The Use of Remotely Sensed Data for Land Cover Classification and the Investigation of Land Cover Change in the North York Moors National Park

by

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ABSTRACT

This thesis is an account of a research work undertaken to assess whether remotely sensed data can be effectively used in inventorying and monitoring moorland communities and related land cover. The study area is contained within the North York Moors National Park and the data used are Landsat TM images for spring 1985 and summer 1991. Analysis was carried out on a Reading-Copenhagen Image Processing System. Maps, aerial photographs and ground data provided additional information to extend the analysis, and to verify results obtained.

Analogue displays of the image data were visually analysed to assess whether different land cover categories could be identified. Pixel value statistics were obtained for the different land cover types and were used in calculating a normalised index of spectral separability to assess their spectral distinctiveness. Maximum likelihood, minimum distance and parallelepiped classification approaches were followed in trying to generate thematic data bases from the raw image data sets. The results obtained were assessed for accuracy. Post-classification comparison; direct-multi date classification; image differencing; image ratioing; principal component analysis; and classification of residual, ratio and higher-order principal component images were the techniques employed in investigating land cover change on the 1985/91 multi-temporal data sets.

Results showed that moorland communities and related land cover types can be visually and spectrally discriminated using the Landsat data; maximum likelihood classification can produce reliable thematic data bases; and changes such as bracken encroachment, dead bracken, moorland regeneration, neglected/fallow farmland, and cleared woodland can be detected through the techniques of post-classification comparison, and classification of residual, ratio and higher-order principal component images. The other classification and change detection approaches produced results which were relatively less satisfactory. Implications of the results for resource inventorying and monitoring are discussed; limitations of the techniques employed are explained, and suggestions for overcoming them are presented.

DECLARATIONS

(i) I, *Twahiri Amani Saidi*, hereby certify that this thesis, which is approximately 80 000 words in length, has been written by me, that it is a record of work carried out by me and that it has not been submitted in any previous application for a higher degree.

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(ii) I was admitted as a research student in *July, 1992* and as a candidate for the degree of *Doctor of Philosophy* in *July, 1992*; the higher study for which this is a record was carried out in the University of St. Andrews between *1992* and *1995.*

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(iii) I hereby certify that the candidate has fulfilled the conditions of the Resolution and Regulations appropriate for the degree of *Doctor of Philosophy* in the University of St. Andrews and that the candidate is qualified to submit this thesis in application for that degree.

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"The management of a National Park involves making policies and taking decisions about the use of the Park for a wide variety of purposes. Always it is necessary to uphold the twin aims of conserving the landscape and promoting its enjoyment by all who wish to use it. A comprehensive and up-to-date data bank of the Park's natural resources is an essential requirement if decisions are to be soundly based."

D.C. Statham [former North York Moors National Park Officer]; *Foreword* in Sykes (1993) **p 1**

CHAPTER 1
INTRODUCTION

The introductory chapter describes moorland environment, its importance and the pressures threatening its survival. It also presents the background to the present study and outlines the objectives of the research project. Principles of data acquisition by way of remote sensing are also discussed. The final part of the chapter reviews a number of moorland studies carried out using remotely sensed data.

1.1 NATURE AND IMPORTANCE OF MOORLAND ENVIRONMENT

Moorlands constitute the largest and probably the most important semi-natural terrestrial environment in Britain (Lance, 1977). They occur mostly in the sub-montane uplands and are fairly widespread in the country, but the most extensive tracts are found in Wales, Scotland and northern England (Ratcliffe, 1977).

The sub-montane uplands have an oceanic climate characterized by high levels of precipitation and atmospheric humidity, low temperatures and windy conditions (Pritchard, 1977). The high levels of precipitation promote soil leaching, whilst the low temperatures tend to slow down processes of chemical weathering and decomposition of organic matter. Under these conditions, the soils are normally acidic and base-deficient. They range from deep blanket peat on flat or gently sloping ground, to thin skeletal brown semi-podzols on steep slopes (Ratcliffe, 1977).

Moorland vegetation is basically that of shrubby and grassy heath. The shrubby heath vegetation is characterized by dwarf ericaceous shrubs like *Calluna vulgaris* (heather), *Vaccinium myrtillus* (bilberry), *Vaccinium vitis ideae* (cowberry), *Erica cinerea* (bell heather), *Erica tetralix* (cross-leaved heather), and *Empetrum nigrum* (crowberry). These are very common on the least fertile acidic soils (Ball *et al*, 1982). The grassy heath vegetation is also predominantly characterized by acid grass species

like *Nardus stricta* (mat grass), *Deschampsia flexuosa* (wavy hair grass), *Festuca ovina* (sheep's fescue), *Agrostis canina* and *A. tenuis* (bents), and *Molinia caerulea* (purple moor grass) (Ball *et al,* 1982).

Moorlands support a wide variety of fauna. Rare heath grasshoppers, tiger beetles, emperor moths and a wide variety of spiders are usually found on the drier moorland areas. Dragon flies, a wide variety of grasshoppers and other insects are also found in moister areas (Foody and Trodd, 1993).

Traditionally, the moorland shrubby and grassy heath vegetation has been used as free-range pasture for domestic animals. Moorlands have therefore always supported the meat production industry which is an important sector of the British rural economy. Previously, the predominant domestic animal was cattle because there used to be a large market for beef and other cattle products. Nowadays, the moors are rangelands almost exclusively for sheep flocks (Miller and Watson, 1974; Taylor, 1978).

Moorlands are also the favoured habitats of the red grouse (*Lagopus lagopus*). The shooting of this bird in summer is a traditional sporting activity. It is still a highly fashionable sport that brings substantial amounts of money to land owners (Tivy, 1973). The sport is obviously resource-based, and its survival in future is dependent on the continued existence of the moorland environment.

The sub-montane moorland areas are also rich in water resources (Taylor, 1978). Most of them are watershed zones feeding water to many streams and rivers which have traditionally provided water to domestic animals and people in the surrounding areas. They also support aquatic plant and animal species.

It is clear from the preceding paragraphs that the moorland environment is an essential natural resource. Recently, however, technological advancements and the desire to

obtain maximum economic returns from whatever resources are available have led to changes in attitude towards the use of moorland environment (Lance, 1977). Under the traditional use as free-range pastureland, the economic productivity of the moorlands is actually very low (Miller and Watson, 1974). With technological advancements, land owners can now choose to increase productivity by converting moorland into seeded pasture that has higher carrying capacities per unit of land. Similarly, large tracts of moorland can be reclaimed and planted with coniferous trees to produce wood products. Although the economic benefits of forestry do not start to come until after many years, people have been attracted by tax concessions to invest in forestry (Gimingham, 1972; Miller and Watson, 1974). In modern times, moorlands have also shown the potential of becoming prime areas of leisure and recreational activities in countryside Britain (Pritchard, 1977). Technological advancements have also meant that the water resources can be more effectively tapped by erecting water reservoirs in the upland areas.

Whilst moorland reclamation for improved agriculture or afforestation, as well as the increased tourist activities and the construction of water reservoirs tend to increase the economic utility value of the moorland environments, they obviously pose a threat to the survival of this ecologically valuable ecosystem. Reclamation, for instance, does not only lead to loss of the original shrubby and/or grassy heath vegetation, but where it is not properly carried out, or where the input of labour into the management of the reclaimed land is drastically reduced, it also encourages the spread of ecologically and/or economically undesirable plant species like *Pteridium aquilinum* (bracken) (Taylor, 1978). Bracken also spreads rapidly into open moorland areas where the continuous cover of the ericaceous shrubs has been disturbed through such activities as overgrazing and severe uncontrolled fires (Taylor, 1978).

Bracken itself is an ecologically disastrous weed. It is a very robust competitor for space and nutrients, and therefore it often succeeds in inhibiting the growth of other species in the areas it becomes fully established. At the same time, it produces large

amounts of litter that harbour sheep tick. This tick transmits a virus disease (tick pyaemia) to sheep, grouse and other vertebrates. The unusually deep litter that accumulates after a chemical treatment of bracken can also render an area sterile, thereby deterring any early plant re-colonization. The trampling effect of grazing sheep or human activity may make such bare areas much more unstable. Senescent bracken fronds are also a fire hazard. Further, the bracken plant itself is toxic if consumed directly by vertebrates at certain times of the year (Brown, 1986).

The conversion of moorland into forest plantations has been the single largest activity that has transformed the appearance of sub-montane upland areas. Whilst it is argued that the afforestation programme is in fact a way of bringing back the original woodland vegetation to the uplands (Miles, 1988), the plantations do not have the same species diversity as the pre-moorland climax woodland vegetation. In fact, most of the plantations have one type of coniferous species and they therefore create unspectacular monotonous landscapes over most of the upland areas.

The spaciousness, relative quietness and wilderness of moorland areas attract tourists from cities. As demand for recreational use of moorland areas grows, damage to the moorland vegetation and soils increases through the trampling and erosion of paths, as well as through the proliferation of roads, car parks and service facilities (Lance, 1977).

The construction of water reservoirs has the potential of disrupting the ecological balance of ecosystems. The dams are "alien" features that replace the natural landscapes thereby changing the whole local ecosystems. Similarly, there is always the possibility of the dams being overfilled with water from very heavy rainfall or melting snow leading to floods that may have devastating effects to the local environments.

Loss of moorland through improved agriculture, bracken encroachment, afforestation, impacts of increased tourism and reservoir construction are real problems facing the moorland environment in Britain today. Concern for the survival of these ecosystems led to some areas of moorland in England and Wales being designated national parks to offer them some form of protection. Nearly all national parks enclose varying extents of moorland ecosystems with the exception of the Broads. In the Pembrokeshire Coast National Park, for instance, moorland constitutes 15% of the Park's area. It is restricted to the Preseli Hills and to some coastal zones. In all of the other national parks, upland moor constitutes between one-third and one-half of their areas (Silsoe College, 1991). But of all the national parks, the North York Moors National Park encloses the most extensive tracts of heather moorland, and the national park status was designated principally to conserve these (Brown, 1986; NYMNP 1990a). The North York Moors is therefore considered a very suitable area for studying moorland environment and the changes it is undergoing.

1.2 BACKGROUND AND OBJECTIVES OF THE STUDY

One of the main responsibilities of National Park Authorities is conservation (NYMNP, 1990a). In this respect, National Park Authorities/Committees are resource management institutions that have the duty to produce resource management plans and help in implementing the policies outlined in them. The National Park Authorities help in the implementation of such plans by making management agreements with farmers, foresters and land owners to manage land in accordance with the outlined resource management priorities (NYMNP, 1977).

Land resource planning is an activity that is normally undertaken by specialists of different fields. These include foresters, agriculturists, ecologists/conservation scientists, recreation scientists, and town and country planners. The diversity in backgrounds of those involved in land resource planning has resulted in a wide variety of approaches to the planning process. However, there are some steps that

planners of all backgrounds normally include in the planning process. These are as follows:

(1) formulation of long-term land resource management goals;

(2) collection of information about the resources;

(3) evaluation of alternative strategies for meeting the long-term goals;

(4) designing and adoption of policies to meet the goals;

(5) implementation of the policies; and

(6) monitoring the effects of the policies that have been implemented (Dale and McLaughlin, 1988; Lindgren, 1985).

The long-term goals formulated at the beginning of the planning process are actually the resource management objectives. Common objectives are to solve land use conflicts; to prevent degradation or loss of resources; and to conserve a certain plant or animal species. The second step in the planning process is to collect information about the resources. This involves carrying out an inventory and the information normally collected is about the types and quantity of resources available, their spatial distribution, conditions and how they have been utilized prior to the inventory. This information helps the planner to know exactly what the resource problems are, where they occur, and what their scale or intensity is. Thus, after carrying out the inventory, the planner would be able to know whether the problems of land use conflicts, resource degradation, or threat to the survival of some species actually exist; and if so, where exactly in the resource base do the problems exist; and how serious they are. The third step involves the exploration of various options for solving the resource problems in order to meet the defined resource management objectives. The information collected at the second step would greatly determine the number and kind of options available for consideration. Many options would normally be available if the information collected at the second stage is both sufficient and of good quality. The fourth step is where the option found to be the most appropriate is finally adopted as a resource management policy/ strategy. The implementation of the adopted policies is the fifth step in the planning process. The final step is monitoring the

effects of the policies that have been implemented (Dale and McLaughlin, 1988). It involves carrying out intermittent surveillance of the resources to assess the extent to which the adopted policies have succeeded in meeting the defined resource management goals (Hellawell, 1992).

Information is the basic resource in any planning activity (Dale and McLaughlin, 1988). Steps 2 and 6 of the planning process outlined above are therefore vital in resource planning. Step 2, resource inventorying, provides information for an original plan; and step 6, resource monitoring, provides information for the revision of existing plans. The conventional way of inventorying land resources is by carrying out ground-based resource surveys. Similarly, the conventional way of monitoring land resources is by undertaking intermittent ground-based surveillance work. The national parks' authorities as resource management institutions, are required to have comprehensive data-bases of all resources in their respective parks, and to update them regularly at 5-year intervals (Countryside Commission, 1991). Using the conventional methods of acquiring resource data, this would be accomplished by carrying out comprehensive ground-based surveys every 5 years. The cost of such repetitive ground-based resource surveys can be prohibitive especially where the area to be covered is so large as is the case in the North York Moors National Park where the total area is 1432Km^2. This reality has led to a re-evaluation of the strategies for acquiring land resource data.

Satellite remote sensing is now considered as a potential alternative source of land resource data. Satellites acquire data for very large areas at any particular time. For example, the Landsat Thematic Mapper images a scene of 185Km x 185Km in dimensions in only 25.87 seconds (Harris, 1987). Some areas within such a large scene might be less accessible to ground surveyors, and thus would more likely remain as data voids when information is acquired through ground-based resource surveys. The large area coverage also allows flexibility in the choice of the scale of resource study. Thus, given a 185Km x 185Km Landsat TM scene, the analyst is able

to decide whether to extract a very small area from the imagery and carry out an intensive study, or to extract an entire district or province in order to carry out an extensive study. The frequency of data collection is also greatly improved using satellite remote sensing. For instance, Landsat TM satellites pass over the same point on the Earth every 16 days, and SPOT can view the same part of the Earth on successive days by off-nadir viewing (Harris, 1987). More importantly from the economic point of view, the cost of satellite data per unit of ground covered are usually reasonable. In 1991, for instance, the average cost of archival satellite data for every $1Km^2$ of ground was 1 penny for 4 bands of Landsat MSS; 6 pence for 7 bands of Landsat TM; and 22 pence for SPOT multispectral and panchromatic data (Budd, 1992). Where the required hardware and software are available, the analysis of such data is not costly either. On commercial basis, the analysis of one full scene of Landsat MSS used to cost £250-£500 in 1980 (Dent and Young, 1981). This gives an average of £1 for every $100Km^2$ since the scene of Landsat MSS and TM covers $34225Km^2$ of ground. Even if we assume that the cost of analysing Landsat TM or SPOT data today is four times the values stated above, the cost of using satellite data would still be lower than that of carrying out comprehensive ground surveys.

A paper map is normally the ultimate medium of presenting and storing the information collected from ground surveys. But once such a map is printed, revising it is not an easy task (Burrough, 1986) and therefore cannot be undertaken at short successive intervals. Thus, the paper map may not be the ideal form of data to be used in long-term change monitoring programmes. By contrast, satellite data are normally in a digital form and are easily manipulated by computers. Whilst paper maps and/or hard copies can be produced from the results of a digital satellite data analysis work, the actual data-base remains in digital form on tapes and/or disks. It is easy to retrieve the data from the digital data-base in order to revise them, or to collate them with other types of spatial data which are also in digital form.

