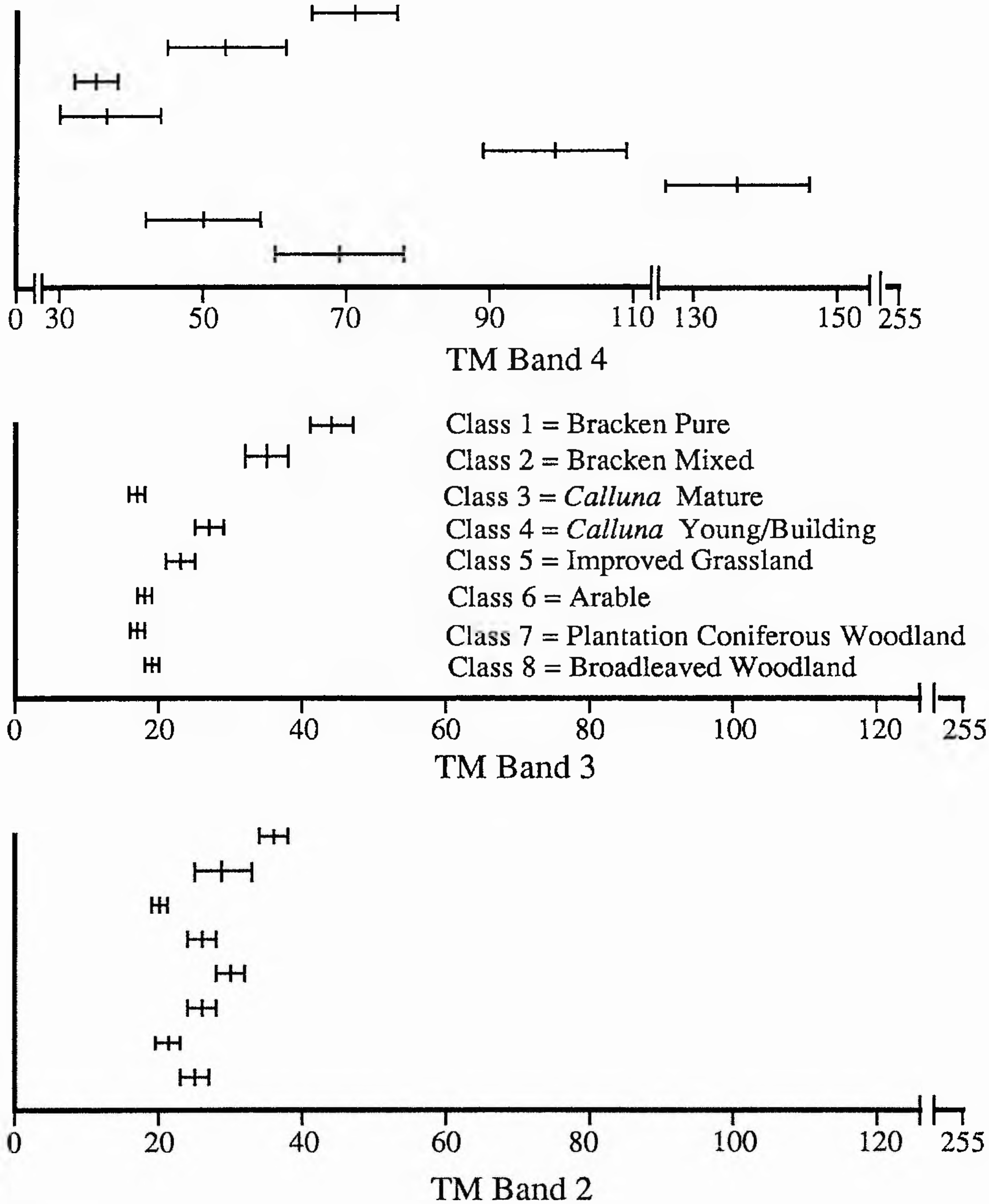


Figure 4.2 Coincident Spectral Plots of Egton Training Data. (The Mean +/- 1 Standard Deviation).

Note: See Table 4.7

were overlapping in one band but separable in another band, for example plantation coniferous woodland (class 7) overlaps with *Calluna* mature (class 3) in bands 2 and 3 but is separable in band 4. All cover types have greatest the variance in band 4.

In the Farndale study extract (Figure 4.3), acid flush (class 6) and acid grassland (class 7) overlap in all three bands whilst improved grassland (class 5) was separable from other cover types in band 4. Most of the cover types which overlap in band 2 and 3 are separable in band 4.

In the Glaisdale study extract (Figure 4.4), only bracken (class 1) was separable in all bands whilst semi-improved neutral grassland (class 4), improved grassland (class 5) and bryophytes (class 6) were separable from other classes in band 4. Most of the cover types show overlap in band 3 but can be separated in band 2 or 4. For example, *Calluna* mature (class 2) overlaps with improved grassland (class 5) and bryophytes (class 6) in band 3 but is separable in band 2 and 4.

In the Whitby study extract (Figure 4.5), bracken (class 1) can be separated from other classes in band 2 and 3 while most of the other classes overlap in bands 2 and 3. The greatest variance occurs in band 4 for improved grassland (class 4) which overlaps with all cover types except *Calluna* mature (class 2) and arable cropland (class 5).

Using coincident spectral plots to analyse training data indicates that some classes cannot be accurately classified. However, Lillesand and Kiefer (1987) suggested that two-dimensional scatter diagrams will provide better representation of the spectral response pattern distributions. It is the easiest way to perceive the distribution of pixel values measured on two different bands (Mather, 1987). In these

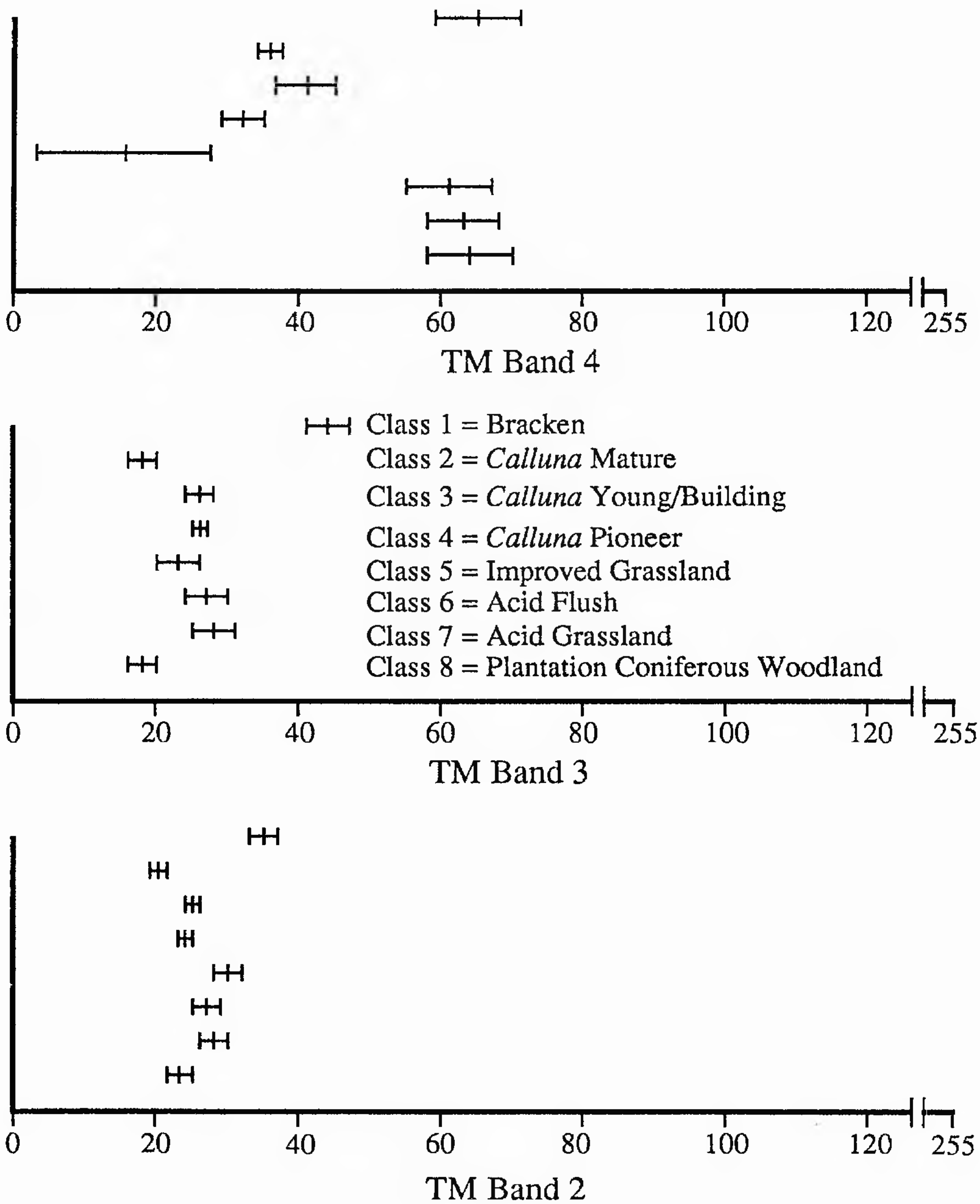


Figure 4.3 Coincident Spectral Plots of Farndale Training Data. (The Mean +/- 1 Standard Deviation).

Note: See Table 4.8

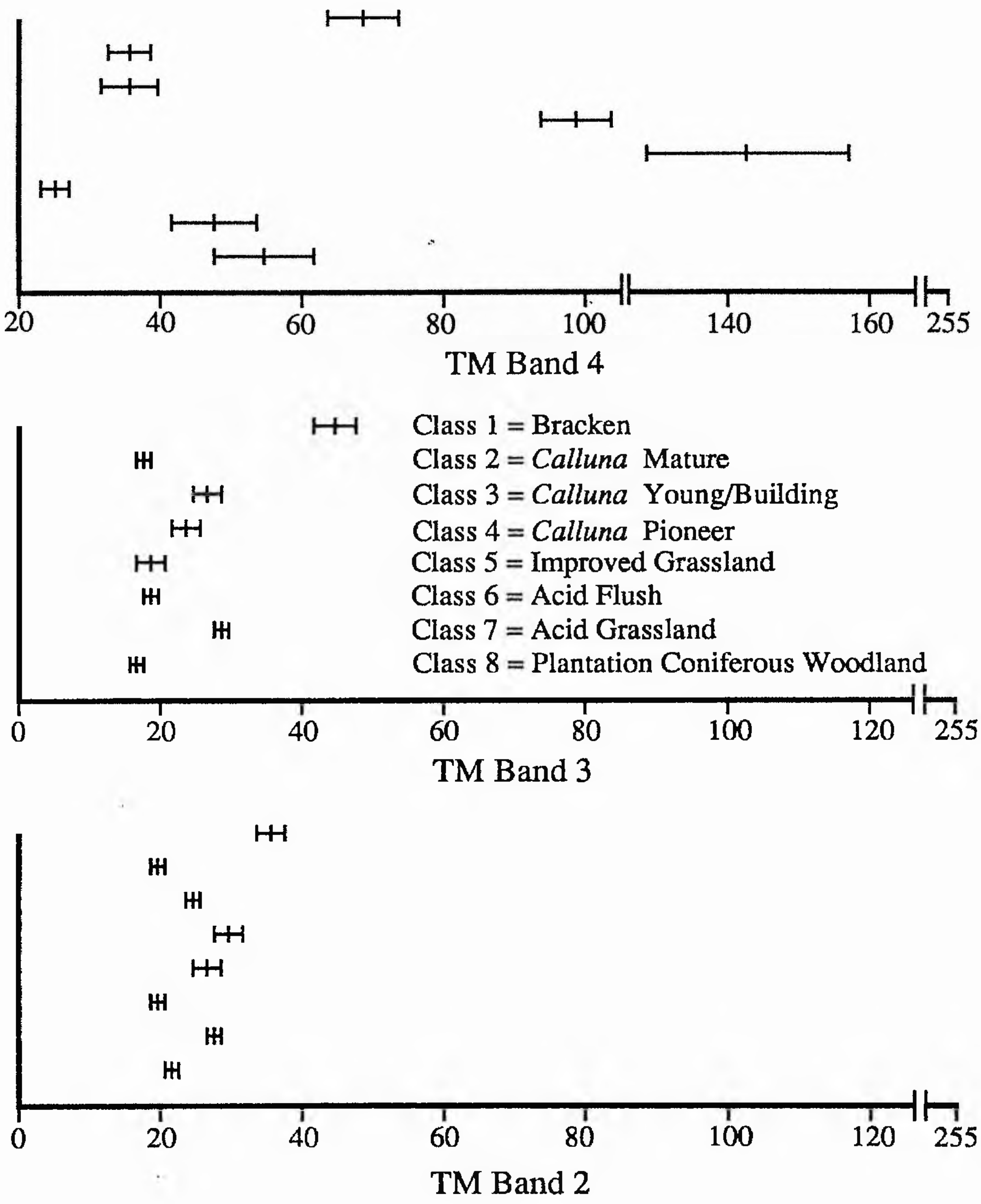


Figure 4.4 Coincident Spectral Plots of Glaisdale Training Data. (The Mean +/- 1 Standard Deviation).

Note: See Table 4.9

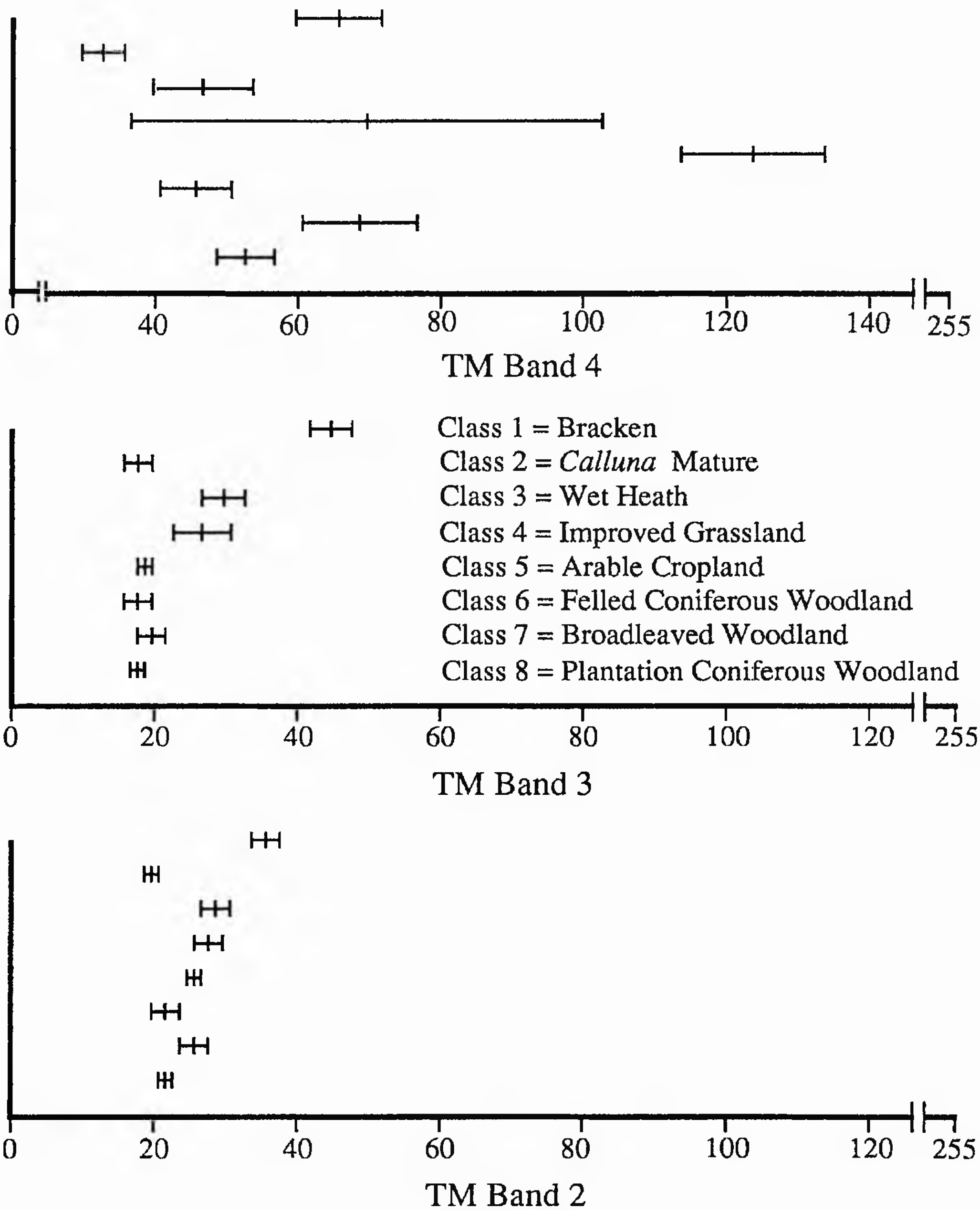


Figure 4.5 Coincident Spectral Plots of Whitby Training Data.
(The Mean +/- 1 Standard Deviation).
Note: See Table 4.10

coincident spectral diagrams (Figures 4.6 - 4.10), TM band 4 digital numbers have been plotted on the **x** axis and TM band 3 digital numbers on **y** axis. Fifteen pixel values of band 3 and 4 were selected from training classes data of each study extract including minimum and maximum values. After all data have been plotted, the compactness of a cluster can be visually recognized on the basis of scatter of points around the cluster centre. The degree of separation of the clusters can also can be estimated by looking at the distance between their centres and the scatter of points surrounding those cluster centres. However, it should be noted that the presentation of these scatter diagrams are influenced by the scale of the numerical values on **x** and **y** coordinates. If the values of the **x** and **y** coordinates were multiplied or divided by a scaling factor, therefore, the visual interpretation of the inter-point relationships will be affected (Mather, 1987).

In the Blakey study extract (Figure 4.6), it is shown that bracken, *Calluna* young/building (class 3), bracken mixed (class 4), and improved grassland (class 5) can be discriminated. *Calluna* mature (class 2) can partly be discriminated, however, there is also an overlap pixel with broadleaved woodland (class 8). Most of the semi-improved grassland (class 6) can be discriminated even if there is an overlap pixel with acid flush (class 7). Acid flush (class 7) was mixed and also has an overlapping pixel with broadleaved woodland (class 8). The most difficult class to discriminate is broadleaved woodland (class 8) which is broadly scattered and mixed with *Calluna* mature (class 2) and acid flush (class 7) and only one third of this class can be distinguished.

In the Egton study extract (Figure 4.7), only improved grassland (class 5) and arable cropland (class 6) can be easily discriminated. Bracken (class

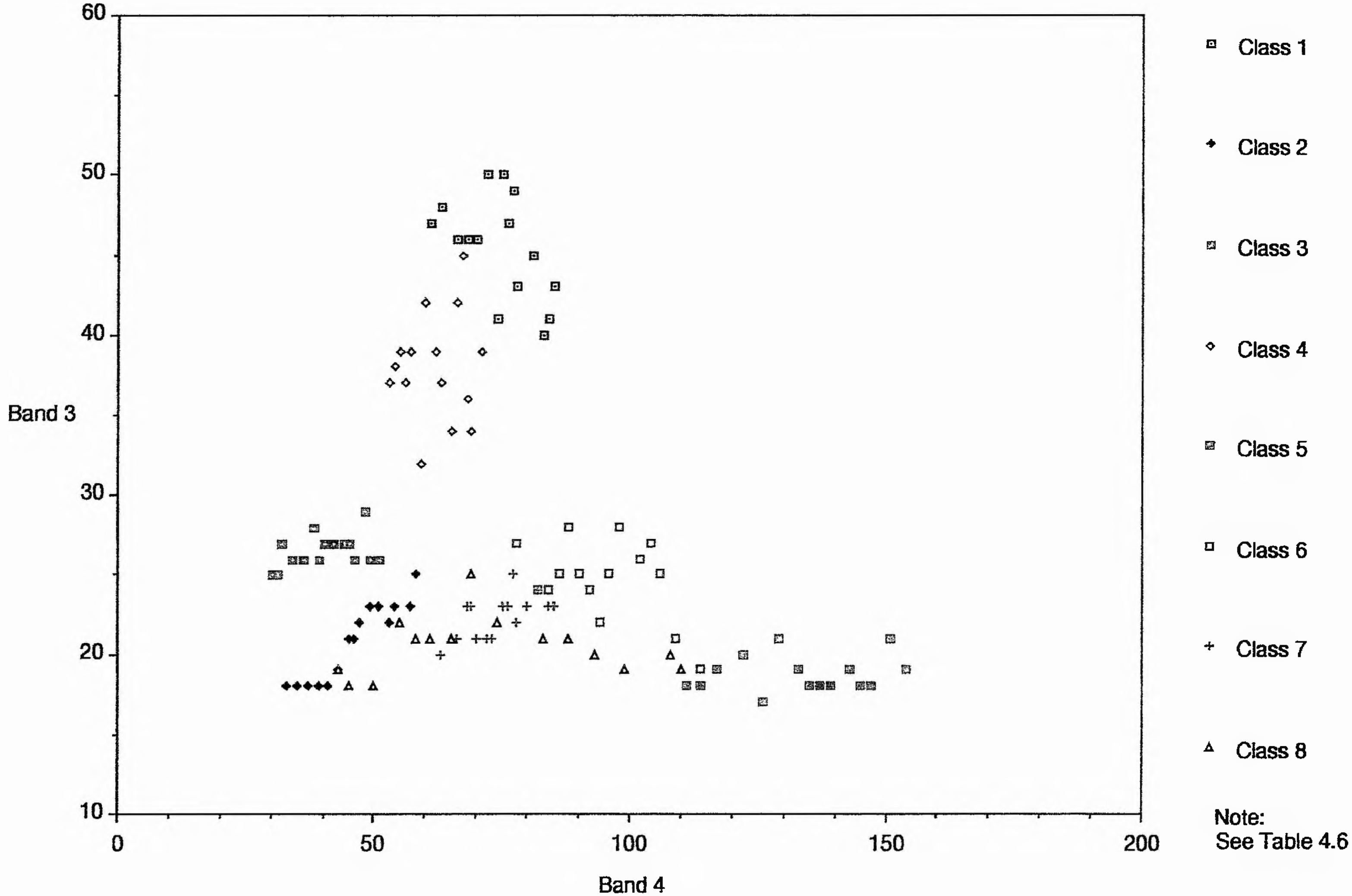


Figure 4.6 Scatter Diagram of Blakey Study Extract.