Large area coverage, improved frequency of data acquisition, cost-effectiveness, amenability to quick computer processing, and relative ease of retrieving, revising and collating digital satellite data with other forms of spatial data in digital form, have all combined to make satellite data a potentially more favoured alternative source of information for land resource management purposes so that resource management institutions increasingly consider satellite data as a solution to the problems faced in acquiring resource information. For instance, the North York Moors National Park Committee intends to acquire and develop the equipment for analysing remotely sensed data so that it could use the techniques for monitoring management trends and moorland changes (NYMNP, 1991a; 1991b). But the proposed operation has to be preceded by research to evaluate the suitability of the remotely sensed data for mapping and monitoring moorland and related land cover; and to discover the limitations and other problems that remotely sensed data may have. In the North York Moors National Park, some work within the research theme stated above has already been carried out by researchers. Weaver (1986; 1987a) carried out investigations to discover whether remotely sensed data could provide reasonably detailed information about important moorland cover types like heather and bracken. Jewell and Brown (1987) undertook some work to discover whether different land cover types could be discriminated on colour composite displays of Landsat TM imagery. They also assessed the effectiveness of box classification in extracting land cover information from multispectral Landsat TM digital data. Ward *et al* (1987; 1989) evaluated the effectiveness of using multi-temporal Landsat TM data for monitoring moorland burning practices. Alam and Southgate (1987) also looked at the problem of distinguishing moorland cover types on digital remotely sensed data. Southgate (1989) analysed multi-sensor data acquired during different seasons in order to establish the sensor that gives more detailed information; as well as to establish the time/season of acquisition that might be optimum for moorland mapping purposes. Kardono (1992) assessed the effectiveness of box and maximum likelihood classification techniques in extracting and presenting information about different vegetation communities from multispectral Landsat TM digital data.

The present work is within the same general research theme of evaluating the suitability of remotely sensed data for use in the identification, discrimination, mapping and monitoring of moorland and related land cover types. In particular, the present work evaluates the prospects and problems of using remotely sensed data, particularly Landsat TM, for inventorying land cover types that have management priorities and for detecting changes in those land cover types over a period of 6 years. The specific research objectives are as follows:

- To discover if analogue displays of Landsat data bands contain enough information to allow different moorland and related cover types to be visually distinguished;
- To discover if different land cover types can be discriminated using the brightness intensity (DN) values they registered on the Landsat TM imagery;
- To assess the effectiveness of image classification approaches in extracting and presenting information about moorland and related land cover types from sets of remotely sensed data; and
- To discover if temporal changes in moorland and related land cover types can be effectively detected on multi-temporal satellite data using digital change detection techniques.

1.3 THE REMOTE SENSING METHOD OF DATA ACQUISITION

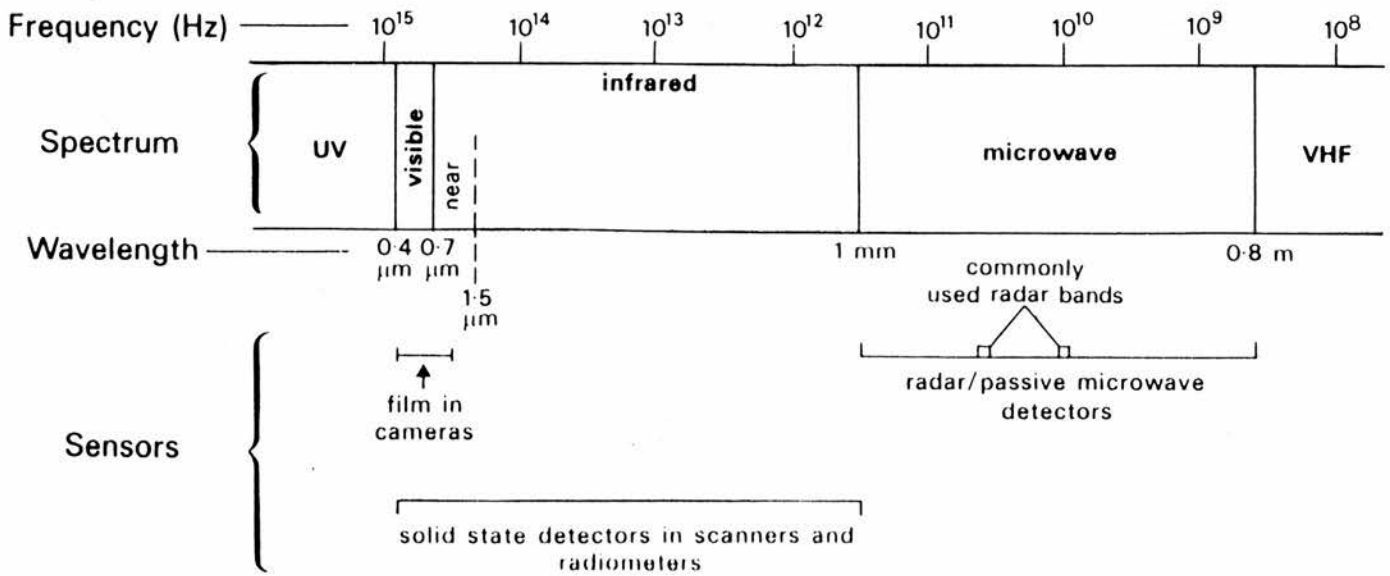
In the preceding section, the potential advantages of using remotely sensed data for land resource appraisal were discussed. In this section, the way such data are acquired is described briefly. The characteristics of Landsat Thematic Mapper data, which are the main remotely sensed data used in this work, are also presented. A brief summary about the general pattern of reflectance of major land cover components is also given.

1.3.1 Fundamentals of Remote Sensing

Remote sensing is a term first coined in the 1960s to describe any method whereby data or information relating to an object are obtained by some sensing device located at a distance from the object (Ritchie *et al*, 1988). Remote sensing of the Earth's surface uses radiation in different parts of the electromagnetic spectrum as a carrier of information regarding various phenomena of the Earth (Olsson, 1986). The sensing devices (sensors) measure and record the amount of radiation reflected or emitted from the ground. At the present level of development, only radiation in the visible, infrared and microwave sections of the electromagnetic spectrum are used in remote sensing (Figure 1.1). Most aerial cameras are sensitive in the visible bands only, but there are others that can also sense radiation in some parts of the infrared section. Scanners on board satellites and high altitude air crafts are normally sensitive in both the visible and infrared sections of the electromagnetic spectrum. Remote sensing in the microwave band is normally undertaken using radar systems.

Sensors like aerial cameras record the reflected signal in analogue form. The resulting data acquired are analogue images/photographs showing the target objects. More modern sensors, particularly those on board satellites, initially record signals in analogue form, but they have on-board devices that convert the analogue signal into digital form. The digital data consists of individual picture elements called pixels, each one of which has a brightness intensity value recorded as a digital number (DN), and a locational "address" in a two dimensional space (Curran, 1985).The address is normally presented as values on an x,y co-ordinate system. The digital data can be stored on tapes or disks and are amenable to computer processing and analysis.

Fundamental to the remote sensing technique of data acquisition is the fact that objects or features reflect varying proportions or levels of incident radiation in the different bands of the electromagnetic spectrum (Budd, 1992). This makes different features appear with different degrees of brightness on analogue remotely sensed



1 μm (micrometre) = 1000 nm (nanometres) = 10^{-6} m (metres)

FIGURE 1.1 SCHEMATIC REPRESENTATION OF SECTIONS OF THE ELECTROMAGNETIC SPECTRUM USED IN REMOTE SENSING (After Hardy, 1981)

images like aerial photographs. On aerial photographs, features that reflect more of the radiation that the cameras are able to record will appear in tones that are different from those of the features that are not very good reflectors of the same radiation. Similarly, different features will register different brightness intensity (DN) values on digital remotely sensed data. Differences in DN values of contiguous pixels therefore suggest spatial differences in land cover types or in the condition of these. Thus, on either analogue or digital remotely sensed data, the differences in spectral response of ground features give clues to their identity and/or condition. Analysis of remotely sensed data may therefore give information about the identity and condition of features, as well as their locations, spatial distribution and extent.

Since the 1970s, remote sensing has been closely associated with satellites although remotely sensed data can also be acquired by sensor on aircrafts, balloons, kites and many other platforms. They can also be acquired using hand-held cameras and radiometers (Budd, 1992). The first satellite to be designed specifically for the acquisition of land resource data was the Landsat 1, originally named as the Earth Resource Satellite-1 (ERTS-1), which was launched in 1972 (Ritchie *et al*, 1988).The Landsat programme has continued since then and more satellites have been launched carrying sensors of improved capability (Figure 1.2).Whilst the Landsat programme has been principally an American venture, since 1986 France with the co-operation of other European nations has also been operating a successful land resource satellite programme :the SPOT series (Campbell, 1987).

The trend in satellite remote sensing seems to be that in which each new satellite being launched carries a sensor that has improved spatial and spectral resolutions than that of its predecessor. The spatial resolution of a sensor is a measure of the smallest unit of ground from which the sensor is able to record a distinct signal (Jensen, 1986; Ritchie *et al,* 1988).This varies from sensor to sensor. For instance, the Multispectral Scanner (MSS) on board Landsat 1-3 could record distinct signals from ground areas of not less than 79m x 79m. The Thematic Mapper (TM) on board Landsat 4-5 can

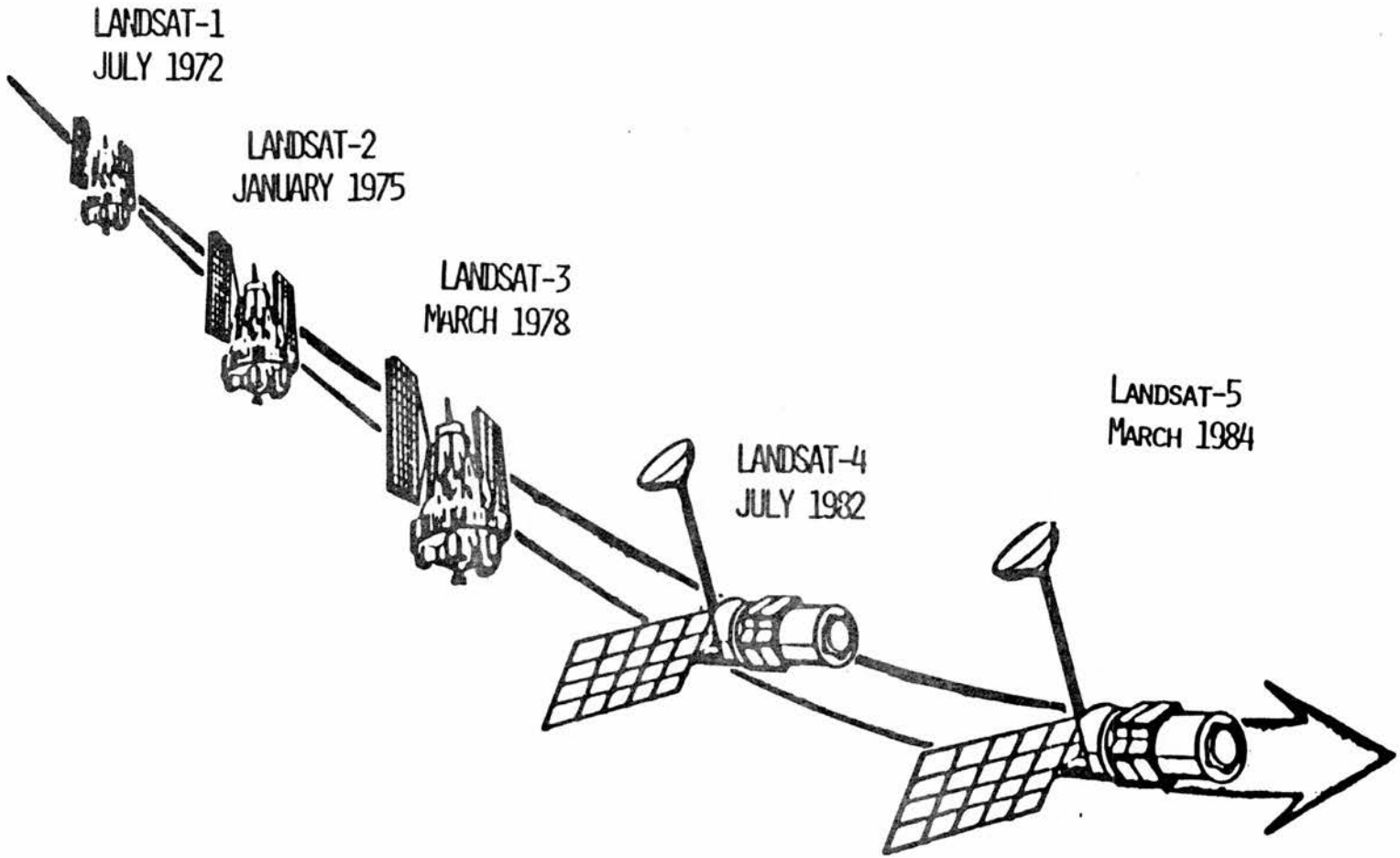


FIGURE 1. 2: LAUNCH PROGRAMME OF LANDSAT SERIES (After Vogel, 1987)

record distinct signals from relatively smaller areas, but of not less than 30m x 30m in size. The Thematic Mapper is therefore said to have a higher spatial resolution than the Multispectral Scanner. Obviously, the higher the spatial resolution of the sensor, the more detailed the information one is able to obtain from a set of remotely sensed data.

Spectral resolution refers to the number and width of wavelength intervals in the electromagnetic spectrum to which a sensor is sensitive (Jensen, 1986; Ritchie *et al,* 1988). A sensor like the black and white aerial camera is sensitive to radiation in only one broad band, the visible (0.4-0.7μm). The Multispectral Scanner (MSS) is sensitive in 4 relatively narrow bands: green (0.5-0.6μm); red (0.6-0.7μm); near-infrared 1 (0.7-0.8μm); and near-infrared 2 (0.8-1.1μm). The Thematic Mapper(TM) is sensitive in 7 narrower bands. The MSS is therefore said to have a higher spectral resolution than the panchromatic aerial camera. The spectral resolution of TM is even higher than that of MSS. Sensors with higher spectral resolution give more detailed information.

1.3 2 Characteristics of Landsat Thematic Mapper Data

The Thematic Mapper (TM) is the primary sensor on board Landsat 4 and 5 (Figure 1.3). It records signals in 7 wavebands from a scene 185Km x 185Km in size. The bands were carefully chosen with the ultimate application of the data more firmly in mind (Harris, 1987). The bands and their uses are as follows:

Band 1: blue-green (0.45-0.52μm) for coastal water mapping and soil/vegetation separation

Band 2: green (0.52-0.60μm) for vegetation vigour assessment

Band 3: red (0.63-0.69μm) for plant species discrimination

Band 4: near-infrared (0.76-0.90μm) for biomass surveys ; delineation of water bodies and soil moisture detection

Band 5: mid-infrared (1.55-1.75μm) for assessment of vegetation moisture content and snow/cloud discrimination

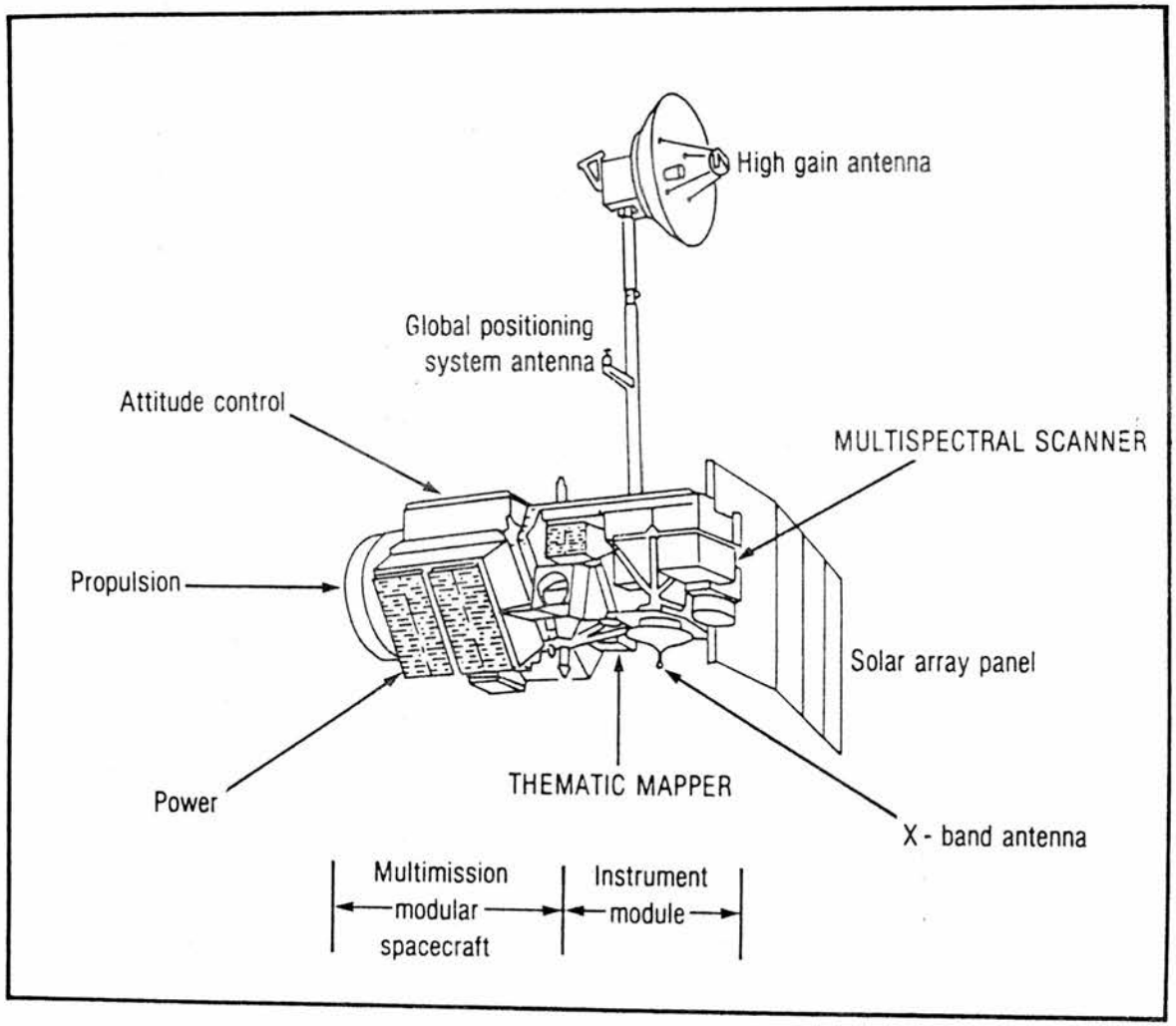


FIGURE 1. 3: LANDSAT 4 AND 5 PLATFORM AND SENSORS (After Harris, 1987)

Band 6: thermal-infrared (10.4-12.5μm) for hydrothermal mapping including plant stress

Band 7: mid-infrared (2.08-2.35μm) for geological mapping and assessment of plant heat stress (Campbell, 1987; Harris, 1987; Lillesand and Kiefer, 1987).

The spatial resolution of the Thematic Mapper is 30m in the six non-thermal bands and 120m in the thermal-infrared band. Thus, on TM data each pixel represent a ground unit of 30m x 30m in size in the six non-thermal data bands. In band 6 (thermal-infrared) each pixel represents a ground unit of 120m x 120m in size. The digital TM data are quantized into 256 brightness intensity levels. Thus, the DN values of pixels on TM data range from 0 to 255

1.3.4 Reflectance Patterns of Surface Features

In order to be able to make effective interpretation and use of remotely sensed data, it is necessary to know the general reflectance patterns of the major components of landscape, namely water, soil and vegetation. The reflectance patterns of these in the visible and near-infrared bands are described very briefly.

1.3.4.1 *Reflectance Patterns of Water*

Much of the radiant energy incident on a water body is either transmitted or absorbed. Very little is directly reflected. The transmitted energy normally ends up finding its way back to the atmosphere as back scatter. Much of the radiation that sensors record from bodies of water is therefore this back scatter. In clear water, the level of back scatter is highest in the blue-green (0.44-0.54μm) region as Figure 1.4 illustrates (Campbell, 1987; Meyer and Welch; 1975). Rayleigh's law of scattering postulates that small particles will have the tendency to cause severe scattering of radiation whose wavelength is less than the diameter of the particles. It would therefore be expected for the relatively small pure water molecules to cause severe scattering of the shorter wavelength blue-green radiation. The intensity of scattering is normally

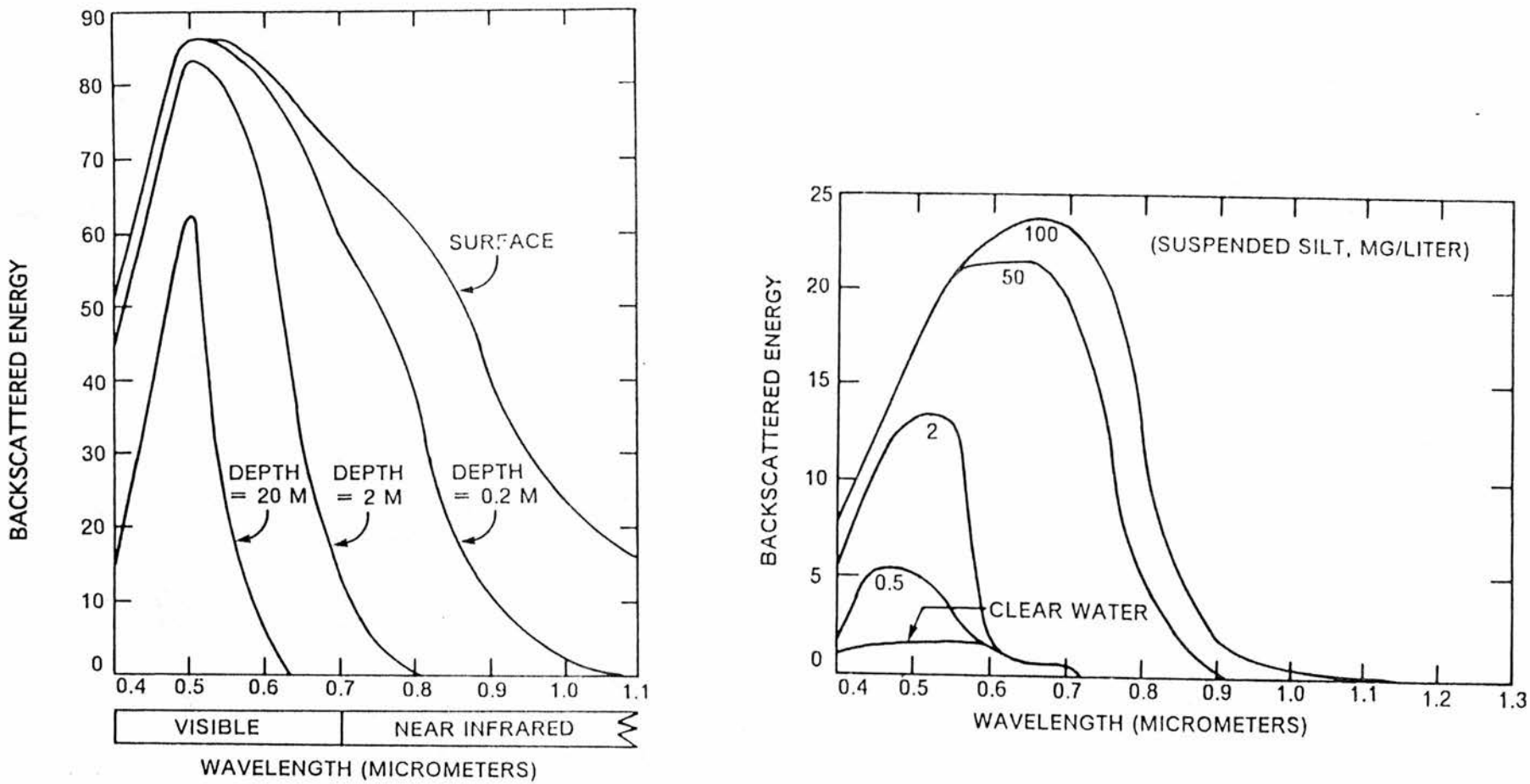


FIGURE 1. 4: REFLECTANCE CURVES OF CLEAR WATER (a) AND SEDIMENT-RICH WATER (b) (After Campbell, 1987)

positively related with depth of the water body. In deep water bodies, scattering of the blue-green radiation can be so intense, and this high intensity scattering normally gives deep water bodies a blue-green surface appearance (Campbell, 1987; Meyer and Welch, 1975).

At longer wavelengths, radiation absorption by water molecules is almost the rule. In the near-infrared, for instance, only negligible proportions of incident energy are not absorbed. Because of this, the back scatter/reflectance curve of water tends to slope down so rapidly after the 0.54μm mark, and it almost comes to zero in the near-infrared (Figure 1.4a).

Sediments in a water body may alter the general spectral response pattern of water. Generally, the sediments increase the proportion of backscattered energy in the visible bands. Quite often, the sediment particles are larger in size than the pure water molecules, and the presence of such large particles means that the wavelength of maximum scattering should shift towards the green region (Campbell, 1987) as Figure 1.4b illustrates.

1.3.4.2 *Reflectance Patterns of Soil*

Larger proportions of radiant energy incident on a soil are either reflected or absorbed. Only very little is transmitted. The spectral response pattern of the majority of soils is basically the same: the reflectance levels increase with increasing radiation wavelength (Curran, 1985). But in each waveband, the reflectance of soil can be higher or lower than the average depending on texture and content levels of soil moisture, organic matter and iron oxide (Lillesand and Kiefer, 1987).

With respect to texture, studies have shown that soil reflectance at all wavelengths increases exponentially with a decrease in the size of soil particles (Bowers and Hanks, 1965). Soil moisture, on the other hand, reduces the levels of reflectance at all

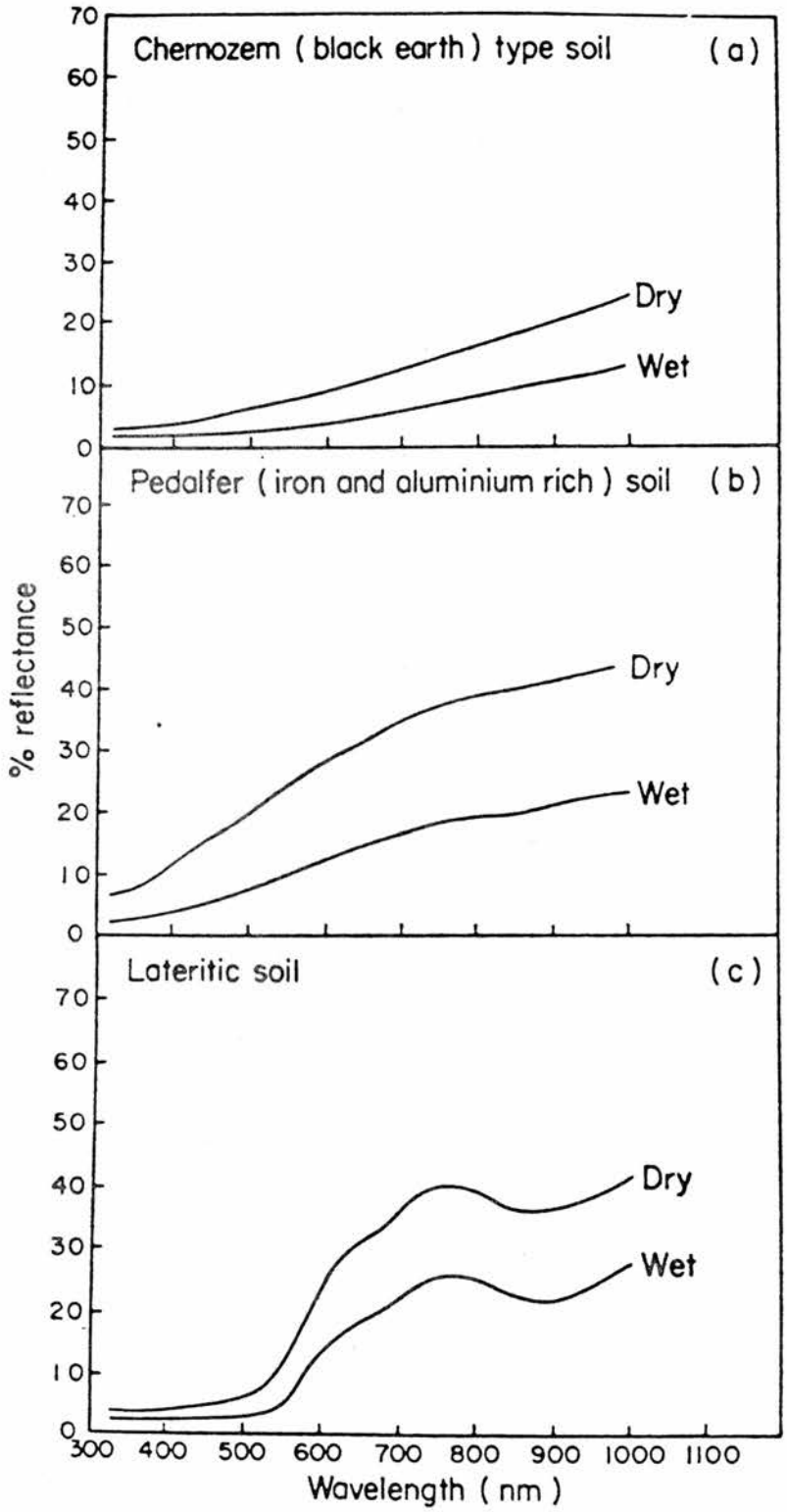


FIGURE 1. 5: REFLECTANCE CURVES OF DIFFERENT TYPES OF SOILS

(After Barret and Curtis, 1976)

wavelengths owing to the absorption of radiant energy by water molecules (Bowers and Hanks, 1965). Thus, wet/moist soil tends to have lower reflectance levels at all wavelengths relative to dry soil of the same type as Figure 1.5 demonstrates. However, the effect of moisture content on soil reflectance is great in the near-infrared, where remarkably higher levels of radiation absorption by water molecules takes place at 0.9μm, 1.4μm, 1.9μm and 2.2μm (Lillesand and Kiefer, 1987).

The amount of organic matter available in a soil tends to be negatively related with reflectance at all wavelengths (Hoffer, 1978). An increase in organic matter content of a soil causes a decrease in its reflectance levels, and this effect is greater where the organic matter is much decomposed (Harris, 1987). Thus, in Figure 1.5 the humus-rich black-earth soil (chernozem) has lower reflectance levels at all wavelengths compared to the other less humus-rich soils. The amount of iron oxides in a soil also tends to be negatively related with reflectance. An increase in levels of iron oxide content causes a decrease in soil reflectance levels (Harris, 1987).

1.3.4.3 *Reflectance Patterns of Vegetation*

Vegetation canopies are composite structures consisting of leaves and supporting material like trunks, stalks, petioles and others. However, in most cases it is the leaves that are exposed to the view of sensors and are therefore a major contributor to the overall reflectance pattern of canopies (Milton and Wardley, 1987). Understanding the spectral behaviour of leaves is therefore a key towards the understanding of the spectral characteristics of canopies.

1.3.4.3.1 Spectral Characteristics of a Leaf

The structural arrangement of a leaf is the major determinant of its spectral response pattern (Gates *et al,* 1965). The outer epidermis of a leaf, the cuticle, is a poor

reflector. It transmits almost all incident energy to the layers of cells inside the leaf. Just under the upper epidermis lies a layer of closely-packed palisade mesophyll cells that contain chlorophyll, the green matter used in photosynthesis. Chlorophyll absorbs much of radiation in the visible wavelengths particularly blue and red bands. Chlorophyll *a* absorbs energy at wavelengths 0.43μm and 0.66μm; whilst chlorophyll *b* absorbs energy at wavelengths 0.45μm and 0.65μm (Curran, 1985). Radiation in the green band is not absorbed by chlorophyll. Instead, it is reflected by the palisade mesophyll cells . Since reflected green radiation is perceptible to the human eye, leaves are therefore mostly associated with the green colour (Jensen, 1983; Knipling, 1970).

Near-infrared radiation is not absorbed by chlorophyll. It is, however, strongly scattered by the less well-packed spongy mesophyll cells and their inter-cellular air spaces. These are situated below the palisade mesophyll layer. About 45-60% is scattered in this way. Much of this is scattered to the outer environment resulting in higher back scatter/reflectance levels in the near-infrared band as Figure 1.6 demonstrates. Gausman (1974) explained that the higher scattering rate which leads to higher reflectance level in the near-infrared is caused by reflective index discontinuities between the cell-walls of the spongy mesophyll and the air in the inter-cellular spaces. He explained that turgid spongy mesophyll cells have a reflective index of 1.425 whereas that of air is 1.0; and with this reflective discontinuity, radiation passing from the turgid cells tends to be heavily scattered at the cell-wall/air interface.

Any disorder involving the spongy mesophyll cells tends to affect the general reflectance pattern of a leaf in the near-infrared band. The spectral response pattern of a leaf in the near-infrared band is therefore regarded as an indicator of plant health. Insect attack or disease infestation on crops and forests, for instance, can be detected by modelling the spectral reflectance pattern of leaves in the near-infrared band (Campbell, 1987; Myers, 1975).