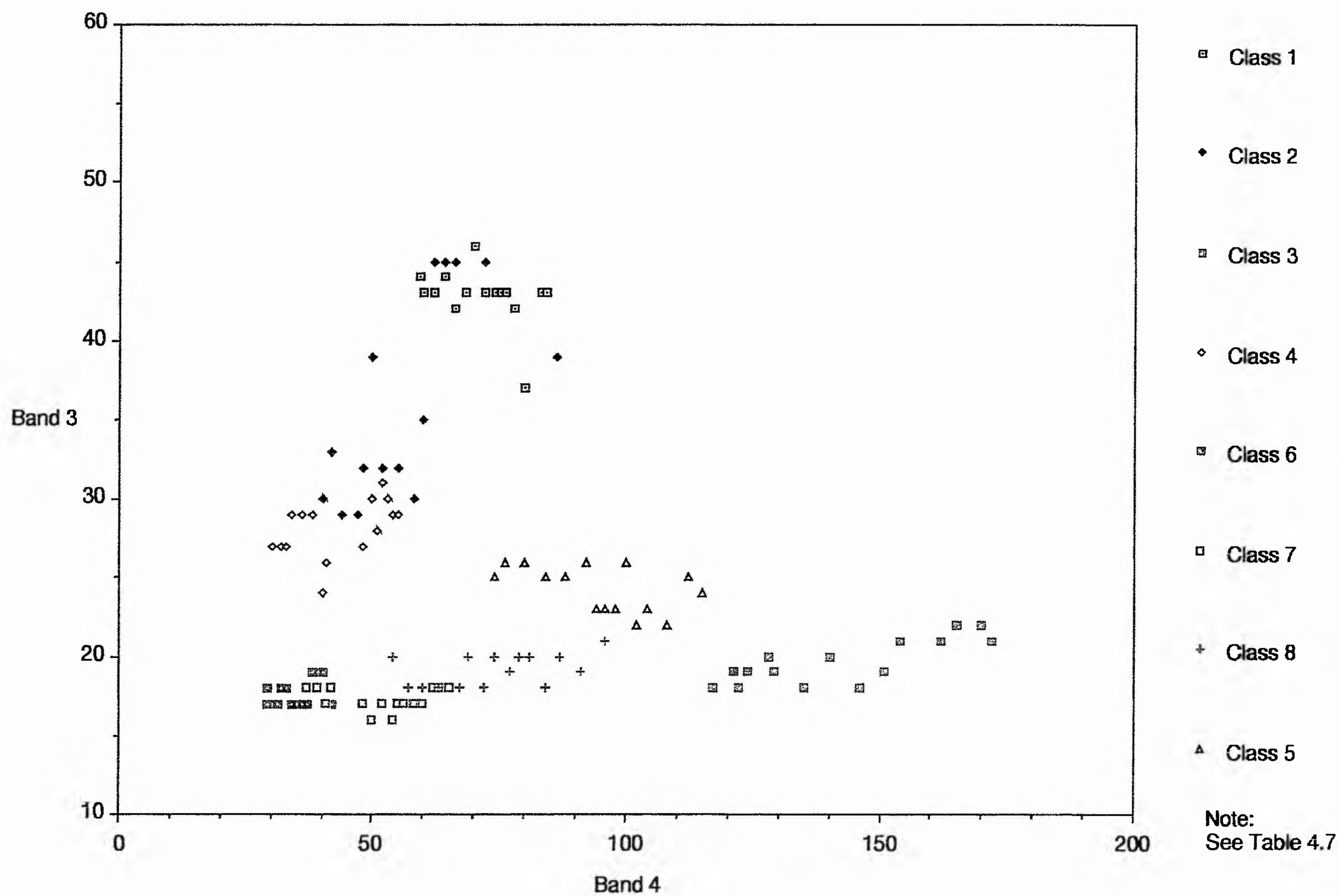


Figure 4.7 Scatter Diagram of Egton Study Extract.

1) was particularly compact and easy to discriminate, however, there were two pixels which scattered far from the cluster centre. The cluster of the bracken mixed (class 2) was not compact and only part of the pixels can be distinguished whilst some pixels were laid among the *Calluna* young/building (class 4). In particular, the cluster of the *Calluna* mature (class 3) was compact but it also overlapped with plantation coniferous woodland (class 7). Most of the broadleaved woodland (class 8) were easy to distinguish, but, some pixels overlap with plantation coniferous woodland (class 7). Only a part of plantation coniferous woodland was separable as some pixels overlap with *Calluna* mature (class 3) and broadleaved woodland (class 8).

The scatter diagram of the Farndale study extract (Figure 4.8) showed that bracken (class 1), *Calluna* mature (class 2), improved grassland (class 5) and plantation coniferous woodland (class 8) were easily discriminated. Acid flush (class 6) and acid grassland (class 7) were mixed together and difficult to distinguish, whilst a part of *Calluna* young/building (class 3) and *Calluna* pioneer (class 4) were also mixed together and only small parts can be distinguished.

In the Glaisdale study extract (Figure 4.9), the clusters of bracken (class 1), *Calluna* young/building (class 3), semi-improved neutral grassland (class 4), semi-improved grassland (class 5), bryophytes (class 6), and plantation coniferous woodland (class 8) were easy to distinguish. However, *Calluna* mature (class 2) and wet heath/acid grassland (class 7) were mixed together and difficult to discriminate.

In the Whitby study extract (Figure 4.10), only bracken (class 1), arable cropland (class 5) and also part of the broadleaved woodland (class 7)

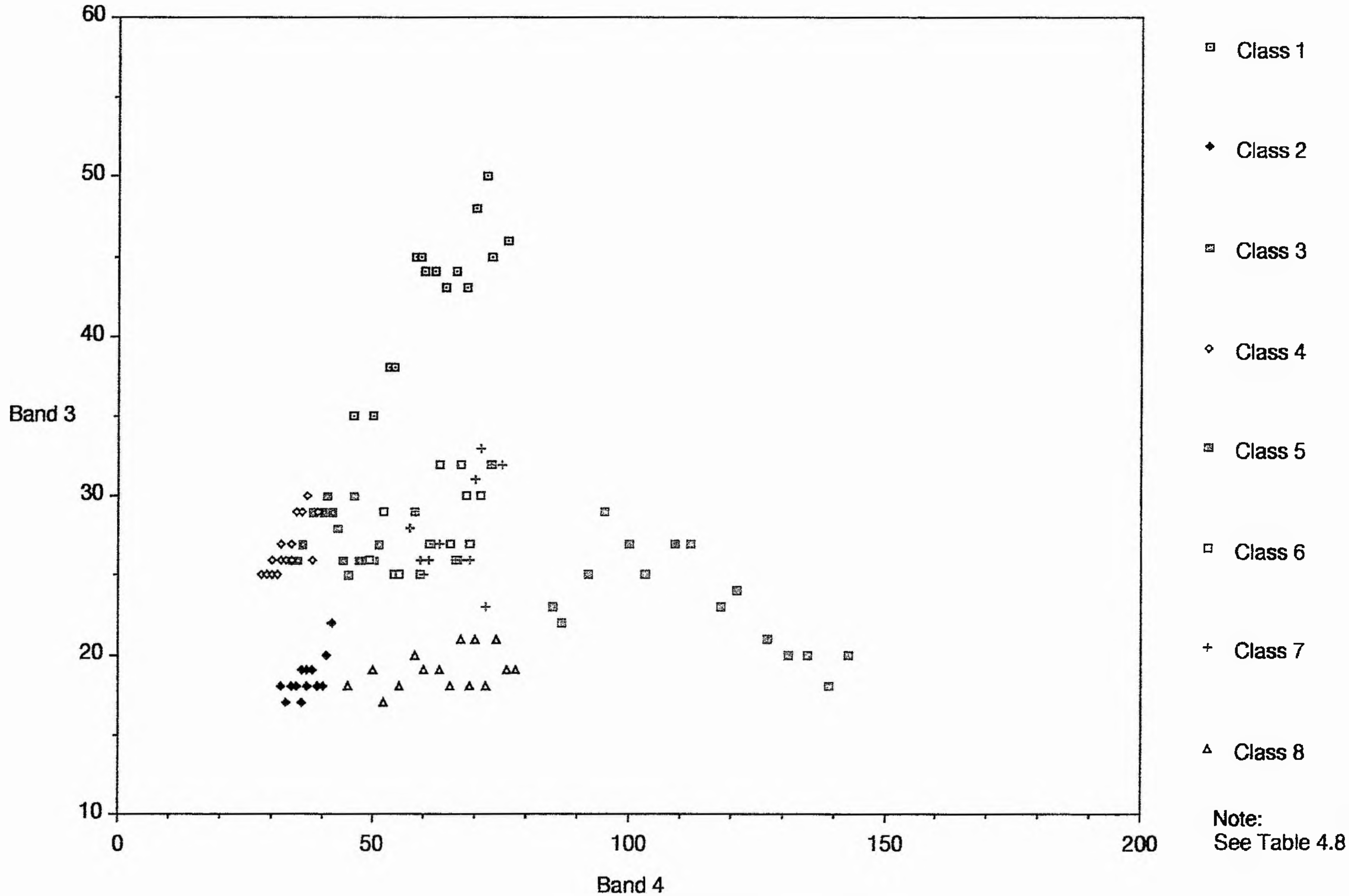


Figure 4.8 Scatter Diagram of Farndale Study Extract.

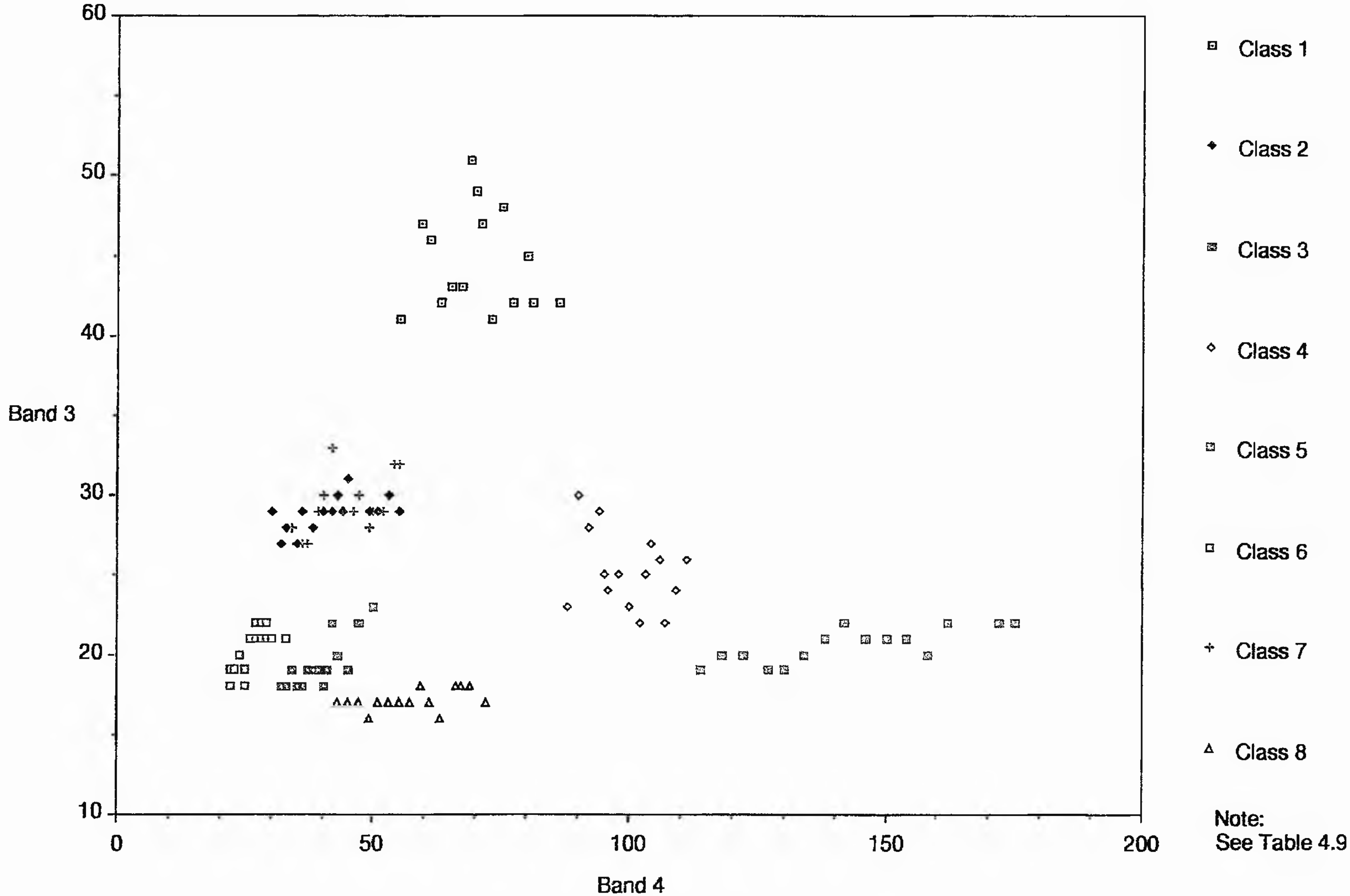


Figure 4.9 Scatter Diagram of Glaisdale Study Extract.

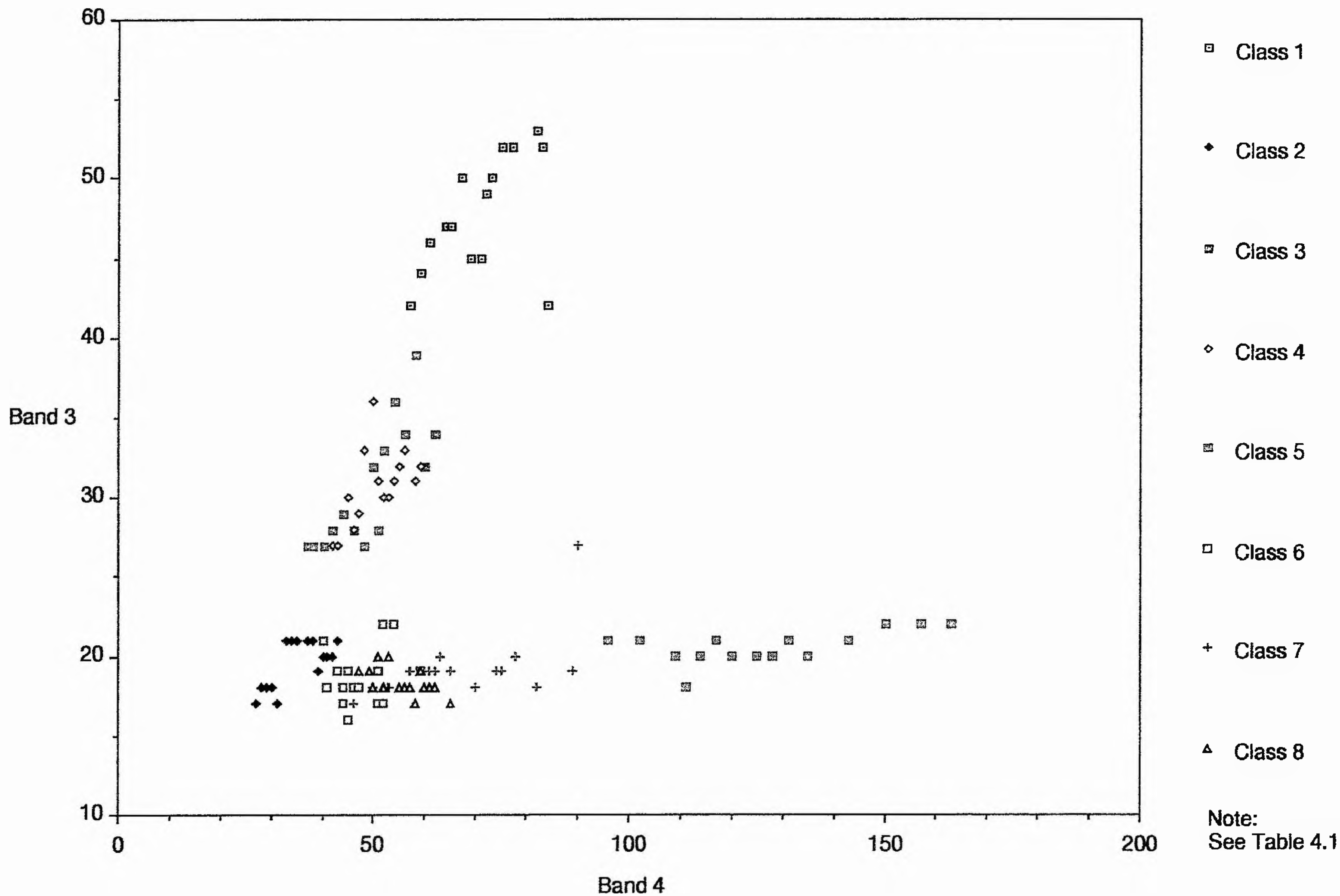


Figure 4.10 Scatter Diagram of Whitby Study Extract.

were easy to distinguish. Wet heath (class 3) was mixed with improved grassland (class 4). Only a part of *Calluna* mature (class 2) can be discriminated and it was also mixed with felled coniferous woodland (class 6). Plantation coniferous woodland (class 8) was mixed together with felled coniferous woodland (class 6) and some pixels also overlap with Broadleaved woodland (class 7).

4.5 Supervised Classification and the Detection of Upland Vegetation Communities.

Detection of upland vegetation communities in the five study extracts of the North York Moors National Park will be presented based upon the result of box and maximum likelihood classifications. The principle and the result of the box classification technique will be described in section 4.5.1 whilst the next section will present the technique and the result of maximum likelihood classification. The result of both classifications are summarized for convenience in Table 4.16

4.5.1 Box classification.

Box classification or parallelepiped classification is currently the most popular supervised classification technique use for remote sensing applications. It is easy to program, faster and more efficient than other classification techniques (Curran, 1985; Mather, 1987).

The basics of the decision of box classification is the scatter diagram of two or more different bands. Box classification can be used to establish qualitatively that a pixel belongs to a specific cluster. The decision boundaries will be defined to separate groups off and differentiate these from each other by fixing the limits of upper and lower bounds of digital number values in each band of training classes.

This classification region will appear as a rectangular or square box around each training area cluster in the scatter diagram (Figure 4.11). The most common problem of this classification technique occurs: first, when unknown pixels appear in the decision area. These will usually be classified according to class limits. Second, when an unknown pixel lie out side the decision boundaries, it will be grouped as unclassified. The third problem is more complicated, therefore, when the pixels lie in two or more overlap decision boundaries. This is usually caused by spectrally similar classes or high degree of correlation between spectra of objects in different bands. In such cases, usually the pixel will be assigned to the first class for which it fulfil all criteria (Curran, 1985; Jensen, 1986; Lillesand and Kiefer, 1987; Mather, 1987). However, the box classification technique can be considered as a cheap and rapid, even though not particularly accurate, method compared with maximum likelihood classification. The results of box classification of the study extracts are given in the following section.

4.5.1.1 **Blakey study extract.**

It was stated in the previous section that the image of the Blakey study extract had been classified into six major vegetation communities: bracken, *Calluna vulgaris*, improved grassland, acid flush, and broadleaved woodland with some sub-divisions. The image

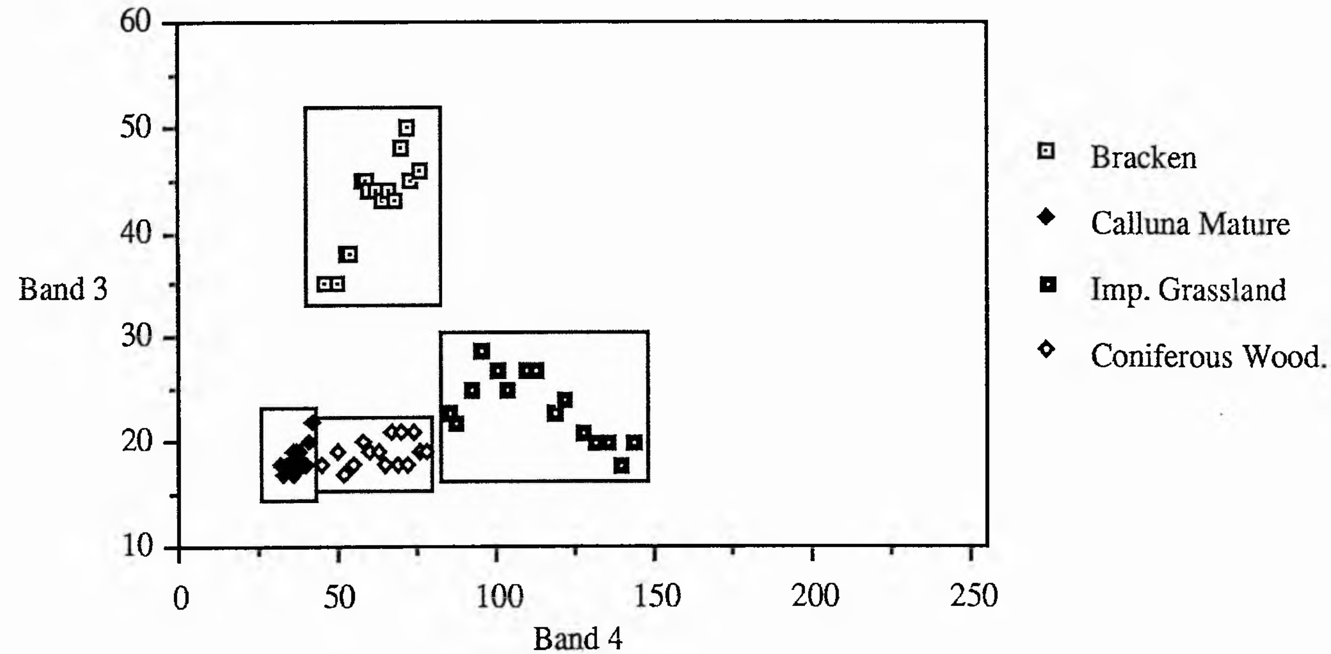


Figure 4.11 Box Classification Strategy

classification result can be seen in Plate 6 whilst the percentage classification result is shown in the Table 4.6.