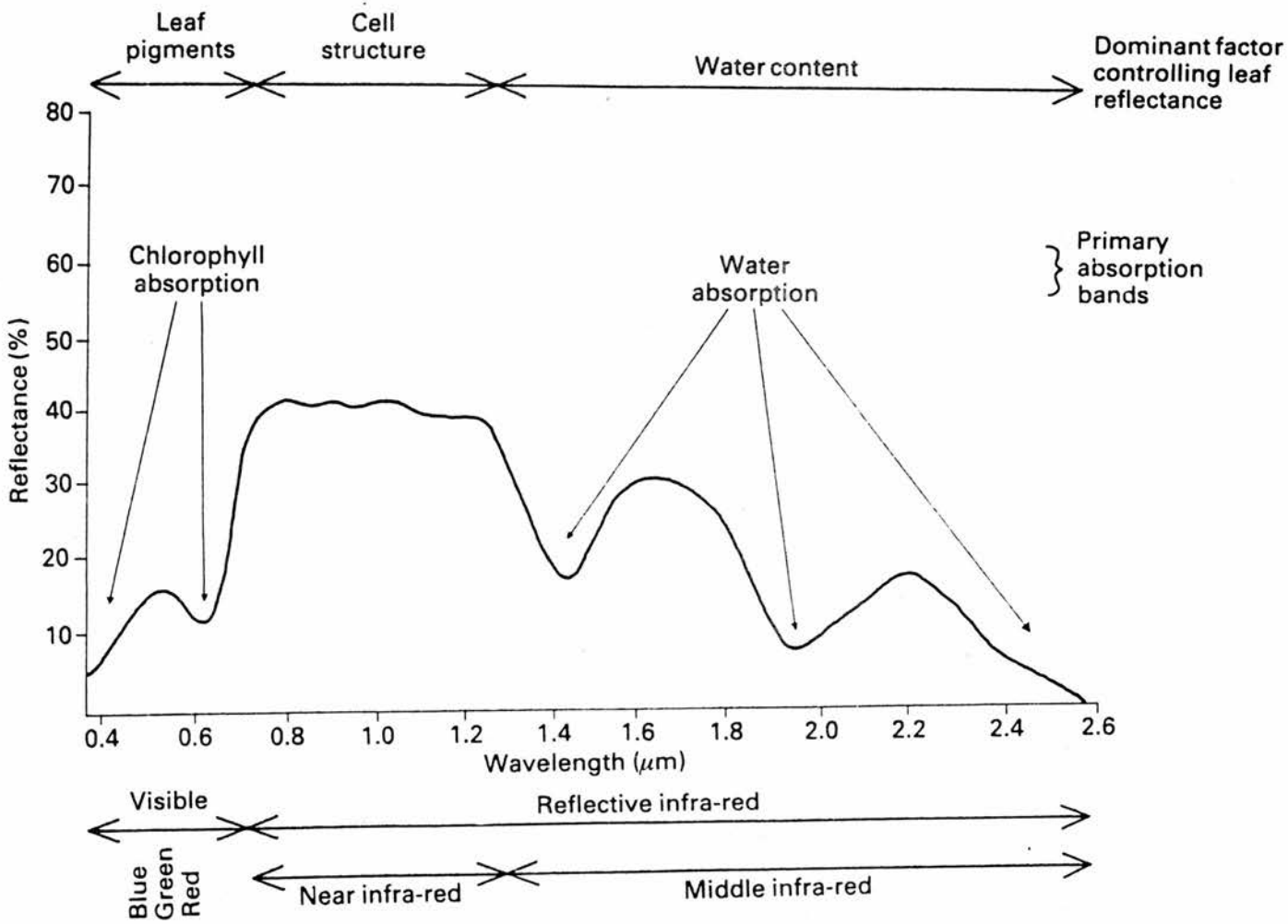


FIGURE 1. 6: REFLECTANCE CURVE OF A GREEN LEAF (After Budd, 1992)

Middle-infrared radiation is neither highly absorbed by chlorophyll nor highly scattered by the spongy mesophyll cells. Instead, it is highly absorbed by leaf moisture, and the general leaf reflectance in this section is lower, particularly at some wavelengths where absorption of radiation by water molecules is remarkably high (Figure 1.6).

1.3.4.3.2 Spectral Characteristics of Canopies

There are differences between the spectral behaviour of a leaf and that of a canopy. This is because canopy reflectance is like a weighted average of the reflectances of leaves, supporting structures and soil background . Generally, canopy reflectance level is normally lower than that of an individual leaf in both the visible and infrared wavelengths. Knipling (1970) cited studies that had shown that the average reflectance of single leaves in the visible was 10%, whereas that of a canopy of the same plant species was 3%-5%. In the near-infrared, the reflectance levels were 50% for the individual leaves and 35% for the canopy. In relative terms, these values mean that the reflectances of individual leaves in the visible and near-infrared are respectively 100-233% and 43% higher than that of canopies of the same plant species. Thus, the difference is relatively less in the near-infrared. This is so because in canopies there is a multiple transmission of near-infrared radiation that results in an enhanced overall back scatter/reflectance. As is illustrated in Figure 1.7, near-infrared radiation that is transmitted through the upper layers of the canopy is reflected from lower layers and gets re-transmitted upwards through the upper layers to enhance the total amount of energy reflected by the canopy (Campbell, 1987; Hoffer, 1978).

Since leaves are normally the main component of most canopies, then the reflectance patterns of canopies largely resemble that of individual leaves. However, the actual amounts of energy reflected by canopies in a specific waveband are largely controlled by some factors such as leaf area index (LAI)/percentage vegetation cover; soil

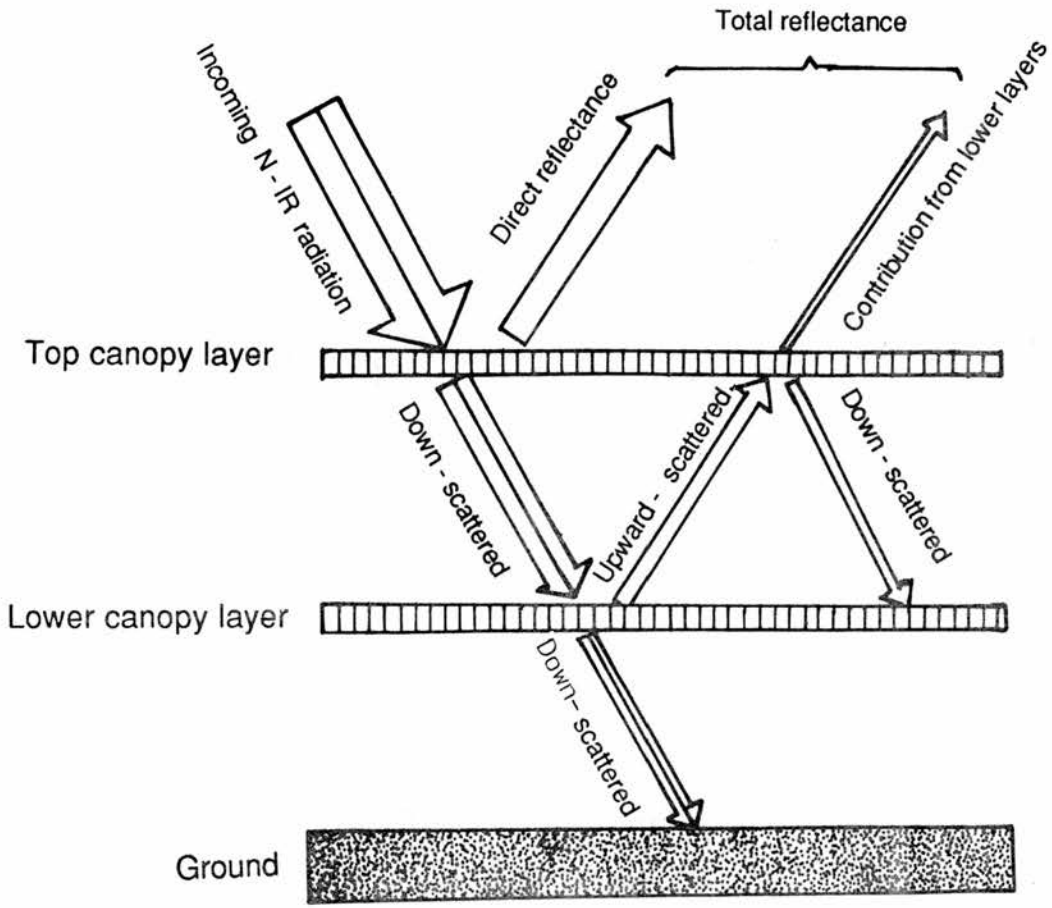


FIGURE 1. 7 : CANOPIES' NEAR-INFRARED REFLECTANCE ENHANCEMENT PROCESS

(Adapted from Hoffer, 1978)

background; solar illumination angles; azimuth angles; sensor look angle; phenology; topography and canopy geometry. The effect of leaf area index (LAI) and/or percentage vegetation cover on canopy reflectance has been researched and described by many scientists including Curran (1983a; 1983b; 1985); Curran and Milton (1983); Colwell (1974); Pollock and Kanemasu (1979); and Tucker (1976; 1977). Huete *et al* (1985) showed how canopy reflectance pattern can be affected by differences in the type of soil background. Many scientific studies have also been carried out to look at the effect of solar illumination angles, azimuth angles, and sensor view angles on canopy reflectance. Published works on these include that of Ahmad and Lockwood (1979); Barnsley (1984); Duggin (1977); Eaton and Dirmhirn (1979); Egbert and Ulaby (1972); Jackson *et al* (1979a; 1979b); Kimes (1983); Kimes and Kirchner (1983); Kirchner *et al* (1982); Ranson *et al* (1985); Shibayama and Wiegand (1985) and Suits (1972). Kanemasu (1974) and Tucker *et al* (1979) are among those who have demonstrated the effect of phenology on canopy reflectance. The effect of topography has been described by Hall-Konyves (1987); Holben and Justice (1980; 1981) and Justice *et al* (1981) among others; while Milton and Wardley (1987) have also discussed the effect of canopy geometry in their review of literature on vegetation reflectance models.

1.4 PREVIOUS MOORLAND STUDIES USING REMOTELY SENSED DATA

Research has been undertaken to evaluate the suitability of remotely sensed data for studying and mapping of moorland and related environments in Britain. The following is a review of a number of these studies.

Alam and Southgate (1987) used spectral reflectance data acquired with ground radiometers to try to detect and discriminate different land cover types in the North York Moors. The radiometers they used in acquiring the data were of two types. One could record signals in 4 wavebands comparable to Landsat MSS bands 4, 5, 6 and 7; and the other could record signals in 4 wavebands comparable to Landsat TM bands

2, 3, 4 and 5. The reflectances were recorded for land cover in Glaisdale and Blakey Ridge areas. Computer analysis of the spectral data revealed that it was possible to distinguish various land cover types like heather moorland, peat and soil. It was further discovered that more land cover types could be better discriminated in the infrared bands particularly the equivalent of TM band 5 or MSS band 7.

Foody and Wood (1987) sought to integrate Landsat TM data with other types of spatial data in digital form into a Geographical Information System (GIS) for a heathland area in Surrey. However, they found that conventional image classification techniques could not give the higher accuracy level that is expected for remotely sensed data to be effectively incorporated into a GIS. In a later work (Wood and Foody, 1989), they therefore tried to improve classification accuracy by incorporating ordination principles in the classification algorithm, arguing that conventional classification techniques cannot, on their own, bring out clearly the complex spatial configuration of moorland cover types.

Foody and Trodd (1990; 1993) used simulated airborne Thematic Mapper data covering the heathland region of Surrey to demonstrate how modelling techniques could improve the results of classification methods in heathland areas where the complex structure of land cover presents problems to conventional classification techniques. They used probability function values derived from a maximum likelihood classification, and fuzzy membership functions derived from linear discriminant (fuzzy c-means) analysis to model the continuous character of heath vegetation.

Jewell and Brown (1987) analysed two sets of Landsat TM images covering the North York Moors. One set was acquired on April 26, 1984 and the other was acquired on May 31, 1985. They prepared colour composites consisting of TM bands 3, 4, and 5 and carried out visual analysis on them. They discovered that they could easily identify areas of established heather, regenerating heather, bracken and fire

damaged zones. They also carried out image classification for the 1984 data. The results were very satisfactory and led them to conclude that Landsat TM data could actually be used for mapping moorland vegetation.

Jones *et al* (1987) in a work that is also reported in **Jones and Wyatt** (1988) used SPOT High Resolution Visible (HRV) data covering southern Snowdonia, Wales to carry out an investigation into ways of alleviating the degradation in quantity and quality of information on satellite data that result from the effect of rugged topography. They incorporated topographic data in form of a digital terrain model (DTM) into the satellite digital data base and carried out classification on such data. They discovered that better classification results were obtained from the classification of satellite data in which the DTM had been incorporated than from that of data in which no DTM had been incorporated. They therefore concluded that the effect of rugged topography can be corrected by incorporating DTMs in satellite digital data before classifying them.

Kardono (1992) used classification techniques to discriminate and map moorland vegetation communities in the North York Moors. He classified Landsat TM data of May 1985 comprising TM bands 2, 3 and 4 using box and maximum likelihood approaches. He discovered that both approaches gave satisfactory results, but the results derived from the maximum likelihood classification were even more encouraging.

Milton and Rollin (1988; 1990) used spectral reflectance data acquired with a Milton Multiband Radiometer in the New Forest heathland area to assess if heath canopies of different stages of development could be discriminated based on their spectral properties. The radiometer could record signal in four wavebands: green (0.54-0.57μm); red (0.62-0.64μm); near-infrared (0.78-0.96μm); and near-infrared (0.80-1.7μm). Data were collected on 14 dates between May and December, 1985. After analysis, they found that heath canopies of different stages of development could be

discriminated using the spectral data. However, they discovered that in summer, heather flowers reduced the spectral separability of these in the red band. Heather flowers are the same, whether they develop on 20-year old or on 10-year old heather. They reflect in the same way with particularly high reflectance in the red band. Since flowers constitute a very significant component of all post-burn heather canopies, the result is that their reflectance levels in the red band are not very different during the flowering period.

Morton (1986) worked with Landsat MSS data acquired on 29th May , 1982 to study moorland plant communities in an area 5Km north-east of Plynlimon, Wales. He combined ordination principles and a kind of unsupervised classification to extract information about moorland cover types and spatial patterns. He discovered that greater details about the complex structure of the moorland cover could not be obtained through the analysis of the Landsat MSS data.

O'Hare (1987) used Landsat TM data acquired on April 26, 1984 to discriminate and classify land use and land cover types in the High Peak heathland area, Derbyshire. He discovered that the spectral response of different land cover types were more distinct in TM bands 3, 4, 5 and 7 and less distinct in TM bands 1, 2 and 6. He therefore suggested that colour composites comprising TM bands 3, 4 and 5 or alternatively bands 4, 5 and 7 would be the more suitable for use in the study of heathland cover. He further classified the data using maximum likelihood and centroid classifiers. Less satisfactory results were obtained from both types of classification and this was attributed to the complex nature of the land cover, and also to the effect of topography.

Southgate (1987; 1989) used ground radiometer data, simulated airborne Thematic Mapper and Landsat Thematic Mapper data acquired during different seasons, to assess their utility value for routine mapping of the distribution of moorland vegetation in the North York Moors. The main objective of the work was to determine

the optimum season of data acquisition, optimum spectral band and optimum spatial resolution for the purposes of discriminating moorland vegetation communities. The results showed that there was no single season of data acquisition that could be regarded as optimum. However, late summer appeared to be the most practical time because during this time, in late August and early September, thriving bracken can be easily distinguished from dead bracken, bare surfaces and deciduous grass; and the summer flowering ericaceous shrub species can be distinguished from bracken and deciduous woodland. No single spectral band could be regarded as optimum either, although the near-infrared generally proved to be the most useful. In terms of spatial resolution, it was found that the airborne scanner data with a 10m spatial resolution gave more detailed information than the Landsat TM data with a 30m spatial resolution.

Ward ***et al*** (1987; 1989) carried out an analysis of Landsat TM data acquired at two different dates to assess if it would be possible to monitor heather burning practices in the North York Moors using such multi-temporal satellite data. One data set was for May 1984, and the other was for May 1985. They discovered that displays of the near-infrared band (TM4) showed burnt areas, lines of fire breaks made around over-aged heather, as well as the areas devastated by the 1976 summer fires. These observations suggested that newly acquired satellite data could be used for plotting newly burnt areas.