In this study area, bracken communities exist in the east slopes of Blakey ridge and Farndale west. About 6.09% of the study extract was classified as bracken (black colour). This technique mainly classified only for pure bracken. Therefore, misclassification also occurs particularly in the farmland/urban areas as these areas have similar spectral responses. Mixed bracken (dark blue colour) has been classified as having a much greater area than pure bracken (14.70%). However, despite bracken being mixed with *Calluna* which gives a lower spectral response, this was also classified as pure bracken on the west slope of Blakey ridge, which also has a lower spectral response due to slope illumination factors. Confusion also occurs, particularly in the farmland or urban areas; this can be seen among the improved grassland area.

Calluna vulgaris has been classified into two different classes: *Calluna* mature (red colour), and *Calluna* young/building phase (green colour). About 14.43% of the study extract was classified as *Calluna* mature, while 8.73% was classified as *Calluna* young/building. *Calluna* mature was more accurately classified as there is no distinctive confusion occurring. In particular, there was no misclassification in the *Calluna* young/building group. However, omission errors occur due to various spectral responses where some pixels are not classified in the young *Calluna* group.

Improved grassland (pink colour) which occupied 9.36% of the study extract seems to be an impure group. Confusion occurs with semi-

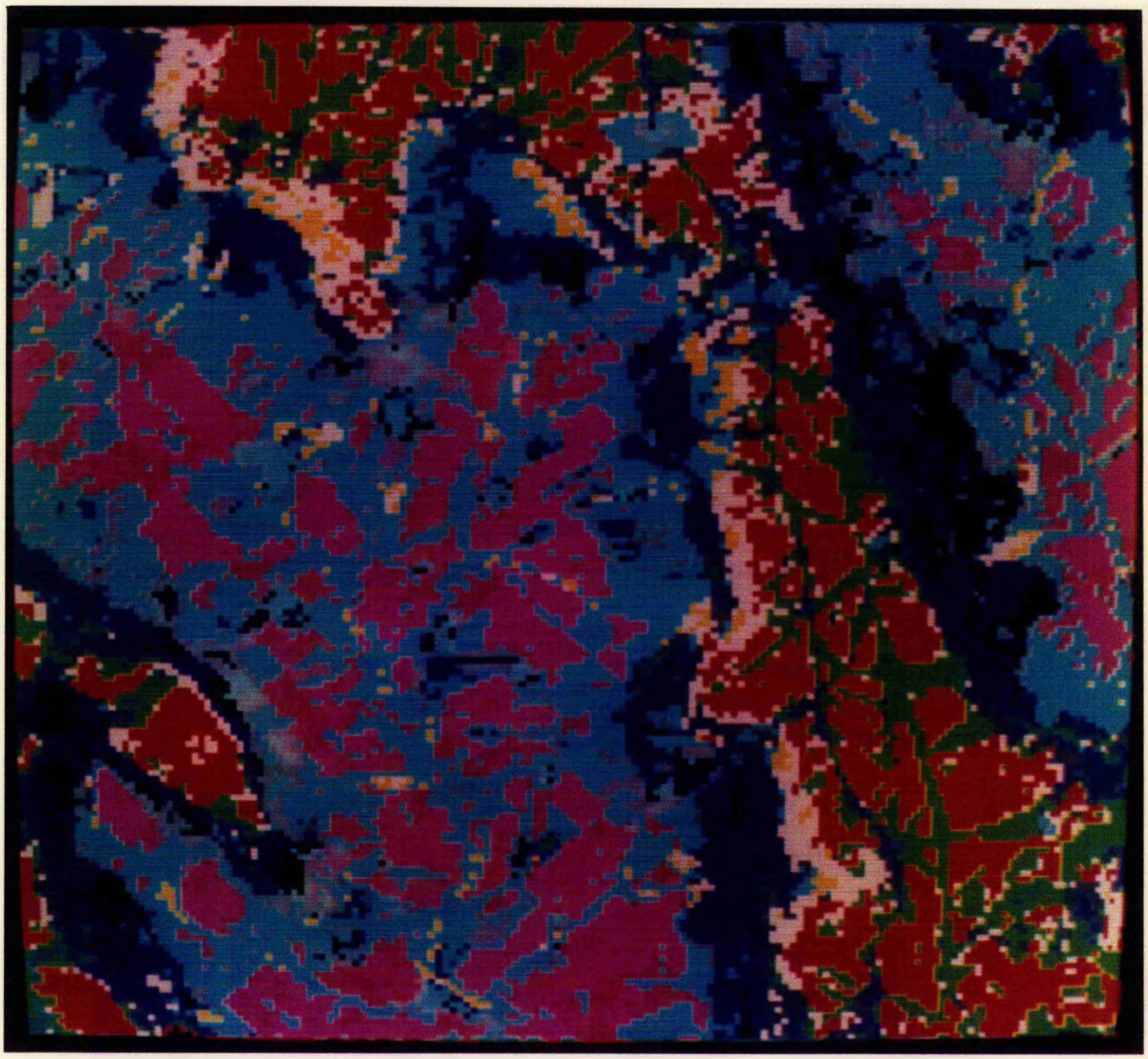


Plate 6 Classified Image of Blakey Study Extract Using Box Classification.

0 1.5 Km

Class	Colour	Number of pixels	% of image
1	Black	15954	6.09
2	Red	37839	14.43
3	Green	22897	8.73
4	D.Blue	38547	14.70
5	Pink	24528	9.36
6	L.Blue	78081	29.79
7	Yellow	5397	2.06
8	White	10884	4.15
Unclassified		28017	10.69

Table 4.6 Percentage Image Classification Results of Blakey Study Extract Using Box Classification.

Class 1 = Bracken.
Class 2 = *Calluna* Mature.
Class 3 = *Calluna* Young/Building.
Class 4 = Bracken Mixed.
Class 5 = Improved Grassland.
Class 6 = Semi-improved Acid Grassland.
Class 7 = Acid Flush.
Class 8 = Broadleaved Woodland.

improved acid grassland (light blue colour), therefore, which covers 29.79% of the extract. Misclassification also occurs for broadleaved woodland (white colour) which occupies 4.15% of the study extract. Most of the confusion occurs on the west slope of Blakey ridge, Low Blakey moor and High Blakey moor. Acid flush (yellow colour) was classified for about 2% of the study extract, but confusion occurs with improved grassland. In this study extract, about 10.69% of the area was unclassified, mostly in the mixed bracken and acid grassland, farmland, and arable cropland groups.

4.5.1.2 **Egton study extract.**

Six vegetation types have been classified in the Egton study extract: bracken, *Calluna vulgaris*, improved grassland, arable cropland, coniferous plantation, and broadleaved woodland. The result of image classification can be seen in Plate 7, and the percentage classification result is shown in Table 4.7.

Most of this study extract was covered by *Calluna* located in Egton high moor, whereas 21.83% was classified as *Calluna* young/building phase (dark blue) and about 12.66% as *Calluna* mature (green). Problem of misclassification occurred mostly with coniferous plantations which have a similar spectral response with *Calluna* mature.

Improved grassland (pink) which is located on Glaisdale Side and Egton Grange covered 16.88% of the study extract. In certain areas, this class was mixed with arable cropland (light blue) which occupied 6.38% of the study extract.

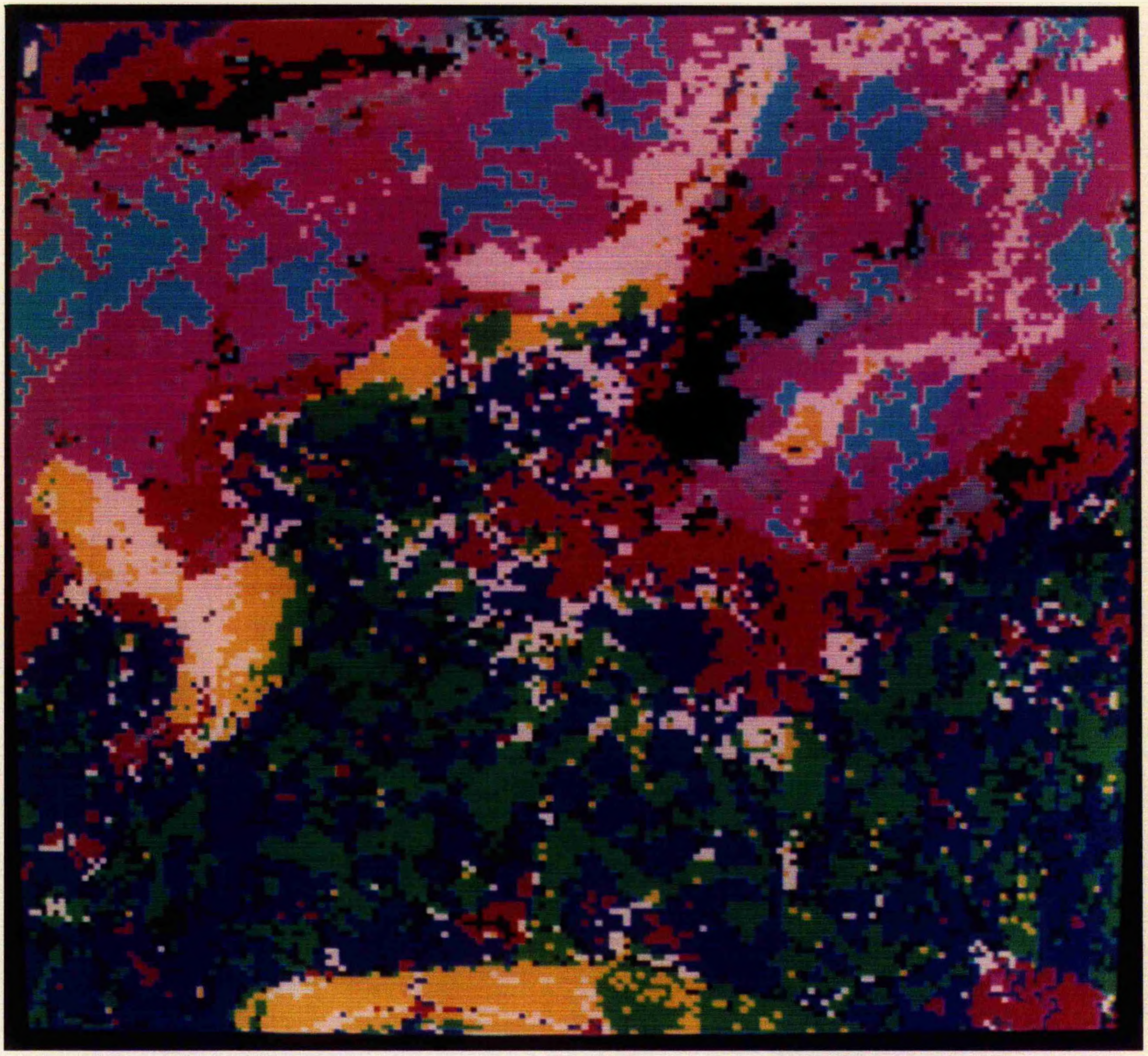


Plate 7 Classified Image of Egton Study Extract Using Box Classification.

0 1.5 Km

Class	Colour	Number of pixels	% of image
1	Black	10644	4.06
2	Red	27325	10.42
3	Green	33189	12.66
4	D.Blue	57239	21.83
5	Pink	44257	16.88
6	L.Blue	16734	6.38
7	Yellow	11043	4.21
8	White	21336	8.14
Unclassified		40377	15.40

Table 4.7 Percentage Image Classification Results of Egton Study Extract Using Box Classification.

Class 1 = Bracken Pure.
Class 2 = Bracken Mixed.
Class 3 = *Calluna* Mature.
Class 4 = *Calluna* Young/Building.
Class 5 = Improved Grassland.
Class 6 = Arable.
Class 7 = Plantation Coniferous Woodland.
Class 8 = Broadleaved Woodland.

About 14.48% of the study extract was classified as bracken (black) in which about 4% was classified as pure bracken and 10.4% as mixed bracken (red). Misclassification occurred as some pixels were occupied by young *Calluna* communities. Another particular confusion which occurs in this study extract is for broadleaved woodland (white) which combines mostly with coniferous woodland and also with mature *Calluna*. Coniferous plantation (yellow) was classified as 4.2% of the study extract. About 15.4% of the study extract was unclassified. The unclassified pixels mainly occupied the area of scattered bracken/mixed bracken, and acid grassland.

4.5.1.3 **Farndale study extract.**

Eight training classes have been used to classify the Farndale study extract to represent six vegetation communities namely bracken, *Calluna* (3 sub-groups), improved grassland, acid flush, acid grassland, and coniferous plantation (Plate 8).

A total of 61.3% of the study extract have been classified as *Calluna vulgaris* in which 35% have been classified as *Calluna* young/building (green), about 20.8% as *Calluna* mature (red), and about 5.3% was classified as *Calluna* pioneer (dark blue) (Table 4.8). Confusion occurs only in a small area of coniferous woodland near Ingleby moor. Another problem of misclassification appears for the acid flush class (light blue) which covers 12.5% of the area. Most of this class occupies the area of scattered bracken/mixed bracken, semi-improved acid grassland, acid grassland mixed with bracken and also in the *Calluna* pioneer stage. However, only about 7.7% of the study extract was

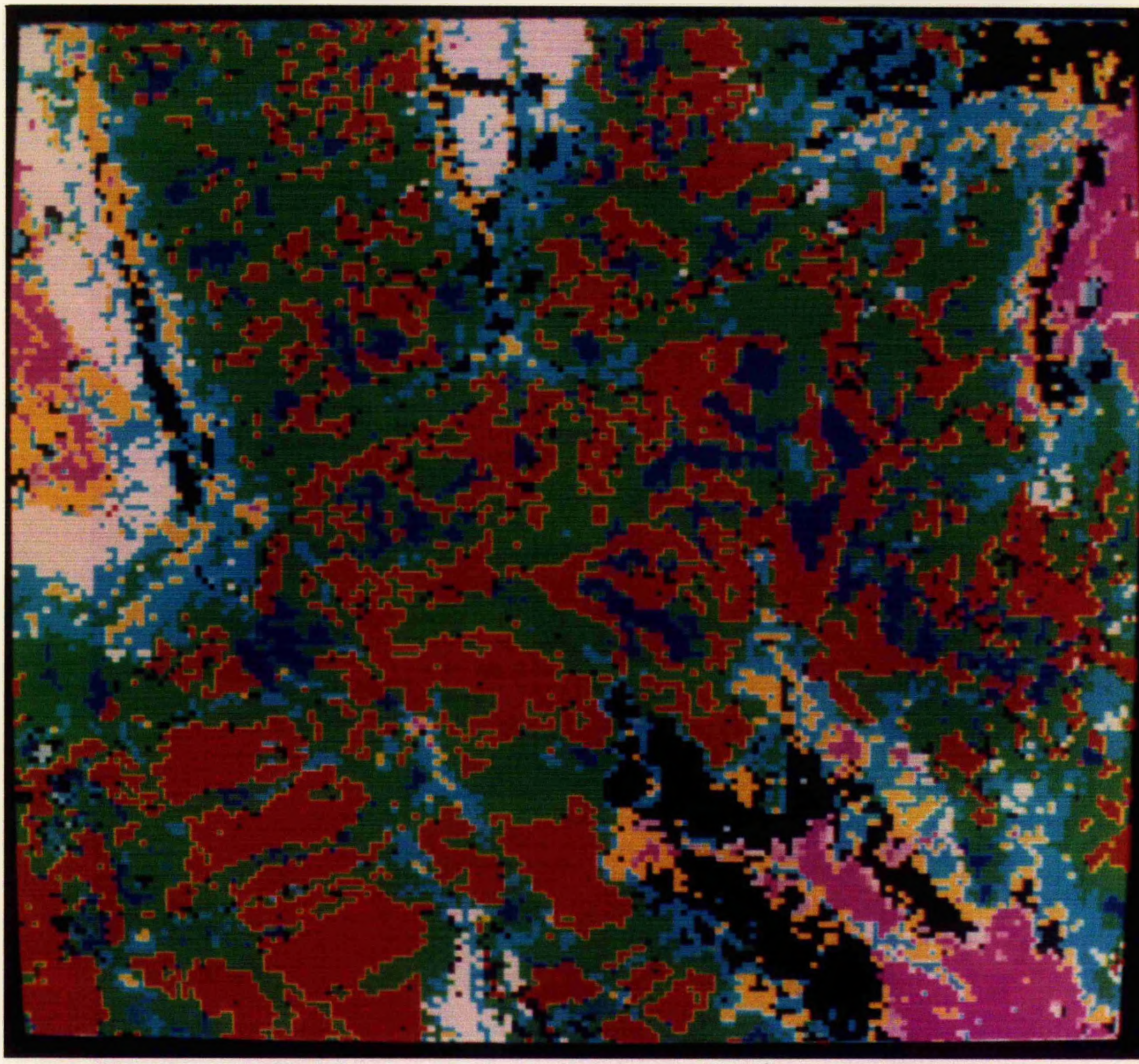


Plate 8 Classified Image of Farndale Study Extract Using Box Classification.

Class	Colour	Number of pixels	% of image
1	Black	20186	7.70
2	Red	54621	20.84
3	Green	91956	35.08
4	D.Blue	14097	5.38
5	Pink	10995	4.19
6	L.Blue	32976	12.58
7	Yellow	14085	5.37
8	White	10638	4.06
Unclassified		12590	4.80

Table 4.8 Percentage Image Classification Results of Farndale Study Extract Using Box Classification.

Class 1 = Bracken.
Class 2 = *Calluna* Mature.
Class 3 = *Calluna* Young /Building.
Class 4 = *Calluna* Pioneer.
Class 5 = Improved Grassland.
Class 6 = Acid Flush.
Class 7 = Acid Grassland.
Class 8 = Plantation Coniferous Woodland.

classified as bracken (black) in which some pixels were also confused with *Calluna* and bare ground. Most of the bracken on the slope facing to the west near Greenhow moor was not classified where it was known to occur.

Improved grassland (pink) occupied only about 4.1% of the study extract whilst acid grassland (yellow) covered about 5.3% of the area. Classification problems also occur for acid grassland which is mostly confused with scattered bracken.

About 4% of the study extract was classified as coniferous plantation (white). However, misclassification also occurred particularly with mature *Calluna*. About 4.8% of the area was unclassified which mainly occurs in the improved grassland area.

4.5.1.4 **Glaisdale study extract.**

The Glaisdale extract has been classified into seven vegetation types namely bracken, *Calluna vulgaris*, semi-improved neutral grassland, improved grassland, bryophytes, wet heath/acid grassland, and coniferous plantation (Plate 4.9).

In this area, *Calluna vulgaris* has been classified for about 43% in which about 23.2% was classified as *Calluna* mature (red) and 19.75% for *Calluna* young/building (green) (Table 4.9). Misclassification occurs only in a small area of coniferous plantation, particularly with mature *Calluna* which has a similar spectral response.

About 11.9% of the study extract was classified as semi-improved neutral grassland (dark blue) and about 8% was classified as bracken

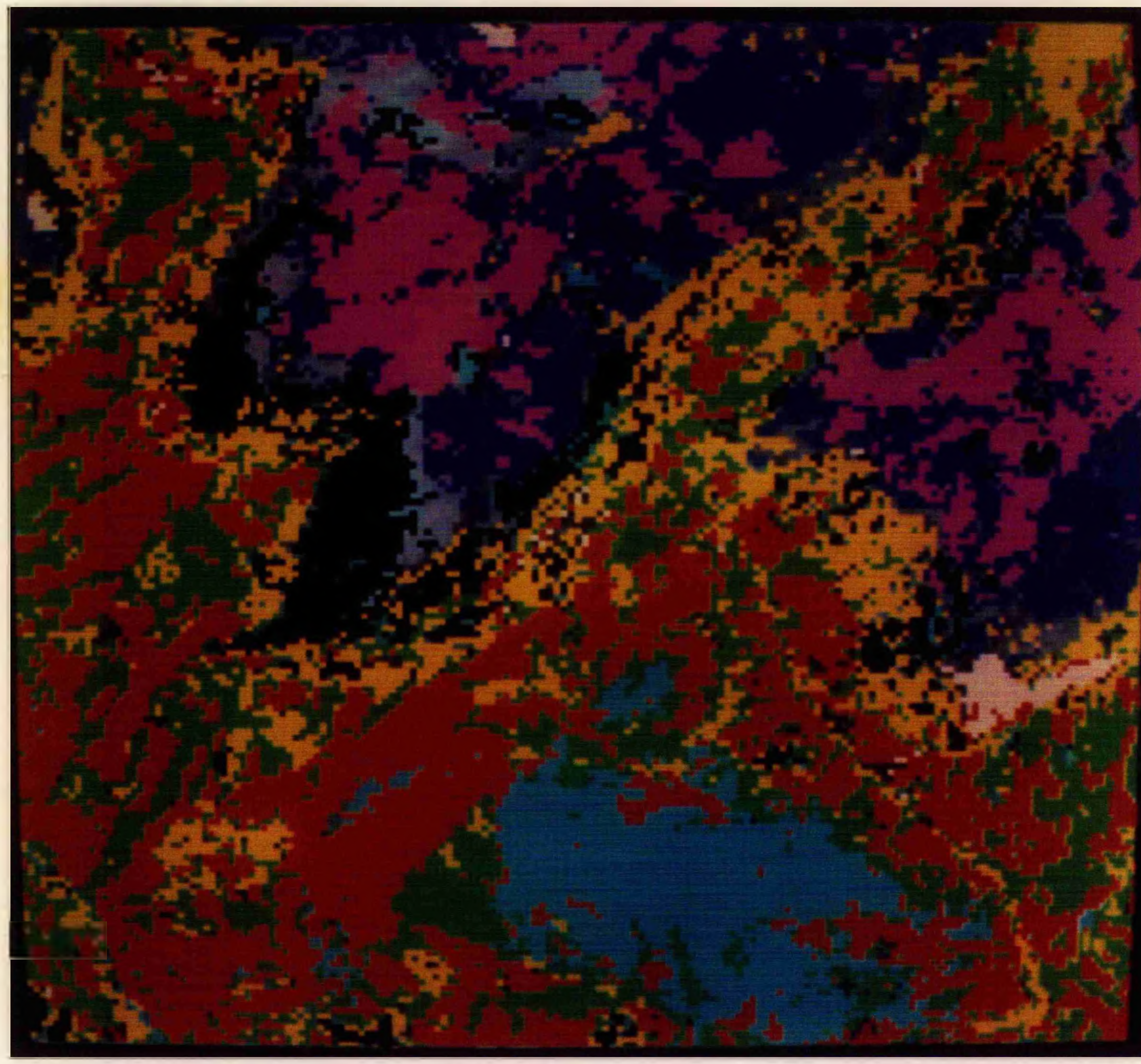


Plate 9 Classified Image of Glaisdale Study Extract Using Box Classification.

0 1.5 Km

Class	Colour	Number of pixels	% of image
1	Black	20949	7.99
2	Red	60970	23.26
3	Green	51767	19.75
4	D.Blue	31200	11.90
5	Pink	21843	8.33
6	L.Blue	15999	6.10
7	Yellow	31042	11.84
8	White	2124	0.81
Unclassified		26250	10.01

Table 4.9 Percentage Image Classification Results of Glaisdale Study Extract Using Box Classification.

Class 1 = Bracken.
Class 2 = *Calluna* Mature.
Class 3 = *Calluna* Young/Building.
Class 4 = Semi-improved Neutral Grassland.
Class 5 = Improved Grassland.
Class 6 = Bryophytes.
Class 7 = Wet Heath/Acid Grassland.
Class 8 = Plantation Coniferous Woodland.

(black). However, confusion also occurs mostly with improved grassland. Wet heath/acid grassland (yellow) occupies 11.84% of the study extract. Confusion occurs mainly with acid dry heath/*Calluna vulgaris,* and also with *Calluna* mixed with *Erica tetralix* on the east and west slopes of Glaisdale Rigg and Danby Rigg.

Improved grassland (pink) located in Great Fryup Dale and Glaisdale occupied 8.33% of the area. Bryophytes (light blue) on Egton High moor/Glaisdale moor covered about 6% of the study extract. In particular, this area was also occupied by *Calluna* and *Eriophorum angustifolium* but the spectral reflectance of this area was dominated by peat soil, giving a low spectral response on TM band 4. The smallest class in the Glaisdale study extract was coniferous plantation (white) which occupied only 0.81% of the area, nevertheless, this class was more accurately defined than the others. However, about 10% of the study extract was unclassified and this is composed of mixed bracken, farmland and arable cropland.

4.5.1.5 **Whitby study extract.**

Eight vegetation communities have been used to classify the Whitby study extract which include bracken, *Calluna vulgaris* (mature), wet heath which is mixed with *Calluna, Molinia caerulea,* and *Erica tetralix,* improved grassland, arable cropland, felled coniferous woodland, broadleaved woodland and coniferous plantation (Plate 4.10).

Most of the area was covered by wet heath (green) with *Calluna* as the dominant which accounted for about 38.7% of the study extract (Table

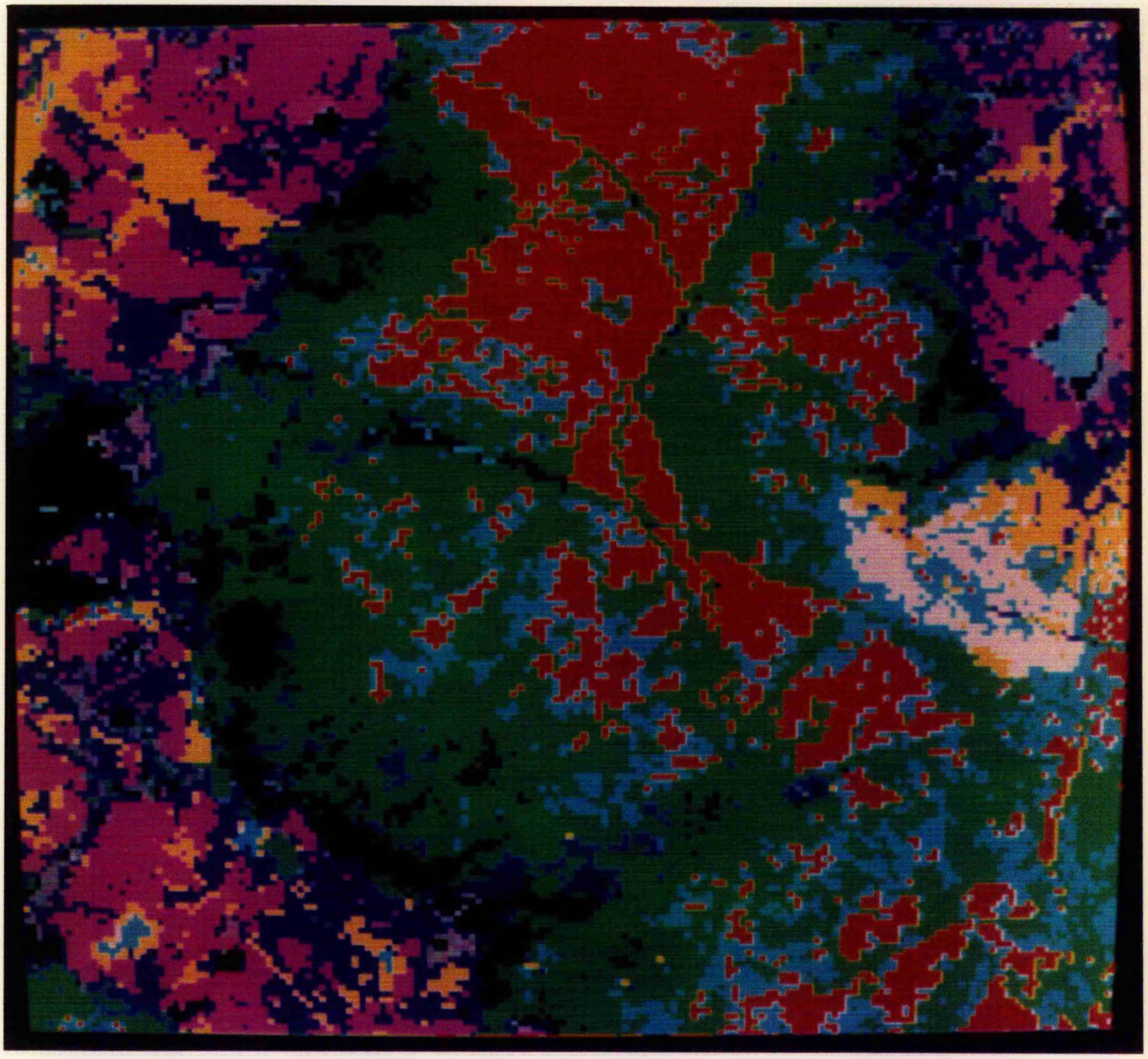
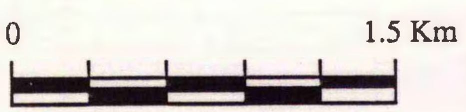


Plate 10 Classified Image of Whitby Study Extract Using Box Classification.



4.10). However, confusion occurred in this class, particularly with the *Calluna* mature class. Bracken (black) was occupied 5.24% of the study extract which mainly confused with improve grassland (farmland area).

The *Calluna* class (red) occupied about 15.7% of the area mainly representing *Calluna* mature. Misclassification occurs for mature *Calluna* which is confused with coniferous woodland. Improved grassland (pink) covered about 15.75% of the area which mainly showed confusion with arable cropland and wet heath.

Arable cropland (dark blue) occupied about 9.1% of the study extract whilst coniferous plantation (white) only occupied about 1.4% of the area. Confusion occurs in the coniferous area as most of this area was occupied by broadleaved woodland, felled coniferous plantation and mature *Calluna*.

Broadleaved woodland (yellow) covered about 4.1% of the area whilst felled coniferous woodland (light blue) occupied about 7.5% of the study extract. However, there were a lot of broadleaved pixels contained within the area of coniferous plantation. Confusion was also present in the felled coniferous class as most of these pixels occurred in the area of mature *Calluna*. However, only about 4.75% of the study extract was unclassified, this is mainly accounted for by farmland and improved grassland areas.

Class	Colour	Number of pixels	% of image
1	Black	17607	6.72
2	Red	30841	11.76
3	Green	101508	38.72
4	D.Blue	41360	15.78
5	Pink	23869	9.11
6	L.Blue	19827	7.56
7	Yellow	10902	4.16
8	White	3786	1.44
Unclassified		12444	4.75

Table 4.10 Percentage Image Classification Results of Whitby Study Extract Using Box Classification.

Class 1 = Bracken.
Calss 2 = *Calluna* Mature.
Class 3 = Wet Heath.
Class 4 = Improved Grassland.
Class 5 = Arable Cropland.
Class 6 = Felled Coniferous Woodland.
Class 7 = Broadleaved Woodland.
Class 8 = Plantation Coniferous Woodland.

4.5.2 Maximum likelihood classification.

Up to now, maximum likelihood classification is still the most common supervised classification method used with remote sensing data (Richards, 1986). This is usually the most expensive and also the most accurate classifier (Curran, 1985). As in box classification, this method also needs training data sets. The principle of maximum likelihood classifier operates by calculating the mean vector, variance, and correlation for each class in the training data. It assumes that the data for each class are normally distributed, therefore, the spread of pixels around each mean vector can be described using a probability function (Curran, 1985). The unidentified pixels will be classified to the specific category based upon the highest probability value, so that every pixel in the image will have one likelihood of belonging to a certain class. The probability of a pixel belonging to a specific class will decrease with distance from the mean vector. The higher probability will belong to the pixels which are close to the main vector. The maximum likelihood classifier's decision boundaries can be represented as a series of ellipsoidal equiprobability contours delineated on the scattergram (Figure 4.12). The shape of the contours express the sensitivity of the likelihood classifier to co-variance.

The maximum likelihood, which is implemented quantitatively to consider a number of classes and several spectral bands simultaneously, forms a potentially powerful classification technique. It requires a large number of computations to classify each pixel, so that more computer resources are required. This classification method is thus much slower computationally than the box classifiers (Lillesand and Kiefer, 1987).

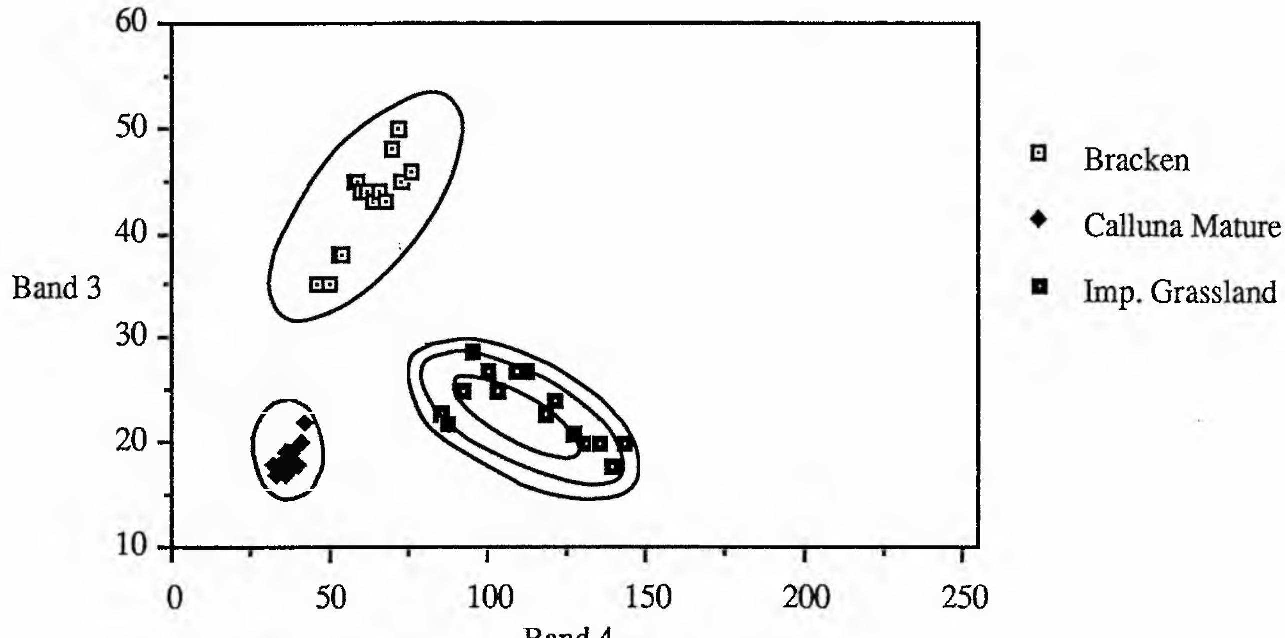


Figure 4.12 Maximum Likelihood Classification Strategy

The result of maximum likelihood classification for the five study extracts will be discussed in the following section.

4.5.2.1 **Blakey study extract.**

The maximum likelihood classification of the Blakey study extract shows that most of the area can be classified into six vegetation communities (Plate 11), whereas only 0.12% of the area was unclassified (Table 4.11). Only about 4.92% of the area has been classified as pure bracken (black) which is smaller than the box classification result. However, mixed bracken (green) was classified at about 16.18% or 1.48% bigger than the box classification result. Confusion still occurs for pure bracken and mixed bracken, being mainly confused with farmland.

Calluna vulgaris was classified for a total of 23.32% of which 13.49% was classified as mature *Calluna* (red) and 9.83% as *Calluna* at the young/building stage (dark red). This statistical result was smaller than the box classification result. As can be seen in Plate 4.11, this classification result was better than the box classification even though misclassification still occurs with farmland areas.

Improved grassland (dark green) accounted for about 13% of the study area or about 3.7% bigger than the box classification result. However, big changes also occur for semi-improved acid grassland (brown) which was classified at 33.35% or about 3.5% bigger than box classification result. This additional area occurred mainly from previously

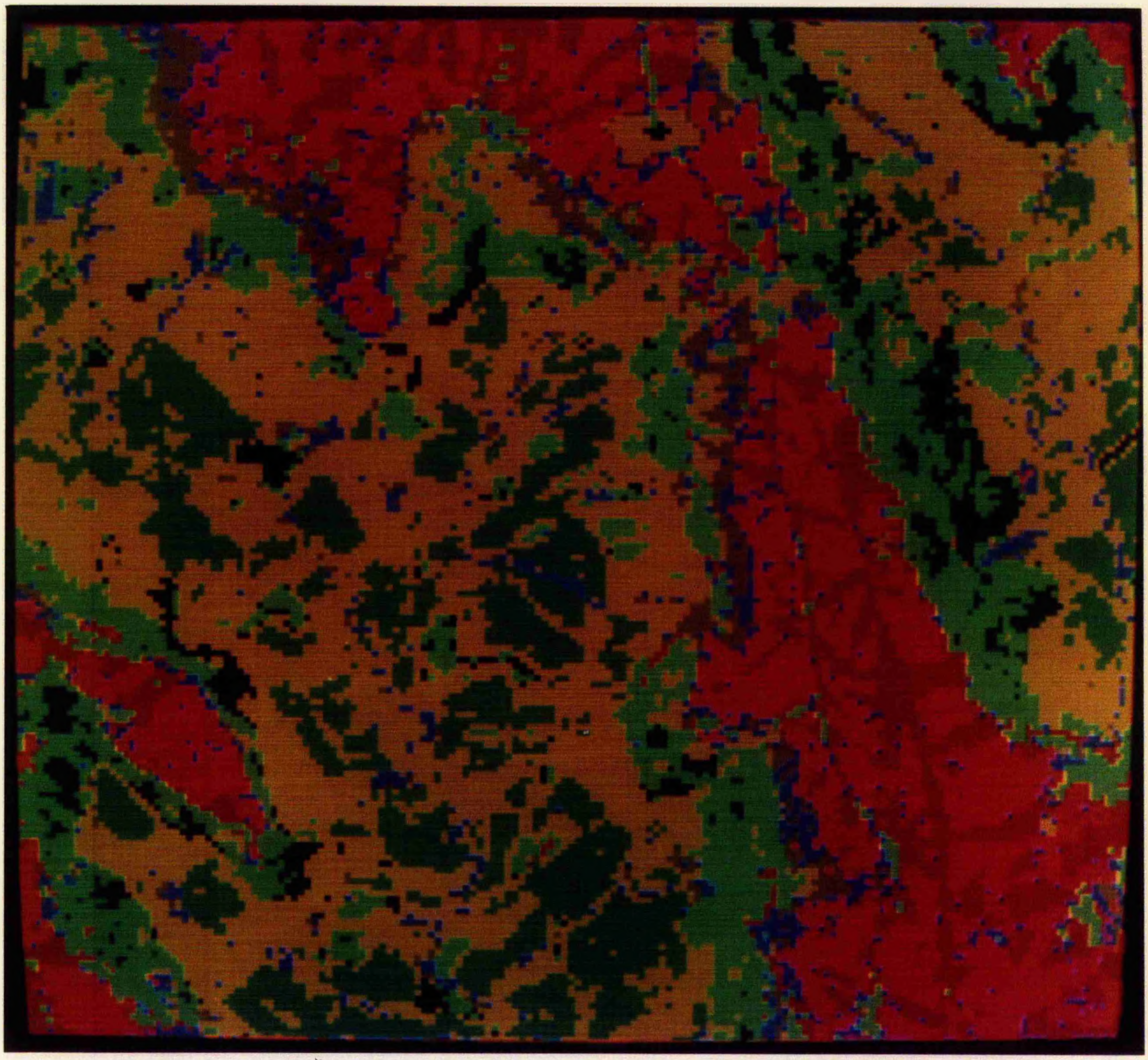


Plate 11 Classified Image of Blakey Study Extract Using Maximum Likelihood Classification.

0 1.5 Km

Class	Colour	Number of pixels	% of image
1	Black	12900	4.92
2	Red	35359	13.49
3	D.Red	25756	9.83
4	Green	42420	16.18
5	D.Green	34299	13.08
6	Brown	87417	33.35
7	D.Brown	10353	3.95
8	Blue	13316	5.08
Unclassified		324	0.12

Table 4.11 Percentage Image Classification Results of Blakey Study Extract Using Maximum Likelihood Classification.

Black	=	Bracken.
Red	=	*Calluna* Mature.
Dark Red	=	*Calluna* Young/Building.
Green	=	Bracken Mixed.
Dark Green	=	Improved Grassland.
Brown	=	Semi-improved Acid Grassland.
Dark Brown	=	Acid Flush.
Blue	=	Broadleaved Woodland.

unclassified areas around the Horn Ridge, Farndale and Sturdy Bank areas.

Acid flush (dark brown) and broadleaved woodland (blue) were also classified as slightly bigger than the box classification result . About 3.95% was classified as acid flush while about 5.8% was classified as broadleaved woodland. However, confusion also occurs particularly for broadleaved woodland with mature *Calluna*.

4.5.2.2 **Egton study extract.**

As was mentioned in the previous section the maximum likelihood classifier will assigned every single pixel into a specific class. Therefore, it will reduce the unclassified pixels. In this study area, only 78 pixels or about 0.03% of the study extract were unclassified. The classification result for all classes were increased except for young or building *Calluna* (green) which was reduced to about 2.33% of the area.

The biggest classification result occurs for mature *Calluna* (dark red) which is increased to about 22.8% or about 10% bigger than the box classification (Table 4.12). However, misclassification also occurred particularly with farmland. The coniferous plantations were not appropriately classified in this area, being assigned to *Calluna* mature. *Calluna* at the young/building stage has been classified as occupying about 19.5% of the study extract. Confusion was also found in the small area of farmland.

The bracken class has been classified as a total of 16.45% of the study area in which 5.4% was classified as pure bracken (black) and about

Class	Colour	Number of pixels	% of image
1	Black	14151	5.40
2	Red	28965	11.05
3	D.Red	59835	22.83
4	Green	51393	19.50
5	D.Green	49693	18.96
6	Brown	22647	8.64
7	D.Brown	14397	5.49
8	Blue	20985	8.01
Unclassified		78	0.03

Table 4.12 Percentage Image Classification Results of Egton Study Extract Using Maximum Likelihood Classification.

Black = Bracken pure.
Red = Bracken Mixed.
Dark Red = *Calluna* Mature.
Green = *Calluna* Young/Building.
Dark Green = Improved Grassland.
Brown = Arable.
Dark Brown = Plantation Coniferous Woodland.
Blue = Broadleaved Woodland.

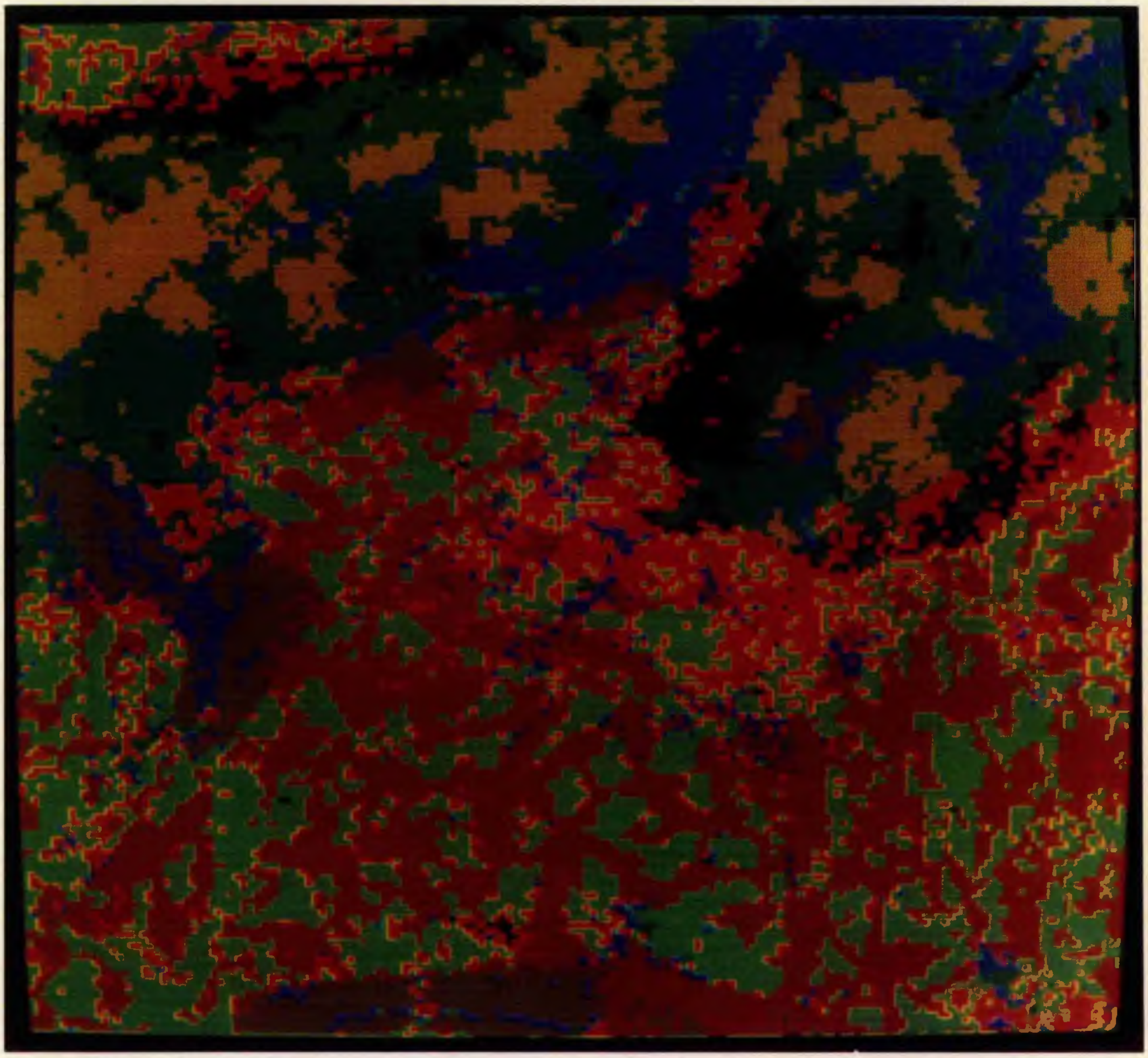


Plate 12 Classified Image of Egton Study Extract Using Maximum Likelihood Classification.