Wardley ***et al*** (1987) investigated species separability in the New Forest heathland using spectral data acquired with a ground radiometer sensitive in four wavebands comparable to Thematic Mapper bands 2, 3, 4 and 5. They also used air borne Thematic Mapper data. They discovered that they could discriminate different vegetation communities particularly in the near-infrared and mid-infrared bands of the data.

Weaver (1986) looked at the problem of bracken encroachment in the North York Moors National Park using May 1977 Landsat MSS data; May 1984 and July 1984 simulated SPOT data ; and September 1983 simulated Thematic Mapper data. She wanted to assess if it would be possible to discriminate areas dominated by active bracken; those where the bracken had been treated; and those where encroachment was taking place, using these data sets. She discovered that bracken could be more clearly distinguished from other land cover types like heather moorland and agro-pastoral land in MSS band 7, i.e near-infrared 2. Using the simulated SPOT data, it was possible to distinguish different stages of bracken development and different conditions of bracken. Band 6 (thermal infrared) of the simulated Thematic Mapper data proved effective in distinguishing the often confused classes of regenerating heather and green (live) bracken.

Weaver (1987a) also used simulated airborne Thematic Mapper data to assess their effectiveness in presenting general information about land cover types on the Danby High Moor area in North York Moors. She discovered that it was possible to discriminate different land cover types, as well as different stages of development of heather. However, the results also indicated that there was no single waveband that could be regarded as optimum for the discrimination of the moorland cover types.

Weaver (1987b) also sought to discriminate species involved in the successional changes from woodland to moorland using simulated Thematic Mapper data acquired in May 1985, for the Muir of Dinnet Nature Reserve area, Scotland. She discovered that while it was possible to distinguish moorland communities and other species in TM bands 2, 3, 4 and 5; trees, herbs and shrubs could only be distinguished from each other in TM band 6 where the spatial resolution (120m) is too coarse to allow effective mapping at a reasonable scale.

Williams (1987a; 1987b; 1988) used Landsat TM data covering a heathland area in Snowdonia to demonstrate how the accuracy of land cover classification in areas with

rugged terrain and complex vegetation structure can be improved. He subdivided broad land cover classes into subclasses depending on slope and aspect during the classification stage, and amalgamated them again at the time of presenting the classification results. He discovered that this increased classification accuracy because it reduced the probability of misidentifying and/or misclassifying the same type of vegetation owing to the fact that it might have registered different spectral signals at different locations because of the effect of topography. He also demonstrated that image filtering could help in improving the accuracy of image classification in such upland areas. In particular, high pass filters (i.e with large kernels) proved to have the greatest accuracy-improvement effect.

"The North York Moors have a character magnificently their own.....If one were to be asked to name the chief quality of the moors perhaps this would be it: space, solitude, wildness. In the North York Moors these combine into a landscape by which man may renew himself and begin to sense his place in the scale of things."

H. Mead (1975), **pp 116 -117**

CHAPTER 2
THE STUDY AREA, DATA ACQUISITION AND METHODOLOGY

This chapter describes the environment in the area of study and the data acquired for use in this work. A brief summary of the research methods followed is also given.

2.1 THE ENVIRONMENT IN THE STUDY AREA

This part describes main aspects of the physical environment in the study area which include physiography, geology, soils, climate, and vegetation. The major land uses in the area are also discussed.

2.1.1 Geographical Setting and Physiography

The North York Moors National Park is found in north-eastern England. It is one of the biggest national parks in England and Wales covering an area of 1432 Km^2 (NYMNP, 1977). It is centrally located between areas of high population concentrations: to the north lies the Teesside Conurbation ; to the south are York and Humberside, with the densely populated urban areas of West and South Yorkshire to the west. The national park is therefore strategically located in terms of serving the public (Brown, 1986; 1988; NYMNP, 1977).

Physiographically, it consists of an isolated upland block bounded by a great escarpment overlooking the Tees Basin to the north; another escarpment to the west; a chain of sea cliffs to the east; and flat-topped hills overlooking the Vale of Pickering to the south (Figure 2.1). Incised in this upland block are some winding dales. The longer and broader ones are Ryedale, Bilsdale, Bransdale, Farndale, Rosedale and Newtondale all of which lead southwards to the Vale of Pickering. The relatively shorter ones are Westerdale, Danbydale, Fryupdale, Glaisdale and Wheeldale. They run northwards to Esk Valley (Carroll and Bendelow, 1981).

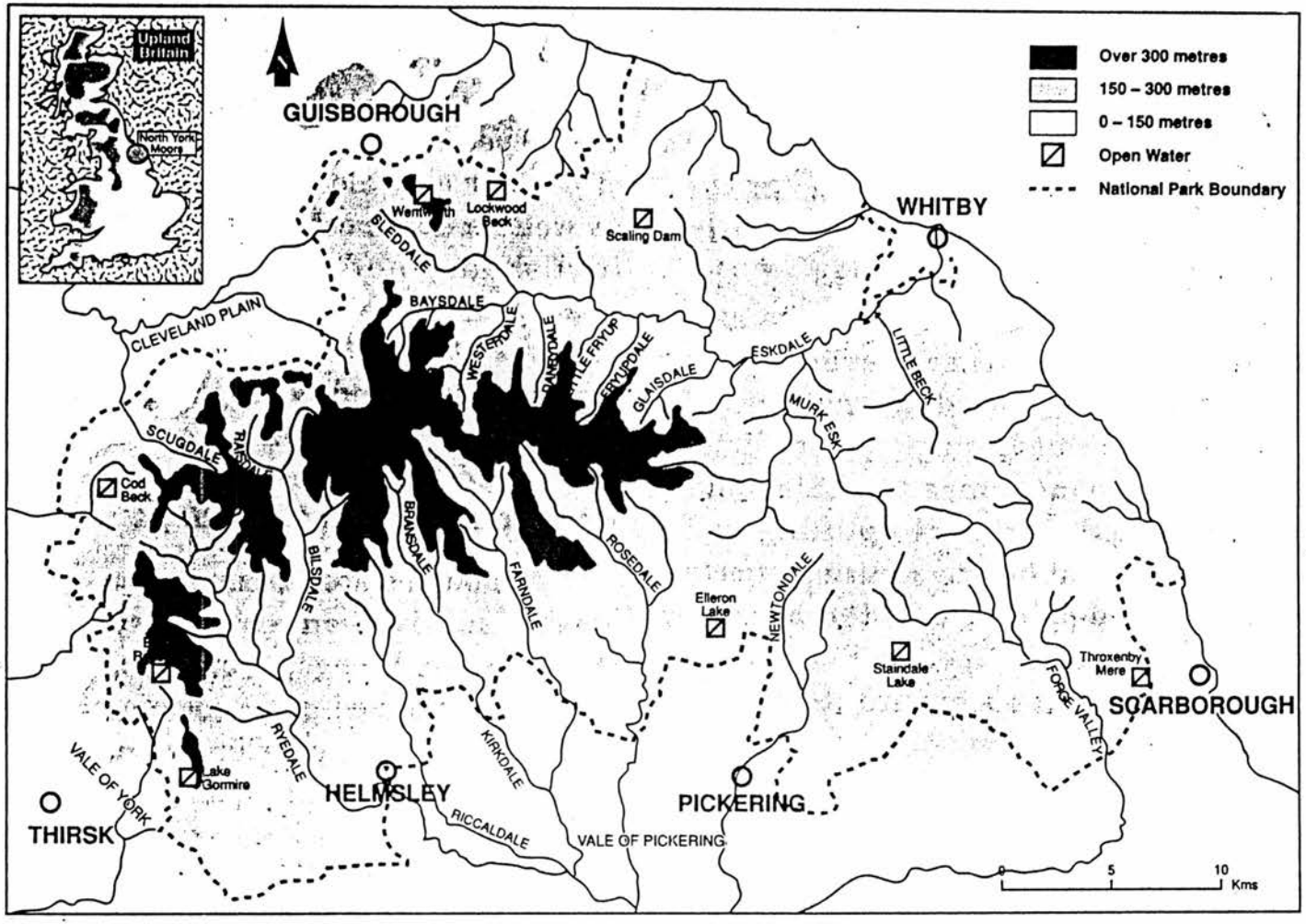


FIGURE 2.1 : MAP OF THE AREA OF STUDY SHOWING MAIN PHYSICAL FEATURES

(After Sykes, 1993)

2.1.2 Geology

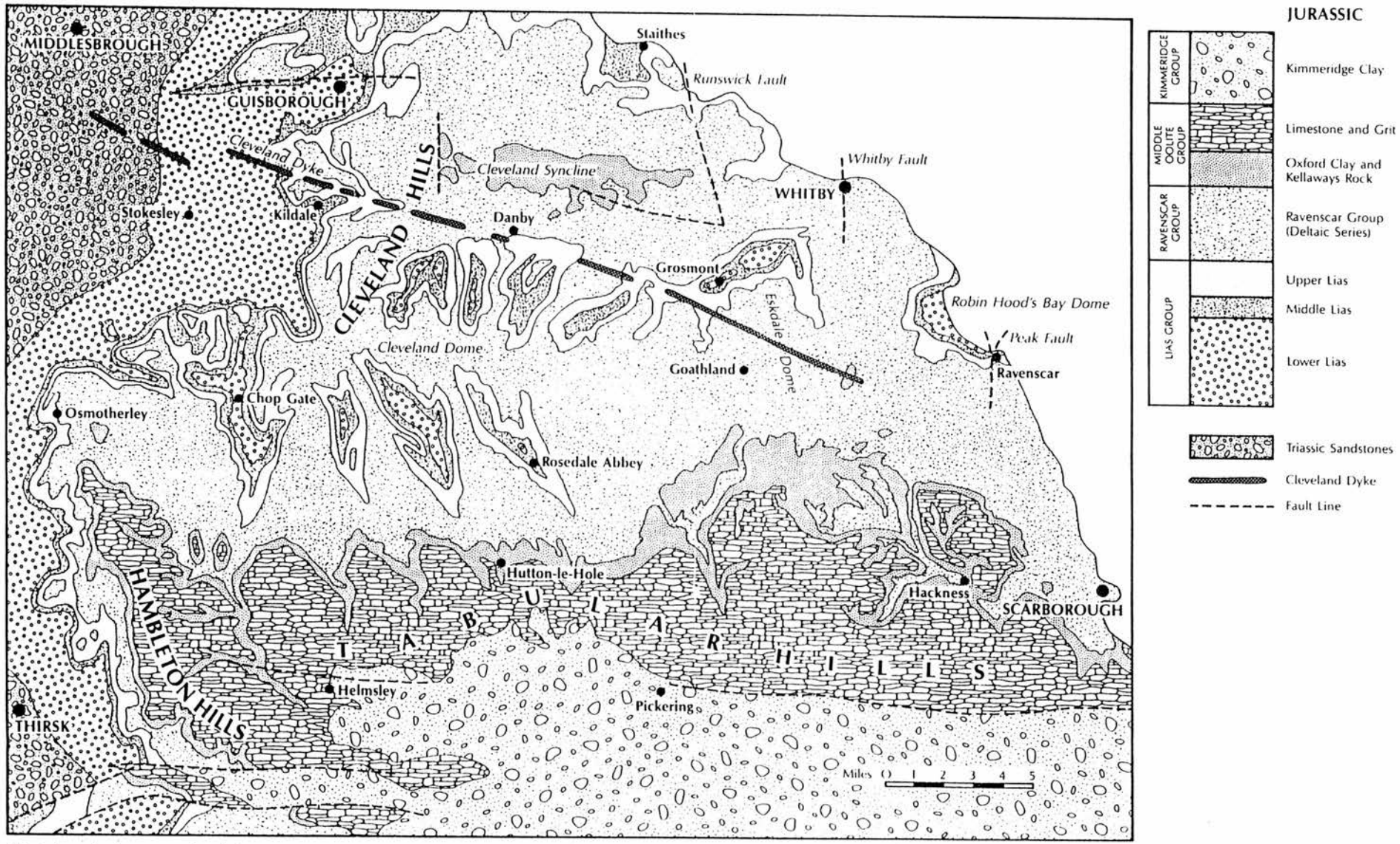
The North York Moors area originally formed under sea and was uplifted to the surface during the late Tertiary Era (Carstairs, 1987). The area is therefore almost entirely underlain by sedimentary rocks. An exception is the Cleveland Dyke or Whinston Ridge (Figure 2.2) which comprise rocks formed from a stream of molten lava that was injected into the original sedimentary rocks around 58 million years ago (NYMNP, 1990b).

The sedimentary rocks were formed from material deposited in the seas or river deltas that covered this area during the Jurassic Period from about 213 to 63 million years ago. During the early part of this period, sea-bed sedimentation created layers of deposited sand, mud and other materials such as shells of marine animals. The successive strata of sediments ultimately compressed to form layered grey shale called *lias,* a word that comes from Gaelic *laec,* meaning a flat stone (Carstairs, 1987).

The *lias* layers were buried by later strata of sedimentary rocks. However, *lias* outcrops along the coastline from Redcar to Ravenscar, often capped with younger sandstone of the Deltaic Series (NYMNP, 1990b). *Lias* also forms the floors and sides of the dales (Carroll and Bendelow, 1981).

After the early Jurassic Period, conditions changed resulting in the area being covered by a great river delta (NYMNP, 1990b). Sand and mud deposited in the delta later compressed to form sandstone, siltstone and shale (Hemingway, 1974). These Deltaic Rocks Series, also commonly known as the Ravenscar Group, (NYMNP, 1990b) are found on the moorland outside the dales and include the Moor Grit, the boulders of which are commonly found across the surface of the moorland (Carroll and Bendelow, 1981).

Geological Map of the North York Moors



Glacial and other superficial deposits are not represented on this map.

FIGURE 2.2 : GEOLOGICAL MAP OF THE AREA OF STUDY (After NYMNP, 1990b)

Later in the Jurassic Era, the area was once again predominantly under sea, though the seas were relatively shallow. Alternating layers of sandstone, clays and limestone developed from the sediments in the shallow seas. Many of the limestone were oolitic, consisting of tiny rounded grains about the size of a pin head. The main Oolitic Series in the area are the Kellaways Sandstone, Oxford Clay, Lower Calcareous Grit, Coralline Oolite and the Upper Calcareous Grit (NYMNP, 1990b). The Oxford Clays [and Kellaways Rocks (Figure 2.2)] occur in a narrow band at the base of the scarps of the Tabular Hills from Scarborough to Black Hambleton (Carroll and Bendelow, 1981; Hemingway, 1974; Palmer, 1973). The limestone and grit group (Coralline Oolite, and Calcareous Grit) form the plateau mass of the Tabular, Hackness and Hambleton Hills (Figure 2.2).

The youngest Jurassic sedimentary rocks in the area are the Kimmeridge Series which are very fossiliferous clays (NYMNP, 1990b). They are now overlain by Quaternary sediments especially in the Vale of Pickering. They outcrop in the hills around Flamingo Park and the southern end of Filey Bay (Palmer, 1973).

2.1.3 Soils

The variety and spatial distribution of soils in the area are closely related to the variety and spatial distribution of the underlying rocks (Figure 2.2) which provide the parent material. Over the Deltaic Series have developed what are simply known as moorland soils (Crompton, 1961). These soils are loamy in texture and reasonably well-drained. Under the conditions of moderate to high rainfall that characterize the area and other uplands, these soils suffer from leaching, a process in which humus and/or sesquioxides are translocated from the top layer to lower horizons where they are deposited, forming poorly permeable seams of iron or of iron and humus. These iron pans and/or humus-iron pans provide an effective check to any further downward seepage of water thereby encouraging the maintenance of wetness in the top layers of the profile. They also encourage the accumulation of structureless spongy

peat surface horizon (Ball, 1977; Curtis *et al,* 1976). In the North York Moors, these soils are characterized by a very acidic top layer of organic matter and a strongly leached mineral layer. The leached layer has whitish or ashy appearance, with an orange-brown humus-iron pan at depths of about 30cm (Crompton, 1961).

On the floors of the dales occur poorly-drained clayey and/or loamy soils (NYMNP, 1977). These apparently developed from the underlying *lias* strata. When adequately drained, these clay-loam soils are very productive , especially with the application of fertilizers (NYMNP, 1977).

Between Helmsley and Thornton Dale, there are rich brown calcareous soils over limestone or drift containing limestone (NYMNP, 1977). The brown calcareous soils have a well structured top organic layer (A-horizon) which is usually a granular mull. They are neutral or somewhat alkaline in reaction (Curtis *et al,* 1976). They are suitable for agricultural use and in the North York Moors, there are actually extensive stretches of long-cultivated brown calcareous soils (Eyre, 1973).