0 1.5 Km

11.05% as mixed bracken (red). Misclassification still occurred in a small area of young *Calluna*. Photographic reproduction problems, make it difficult to distinguish between bracken mixed (red) and degenerate *Calluna* (dark red).

Improved grassland (dark green) was classified as being smaller than in the box classification at about 18.96% of the study extract. The classification result of arable cropland (brown) was about 2.2% bigger than the box classification result whilst plantation coniferous woodland (dark brown) occupied about 4.2% of the study extract. However, confusion still occurred mainly with mature *Calluna* around Pike Hill. The classification result of broadleaved woodland (blue) was not really different from the box classification result. However, as can be seen in Plate 12, this class was better defined particularly in the area of Glaisdale Side and Egton Grange.

4.5.2.3 **Farndale study extract.**

The maximum likelihood classification result of the Farndale study extract, as in the previous study extract, was better than the box classification (Plate 13). Only 105 pixels or 0.04% of the study area was unclassified (Table 4.13).

Calluna vulgaris, which covered most of the study area, has been classified for a total of 63.19% which only 1.89% bigger than the box classification result. Different results occur within the *Calluna* mature and *Calluna* young/building classes. *Calluna* mature (red) has been classified for about 34.78% of the area, or almost 14% bigger than the box classification. In contrast, *Calluna* at the young/building stage (dark

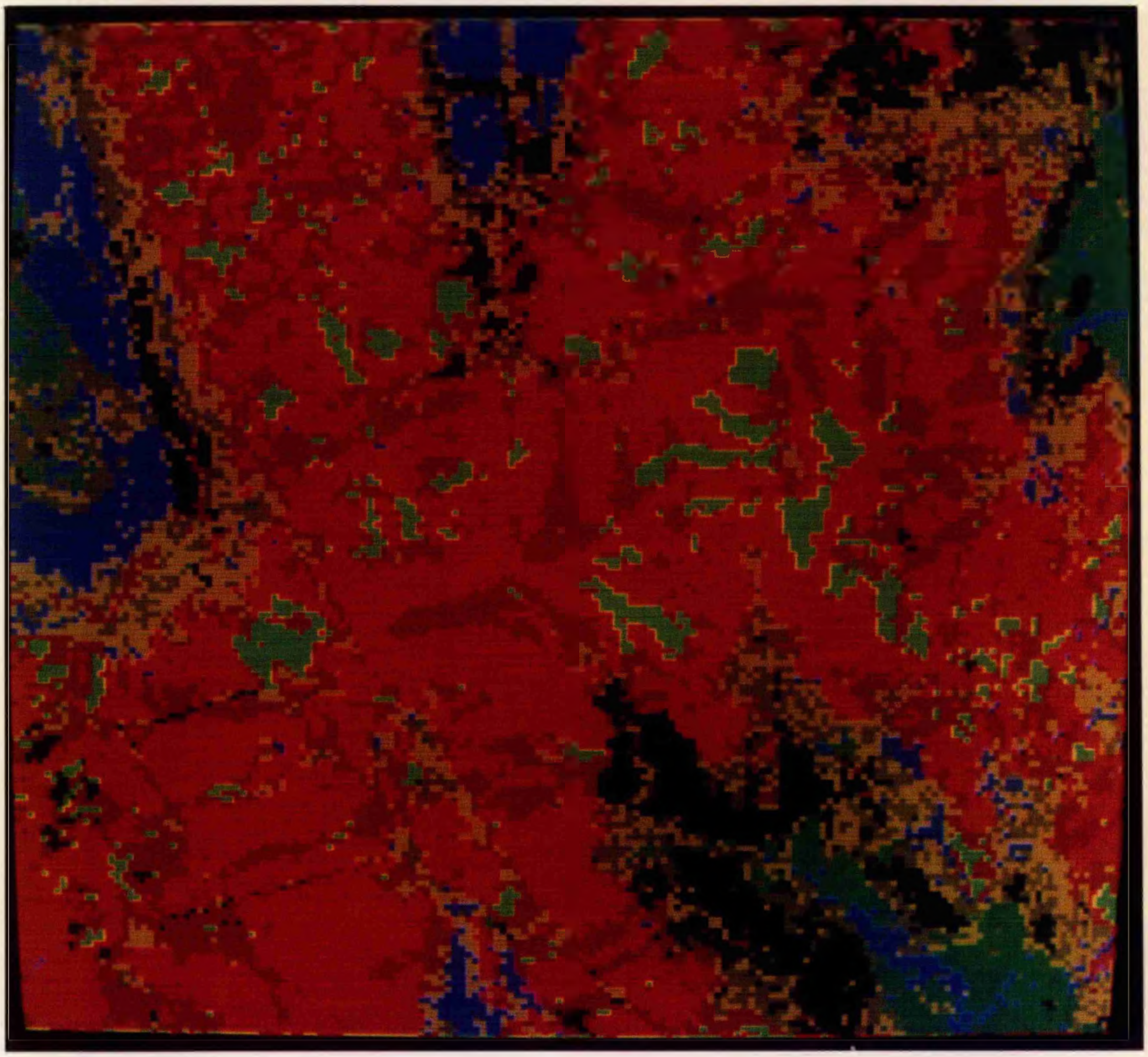


Plate 13 Classified Image of Farndale Study Extract Using Maximum Likelihood Classification.

0 1.5 Km

Class	Colour	Number of pixels	% of image
1	Black	20101	7.67
2	Red	91176	34.78
3	D.Red	62213	23.73
4	Green	12273	4.68
5	D.Green	10713	4.09
6	Brown	29169	11.13
7	D.Brown	21421	8.17
8	Blue	14873	5.71
Unclassified		105	0.04

Table 4.13 Percentage Image Classification Results of Farndale Study Extract Using Maximum Likelihood Classification.

Black	=	Bracken.
Red	=	*Calluna* Mature.
Dark Red	=	*Calluna* Young/Building.
Green	=	*Calluna* Pioneer.
Dark Green	=	Improved Grassland.
Brown	=	Acid Flush.
Dark Brown	=	Acid Grassland.
Blue	=	Plantation Coniferous Woodland.

red) has only been classified as 23.73% of the study extract or about 11.35% smaller than the box classification result. *Calluna* pioneer (green) was only classified for about 4.68% of the study area. However, the maximum likelihood classification produced a better classification result where only only a few *Calluna* pixels were mixed with coniferous plantation, and bracken mixed with *Calluna*.

In this study extract, bracken (black) has been classified for about 7.67% of the total area or almost same as box classification result (7.70%). However, confusion was also occurring particularly with bare ground. The result of improved grassland (dark green) (about 4.09%) was almost the same as in the box classification (4.19%), and confusion with other cover types was also reduced.

The result of the acid flush (brown) was also reduced, however, confusion was still occurring for this class which mostly appears in the acid grassland mixed with scattered bracken in Greenhow Moor and Baysdale Moor.

Acid grassland (dark brown) under maximum likelihood occupies about 8.17% of the total area. This is about 2.8% bigger than the result of the box classification. However, confusion occurred with improved grassland mixed with bracken in the Farndale area and also with coniferous plantation on Greenhow Moor. Coniferous plantation (blue) has been classified for about 5.7% of the study extract or about 1.6% bigger than the box classification result. However, misclassification occurs with *Calluna* mixed with bracken and also with broadleaved wood in Farndale.

4.5.2.4 Glaisdale study extract.

As in previous study extracts, the Glaisdale study extract has improved upon the box classification (Plate 14). Only 0.04% of the total area was unclassified, compared with 10.01% for box classification (Table 4.14). However, *Calluna* has been classified as occupying about 42.74% of the total area, or about 0.27% smaller than the box classification result. *Calluna* mature (red) has been seen to occupy about 31.4% of the study extract which was bigger than the box classification result. However, *Calluna* young/building (dark red) has been classified for only 11.3% of the total area. Confusion occurs where *Calluna* at the young/building stage showed pixels which occupied farmland area.

In this study extract, bracken (black) has been classified as slightly bigger than the box classification result which total about 8.77% for maximum likelihood and 7.99% for box classification. Misclassification occurs mainly with farmland and also with bare ground. Semi-improved neutral grassland (green) has been classified for 15.32% of the area. However, confusion occurs mainly with improved grassland (dark green) which was classified for about 9.33% of the study extract.

Bryophytes (brown) have been classified as covering 7.67% of the total area. This was 1.5% bigger than the box classification result. Misclassification occurs mainly with mature *Calluna* on Egton High Moor and also on Traverse Moor. Wet heath/acid grassland (dark brown) has been classified for about 14.48% of the total area. In particular, this cover type appeared in the north of Glaisdale Rigg. However, misclassification occurs with *Calluna* acid dry heath, acid grassland mixed with scattered bracken, with bracken on the west

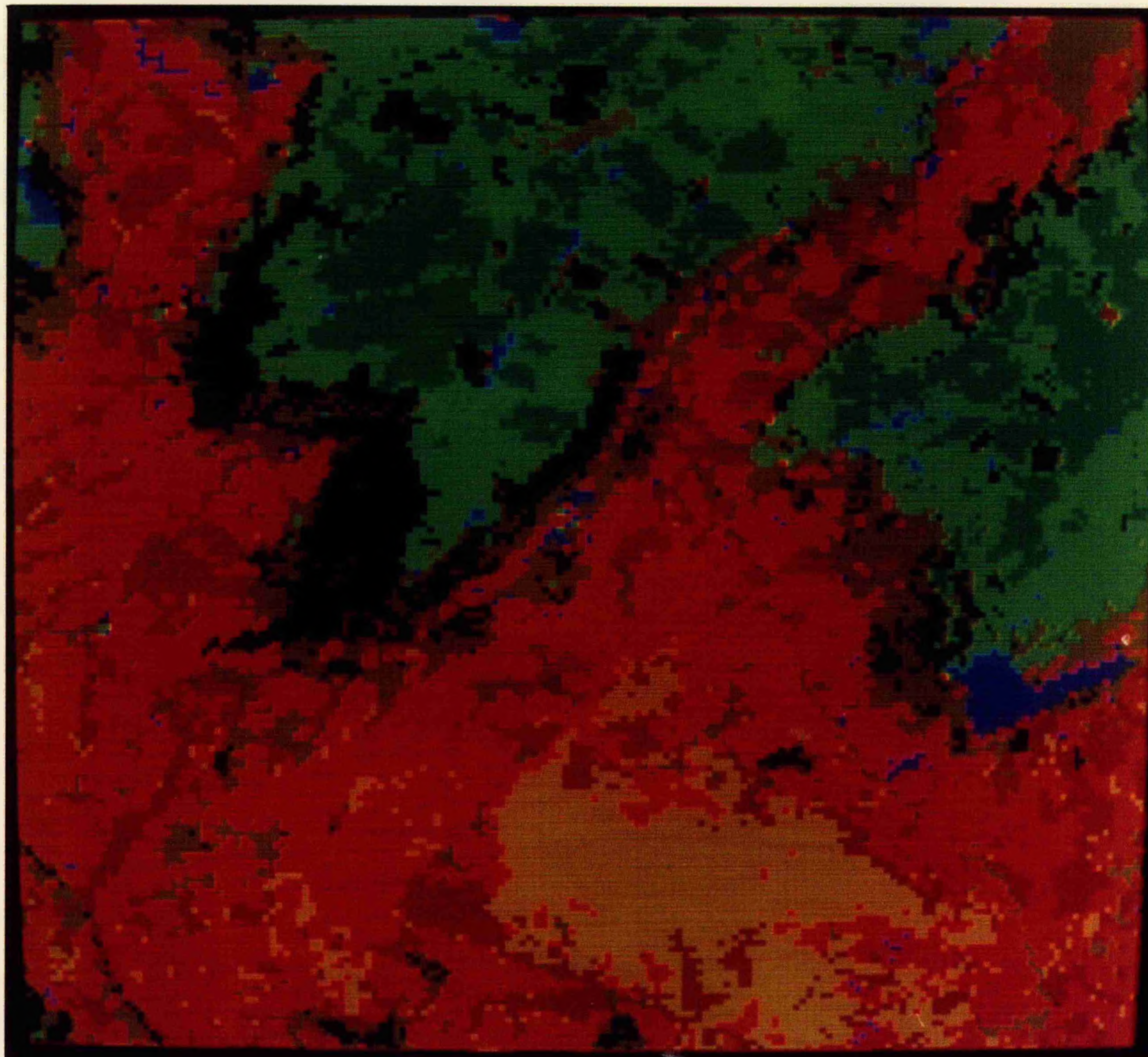
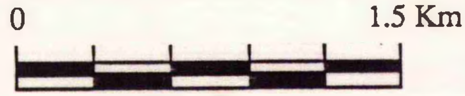


Plate 14 Classified Image of Glaisdale Study Extract Using Maximum Likelihood Classification.



Class	Colour	Number of pixels	% of image
1	Black	22986	8.77
2	Red	82381	31.43
3	D.Red	29651	11.31
4	Green	40149	15.32
5	D.Green	24456	9.33
6	Brown	20115	7.67
7	D.Brown	37954	14.48
8	Blue	4344	1.66
Unclassified		108	0.04

Table 4.14 Percentage Image Classification Results of Glaisdale Study Extraact Using Maximum Likelihood Classification.

Black	=	Bracken.
Red	=	*Calluna* Mature.
Dark Red	=	*Calluna* Young/Building.
Green	=	Semi-improved Neutral Grassland.
Dark Green	=	Improved Grassland.
Brown	=	Bryophytes.
Dark Brown	=	Wet Heath/Acid Grassland.
Blue	=	Plantation Coniferous Woodland.

slopes of Glaisdale Rigg and is also confused with the roads across the moor.

Coniferous plantation (blue) has also been classified as slightly bigger than the box classification result at about 1.66% of the total area. However, there is again misclassification with mature *Calluna* and also with broadleaved woodland.

4.5.2.5 **Whitby study extract.**

In the Whitby study extract, the maximum likelihood classification result (Plate 15) shows that only 0.21% of the study extract was unclassified (Table 4.15). Bracken areas (black colour) were slightly smaller than the box classification result, and only covered about 5.24% of the study extract. Confusion occurs mainly with farmland in the east of Parsley Beck Rigg.

Calluna vulgaris (red) has been classified as larger than the box classification which occupied about 20.97% of the study extract. Wet heath (dark red) which mainly consists of mixed *Calluna vulgaris* with *Molinia caerulea and Erica tetralix,* has been classified for 32.2% of the study extract. Compared with the box classification result, this class was reduced by approximately 6.5%. However, confusion also occurs mainly with farmland area near Parsley Beck Rigg. Improved grassland (green) has been classified at about 20.84% of the area and confusion occurs mainly with wet heath and *Calluna vulgaris*.

Arable cropland (dark green) has been classified at about 7.76% of the total area whilst felled coniferous woodland (brown) was classified for

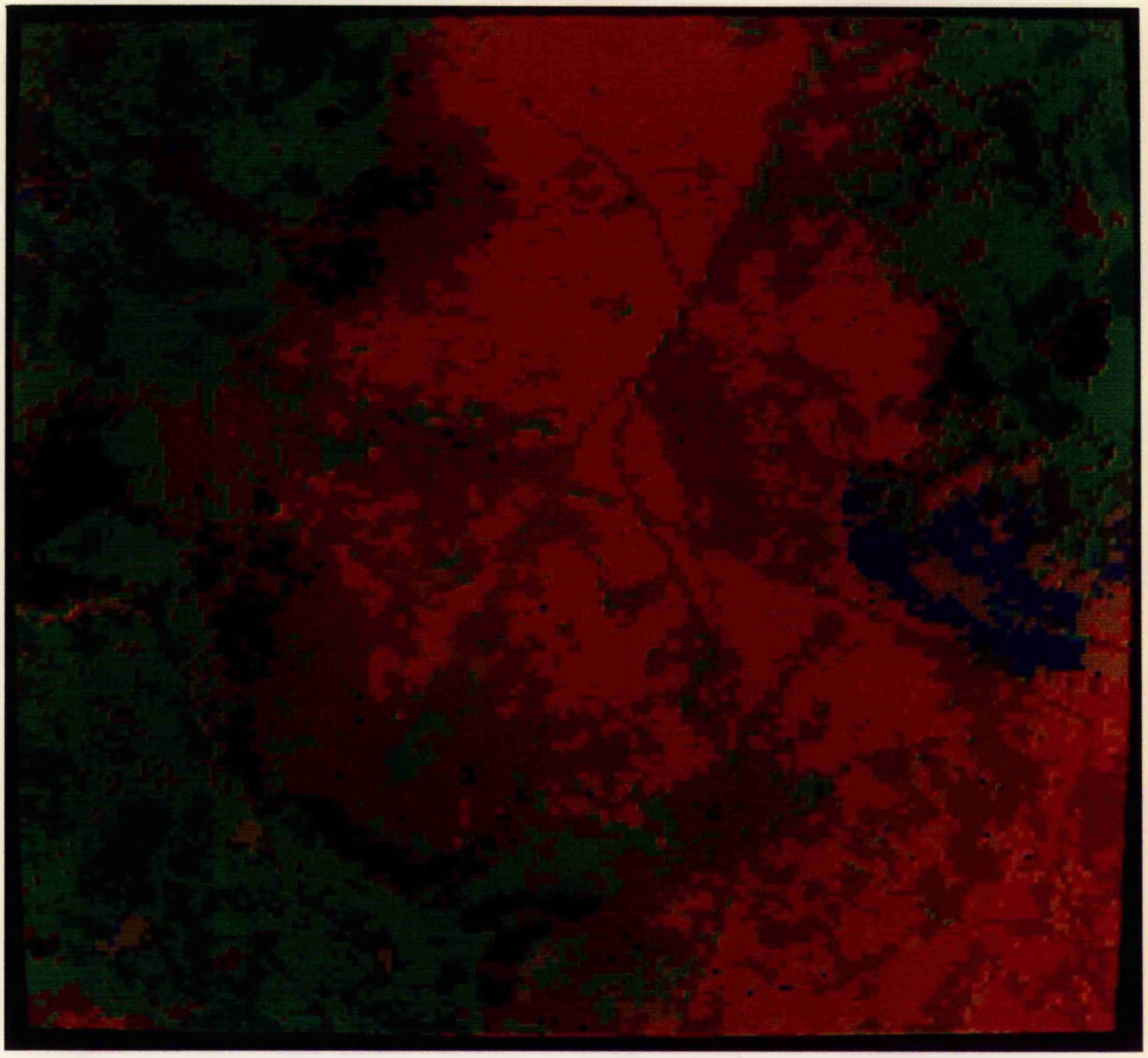


Plate 15 Classified Image of Whitby Study Extract Using Maximum Likelihood Classification.

Class	Colour	Number of pixels	% of image
1	Black	13749	5.24
2	Red	54973	20.97
3	D.Red	84402	32.20
4	Green	54640	20.84
5	D.Green	20349	7.76
6	Brown	13215	5.04
7	D.Brown	15404	5.88
8	Blue	4872	1.86
Unclassified		540	0.21

Table 4.15 Percentage Image Classification Results of Whitby Study Extract Using Maximum Likelihood Classification.

Black	=	Bracken.
Red	=	*Calluna* Mature.
Dark Red	=	Wet Heath.
Green	=	Improved Grassland.
Dark Green	=	Arable Cropland.
Brown	=	Felled Coniferous Woodland.
Dark Brown	=	Broadleaved Woodland.
Blue	=	Plantation Coniferous Woodland.

about 5.04% of the study extract. Confusion occurs mainly with coniferous plantation. Broadleaved woodland (dark brown), which is also confused with coniferous woodland in the Newton House Plantation, has been classified for about 5.88% of the total area, whilst coniferous plantation (blue) was classified for about 1.86% of the study extract. Confusion occurs only for a few pixels which occupy the wet heath areas.

4.6 **Classification Analysis.**

As discussed above, the maximum likelihood classification has a better result compared with box classification, comparison being based upon the percentage of classified training areas. Campbell (1987) suggested that the simplest method of evaluation is to compare the two classmaps with respect to the areas assigned to each category. The comparison is based on the total areal proportion of each categories, usually in percentage classified areas. This comparison usually does not described the locational errors or misclassification, therefore, this can cause inaccurate estimation as it does not consider agreement between the two classmaps at a specific location.

The result of box and maximum likelihood classmaps can be briefly summarized as follows:

a) The box classification result of the five study extracts showed that most of the pixels within study extracts were successfully classified. The lowest number of unclassified pixels was found for the Whitby study extract which showed that only 4.75% of the study extract or 12.444 pixels were not assigned to any specific training class. The highest number of unclassified pixels occurred in the Egton study extract in which 15.4% of the study extract or 40.377 pixels were unidentified. In summary using the box classification technique, the average of unclassified data is approximately 9% of the study extracts. However, it also showed that different field conditions may produce a different classification result. The unclassified data mainly have spectral values which are out of the spectral range of the training classes. This mainly includes bare ground (*e.g.* near Grenhow Moor, in Farndale study extract), urban/farmland or bare soils in arable cropland, and also various spectral values of improved grassland.

b) By using the maximum likelihood classification technique, a better result has been achieved for all five study extracts. It shows that the average of unclassified data was about 0.09% of the study extract, or about 235 out of 262.144 pixels. However, this does not mean that all classified data was correctly allocated. This mostly occurred with farmland and bare ground. In the box classification, they were unclassified as they are not included in any specific class. As the spectral values of farmland and bare ground are similar to bracken values, in the maximum likelihood classification system the probability is that these two cover types may belong to the bracken class. The overall accuracy of the maximum likelihood classmaps will be discussed later in the section 5.4.

Vegetation Community Classes	Box Classification (%)	Maximum Likelihood Classification (%)	% Differences
Blakey Study Extract:			
- Bracken	6.09	4.92	- 1.17
- *Calluna* Mature	14.33	13.49	+ 0.84
- *Calluna* Young/Building	8.73	9.83	+ 1.10
- Bracken Mixed	14.70	16.18	+ 1.48
- Improved Grassland	9.36	13.08	+ 3.72
- Semi-imp. Acid Grassland	29.79	33.35	+ 3.56
- Acid Flush	2.06	3.95	+ 1.89
- Broadleaved Woodland	4.15	5.08	+ 0.93
- UNCLASSIFIED	10.69	0.12	- 10.57
Egton Study Extract:			
- Bracken	4.06	5.40	+ 1.34
- Bracken Mixed	10.42	11.05	+ 0.63
- *Calluna* Mature	12.66	22.83	+ 10.17
- *Calluna* Young/Building	21.83	19.50	- 2.33
- Improved Grassland	16.88	18.96	+ 2.08
- Arable Cropland	6.38	8.64	+ 2.26
- Plant. Coniferous Wood.	4.21	5.49	+ 1.28
- Broadleaved Woodland	8.14	8.01	- 0.13
- UNCLASSIFIED	15.40	0.03	- 15.37
Farndale Study Extract:			
- Bracken	7.70	7.67	- 0.03
- *Calluna* Mature	20.84	34.78	+ 13.94
- *Calluna* Young/Building	35.08	23.73	- 11.35
- *Calluna* Pioneer	5.38	4.68	- 0.07
- Improved Grassland	4.19	4.09	- 0.10
- Acid Flush	12.53	11.13	- 1.40
- Acid Grassland	5.37	8.17	+ 2.80
- Plant. Coniferous Wood.	4.06	5.71	+ 1.65
- UNCLASSIFIED	4.80	0.04	- 4.76
Glaisdale Study Extract			
- Bracken	7.99	8.77	+ 0.78
- *Calluna* Mature	23.26	31.43	+ 8.17
- *Calluna* Young/Building	19.75	11.31	- 8.44
- Semi-imp. Acid Grassland	11.90	15.32	+ 3.42
- Improved Grassland	8.33	9.33	+ 1.00
- Bryophytes	6.10	7.67	+ 1.57
- Wet Heath/Acid Grassland	11.84	14.48	+ 2.64
- Plant. Coniferous Wood.	0.81	1.66	+ 0.85
- UNCLASSIFIED	10.01	0.04	- 9.97
Whitby Study Extract:			
- Bracken	6.72	5.24	- 1.48
- *Calluna* Mature	11.76	20.94	+ 9.18
- Wet Heath/Acid Grassland	38.72	32.20	- 6.52
- Improved Grassland	15.78	20.84	+ 5.06
- Arable Cropland	9.11	7.76	- 1.35
- Felled Coniferous Wood.	7.56	5.04	- 2.52
- Broadleaved Woodland	4.16	5.88	+ 1.72
- Plant. Coniferous Wood.	1.44	1.86	+ 0.42
- UNCLASSIFIED	4.75	0.21	- 4.54

Table 4.16 Percentage of Box and Maximum Likelihood Classification

CHAPTER 5

CLASSIFICATION ACCURACY ASSESSMENT

5.1 Introduction.

Remote sensing systems and applications have been developed over the past decade in order to fulfil the needs of a wide variety of mapping problems (Aronoff, 1985). Aronoff (1982a) suggested that the important criteria used in selecting a remote sensing system is the accuracy of the information produced. This is because of possibilities of errors which may occur in any classification method. Campbell (1987) and Hord and Brooner (1976) showed that in manual interpretation, errors may be caused by excessive generalization, boundary line errors, misidentification of parcels, errors in registration, variations in interpretation detail, and other factors. On the other hand, classification error in machine analysis of digital remote sensing data is more complex, it usually results from sensor resolution, complex interaction between the spatial structure of the landscape, classification procedures, or mixed pixels.

In order to achieved wider acceptance among users, the interpreter must be able to specify the accuracy of the mapping result (van Genderen and Lock, 1977). Therefore, this requires a valid sampling procedure to estimate classification accuracy. The accuracy is commonly assessed by selecting sample test points in each class assigned by the analysis of the satellite remote sensing data and compared with some verification or reference data such as ground checking, thematic maps, aerial photographs or other sensor (Harris, 1987). The result of accuracy of such image/maps are usually represented by the percentage of the map area that has been correctly classified when compared with reference data or ground truth (Story and Congalton, 1986). As valid sampling procedures for estimation classification accuracy are required, there are some criteria which should be considered during sampling decision:

a) Sample test points should be selected according to simple random sampling, stratified random sampling or stratified systematic unaligned sampling (Ginevan, 1979; Harris, 1987; Quirk and Scarpace, 1980; van Genderen and Lock, 1977; van Genderen *et al.*, 1978). However, Congalton (1983) stated that simple random and stratified random sampling provided satisfactory results.

b) The training class should not be used to assess the accuracy of the image classification (Harris, 1987). It is difficult to have confidence because the number of training sample pixels are usually small in relation to the number of pixels to be classified (Lillesand and Kiefer, 1987).

c) The minimum number of sample points at least should be about 30 to 50 for each class depending upon the area units of each class. For a small area of any one cover type it is not necessary to have large number of sample points. Hay (1979) and Ginevan (1979) have indicated the specific number of sample points necessary to achieve a desired confidence level of the classification. Many researchers including Hord and Brooner (1976), Rosenfield (1982) and van Genderen *et al.* (1978), have discussed equations and guide-lines for choosing the appropriate sample size.

d) Once the sample has been gathered, the image classification and the reference data are arranged in a two dimensional classification matrix/error matrix/confusion matrix (Arronof, 1982b; Congalton, 1989; Congalton *et al.*, 1983; Story and Congalton, 1986). An error matrix is a square array of numbers provide with rows and columns usually indicate the reference/verified data which are assumed to be correct, and the rows represent the image classification category such as Landsat TM data (Congalton *et al.*, 1983).

5.2 Accuracy Assessment Approach.

Accuracy of digital image processing for land use/land cover is a complex issue for both definition and measurements. In particular, there is no simple, standardized and generally accepted methodology for determining classification accuracy (Lillesand and Kiefer, 1987). However, the most common approach to accuracy assessment is to compare the results of digital image classification with the known identity of land cover derived from reference data which is assumed to be correct. The assumed true map may be derived from *in situ* investigation or quite often from interpretation of remotely sensed data at a higher resolution or larger scale. Jensen (1986) suggested however that as both maps are defined from the interpretation of remotely sensed data, there is no rigourous foundation to build on.

To determine the overall accuracy of image classification result, it is necessary to define whether the map meets or exceeds some predetermined classification accuracy criteria. Anderson *et al.* (1976) and Fitzpatrick-Lins (1981) suggested that the overall accuracy of land use map should generally be 85% and the accuracy for most categories must be approximately equal. In particular, overall accuracy assessment evaluates the agreement between the two maps for total area in each category (Jensen, 1986). The procedures of evaluating two maps and accepting or rejecting such hypotheses are reviewed by Arronof (1982a), Ginevan (1979), Prisley and Smith (1987), and Rosenfield and Fitzpatrick-Lins (1986).

As was mentioned above, the most common way to represent the classification accuracy of remotely sensed data is to form an error matrix. This error matrix can than be used as a basis for a statistical analysis. Overall accuracy, the most common and simplest descriptive statistics, is calculated be dividing the total correct number of sample points (for example the sum of the major diagonal) by the the total number of samples in the row or column error matrix. This technique is a very effective way to represent accuracy in which the accuracies of each class are described with both the errors of inclusion (commission error) and errors of exclusion (omission error) present in the classification result (Congalton, 1989). To arrange the error matrix, the reference data and the image classmaps must be compared on a point by point basis to determine exactly how each category in the reference data is represented in the classification. Therefore, these two data must be registered to one another. Error in registration will leads to error in the assessment accuracy. Campbell (1987), suggested that the most difficult task of comparing these two data sets are when the reference map is in manuscript form while the map to be evaluated is in digital form. In this research, the assessing of classification accuracy will be done by comparing the classification result of Landsat TM data with the existing

Habitat map. Because of the differences between the date when Landsat TM data was collected and the date of compilation of the Habitat map, the field check data and quadrat samples have been used for further verification. The Habitat map of each study extract, which are used as a reference data have been superimposed on the box and maximum likelihood classmaps. This comparison have been done manually using a stereoscope. However, to facilitate the comparison and to reduce the differences of the scale (between reference data and the image classmaps), the Habitat map have been reduced by about 70%. Based upon the differences of each category coverage, at least 50 sample points of each class were selected using stratified random sampling. The sample points of each class have been plotted onto transparencies which were then overlaid onto the hard copy of the image classmaps. Because of computer screen distortion which occurred when the image classmaps were obtained using static camera, the sample points have not been plotted at the edges of image classmaps. To facilitate detecting activities, a 1 km grid was constructed (based upon the National Grid Map at a scale of 1:10.000) by drawing lines on the transparencies. The result of box classification is shown in Tables 5.1 to 5.5, for maximum likelihood classification in Tables 5.6 to 5.10, and the result are summarized in Table 5.11.

5.3 The Accuracy of Box Classification.

The result of the confusion matrix for each study extracts will be briefly discussed in the following section. The extent of correspondence and non-correspondence between the box classmap and the Habitat map in the confusion matrix of each study extract are displayed in Tables 5.1 to 5.5.

This confusion matrix indicates the number of occasions of the box classification result which are correct or incorrectly allocated to the habitat maps. The diagonal entries shows the correct interpretations. Assuming that the Habitat maps give the correct interpretation, therefore, the top right half of the confusion matrix indicates the errors of commission whilst the lower left half of the error matrix shows the errors of omission. In this section, the result of confusion matrix for the box classification result will be discussed based upon the result shows on Tables 5.1 to 5.5. This was summarized in Table 5.11.

In the Blakey study extract, a total of 434 sample points have been randomly selected in which 317 of those were correctly allocated. As shown in the Table 5.1, therefore, the overall accuracy of the Landsat TM map of Blakey study extract compared with the Habitat map is 73%. This is an overall average result of a wide variety in the accuracy of individual vegetation types. For example, the image box classification with the lowest degree of association with Habitat Map is broadleaved wood. With 24 correctly allocated sample points out of a possible 53, the percentage accuracy of this cover type is 45%. On 21 occasions broadleaved wood was classified on a Habitat map as a mixed bracken community particularly in the west face slope of Blakey ridge, and on 8 occasions as mature *Calluna* . This may be caused by spectral influences of improved grassland as broadleaved wood appears in small patches among the improved grassland.

Box Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	*Calluna* Y.	Brack. Mix.	Improv. Grass.	Sem. Im. Acid G.	Acid Flush	Broad. Wood.			
Bracken	41				2				43	95	5
Calluna Mature		56		2			3		61	92	8
Calluna Young			54	2					56	96	4
Bracken Mixed	12		1	44	3	2	4		66	67	33
Improved Grassland					40	15			55	72	28
Semi- improved Acid Grassland				5	24	28	2		59	47	53
Acid Flush				5	2	1	30	3	41	73	27
Broadleaved Woodland		8		21				24	53	45	55
Totals	53	64	55	79	71	46	39	27	434		
% Omission	23	12	2	44	44	39	23	11			

Table 5.1 Box Classification Accuracy Error Matrix For Blakey Study Extract.

Another low score occurs for semi-improved acid grassland which is only 47% correct (28 correct allocation from a total of 59 point samples). The most confusion occurs with improved grassland as 24 sample points are located in this class. The similarity in spectral reflectance of these two vegetation types may caused this problem.

The most successful result which produced very high results are pure bracken, mature *Calluna* and young *Calluna*. which showed 95%. 91% and 96% correct classification. This is explained by the fact that bracken and *Calluna* are easy to distinguished from other land covers. Even mixed bracken is only 67% correct (44 out of 66 sample points). Most problems occurred with bracken pure for which 12 points are located in this class. This is probably caused by illumination problems, particularly for bracken laid on the west facing slopes of Blakey ridge.

For the Egton study extract, as show in Table 5.2, 430 sample points have been randomly selected in which 343 are correctly allocated, giving an overall accuracy of 80%. The highest accuracy of the box classification results, compared with the Habitat map, are pure bracken and young *Calluna* which display about 95% and 96% accuracy. Bracken pure showed that 37 out of a possible 39 pixels were allocated correctly. On 2 occasions the pure bracken class was shown as improved grassland, however, this confusion was not particularly with improved grassland but farmland areas. As also occurred in the Blakey study extract, broadleaved woodland has the lowest accuracy where only 19 sample points were correctly allocated from a total of 40. Most confusion occurs with plantation coniferous woodland (on 12 occasions) whilst 5 other occasions of broadleaved woodland were

Box Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack. Pure	Brack. Mixed	*Calluna* M.	*Calluna* Y.	Improv. Grass.	Arable Crop.	Pl.Con. Wood.	Broad. Wood.			
Bracken Pure	37				2				39	95	5
Bracken Mixed	2	33		6	1				42	79	21
Calluna Mature			48	1			7		56	86	14
Calluna Young		2		64	4		1		71	90	10
Improved Grassland		3		2	53	5			63	84	16
Arable Cropland	1				20	37			58	64	36
Plantation Coniferous W.			7				52	2	61	85	15
Broadleaved Woodland		1	1	2	5		12	19	40	48	52
Totals	40	39	56	75	85	42	72	21	430		
% Omission	7	15	14	15	38	22	28	10			

Table 5.2 Box Classification Accuracy Error Matrix For Egton Study Extract.

allocated to the improved grassland class. The mature *Calluna,* improved grassland and plantation coniferous woodland have a fairly high accuracy with 86% (48 out of 56 occasions), 84% (53 out of 63 occasions) and 85% (52 out of 61 occasions) respectively. Most problems of confusion arise for mature *Calluna* with plantation coniferous woodland (on 7 occasions), improved grassland confused with arable cropland (5 occasions), bracken mixed (3 occasions) and young *Calluna* (2 occasions), whilst coniferous plantations are mostly confused with mature *Calluna* (7 occasions).

For the Farndale study extract, 85% classification accuracy has been achieved where 337 out of 395 occasions was correctly allocated (Table 5.3). Six out of eight classes have been classified within the range 91% to 98% accuracies, shown by bracken (94%), *Calluna* mature (96%), *Calluna* young (93%), *Calluna* pioneer (98%), improved grassland (92%), and coniferous plantation (91%). Acid flush has the lowest accuracy (45%) in which 21 out of 47 occasions were correctly classified whilst confusion occurs with bracken (8 occasions), *Calluna* young (10 occasions), *Calluna* pioneer (1 occasion), improved grassland (2 occasions), acid grassland (2 occasions), and coniferous plantation (3 occasions). This confusion is probably caused by the mixed pixel effect particularly with young *Calluna* and bracken. Acid grassland has also a low accuracy (67%) in which 24 out of 36 occasion was correctly classified. Problems of confusion occur with bracken (5 occasions), *Calluna* young (1 occasion), improved grassland (2 occasions), acid flush (2 occasions), and coniferous plantation (2 occasion). From those two classes which have low accuracies and are confused with many classes, it seems that heterogeneous training pixels may causing this

Box Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	*Calluna* Y.	*Calluna* P.	Improv. Grass.	Acid Flush	Acid Grass.	Plan. Con.W.			
Bracken	49		2	1					52	94	6
Calluna Mature		47						2	49	96	4
Calluna Young	2		54			1	1		58	93	7
Calluna Pioneer	1			40					41	98	2
Improved Grassland	1			2	54		2		59	92	8
Acid Flush	8		10	1	2	21	2	3	47	45	55
Acid Grassland	5			1	2	2	24	2	36	67	33
Plantation Coniferous Wood		3			2			48	53	91	9
Totals	66	50	66	45	60	24	29	55	395		
% Omission	26	6	18	11	10	12	17	13			

Table 5.3 Box Classification Accuracy Error Matrix For Farndale Study Extract.

confusion. Pioneer *Calluna* has the highest accuracy with 40 out of 41 occasion being correctly allocated whereas confusion occurs only with bracken (1 occasion). On 47 out of 49 occasions, mature *Calluna* was correctly allocated and confusion was found only with coniferous plantation (2 occasions). The similarity of spectral response may be causing this problem.

For the Glaisdale study extract, an overall accuracy of 80% has been achieved in which 324 out of 403 occasions were correctly allocated. In this study extract, improved grassland was successfully classified whilst *Calluna* mature and *Calluna* young were classified for 94% and 92% accuracies. As in previously study extract, mature *Calluna* was confused with coniferous plantation on 4 out of 63 occasions (Table 5.4). Confusion in young *Calluna* occurs with 3 occasions being classified as bryophytes and 1 occasion as improved grassland. Bracken has a 89% accuracy with 47 out of 53 occasions correctly allocated. Confusion occurs with improved grassland (5 occasions) mainly within the farmland area, and young *Calluna* (1 occasion). Relatively high accuracy was achieved for bryophytes (88%) in which 37 out of 42 occasions were correctly classified while on 5 other occasions it was confused with mature *Calluna*. Bryophytes are located on the peat soils which are mainly eroded, following fires which destroyed the higher plants, allowing only bryophytes, which are much less demanding, to recolonise the area. Therefore, the reflectance of bryophytes was dominated by peat soils. In some areas, bryophytes were mixed with *Calluna* so that the spectral reflectance in this area was dominated by *Calluna*. Semi-improved neutral grassland and wet heath acid grass have low levels of accuracy. Only 47% (22 out of 47 occasions) was

Box Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	*Calluna* Y.	Sem.im. Neut.G.	Improv. Grass.	Bryos.	Wet H. Acid G.	Plant. Con.W.			
Bracken	47		1		5				53	89	11
Calluna Mature		59						4	63	94	6
Calluna Young			53		1	3			57	92	8
Semi-Improve Neutral Grass.				22	23			2	47	47	53
Improved Grassland					52				52	100	0
Bryophytes		5				37			42	88	12
Wet Heath Acid Grassland	4		23		1		26		54	48	52
Plantation Coniferous Wood		5			2			28	35	80	20
Totals	51	69	77	22	84	40	26	34	403	638	
% Omission	8	14	31	0	38	7	0	18			

Table 5.4 Box Classification Accuracy Error Matrix For Glaisdale Study Extract.

correctly classified as semi-improved neutral grassland and only 48% (26 out of 54 occasions) as wet heath. Most problems of confusion in semi-improved grassland occur with improved grassland (23 occasions) and also with coniferous plantation (2 occasions), whilst wet heath is mostly confused with young *Calluna* (23 occasions), bracken (4 occasions), and improved grassland (1 occasion). Coniferous plantation was correctly allocated on 28 out of 35 occasions giving an accuracy of 80%. It was confused on 5 occasions with mature *Calluna* and on 2 occasions with improved grassland.

In the Whitby study extract, 374 sample points have been chosen and 292 were correctly allocated (Table 5.5) to give 76% classification accuracy. The lowest classification accuracy was felled coniferous woodland with only 23% accuracy. On only 7 out of 30 occasion was it accurately classified. The most confusion was with wet heath (10 occasions) and coniferous plantation (10 occasions). As this class has its original vegetation type same as coniferous woodland, it will have a similar spectral response. Mature *Calluna,* which achieved 89% accuracy, is mainly confused with wet heath in which mature *Calluna* dominated (8 out of 71 occasion). Plantation coniferous woodland was 97% accurately classified in which 35 out of 36 pixels were correctly allocated. The one remaining occasion was confused with felled coniferous woodland. With relatively low accuracy (55%), arable cropland was poorly classified. It is mainly confused with improved grassland (25 occasions). There is almost no differences in spectral reflectance between these two vegetation types. Other cover types gave better results with bracken being correctly allocated on 39 out of 45 occasions given an accuracy of 87%. Confusion occurs with wet heath

Box Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	Wet Heath	Improv. Grass.	Arable Crop.	Fell.Con. Wood.	Broad. Wood.	Plant.Con Wood.			
Bracken	39		5		1				45	87	13
Calluna Mature		63	8						71	89	11
Wet Heath		6	50						56	89	11
Improved Grassland			7	42					49	86	14
Arable Cropland				25	30				55	55	45
Fellen Coniferous Woodland		3	10			7		10	30	23	77
Broadleaved Woodland		1	1		2		25	3	32	78	22
Plantation Coniferous Wood.						1		35	36	97	3
Totals	39	73	81	67	33	8	25	48	374		
% Omission	0	14	38	37	9	12	0	27			

Table 5.5 Box Classification Accuracy Error Matrix For Whitby Study Extract.

on 5 occasions and arable cropland 1 on occasion. Mature *Calluna* has an approximate accuracy of 89% (63 out of 71 occasions) with only 8 occasions misclassified with wet heath. Wet heath was also has a relatively high accuracy with 50 out of 56 occasions being correctly allocated. Confusion occurs mainly with mature *Calluna* and this is not surprising as this might be caused by mature *Calluna* being dominant in this area. Improved grassland has 42 out of 49 occasions correctly allocated with only 7 occasions being confused with wet heath. Broadleaved woodland achieved a 78% accuracy (25 out of 36 events). Confusion occurs with coniferous woodland (3 occasions), arable land (2 occasions), and once each with mature *Calluna* and wet heath.

5.4 **Accuracy of Maximum likelihood.**

The confusion matrix of maximum likelihood classification result compared with the Habitat map is presented in Tables 5.6 to 5.10. It was mentioned above that it is necessary to use the same position of the sample points for every study extract as in the box classification, so that the result can be compared. However, because of the classification system in which pixels are allocated to a certain class based on the highest probability membership, therefore, some unclassified pixels in the box classmaps (*e.g.* farmland) will be classified into one or another class (*e.g.* bracken or mixed bracken). In contrast, it is also possible that some pixels which have already been assigned into a certain class during box classification will be excluded from that class by maximum likelihood classification. This is caused by the higher probability of these pixels belonging to another class. This means that there might be some significant omission errors.