There are also peat (organic) soils in the area. Organic soils are those that have a dominantly organic layer of about 40cm thick formed under wet conditions and starting at the surface or within 30cm depth (Curtis *et al*, 1976). In the North York Moors, there are two types of peat/organic soils, namely basin and hill/blanket peat. The former occur in slacks and fen-carrs , whilst the latter can form on any relatively flat land with poor drainage. There are significant zones of blanket peat on the Egton High Moor, Wheeldale Moor, Rosedale, Farndale, May Moss and Harwood Dale (Cundill, 1977).

The upland block that constitutes the North York Moors escaped glaciation (Elgee, 1912). However, the lower moors near the coast and down the Vale of Pickering were swept over by streams of ice (Palmer, 1973). Glacial boulder clays can therefore also be found in the lower moor areas along the coast (Palmer, 1973).

2.1.4 Climate

In common with other upland areas, the North York Moors area has a wet and cool climate. However, the actual degree of wetness and coolness varies from location to location depending on altitude. The area receives precipitation throughout the year, but only a little of this is in the form of rain. The mean annual rainfall is 1015mm on the higher grounds and only 762mm on the lower grounds (NYMNP, 1977; 1990a). Another form of precipitation received in the area is snow. The plateau zone is normally under snow cover for 45 to 80 days each year. The lower areas are normally under snow for only 20 to 30 days each year. Similarly, the plateau zone experiences 75 days of frost in a year whilst the lower areas experience only 50 days. The plateau zone also experiences bleak winters with mean temperature levels of 1.7°C, low altitude clouds and gusty winds. By contrast, the mean winter temperatures in the lower zones is 4°C (NYMNP, 1977; 1990a).

2.1.5 Vegetation

The characteristic upland vegetation of shrubby and grassy heath (Ball *et al,* 1982) similarly characterize much of the North York Moors. In this particular area, the shrubby heath communities are dominated by one species, *Calluna vulgaris* (heather), hence they are basically heather moorland communities. They are well established on the plateau surfaces (Eyre, 1973) whereas the grassy heath communities are well established on hill sides, on the upper sides of the dales and along the coastal plains (Sykes, 1993). In wetter areas like bogs and mires, shrubby and grassy heath species tend to grow together along with sedges, rushes and mosses forming composite communities commonly known as wet heath. In addition to dry heather moorland, grass moor and wet heath, the area has also both deciduous and coniferous woodland vegetation. The characteristics and spatial distribution of each of these vegetation types are briefly discussed in this section with the exception of coniferous woodland class which is discussed in the section of land use.

2.1.5.1 *Dry Heather Moor*

An expanse of heather moorland stretching almost unbroken from the coast to the western edge of the Hambleton Hills (Figure 2.3) constitute the single largest type of vegetation in the area. It covers much of the central plateau, as well as the ridges between the dales and their slopes. In areas like Black-a-more, the Hambletons, and the Clevelands where peat is deep, then the dominant species, *Calluna vulgaris,* attains its most vigorous and luxuriant development and is usually present almost to the exclusion of other shrub species (Elgee, 1912; Eyre, 1973). But elsewhere, *Calluna vulgaris,* though dominant, grows together with other shrub species. The commonest of these subordinates is *Vaccinium myrtillus* (bilberry) which is especially abundant on steeper slopes over sandstone or rock valley edges (Carroll and Bendelow, 1981). In areas like Kildale Moor, Danby Moor, Westerdale Moor, and Wheeldale Moor the dominant heather canopy has a substantial bilberry understorey (Eyre, 1973).

On the Tabular Hills and the outcrops of Kellaways Sandstone, the peaty surface is usually thinner and the soil underneath is drier. The common associates of heather in such areas are *Empetrum nigrum* (crowberry) and *Erica cinerea* (bell heather) (Carroll and Bendelow, 1981).

Pteridium aquilinum (bracken) is a normal constituent of the heather moorland on steeper slopes with well-drained brown earth. In 1986, 101Km^2 of open moorland in the area were under full bracken cover. However, only 28% (28Km^2) of the total area under bracken were on steep slopes with well-drained brown earth (Brown, 1986). This means bracken is rapidly spreading into moorland areas that would be out of its range under normal circumstances. Damage of moorland by uncontrolled fires; reduction in the intensity of cutting bracken plants for cattle bedding; overgrazing on dry moor areas; clear felling of remaining areas of woodland; and reduction in the

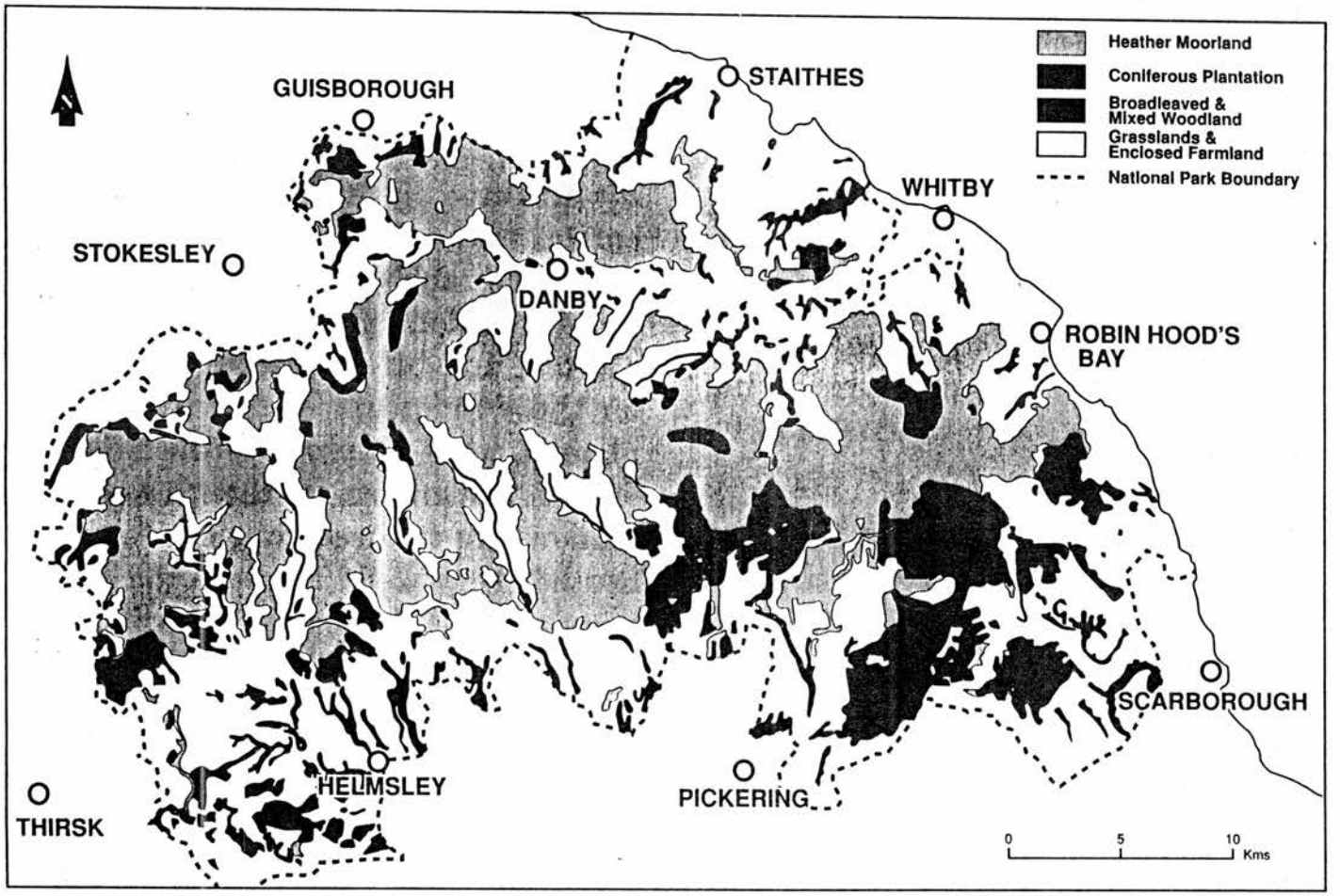


FIGURE 2.3 : VEGETATION AND LAND USE MAP OF THE AREA OF STUDY

(After Sykes, 1993)

intensity of use of marginal, enclosed and well-drained hill zones, are the factors that are promoting the spread of bracken (Brown, 1986).

2.1.5.2 *Wet Heath*

Wet heath communities develop in areas where permanent water-logging takes place. These include areas of saturated peat, seeping spring lines or flushes, and enclosed valley mires. Fylingdales Moor is an important example of an extensive wet heath area. Significant wet heath communities also occur in Wheeldale, Cold Keld, Crabdale, Bogmire Hill, Rudland and Scarthwood Moor (Sykes, 1993). More areas of wet heath are also known by the term "moss" and are essentially blanket bog areas. They cover about 15% of the moorland area (NYMNP, 1984; 1989; Sykes, 1993).

Wet heaths are normally richer in species composition than the dry heather moors. Both shrub and grass species are found growing together in wet heath areas. Common species, however, are *Calluna vulgaris* (heather), *Erica tetralix* (cross-leaved heather), *Molinia caerulea* (purple moor grass), *Eriophorum spp* (cotton grass), *Juncus spp* (rushes) and *Trichophorum cespitosum* (deer grass). These are normally found interspersed with acidic pools and/or runnels bearing rafts of *Sphagnum spp* (bog moss), and *Ranunculus omiophyllus* or *R. hederaceus* (water crowfoot) (NYMNP, 1975; Sykes, 1993). If the normally waterlogged areas become more or less permanently dry for one reason or another, then the species composition changes leading to the development of dry moor conditions on previously wet heath areas. It is observed that most of the places that still carry the name "moss" in the North York Moors have actually dried out to become species-poor dry heather moorland owing to climatic changes (Sykes, 1993).

2.1.5.3 *Grass Moor*

A wide variety of "natural" and cultivated grass cover an area equivalent to about a half of the national park. These range from scrubby moor-edge acid grassland on dalesides, through calcareous grass on hill sides and neutral grassland on the coastal cliffs, to rye grass cultivated on dairy farms and arable land (Sykes, 1993). The latter are described under agriculture in the section on land use.

Nutrient-poor acidic soils cover much of the upper dales and moorland fringe. They support acidic grass species like *Agrostis canina* and *A. tenuis* (bents), *Deschampsia flexuosa* (wavy hair grass), *Nardus stricta* (mat grass) and *Festuca ovina* (sheep's fescue) with other plant species like *Galium saxatile* (heath bedstraw), *Potentilla erecta* (tormentil) and *Campanula rotundifolia* (hare bell). Where these swards are overgrazed by sheep, the unpalatable *Nardus stricta* soon dominates being interspersed with heath rush (*Juncus squarrosus*) and ribbed sedge (*Carex spp*). On poorly drained soils *Deschampsia cespitosa* (tufted hair grass) and rushes are dominant along with *Molinia caerulea* (purple moor grass) indicating wetter conditions (Sykes, 1993).

Another type of grassland, the calcareous grass moor, occurs on shallow calcareous soils on hill sides that are too steep for cultivation; on unstable screes where afforestation has failed; in disused quarries; and on road-side embankments. This type of grassland is in many places under the threat of being ploughed and reseeded to produce improved pasture. A few scattered remnants are still found on south-facing slopes in valleys and old quarries on the corallian limestone between Helmsley and Hawnby; on the western escarpment north of Sutton Bank; and around Kepwick, Hutton-le-Hole, Thornton-le-Dale and Gillamoor (Sykes, 1993). The calcareous grassland is dominated by grasses like *Briza media* (quaking grass) and *Brachypodium pinnatum* (chalk false-brome grass). It is also rich in herbs and orchids (Eyre, 1973).

Small isolated patches of neutral grassland are also found mainly in dales, along the coastal plain and on the north-west perimeter of the national park. Many of these were hay meadows at one time in the past. They are normally rich in plant species most common of which are *Saxifraga granulata* (meadow saxifrage), *Lolium perenne* (rye grass), *Anthoxanthus odoratum* (sweet vernal grass), *Dactylis glomerata* (cocks foot), *Trifolium pretense* (red clover) and orchids (Sykes, 1993).

2.1.5.4 Broadleaved Woodland

About 22% of the total area of the national park is under woodland and just a quarter of this is broadleaved woodland and scrub. The existing plots of broadleaved woodland are mainly remnants of the 18th and 19th century climax woodland cover of oak, birch, willow and rowan (NYMNP, 1975). These are mainly restricted to hill sides that are too steep to plough; coastal inlets; infertile exposed dale heads; and wet river sides that are difficult to drain (Figure 2.3). Small plots of broadleaved woodland are also found on estates where they are managed for economic and amenity purposes (Sykes, 1993). The Forestry Commission aims to increase the area of broadleaved woodland by planting on its own land as well as by encouraging private land owners to do the same on their land (NYMNP, 1975; 1977; 1991a).

2.1.6 Land Use

Major land uses in the North York Moors area are agriculture, forestry and nature conservation. These are described briefly.

2.1.6.1 Agriculture

Agriculture has been a long-standing major land use in the area. There are about 620 registered full-time farmers within the area of the national park. 39% of these are dairy farmers while 36% specialise in the production of beef and mutton. The rest run

arable and mixed farms which cover about 300Km^2 (Sykes, 1993) most of which are in the dales and along the lowland fringe in the southern zone of the national park (Figure 2.3). The arable crops grown include wheat, barley and oats. The mixed farms, which are common near to Scarborough and Pickering, produce arable crops as well as swedes, turnips and species of improved pasture for making hay and/or silage. Beef and mutton producing farms are dominant in most moorland parishes; whereas dairy farming is common in Esk Valley as well as in the north-east and north-west zones (NYMNP, 1977; 1991a). These mostly depend on improved pasture grown in most of the dales (Figure 2.3).

The heather-clad central watershed zone is an area under extensive animal farming. The animals kept are mostly Swaledale and Blackface sheep. These are extremely hardy breeds that can withstand severe winter conditions on the high moors. They are kept on free range and the shoots of heather are their main food (NYMNP, 1990a; 1991a). In particular, they prefer the young tender shoots of heather to the old woody stems. The upland heather is therefore managed by controlled burning of old stands to encourage the growth of the younger and fresher shoots (Eyre, 1973).

2.1.6.2 *Forestry*

As stated earlier (2.1.5.4) 22% of the land in the national park is under woodland vegetation, and of the total woodland area a quarter is under broadleaved forests and the remaining three quarters are under coniferous forest plantations which are managed for economic purposes. Managed forestry is therefore a major land use in the area. Most of the coniferous plantations were established earlier in the century as a direct result of the national policy of expanding local production of wood in order to reduce reliance on imports. Since then, more and more areas of heath and bog have been reclaimed and planted by the Forestry Commission or by some enthusiastic private owners. The area has suffered significant losses of open moorland to forestry. For instance, 15% of the moorland area that was available in 1952 had been turned

into coniferous forest land by 1990 (NYMNP, 1990a). Much of the plantations owned by the Forestry Commission are in large blocks. They therefore create less striking monotonous landscapes over large areas such as Cropton, Dalby and Wykeham (NYMNP, 1975). The main coniferous species involved in the afforestation programmes are Scots Pine, Japanese Larch, Sitka Spruce, Corsican and Lodgepole Pines, and European Larch (Carroll and Bendelow, 1981; NYMNP, 1977).

2.1.6.3 *Nature Conservation*

There is very little land that is solely managed for nature conservation purposes, and given the ever-increasing pressure to use any piece of available land for economic production, it looks unlikely that greater stretches of land will ever be managed purely for nature conservation purposes (NYMNP, 1977). Notwithstanding this discouraging scenario, a number of agencies are involved in nature conservation activities in the area. One of these is English Nature (formerly Nature Conservancy Council) which has power to establish national nature reserves as well as notifying sites of special scientific interest (SSSIs). There are 51 SSSIs in the park covering 5912 hectares in total. There is also one national nature reserve at Forge Valley (Figure 2.4).The National Park Committee is another conservation agency which is active in the area. It created and manages a local nature reserve in Farndale. Other agencies like the Yorkshire Naturalist Trust, the National Trust and the Woodland Trust have some pieces of land in the area which they manage for nature conservation purposes. The Yorkshire Naturalist Trust, in particular, manages 11 sites as nature reserves one of which is the Fen Bog Nature Reserve (Figure 2.4) (NYMNP, 1975; 1977; 1991a).