Using maximum likelihood classification, 81% classification accuracy has been achieved for the Blakey study extract. From Table 5.6 it can be seen that the best classification accuracy has been performed by bracken, mature *Calluna*, and young *Calluna*. Bracken has been classified at 98% accuracy in which 42 out of 43 occasions have been accurately allocated, and only 1 occasion confused with improved grassland. In this classification technique, the farmland area, which is almost unclassified during box classification, will be classified as bracken. Therefore, the statistical report of bracken in maximum likelihood (Table 4.11 - 4.15) will include farmland areas. *Calluna* mature has been classified at 98% accuracy. On 60 out of 61 occasions it was correctly allocated and only on 1 occasion was it mis-classified as acid flush. This confusion may be caused by a mixed pixel where mature *Calluna* is dominant. Young *Calluna* was classified at 96% accuracy with 54 out of 56 occasions being correctly allocated. Confusion occurred with improved grassland (1 occasion) and as acid flush (1 occasion). This problem is probably caused by mixed pixels. A relatively low classification accuracy was produced for mixed bracken, semi improved acid grassland, and broadleaved woodland. For mixed bracken (70% accuracy), only 46 out of 66 pixels were accurately allocated whilst on 12 occasions it was classified as bracken, on 2 occasions as young *Calluna* , 3 occasions as improved grassland, 2 occasions as semi-improved acid grassland and 1 occasion as acid flush. This confusion with various cover types may be caused by various spectral reflectances found in this class. Illumination and topographical factors as well as mixed pixels were the main causes of spectral variation. In particular, mixed bracken was easy to distinguished on the

Maximum Likelihood Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	*Calluna* Y.	Brack. Mix.	Improv. Grass.	Sem. Im. Acid G.	Acid Flush	Broad. Wood.			
Bracken	42				1				43	98	2
Calluna Mature		60					1		61	98	2
Calluna Young			54		1		1		56	96	4
Bracken Mixed	12		2	46	3	2	1		66	70	30
Improved Grassland					46	9			55	84	16
Semi- improved Acid Grasland			3		17	37	2		59	63	37
Acid Flush				3	1	2	34	1	41	83	17
Broadleaved Woodland		7		12				34	53	64	36
Totals	54	67	59	61	69	50	39	35	434		
% Omission	22	10	8	25	33	26	13	3			

Table 5.6 Maximum Likelihood Classification Accuracy Error Matrix For Blakey Study Extract.

colour composite imagery. Compared with the box classification accuracy, improved grassland has gained a much better accuracy with 84%. On 46 out of 55 occasions it was correctly classified whilst on only 9 occasions was it classified as semi-improved acid grassland. Semi-improved acid grassland has gained in the classification accuracy (62%) and shows a reduction of confusion with improve a grassland (17 occasions) but it is also confused with young *Calluna* (3 occasions) and acid flush (2 occasions). Broadleaved woodland also gained better classification accuracy (64%) with a big reduction of confusion with mixed bracken (12 occasion).

For the Egton study extract, 88% accuracy have been achieved with 377 occasions correctly allocated. However, even though the overall accuracy has increased, the accuracy for bracken has slightly decreased (87%). On 34 occasions it was correctly classified, on 2 occasions it was confused with mature *Calluna* (Table 5.7). Confusion also occurred with improved grassland (3 occasions), mainly in the Glaisdale area. As in the previous study extract, this was particularly noticeable for farmland areas. These pixels may have a high probability of belonging to the bracken class. Mixed bracken was more accurately classified (86%) with 36 out of 42 occasions being correctly allocated and confusion with young *Calluna* reduced to only 1 occasion. Mature *Calluna* also had a better classification accuracy (91%) in which 51 out of 56 events were accurately classified and only on 5 occasions was it confused with coniferous plantation. Young *Calluna* has 94% (67 out of 71) accuracy and confusion occurs with bracken mixed (2 occasions), improved grassland (1 occasion) and coniferous plantation (1 occasion). Improved grassland has a 92% accuracy (58 out of 63 occasions) with 3 occasions

Maximum Likelihood Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack. Pure	Brack. Mixed	*Calluna* M.	*Calluna* Y.	Improv. Grass.	Arable Crop.	Pl.Con. Wood.	Broad. Wood.			
Bracken Pure	34		2		3				39	87	13
Bracken Mixed	2	36		1	3				42	86	14
Calluna Mature			51				5		56	91	9
Calluna Young		2		67	1		1		71	94	6
Improved Grassland				2	58	3			63	92	8
Arable Cropland					14	44			58	76	24
Plantation Coniferous W.			4				56	1	61	91	19
Broadleaved Woodland			2	1	4		2	31	40	78	22
Totals	36	38	59	71	83	47	64	32	430		
% Omission	5	5	14	6	30	6	12	3			

Table 5.7 Maximum Likelihood Classification Accuracy Error Matrix For Egton Study Extract.

showing confusion as arable cropland and 2 occasions as young *Calluna*. Arable cropland has the lowest accuracy in this study extract (76%) as only 44 out of 58 occasions are correctly allocated and confusion occurs mainly with improved grassland (14 occasions). The similarity in spectral response (Plate 2) may caused this confusion. Compared with the box classmap, broadleaved woodland showed an improvement even though it is still low in accuracy. On 19 out of 40 occasions it was correctly classified and confusion with coniferous plantations was reduced to only 12 occasions. As in the other study extracts, confusion may be caused by similar spectral response.

The Farndale study extract has a 90% accuracy in which 354 out of 395 was correctly classified (Table 5.8). Most of the classes have an accuracy of over 80%; the highest was achieved by pioneer *Calluna* with 100% accuracy. However, compared with the box classification result, the accuracies of mature *Calluna* has been reduced from 96% to 86% accuracy. Problems of confusion occur mainly with young *Calluna* (4 occasions) and coniferous plantation (3 occasions). As in the box classification result, acid flush was still the group with the lowest accuracy (62%). On 29 out of 47 occasions it was correctly classified whilst confusion occurred with bracken (4 occasions), *Calluna* young (7 occasions), *Calluna* pioneer (2 occasions), improved grassland (2 occasions), acid grassland (1 occasion), and coniferous plantation (2 occasions). Acid grassland has a relatively low accuracy (compared with the other classes) with confusion mostly with bracken (3 occasions), improved grassland, acid flush and coniferous plantation which has 1 occasion of confusion for each class.

Maximum Likelihood Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	*Calluna* Y.	*Calluna* P.	Improv. Grass.	Acid Flush	Acid Grass.	Plan. Con.W.			
Bracken	50		1	1					52	96	4
Calluna Mature		42	4					3	49	86	14
Calluna Young		3	55						58	95	5
Calluna Pioneer				41					41	100	0
Improved Grassland	2				57				59	97	3
Acid Flush	4		7	2	2	29	1	2	47	62	38
Acid Grassland	3				1	1	30	1	36	83	17
Plantation Co niferous Wood.		2			1			50	53	94	6
Totals	59	47	67	44	61	30	31	56	395		
% Omission	15	11	18	7	7	3	3	11			

Table 5.8 Maximum Likelihood Classification Accuracy Error Matrix For Farndale Study Extract.

The Glaisdale study extract has 84% classification accuracy in which 338 out of 403 are correctly classified (Table 5.9). Improved grassland is the best classification accuracy without any confusion. However, wet heath was still poorly classified with only 48% accuracy (26 out of 54 occasions). Most of the confusion occurred with young *Calluna* (21 occasions), bracken (6 occasions) and improved grassland with 1 occasion. This result was same as the box classification. However, confusion with young *Calluna* was reduced but an increase with bracken occurred. Confusion with bracken was seen particularly in the scattered bracken area which is mixed with *Nardus stricta*. The accuracy of bryophytes was slightly reduced (86%) in which 36 out of 42 occasions were correctly classified. On 6 occasions it was classified as mature *Calluna*.

The Whitby study extract has an 87% accuracy in which 325 out of 374 occasions were correctly classified (Table 5.10). The highest classification accuracy occurred for arable cropland and coniferous plantation. With 53 out of 55 occasions, arable cropland was classified for 96% accuracy. Confusion occurs only with improved grassland as it has a similar spectral response. Coniferous plantation was classified at 97% accuracy (35 out of 36 occasions) and confused with felled coniferous woodland (1 occasion). Fairly high accuracy was achieved by bracken, mature *Calluna*, wet heath, improved grassland, and broadleaved woodland. Bracken was classified at 89% accuracy (40 out of 45 occasions) and confusion occurred with wet heath (2 occasions) and improved grassland (3 occasions). In fact, confusion between improved grassland and farmland, which was unclassified in the box classmap, occurred. Mature *Calluna* was classified at 90% accuracy (64 out of 71 occasions)

Maximum Likelihood Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	*Calluna* Y.	Sem.im. Neut.G.	Improv. Grass.	Bryos.	Wet H. Acid G.	Plant. Con.W.			
Bracken	48		2		3				53	91	9
Calluna Mature		60						3	63	98	2
Calluna Young			55			2			57	96	4
Semi-Improve Neutral Grass.				30	15			2	47	64	36
Improved Grassland					52				52	100	0
Bryophytes		6				36			42	86	14
Wet Heath Acid Grassland	6		21		1		26		54	48	52
Plantation Co-niferous Wood		4						31	35	89	11
Totals	54	70	78	30	71	38	26	36	403		
% Omission	11	14	29	0	27	5	0	14			

Table 5.9 Maximum Likelihood Classification Accuracy Error Matrix For Glaisdale Study Extract.

Maximum Likelihood Classification	Habitat Map Class								Totals	% Correct	% Commision
	Brack.	*Calluna* M.	Wet Heath	Improv. Grass.	Arable Crop.	Fell.Con. Wood.	Broad. Wood.	Plant.Con Wood.			
Bracken	40		2	3					45	89	11
Calluna Mature		64	7						71	90	10
Wet Heath		5	51						56	91	9
Improved Grassland		1	5	43					49	88	12
Arable Cropland				2	53				55	96	4
Felled Conifer-ous Woodland		9	1			11		9	30	37	63
Broadleaved Woodland				4			28		32	88	12
Plantation Coni-ferous Wood.						1		35	36	97	3
Totals	40	79	66	52	53	12	28	44	374		
% Omission	0	19	23	17	0	8	0	20			

Table 5.10 Maximum Likelihood Classification Accuracy Error Matrix For Whitby Study Extract.

and confused with wet heath (7 occasions) which was dominated with *Calluna vulgaris*. This also occurred for the wet heath class (91% accuracy) which was confused mainly with mature *Calluna* (5 occasions). Improved grassland has 88% accuracy and is mostly confused with wet heath (5 occasions) and mature *Calluna* (1 occasion) whilst broadleaved woodland has 88% classification accuracy (28 out of 32 occasions) and confused only with improved grassland (4 occasions). The lowest classification accuracy occurred for felled coniferous woodland (37%) in which only on 11 out of 30 occasions was it correctly allocated, 9 occasion's classified as *Calluna* mature, 1 occasion as wet heath and 9 occasions as coniferous plantation. This confusion is mainly caused by similarity of spectral responses also occurred in previous study extract.

5.5 **Summary and Conclusion.**

Based on the accuracy assessment result discussed above, it could be concluded that the box classification technique has been successful to classify the bracken community with an average of 92% accuracy. *Calluna vulgaris* has also been classified to a very high accuracy. Because of different burning patterns, which caused different growth stages, the *Calluna* community was usually divided into two different classes. However, an average of 90% overall accuracy for the *Calluna* community has been achieved in which mature *Calluna* has approximately 91% accuracy and young *Calluna* has approximately 93%. Plantation coniferous woodland also has a fairly high accuracy (about 88%) although confusion with broadleaved woodland and *Calluna* mature cannot be avoided. The lowest accuracies are for acid flush (about 59%) and broadleaved woodland (about 57%). The problem of confusion for acid flush may be caused by heterogeneous training samples which include the spectral reflectance of other classes. Therefore, selecting better training samples may solve this problem. Bracken mixed with other species has an overall accuracy of about 73%. Most of the confusion occurs with pure bracken, particularly in areas of west facing slopes (*e.g.*. in the Blakey study extract). The effect of illumination gives pure bracken values which are lower than average, therefore, this will produce a similar spectral response as bracken mixed.

In the maximum likelihood classification accuracy result, it was shown that the overall accuracy of bracken community is approximately 92%. *Calluna vulgaris* has been classified even higher with an average accuracy of 94% in which mature *Calluna* has about 91% accuracy and young *Calluna* has an approximately 93% accuracy. Improved grassland has been classified with an average accuracy of 92%. Coniferous plantation has performed at an average accuracy of 93% even though confusion still occurs with broadleaved woodland and mature *Calluna*. However, broadleaved woodland and acid flush still only have an average of 76% and 73% accuracies.

Some generalisations may be made regarding the spectral confusion which occurs on both the box classification and the maximum likelihood classification.

Broadleaved woodland, in general, shows low classification accuracy. This may be due to the date of imagery where the trees are not in full leaf in late May, in this somewhat harsh upland environment.

Mature *Calluna* and coniferous woodland both have very dark spectral signatures which are easily confused. This is particularly noticeable in the less sophisticated classification procedures such as density slicing which have not been undertaken in this study.

Much confusion also occurs between improved grassland and arable cropland. Spectral signatures will be similar for grassland and both newly emergent and autumn sown cereal crops in late May. This confusion has been shown to be equally likely in both the box and maximum likelihood classifiers. If the arable cropland and improved grassland classes are combined into a single class of agricultural land use, then 100% classification accuracy will result for this grouping under the maximum likelihood classifier for the Egton study extract.

Some confusions given above can be reduced by the general principle of the merging of class types. Acid and semi-improved acid grassland may be considered appropriate classes to merge under the maximum likelihood classifier to give an acceptable result. Again, in the Blakey study area, if the confusion between "bracken" and "mixed bracken" is resolved by simply drawing up a single class entitled "bracken" then the accuracy for the previous mixed class rises from 70% to 88% accuracy. A carefully considered study of merging of such classes is required.

From these accuracy assessment results, it could be concluded that using classification algorithms for Landsat TM imagery of the North York Moors has successfully classified bracken, *Calluna vulgaris,* improved grassland, and coniferous plantations. The Maximum likelihood classification has resulted in better accuracy than the box classification. However, for fast and relatively cheap image analysis, the box classification was also good in vegetation community separation, particularly in distinguishing bracken from moorland.

Vegetation Community Classes	Box Classification (%)	Maximum Likelihood Classification (%)	% Differences
Blakey Study Extract:			
- Bracken	6.09	4.92	- 1.17
- *Calluna* Mature	14.33	13.49	+ 0.84
- *Calluna* Young/Building	8.73	9.83	+ 1.10
- Bracken Mixed	14.70	16.18	+ 1.48
- Improved Grassland	9.36	13.08	+ 3.72
- Semi-imp. Acid Grassland	29.79	33.35	+ 3.56
- Acid Flush	2.06	3.95	+ 1.89
- Broadleaved Woodland	4.15	5.08	+ 0.93
- UNCLASSIFIED	10.69	0.12	- 10.57
Egton Study Extract:			
- Bracken	4.06	5.40	+ 1.34
- Bracken Mixed	10.42	11.05	+ 0.63
- *Calluna* Mature	12.66	22.83	+ 10.17
- *Calluna* Young/Building	21.83	19.50	- 2.33
- Improved Grassland	16.88	18.96	+ 2.08
- Arable Cropland	6.38	8.64	+ 2.26
- Plant. Coniferous Wood.	4.21	5.49	+ 1.28
- Broadleaved Woodland	8.14	8.01	- 0.13
- UNCLASSIFIED	15.40	0.03	- 15.37
Farndale Study Extract:			
- Bracken	7.70	7.67	- 0.03
- *Calluna* Mature	20.84	34.78	+ 13.94
- *Calluna* Young/Building	35.08	23.73	- 11.35
- *Calluna* Pioneer	5.38	4.68	- 0.07
- Improved Grassland	4.19	4.09	- 0.10
- Acid Flush	12.53	11.13	- 1.40
- Acid Grassland	5.37	8.17	+ 2.80
- Plant. Coniferous Wood.	4.06	5.71	+ 1.65
- UNCLASSIFIED	4.80	0.04	- 4.76
Glaisdale Study Extract			
- Bracken	7.99	8.77	+ 0.78
- *Calluna* Mature	23.26	31.43	+ 8.17
- *Calluna* Young/Building	19.75	11.31	- 8.44
- Semi-imp. Acid Grassland	11.90	15.32	+ 3.42
- Improved Grassland	8.33	9.33	+ 1.00
- Bryophytes	6.10	7.67	+ 1.57
- Wet Heath/Acid Grassland	11.84	14.48	+ 2.64
- Plant. Coniferous Wood.	0.81	1.66	+ 0.85
- UNCLASSIFIED	10.01	0.04	- 9.97
Whitby Study Extract:			
- Bracken	6.72	5.24	- 1.48
- *Calluna* Mature	11.76	20.94	+ 9.18
- Wet Heath/Acid Grassland	38.72	32.20	- 6.52
- Improved Grassland	15.78	20.84	+ 5.06
- Arable Cropland	9.11	7.76	- 1.35
- Felled Coniferous Wood.	7.56	5.04	- 2.52
- Broadleaved Woodland	4.16	5.88	+ 1.72
- Plant. Coniferous Wood.	1.44	1.86	+ 0.42
- UNCLASSIFIED	4.75	0.21	- 4.54

Table 4.16 Percentage of Box and Maximum Likelihood Classification

CHAPTER 6

CONCLUSION

6.1 Introduction.

Almost one third of Britain consists of upland areas, even though being sparsely populated, they still form an important and complex component of the British landscape. They provide water, agricultural products, minerals, timber and also recreation possibilities.

About 40% of the North York Moors National Park is moorland dominated by *Calluna vulgaris*. However, this area now under threat from reduction and loss to agriculture and plantation/forestry, bracken encroachment, erosion and degradation, and changing management practice. Therefore, producing maps that mainly show bracken, moorland, forest and agricultural land which are important to conserve become necessary.

The North York Moors National Park covers an area of approximately 1432 square kilometres. Physical inaccessibility and rough terrain are the most common problems for conventional ground survey, moreover, it is both a) expensive and b) time consuming. Accordingly, remote sensing techniques may offer a relatively cheap solution to the first problem and has a considerable potential for reducing time spent on field work. The high frequency in the availability of satellite remote sensed imagery makes satellite remote sensing an ideal source for monitoring moorland changes.

In this research, a geometrically corrected version of the Landsat TM data of path 203/row 22, taken on 31st May 1985, has been used to discriminate upland vegetation communities of the North York Moors National Park. The main focus of this research involved information extraction from the Landsat TM image to produce a supervised box/parallelepiped and maximum likelihood classmaps of the North York Moors National Park. However, to use full image resolution and to reduce misclassification during the interpretation process, five study extract have been selected namely Blakey, Egton, Farndale, Glaisdale and Whitby. To facilitate image interpretation, field checks, and also to assist in accuracy assessment, the selected study extracts have been chosen using the National Grid system at a scale of 1:10.000.

An accuracy assessment of the box and maximum likelihood classification classmaps have been made by matching the sample points selected randomly from the classmaps to the Habitat maps of the North York Moors National Park. Other ground truth data such as aerial photographs, field checks, and quadrat samples have also been used to assist the assessment accuracy.

This research has shown that it is possible to use Landsat TM data to spatially allocated the major upland communities such as bracken, *Calluna vulgaris*, improved grassland and coniferous plantations. The potential and problems of using remote sensing for upland vegetation mapping and the possibilities of improvements for further work will be discussed in the following section.

6.2 Potential and Problems of the Techniques.

Supervised box/parallelepiped and maximum likelihood classification have been used in this research. In order to compare the classmaps derived from both techniques, training classes selected for box classification have been used for the purpose of running a maximum likelihood classification. Therefore, only eight training classes (the maximum number which can be use for box classification) have been selected for both classifiers. Because of this limitation, the selection of training class was based upon the dominant vegetation species of the various vegetation communities.

Fairly high accuracy has been achieved using the box classification technique. Confusion matrices have showed that an average accuracy for the five training extracts when compared with the Habitat maps was about 77%. In the other hand, maximum likelihood classification produced a higher overall accuracy of approximately 85%. It showed that some vegetation communities were more easily identified or separated from the others. Bracken, mature *Calluna*, young *Calluna*, coniferous plantation, improved grassland, and bryophytes were the better discriminated vegetation communities, whilst acid flush, acid grassland, semi-improved acid grassland were less successfully identified.

In particular, besides the problems which influence the spectral response such as physiological factors (*e.g.* health of vegetation), ecological factors (*e.g.* canopy composition), and atmospheric condition (McMorrow and Hume, 1986; Hall-Könyves, 1987; Hutchinson, 1982; Stohr and West, 1982), there are many other factors which should be considered when considering the inaccuracies of classification algorithms.

a) The relatively low spatial resolution of Landsat TM image in relation to the spatial and spectral complexity of upland vegetation communities.

It has been seen that Landsat TM data can be use to determine the major vegetation communities of the upland areas. However, these data are unable to distinguish between minor vegetation types such as acid flush (*Juncus effusus, Eriophorum angustifolium, Sphagnum* spp.) or some wet acid blanket bog (*Nardus stricta, Molinia caerulea, Juncus squarosus, Erica tetralix*) which are usually mixed together. Spectral values for each pixel, therefore represent an average of mixed vegetation types. Similarly, mixed bracken and also bracken encroachment were also difficult to discriminate.

b) Some different vegetation communities can gives similar reflectance values, therefore, this will lead to spectral confusion.

This problem mostly occurs between bracken and farmland/bare soils in arable land, and also with bare ground. Broadleaved woodland has a similar spectral reflectance to coniferous plantation whilst coniferous plantations have a similar spectral response as mature *Calluna* (*e.g.* in the Egton study area).

c) Topographic/relief factors and aspect have an influence on the spectral response of vegetation communities which are particularly affected by the illumination on the earth's surface.

This problem can cause the same vegetation which is located on different facing slopes giving different spectral reflectance, which could lead to misclassification. For instance, continuous bracken on the west facing slope of Blakey Ridge has a lower spectral response (GR. SE 682963), therefore, most of this area was classified as mixed bracken. On the other hand, the valley mire (VM) at the east facing slopes of Blakey Ridge (GR. SE 691979), which consists of mixed *Juncus effusus* and *Eriophorum angustifolium* have been classified as mixed bracken.

d) Box or maximum likelihood classifiers have advantages and disadvantages.

Using box classification, pixels are assigned to a specific class if they fall within the box regions, which are defined by the training data, and are allocated to the appropriate categories. Problems occurs when pixels fall outside the specific regions or within overlapping regions. This will cause misclassification or unclassified data. Therefore, using box classification the possibilities of having misclassification or unclassified data were high.