2.2 ACQUISITION OF DATA

The main data used in this work were two sets of Landsat 5 Thematic Mapper digital data. Field work was undertaken to acquire "ground truth". Aerial photographs and

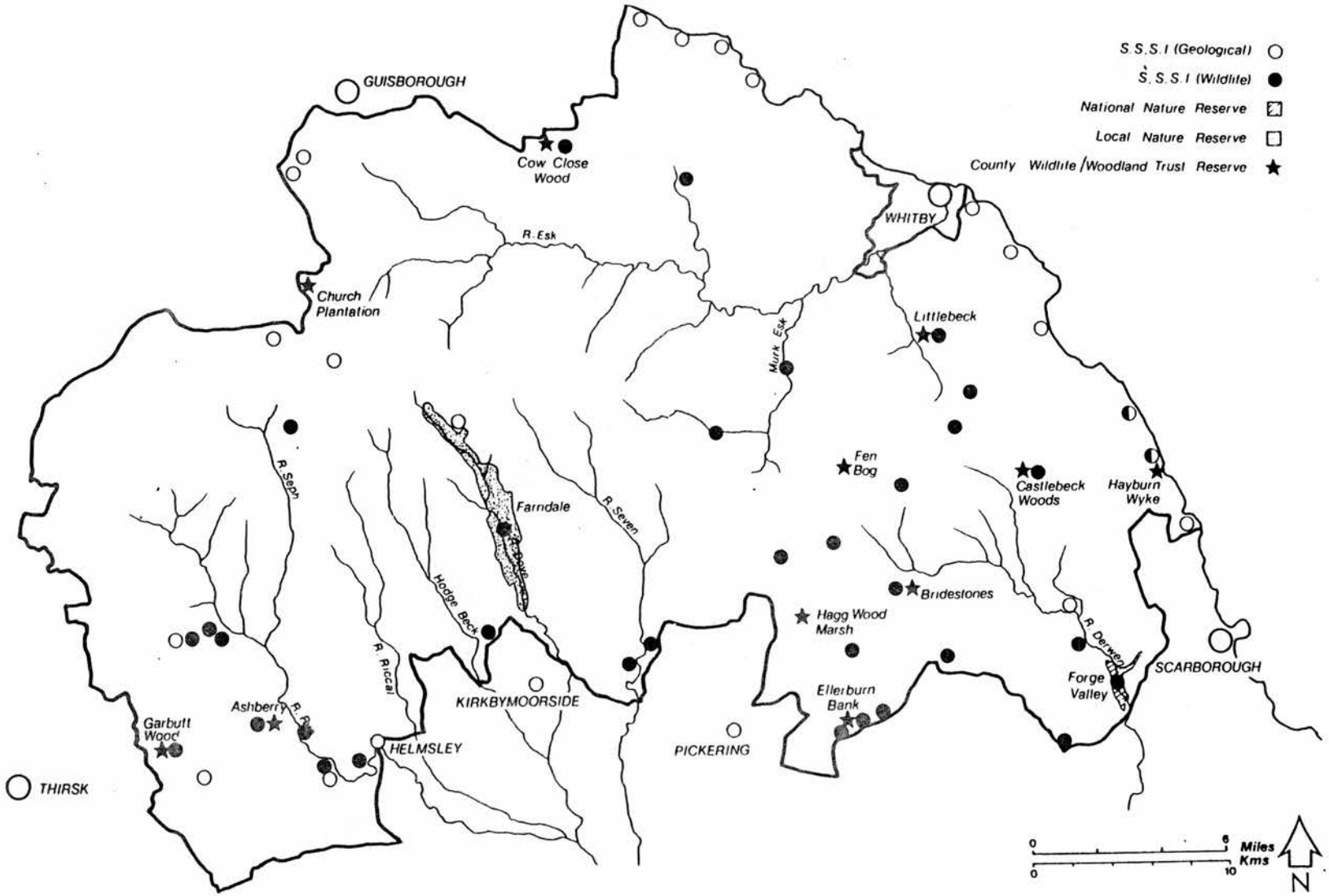


FIGURE 2.4 : NATURE CONSERVATION MAP OF THE AREA OF STUDY

(After NYMNP, 1991a)

maps were other forms of ancillary data acquired and used in this research project. All of these are described in this part.

2.2.1 Landsat 5 Thematic Mapper Data

The area of study falls into the fourth quadrant (south-east quarter) of Landsat TM scene 203/22 (Figure 2.5). Two sets of data for this quarter were obtained from the National Remote Sensing Centre in Farnborough. One set was for data acquired on May 31st, 1985. This set consisted of three bands, namely TM3 (red); TM4 (near-infrared) and TM5 (mid-infrared). The other set was for data acquired on August 20th, 1991 and consisted of all seven TM bands but only TM3, TM4 and TM5 were used in this work.

These two image data sets were chosen because they had little or no cloud cover. The 1985 quadrant had small scattered patches of cloud cover over Farndale West CP and over the Cleveland Hills. The 1991 quadrant was completely cloud-free.

The 1985 quadrant had already been geometrically rectified to the British National Grid by the supplier, the National Remote Sensing Centre Limited, at the time it was obtained. Although the 1991 quadrant was obtained through the National Remote Sensing Centre, it actually came from the European Space Agency's archive. This imagery had not been geometrically rectified and it therefore required pre-processing to correct the geometrical distortions. Details of how this geometrical rectification was performed are given in the next chapter.

2.2.2 Ancillary Data

Ancillary data in remote sensing are non-image data sets (Lillesand and Kiefer, 1987) that provide extra information to enable the analyst to make effective interpretation of

FIGURE 2.5 : MAP OF MAINLAND BRITAIN SHOWING LOCATION OF TM SCENE 203/22

image data. They range from thematic maps, through official reports and statistics, to information collected in the field (Campbell, 1987).

Most image processing tasks require the analyst to have *a priori* knowledge of some kind regarding the area or subject of study. For instance, the popular supervised classification of image data requires the analyst to define land cover classes and to select sample image pixels of each class. The computer then uses the characteristics of the sample pixels (known as training pixels) to classify all the pixels in the image into the predefined classes. Ancillary data like existing maps, reports, aerial photographs and data obtained by carrying out pre-classification field checks provide the *a priori* information that the analyst requires in undertaking supervised classification and similar image processing operations .

Traditionally, ancillary data have also been used to verify results of image interpretation (Lee, 1975). Existing maps, or maps recently compiled by other researchers (research organizations) can be compared with the maps the analyst produces from the analysis of image data in order to find out the extent to which they agree or disagree. Post-classification field checking is also another way to obtain reference data against which the accuracy of image classification can be evaluated (Campbell, 1987; Jensen, 1986).

Ancillary data may also help overcome problems of image data. For instance, topographic maps can be converted into digital terrain models (DTMs) which when incorporated into the image data, provide an effective correction for the problem of non-uniform illumination of landscape (Jones *et al,* 1987; Jones and Wyatt, 1988). Non-uniform illumination of landscape is a severe problem that degrades the quality and/or quantity of information that one can obtain from remotely sensed data for areas with rugged terrain.

Spectral reflectance values recorded using ground non-imaging radiometers provide another form of ancillary data that are equally essential. Such *in situ* spectral data can be used to calibrate sensors on board satellites (Lee, 1975; Milton, 1986). Normally, *in situ* measurements of reflectance are taken under good weather and other physical conditions. The reflectance values recorded are therefore more or less free of the influence of factors that introduce error in the reflectance values recorded by sensors on board satellites. The more or less error-free *in situ* spectral data are therefore normally regarded as suitable for use in calibrating satellite-borne sensors.

The collection and analysis of *in situ* spectral data can also be used to determine the spectral bands, sensor look angles, and season of data acquisition that are most suitable for particular applications of remotely sensed data. They are also essential for development, testing and refinement of models relating biophysical attributes to some characteristics of remotely sensed data (Milton, 1980; 1986). Canopy reflectance models and vegetation indices are good examples of models that have been developed, tested and refined mostly from the use of *in situ* spectral data.

The spectral response patterns or spectral signatures of various features can be worked out from *in situ* spectral data. The information on spectral signatures can be indispensable when working with satellite data for very unfamiliar areas. Such information will help in the recognition of features on the satellite imagery as well as in clearing up cases of ambiguity (Steven, 1986). *In situ* spectral data can also be used to estimate amounts of green vegetation cover at specified locations (Williamson, 1988). The procedure to make such estimation is described later in this chapter (section 2.4.4).

The ancillary data used in this work were ground information about vegetation communities; *in situ* spectral data; aerial photographs; North York Moors National Park conservation maps; Phase 1 habitat maps; Ordnance Survey tourist maps;

unpublished North York Moors National Park bracken control scheme map; and official Forestry Commission Maps. These are described briefly.

2.2.2.1 *Ground Data on Vegetation Communities*

Ground data on vegetation communities were collected in autumn 1992, summer 1993 and summer 1994. The aim for undertaking the field work was to obtain "ground truth" regarding the types, structure and spatial pattern of vegetation communities in the area of study. Such information is necessary in order to be able to make proper identification and interpretation of land cover types on aerial photographs and Landsat imagery. The information was also useful in assessing classification and change detection accuracy.

A general idea about land cover types was obtained by touring the area. The tour covered the central watershed zone, the dales and ridges from Westerdale Moor eastwards to Fylingdales Moor. However, more information about vegetation communities was obtained through detailed ground study carried out in some smaller sites that were purposefully chosen because they had features/land cover types of specific interest to the present study. These included burnt moorland; post-burn regenerating moorland; young heather; mature heather; post-mature and degenerate heather; dry shrubby heath composite communities; live bracken; chemically treated bracken; wet heath; and neglected farmland. Thus in terms of sampling, the study sites were therefore selected using representative sampling strategy (Goldsmith and Harrison, 1976). On average, each site studied was 30m x 30m in size.

A number of analytic characteristics of vegetation communities were observed or worked out and recorded in those study sites. These were floristic composition of the community; stratification; stages of development and vigour; sociability; and cover-abundance. These are briefly explained below.

2.2.2.1.1 Floristic Composition

The character of vegetation communities is largely determined by their floristic composition. Cataloguing species found in an area is therefore normally the first step towards the proper understanding and characterization of vegetation communities (Hanson and Churchill, 1961).

In this research project, the plant species found in each field study site were identified, enumerated and recorded using a step-point method. Under this method, a conspicuous mark is made on the forepart of one of the boots the researcher is wearing in the field. The researcher then wanders in all directions across a study site, and as he does so, he identifies and notes the name of the plant that touches the mark on the boot each time a step is made. A species that is widely distributed on the plot is encountered more frequently. Less widespread species are relatively less encountered. Thus, the method allows the surveyor to discover types of species available as well as the frequency with which a particular species is encountered. The latter gives ideas about species that are common, those that are occasional and those that are rare in a specific study site (Soulsby, Pers. Comm.). In this study, the method was used to compile lists of species found in each study site, as well as the number of times each species was encountered out of 100 step-points of observation made in each study site. The data acquired from some of the study sites are presented in Appendix I.

2.2.2.1.2 Stratification

Stratification is the occurrence of plants at different levels in a stand (Hanson and Churchill, 1961). Some form the visible outer canopy, others may grow as understoreys, while others like lichen and mosses may form the ground layer.

Stratification and the rest of the analytic characteristics were studied mainly in $1m^2$ quadrats thrown at random within the study sites. The throwing of the quadrats

removed subjectivity in the selection of the points where quadrat analysis was to be carried out. Diagrams of a sample of the quadrats are presented in Appendix II.

Stratification was studied in the quadrats by determining whether a plant species contributed to the outer canopy; it grew as an understorey; or it formed the ground layer of the canopy. Not much data, however, were collected on this characteristic because most of the communities studied did not show any clear stratification pattern. Only in *Calluna-Vaccinium* composite communities was a distinct stratification observable : quite often *Vaccinium myrtillus* was found growing as understorey. *Potentilla erecta* (tormentil) was also constantly found growing underneath the heath shrubs. Similarly, *Galium saxatile* (heath bedstraw) was often found growing together with tormentil underneath shrub-grass transition communities on the moorland fringe. Heath bedstraw was also commonly found growing underneath acid grass canopies. Carpets of lichen and mosses were frequently found covering the ground under the shrubby and grassy heath canopies.

2.2.2.1.3 Stages of Development and Vigour

An assessment of stages of development and vigour was carried out for plant species enumerated under the step-point method as well as those studied in the quadrats. Plants were categorized into four broad stages of development: emerging/regenerating; young; mature; and degenerate.

Vigour refers to plants' state of health within a certain stage of development. A seedling or mature plant may be vigorous, or it may be feeble and poorly developed. Vigour is a good indicator of conditions under which plants grow. Those growing under their ideal conditions would normally be luxuriant, whereas those growing under adverse conditions would normally be less vigorous. Vigour is also closely related with stage of development in the plants' life cycle. For instance, plants grow more vigorously and look healthier in the middle of their life cycle. Among the

indicators of vigour are quantity or area of foliage; colour and turgidity of leaves and stems; appearance and development of new stems and leaves; and extent of dead portions (Hanson and Churchill, 1961). These criteria were used to assess vigour of the species studied in the quadrats as well as those encountered under the step-point method. Adjectives denoting vigour like "live", "thriving", "vigorous", "grazed" and "stressed" were added to the names of plant species on the lists compiled under the step-point method and quadrat analysis.

2.2.2.1.4 Sociability

Sociability or gregariousness refers to the proximity of plants or shoots to one another. It is dependent upon the life-form and vigour of plants, habitat conditions, competition and other plant relations (Hanson and Churchill, 1961).

In this work, the sociability of plants was assessed in the quadrats. The Braun-Blanquet scale given below was used for rating the sociability of species.

Class 1: Shoots growing singly

Class 2: Small groups of plants, or scattered tufts

Class 3: Small, scattered patches or cushions

Class 4: Large patches or broken mats

Class 5: Very large mats or stands of nearly pure populations.

2.2.2.1.5 Cover-abundance

Cover-abundance is one of the measures of density of vegetation cover. It is a measure of the area covered by a given plant species at a given location and is normally expressed as a percentage. It can be visually estimated in quadrats by relating the size of area covered by a given species to the whole area in a quadrat. A more objective way to assess cover-abundance is to make actual measurements of the

proportion of ground covered by different species at a number of selected points in a study site (Kershaw, 1973).

In this work, cover-abundance was visually estimated in the quadrats. The Braun-Blanquet scale given below was used for rating the cover-abundance levels of species.

+: Isolated plants with no measurable cover

1: Very sparse plants with an insignificant cover of less than 5%

2: Occasional plant groups with cover in the region of 5-25%

3: Common but less numerous plants with cover in the region of 25-50%

4: Numerous plants with cover in the region of 50-75%

5: Very numerous plants covering more than 75% cover of the area.

2.2.2.2 *In Situ Spectral Data*

Reflectance values of some selected land cover types were recorded at particular points in the field using a Macaulay single-beam radiometer which is sensitive in two bands, namely red band, with peak spectral response at 0.6μm; and near-infrared band with peak spectral response at 0.88μm. The Macaulay radiometer consists of two units: an optical reading head; and a control and display box (Figure 2.6). The reading head contains two detector units one of which is sensitive in the red band and the other is sensitive in the near-infrared band. Radiation reflected from the target scene enters the optical unit through a concave lens, and passes to the detectors via a 50:50 beam-splitting mirror which is set at 45 degrees to the entrance aperture (Figure 2.7). The radiation is then sensed by the detectors and the reflectance values are displayed on a digital panel meter on a control-and-display unit which is connected to the optical head through a signal-and-power cable. The radiometer is powered by 4AA type rechargeable cells which are housed in a compartment within the control-and-display unit. The Macaulay two-band radiometer as a whole weighs less than 1kg and is therefore convenient for use in the field (Macaulay Institute, 1986).