On the other hand, using the maximum likelihood classifier may reduce the possibilities of any pixels being unclassified because of its decision rule. Pixels are allocated to the class with which they have the highest probability of membership. However, some omission errors might occur. For example, a pixel which have high probability (*e.g.* 0.39) of belonging to coniferous plantation will be entirely excluded from that class and assigned to the mature *Calluna* class because it has slightly higher probability (*e.g.* 0.41) with respect to the mature *Calluna* class. This problem also occurred for urban, farmland/bare soil in arable land, and bare ground areas, which were unclassified in the box classification, or being allocated as bracken class.

e) The problem of land use/land cover changes between the date of the acquired Landsat TM (1985) imagery and the date of the Habitat maps compilation (1988/1989) will cause mismatch between each other. This will give problems during accuracy assessment.
This problem can be seen in the Farndale study extract where bare ground was mapped as a larger area than was seen in the Landsat TM image. Problems of mismatch was also occurred between field check data (1991) and the Habitat maps. It shows that the area in Elm Farm (GR. NZ 638005), Farndale study extract, has been mapped as continuous bracken, however, on the time of field check, this area was covered mainly by bare peaty humus with a few bracken fronds (see Appendix B). This area had been treated with Asulam about 3 years before the field check.

In spite of all those problems, remote sensing techniques, particularly using Landsat TM data for discrimination of upland vegetation, remains one of the most important alternatives for the mapping and monitoring of these relatively inaccessible area. Many techniques have been proposed to reduce the problems of, and effects upon, spectral information, and this will be discussed in the following section.

6.3 Recommendation for Further Work.

Compared with the spatial resolution of Landsat MSS (79m x 79m), Landsat TM has finer resolution (30m x 30m). Therefore, it is, in theory, a simple concept to detect upland vegetation communities using

Landsat TM data. However, in practise difficulties arise when producing classmaps of the extreme diversity and complexity in the species composition of these communities.

With the relatively low spatial resolution of Landsat TM, in relation to the complex and various upland vegetation communities, there is still a greater chance of mixed pixels occurring. Therefore, to obtained a better image classification result due to the complex vegetation communities, it is recommended to use the imagery with higher resolution such as SPOT imagery which has a pixel size of 20m x 20m for multispectral data and 10m x 10m for panchromatic data. SPOT data is, however, much more limited in its spectral resolution. Future generations of SPOT satellites may improve this.

There are many methods of image preprocessing which can be used to improved the image quality before classification is carried out. The use of image filtering before classification is performed is a possible way to approach for accuracy improvement (Atkinson *et al.*, 1985; Ehlers, 1982; Williams, 1988). The application of masking techniques may also reduce misclassification. Because of the similar spectral response between pure bracken and bare soil in the arable areas, to use the limited available training class for discriminating moorland vegetation communities, it might be useful to excluded the agriculture/arable land by using masking facilities.

The North York Moors areas consists of relatively rough topography, especially in the finger dales. Topography or relief can affected the spectral response of the earth' surface, particularly by sun illumination. Various spectral reflectance can be produced by one or two vegetation types located in the different slopes. Vegetation located on the east facing slope will have more illumination than on the west. This can cause confusion between or within the vegetation types. This problem may be overcome by using band ratios (Holben and Justice, 1981). Another alternative is performing sub-classes so that one vegetation type can be represented by two or more classes. Jones, *et al.* (1987 and 1988) and Williams (1987) suggested that using a digital terrain model to produce a correction for the non-uniform illumination of the terrain will improved the classification result.

Due to vegetation phenology which may affect the spectral response, therefore, to achieve a better mapping result, it is advisable to use multitemporal data. Morton (1986) showed that phenological information of the vegetation species in moorland communities will be useful data in interpreting remotely sensed data. This also useful to determined optimum times of year to distinguish a particular vegetation community. For example, Weaver (1986) indicates that using image data acquired in late May and again in July (when established and pioneer stands of bracken reach the maximum differences) would achieved the best result.

It was suggested in Chapter 4 that the maximum likelihood classifier is still the best classification technique so far, therefore, it is necessary to use maximum likelihood classification techniques particularly for detecting complex and various vegetation communities. Using the maximum available training classes on the image processing system (usually between 16 to 20) means reducing generalization within various spectral responses of vegetation type, therefore, a more detailed result could be achieved. However, box classification was also useful, particularly for recognising the distribution of vegetation spectral responses. It was also useful to discriminate bracken communities from other moorland areas.

To reduce mismatch and to achieve a better result during assessment accuracy, when using the hard copy of the classmaps to compare with the Habitat maps, it is recommended that a better quality of hard copy output be obtained. The development of improved or alternative photographic techniques to take the classmap from the screen could achieve better accuracy. A direct screen dump to a high quality film writer or plotter is a viable alternative and such a technique has recently been developed for Apple Macintosh systems by Collins and MacSiurtain (1991) using the Adobe Photoshop program. Film writers, as used by the RAE Farnborough, produce excellent results, but the costs of such reproductions tend to be prohibitive.

Through the investigation of using Landsat TM data and remote sensing techniques for discrimination of upland vegetation communities, this research has shown that Landsat Thematic Mapper bands 2, 3 and 4 can be successfully used to produce the general distribution of upland vegetation communities. By complementing the research as suggested above and in conjunction with traditional field mapping, remote sensing techniques have a very sound potential in providing upland vegetation communities distribution maps for moorland management purposes.

APPENDIX 1

Terrestrial Photograps of the Study Area

1. Bracken Treatment by Natural Park Service.

Bracken treated with Asulam Hole of Horcum (NGR. SE 845937) showing dead sward, note batch of *Calluna* unaffected. *Calluna/pteridium* mix on hill side in background.

2. Untreated Bracken - National Park Services.

Untreated mature pteridium (late September) in Hole of Horcum (SE 845937) invading (a) acid grassland with *Juncus* in middle distance and (b) *Calluna/Vaccinium* moor in background. Note small patch of Asulam treated bracken to right of grazing sheep.

1. Bracken Treatment - National Park Service.

2. Untreated Bracken - National Park Service.

3. Stages of *Calluna* Moor Building.

Burned *Calluna* moor with old age plants on left mature heather in middle distance. Near Goathland (NGR SE/854977. *Juncus* and *Vaccinium* (bright green) as mind components of the vegetation.

4. Species Mixture in *Calluna* Moor

Burned *Calluna* moor near Goathland (NGR SE/975854) complex of young *Calluna*, degenerate, *Juncus*, *Vaccinium myrtillus*, *Eriophorum* and *Erica* spp., typical of many moorland habitats.

3. Stages of *Calluna* Moor.

4. Species Mixture in *Calluna* Moor.

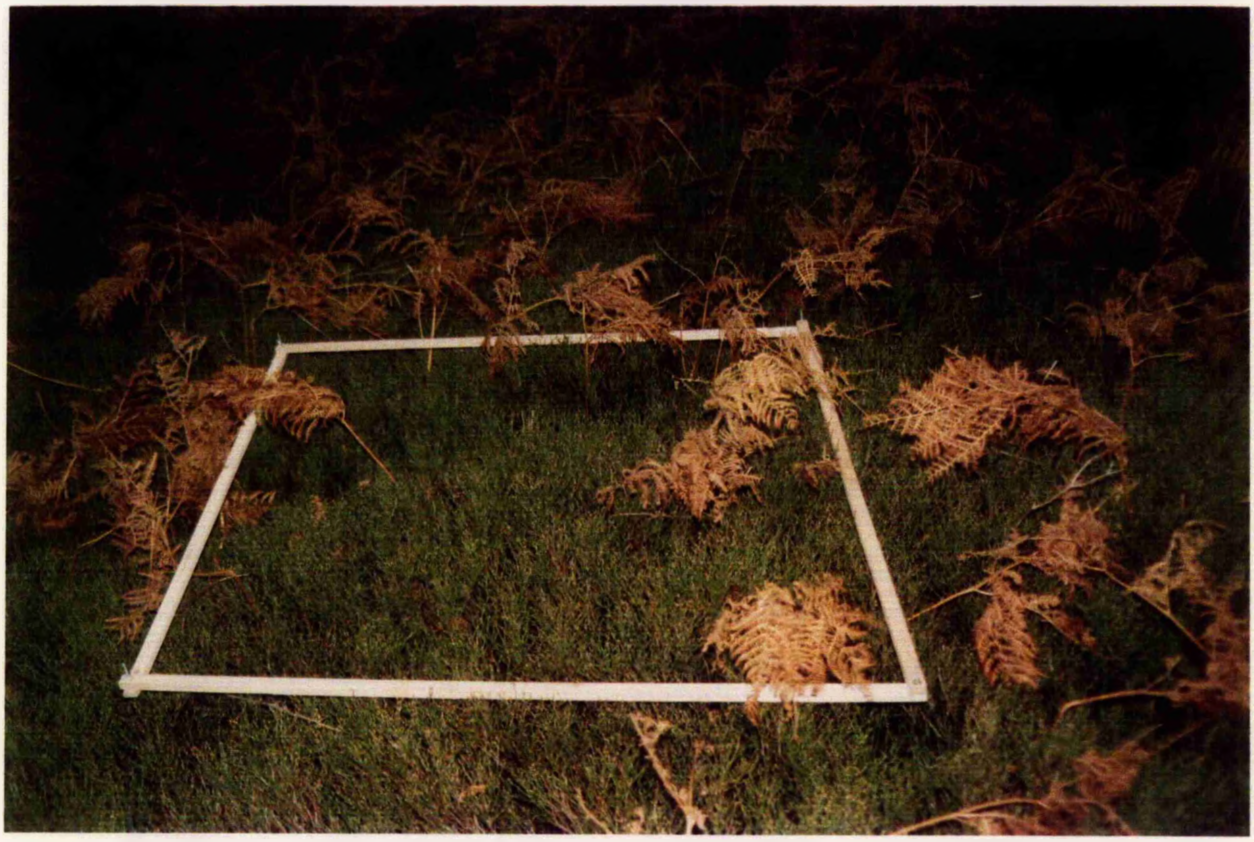
5. <u>Problem of Pasture degeneration.</u>

Pteridium invading pasture at Castleton (November) NGR. NZ 702094.

6. <u>*Pteridium* invasion process.</u>

Metre quadrat at Glaisdale (NZ 766025), showing isolated bracken frond invading *Calluna* moor. Note density of bracken fronds to rear of quadrat, merging into 100% *pteridium* cover.

5. Problems of Pasture Regeneration.



6. *Pteridium* Invasion Process.

7. *Calluna* and *Molinia* domination in mixed moorland communities

Mature *Calluna* at NZ 755055 clearly separated from *Molinia* in foreground. Area of *Molinia* insufficient to produce a clearly defined spectral response but sufficient to give a mixed value for *Calluna*. Moorland in background dominated by a mixed *Calluna/Nardus* community.

8. Mixed Acidic Moorland Dominated by *Calluna* and *Nardus*.

Intimate mixture of *Nardus stricta* and *Calluna vulgaris* of varying ages at NZ 745045. Other species include *Erica tetralix*, not readily visible on the photograph. This acidic moorland community, by virtue of its mixed character, produces particular problems for classification in both field and image processing situations.

7. *Calluna* and *Molinia* Domination in Mixed Moorland Communities.

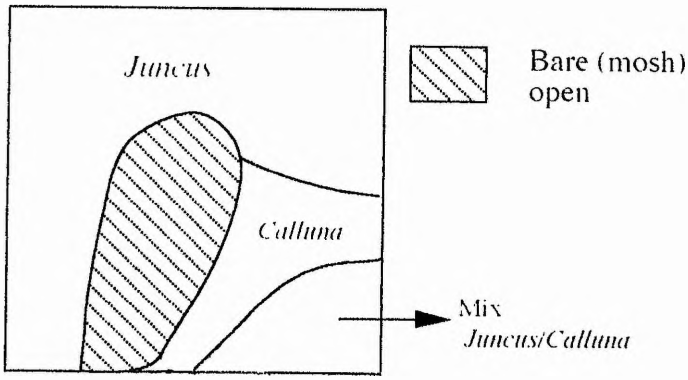
8. Mixed Acidic Moorland Dominated by *Calluna* and *Nardus*.

APPENDIX 2

Sample 1 m^2 Quadrats of Some Vegetation Communities

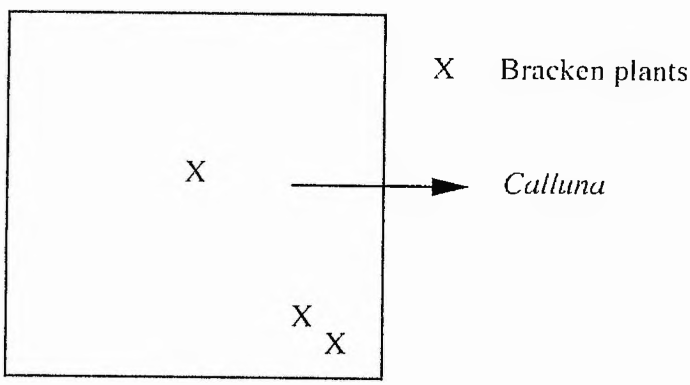
Quadrats represented in this Appendix have been chosen to illustrated the range and complexity of ground cover at local level within the study areas.

(1)



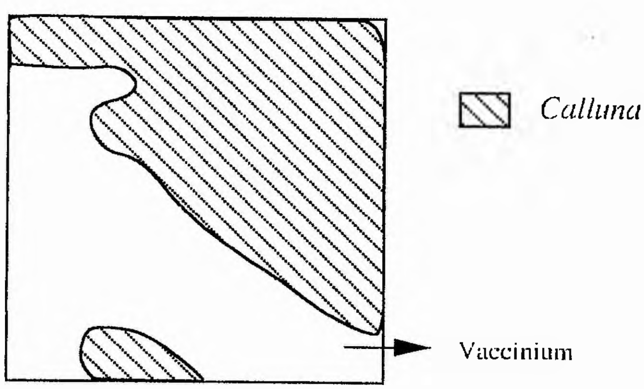
Location:
G.R.: NZ 773012
Slope : 5^0
Juncus : 90 cm high
Calluna : 53 cm high

(2)



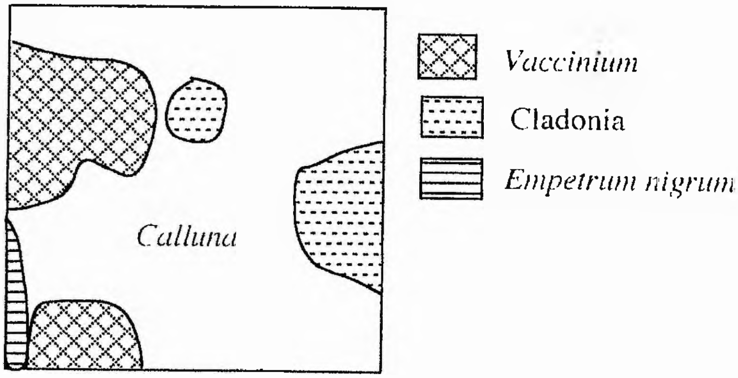
Location:
G.R. NZ 784016
Slope : 7^0
Calluna : 30 cm high.

(3)



Location :
G.R. NZ 784015
Slope : 9^0
Calluna : 31 cm
Vaccinium : 16 cm

(4)

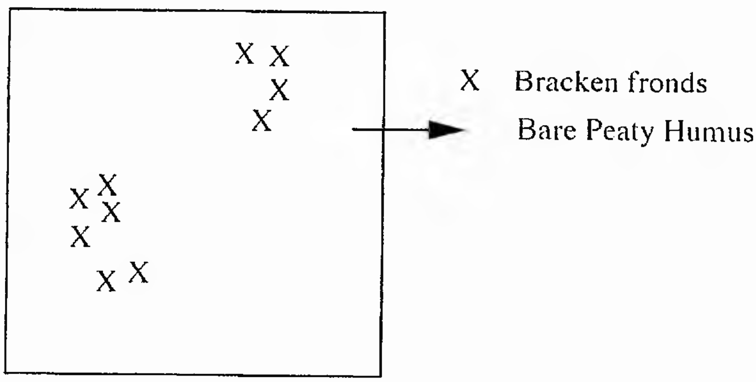


Location :

G.R. NZ 782015

Slope : 11^{0}

(5)



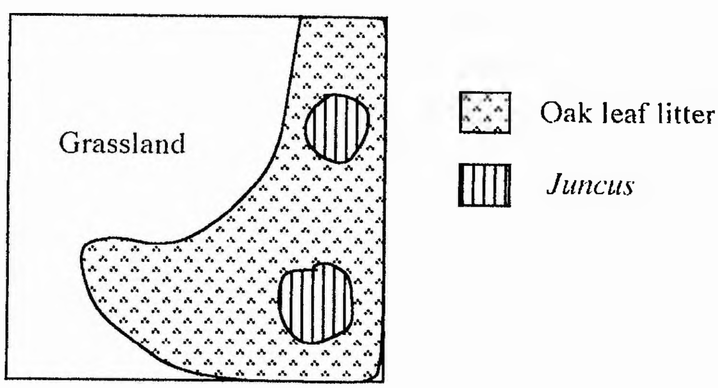
Location :

G.R. NZ 638005

Slope : 17^{0}

Bracken treated with Asulam.

(6)

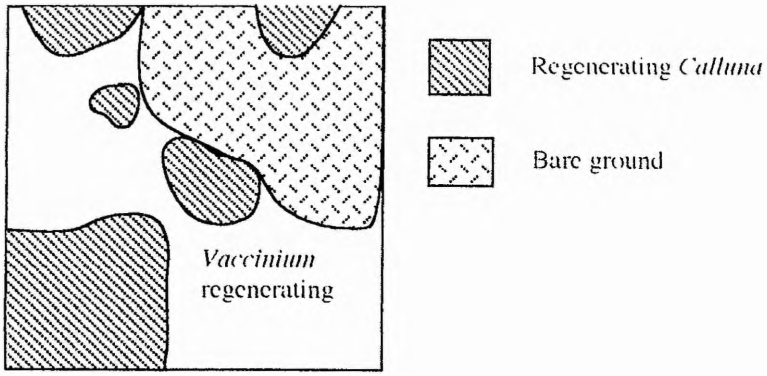


Location :

G.R. NZ 635009

Slope : 11^{0}

(7)



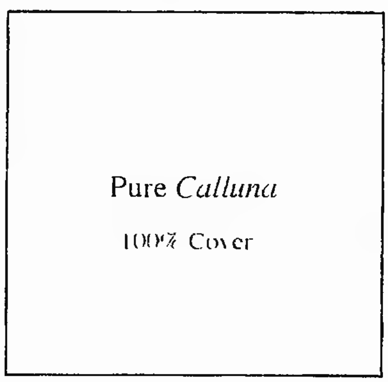
Location :

G.R. NZ 762015

Slope : 2 ^{0}

Calluna burned in 1990

(8)

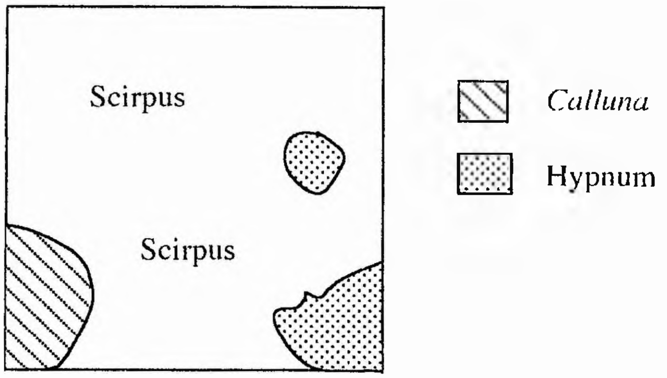


Location :

G.R. : NZ 767016

Calluna degenerate:
- 20 years old
- 72 cm high

(9)



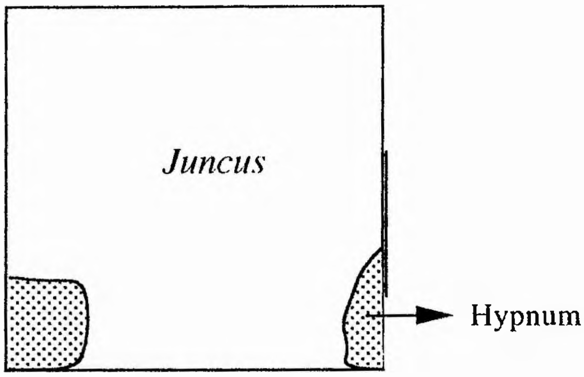
Location :

G.R. NZ 734010

Slope : 2 ^{0}

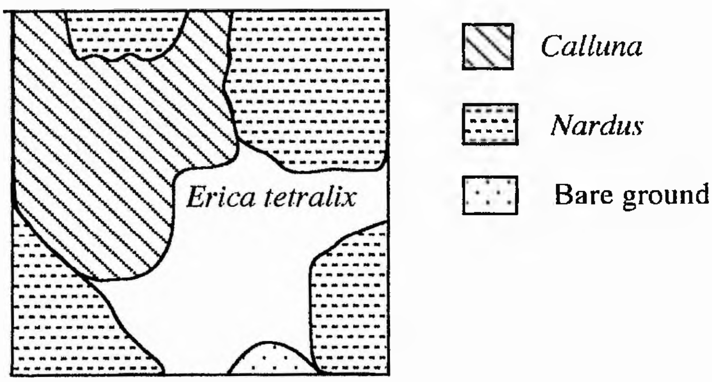
Calluna : 30 cm

(10)



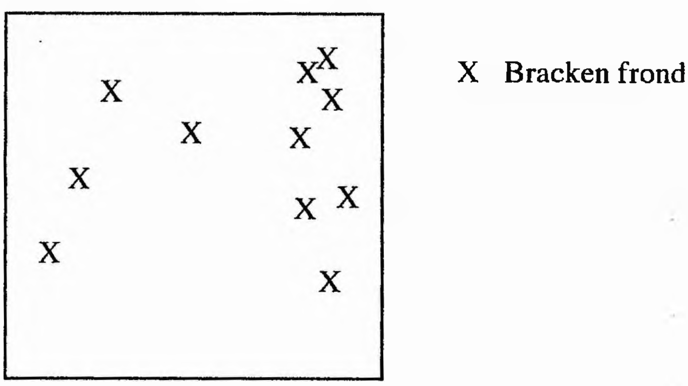
Location :
G.R. NZ 734017
Slope : 3 ^{0}
Juncus : 65 cm high

(11)



Location :
G.R. NZ 736047
Slope : 5 ^{0}

(12)



Location :
G.R. SE 686961
Slope : 9 ^{0}
Bracken: 73 cm high
Vaccinium : 29 cm high

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