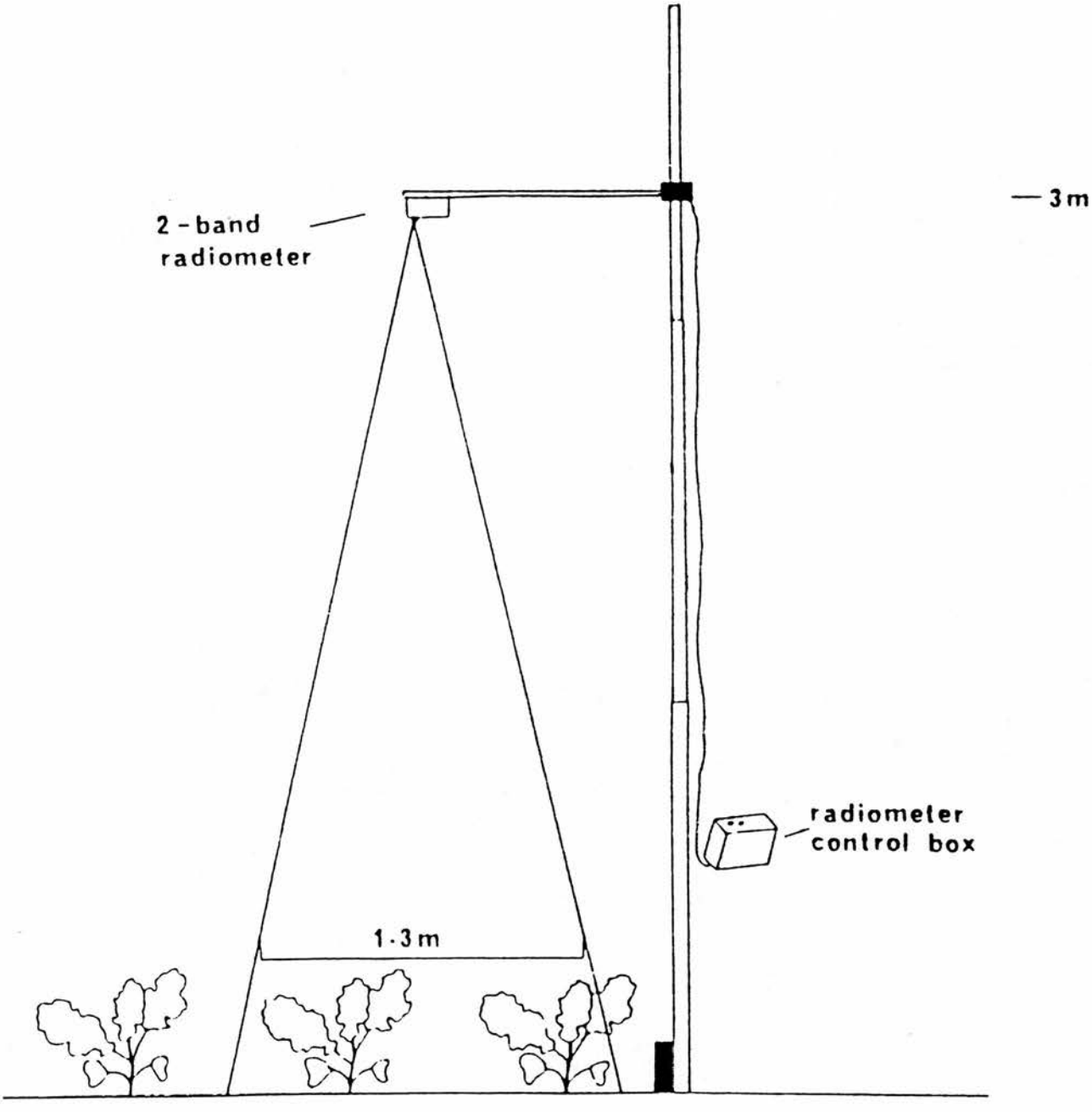


FIGURE 2.6 : DIAGRAM SHOWING MAIN FEATURES OF THE MACAULAY RADIOMETER

(After Macaulay Institute, 1986)

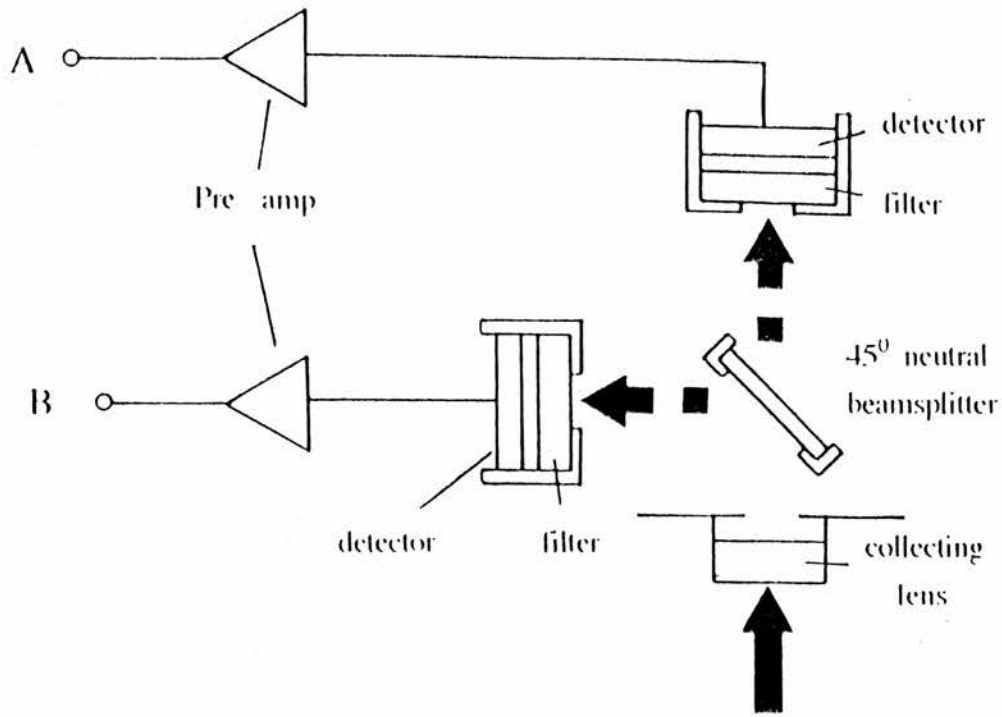


FIGURE 2.7 : SCHEMATIC DIAGRAM OF MACAULAY RADIOMETER READING HEAD

(After Adams *et al*, 1985).

Near-infrared and red reflectance values were recorded for various land cover types as well as for a standard diffuse reflector, a Kodak Grey Card, at different locations in the area of study. For any particular point, the reflectance value for land cover (in either red or near-infrared band) was divided by the corresponding value recorded for the Grey Card to produce a bidirectional reflectance factor (BRF), which is essentially a ratio between the spectral radiance of an object to that of a standard diffuse reflector (Curran, 1985). The standard measure of reflectance used in remote sensing is the bidirectional reflectance (BDR) and is calculated by multiplying the bidirectional reflectance factor (BRF) by a wavelength-dependent constant determined from laboratory calibrations of a standard reflectance surface. From calibrations undertaken at the University of Southampton using a Kodak Grey Card, it was determined that 20.95 is the appropriate constant for use with values for bands equivalent to Landsat TM2 (0.52-0.60μm); and 25.15 for use with values for bands equivalent to TM4 (0.76-0.90μm) (Harris, 1987). The Macaulay radiometer's red band falls around the top end of the TM2 wavelength range, and its near-infrared band is just within the TM4 wavelength range. The two constants given above could therefore also be suitable for use with the readings of a Macaulay radiometer (Soulsby, Pers. Comm.) These two constants were therefore used in this work to calculate bidirectional reflectance values for different land cover types using the following formula:

$$B = \frac{Rg}{Rs} K\lambda \qquad (2.1)$$

[After Harris, 1987]

where B = bidirectional reflectance

Rg = reflectance from ground

Rs = reflectance from standard surface (Kodak Grey Card)

Kλ= wavelength dependent constant

2.2.2.3 *Aerial Photographs*

Panchromatic and colour aerial photographs were obtained for use in this work. The black-and-white ones were acquired from the department's own collection of aerial photographs. They were taken during the summer of 1973 at the scale of 1:7 900. Most of the prints covered Levisham Moor , Lockton High and Lockton Low Moors. This was an area actually enclosed in a rectangle whose four corners are grid points SE 830940, SE 860940, SE 830900 and SE 860900. A few more prints covered the areas around Danby Head (NZ 709006); Great Fryup Head (NZ 717014); West Gill Head (NZ 709006); Middle Head (NZ 716004); the stretch of land from north and west of Clough Dike Head (SE 713995) to north of Dale Head Farm (SE 69995): between Hamer Beck and Hamer Moor; and around Randy Rigg and Randy Mere reservoir on Egton High Moor.

The colour aerial photographs were obtained from the North York Moors National Park Offices. One set was acquired on October 21st, 1991 at a scale of 1:10 000. Only 7 prints were of good quality. The rest had much cloud cover. Among the 7, print 9-38-3 covered West Gill area (Rosedale Moor) with the centre around NZ 713001; print 91-38-9 covered Glaisdale Rigg with the centre around NZ 740040; print 91-38-20 covered Hamer Moor with centre around SE 737988; print 91-38-31 covered north of North Dale with the centre around NZ 718002; print 91-40-53 covered Glaisdale Head with centre around NZ 739009; print 91-40-55 covered CockHead with the centre around NZ 734004; and print 91-40-56 covered North Gill with centre around SE728997.

Another set of colour aerial photographs was acquired in summer 1988 at a scale of 1:20 000. All the prints obtained for this project were of excellent quality. They covered the Eskdale-Goathland region, an area roughly enclosed in a rectangle whose corners are defined by grid points NZ 760060, NZ 820060, SE 760960 and SE 820960.

2.2.2.4 *Maps*

Maps were extensively used in this research project. General information about the area was provided by Ordnance Survey tourist maps. One tourist map was published in 1979 at a scale of 1: 63 360. Another was published in 1983 at a scale of 1: 25 000 and was printed on two double-sided sheets. There were also conservation maps produced by the North York Moors National Park Committee at the scale of 1: 63 360 and 1: 50 000. The former was produced in 1984 in fulfilment of the requirements of Section 43 of the Wildlife And Countryside (1981) Act. The latter was produced in 1989 in fulfilment of the requirements of Section 3 of the 1985 amendment of the Wildlife And Countryside Act. Both maps highlighted areas of moorland and other habitats that are considered to be of high conservation value. The conservation maps were obtained together with their memoirs. A set of 1: 10 000 Phase 1 Habitat Maps published by the North York Moors National Park in 1989 were also obtained and used in this work. On these maps, all community/habitat types in the area are delineated, colour-coded and labelled. These map sheets provide useful ecological data. There were also two unpublished maps which were acquired mainly for use in assessing change detection accuracy. One was obtained from the North York Moors National Park Offices at Helmsley and it showed bracken infested areas that had been treated under the bracken control scheme. Areas treated at different periods were presented in different colours. This map was also at a scale of 1: 63 360. The second unpublished map was obtained from Forestry Commission Offices in Pickering and it showed woodland plots/sections in the North York Moors and the details of management activities being undertaken or planned in each plot/section. The management activities included felling and re-planting. The map was at a scale of 1: 25 000.

2.4 METHODOLOGY

Analysis began with the ancillary data and the information obtained helped in interpreting the Landsat TM data; in selecting training areas for supervised classification of image data; and in assessing accuracy of image classification and change detection operations. A summary of procedures followed in the analysis of ancillary as well as Landsat TM data is given in this section. However, full details of image processing operations and how the information obtained from ancillary data were used in such undertakings are given in the next three chapters.

2.4.1 Aerial Photo Interpretation

Aerial photo interpretation was carried out to acquire information for use in recognising different land cover types on satellite imagery; in identifying and selecting training sites for supervised image classification; and in assessing classification accuracy.

The aerial photographs were qualitatively interpreted using image characteristics of tone, texture, shadow, pattern, association, shape, and position/site. Different land cover types could be identified using these image characteristics. However, tone proved to be the most useful characteristic. On the black-and-white photos, the tone was simply some shades of grey whereas on the colour photos, it was a range of colours. Because the human eye can distinguish different colours more easily than different shades of grey, then expectedly, more information about land cover types and their spatial distribution were obtained from the colour aerial photos than from the black-and-white ones. Details of information obtained from the aerial photos also varied with scale. The 1991 colour aerial photos at a scale of 1: 10 000 gave more details than the 1988 colour aerial photos which were at the scale of 1: 20 000.

SURFICIAL FEATURES	ARE THEY RECOGNIZABLE ON THE AERIAL PHOTOS?	
	BLACK & WHITE PHOTOS	COLOUR PHOTOS
Vegetation		
(a) Woodland		
-Broadleaved/Mixed	Yes	Yes
-Coniferous	Yes	Yes
(b) Upland heath		
-Established	Yes	Yes
-Young/regenerating	No	Yes
-Burnt	Yes	Yes
(c)Bracken		
-Thriving	No	Yes
-Chemically treated	No	Yes
(d)Upland heath/bracken mosaic	No	Yes
(e)Upland grass	No	Yes
(f)Agro-pastoral land	Yes	Yes
Linear Features		
(a) Field boundaries	Yes	Yes
(b)Woodland fringes	Yes	Yes
(c) Roads and/or tracks,	Yes	Yes
(d)Linear crags	Yes	Yes
Isolated Features		
Farm premises	Yes	Yes
Water		
(a) Rivers and streams	Yes	Yes
(b)Reservoirs	Yes	Yes
(c) Spring and flushes	Yes	Yes

TABLE 2.1 CLASSIFICATION OF LANDSCAPE FEATURES RECOGNIZED ON AERIAL PHOTOS

The landscape features identified on the aerial photographs were classified into four broad categories of **vegetation**, **linear features**, **isolated features**, and **water** each of which had also its own sub-classes. This classification was adapted from some parts of the classification scheme used by Hunting Technical Services Limited in the *Monitoring Landscape Change Project* (Deane *et al*, 1987). The adapted classification is shown in Table 2.1 which also shows whether a given type of landscape feature could be identified on one or both of the two types of aerial photos analysed, i.e black-and-white and colour aerial photographs.

2.4.2 Map Analysis

The analysis of maps mainly involved identifying and recording landscape features in each square of the map grid. The number of squares that contained a specific feature/land cover type was worked out in each case. This was further expressed as a percentage of all the squares included in the study. This percentage was equivalent to the phytosociological measure of constancy and it provided a more empirical base for establishing which of the land cover types were much more common; which ones were occasional and which ones were rare in the area. The analysis also revealed the degree to which certain land cover types were restricted to particular squares on the maps, which in turn means that they are restricted to particular regions/zones on the ground. Because the maps have topographical information in the form of contours, it was therefore possible to relate occurrence of a given land cover type to the topographical conditions. For instance, it was discovered that *Pteridium aquilinum* occurred mostly on the slopes on the moorland edge, and *Calluna vulgaris* occurred mostly on the plateau and ridge zones.

The clearest picture about land cover types and their spatial distributions was obtained from the 1: 10 000 Phase 1 Habitat Maps which show different categories of land cover/habitat in different colours and where the boundaries between the different habitats are clearly delineated. The unpublished bracken control scheme map and the

forestry management map were acquired mostly for use as reference data for evaluating the accuracy of the information about land cover change obtained from the analysis of the multi-temporal satellite data. Details of how the maps were used in change detection accuracy assessment are given in chapter 5 (section 5.5.2).

2.4.3 Analysis of Field Land Cover Data

The data on communities' floristic composition, stratification, stages of development and vigour, sociability, and cover-abundance which were acquired from the different field sites were comprehensively compared. The aim of this comparison was to discover similarities and/or differences among the communities in terms of those characteristics. Once discovered, the similarities and differences provided the bases for grouping communities into community/habitat types. This categorisation of communities followed the moor and heathland classification schemes used by Hunting Technical Services Ltd in the *Monitoring Landscape Change Project* and Silsoe College in *Monitoring Landscape Change in National Parks Project*.

2.4.4 Analysis of *In Situ* Spectral Data

The radiometer data were used for estimating amounts of green vegetation in different communities. The use of reflectance values to estimate amounts of green vegetation is based on the simple empirical observation that in most cases, the amount of green cover has a positive relationship with reflectance in the near-infrared and a negative relationship with reflectance in the regions of high chlorophyll absorbance, notably in the red wavelength (Curran, 1980; 1982). A ratio of the near-infrared to red reflectance summarises these relationships and it therefore provides a simple indicator of the amount of green vegetation. However, studies have established that while the simple near-infrared to red ratio is an indicator of the amount of green vegetation, it is affected by specific locational factors and cyclic processes. Some linear transformations of the ratio have therefore been developed to overcome the

weaknesses. These are called vegetation indices. The simplest of them is worked out by dividing the difference between near-infrared and red reflectances by their sum. This index, known as Normalized Difference Vegetation Index (NDVI), is therefore given by the following expression :

$$NDVI = \frac{NIR - R}{NIR + R} \qquad (2.2)$$

[After Curran, 1983a]

where NDVI = Normalized Difference Vegetation Index

NIR = Reflectance in the near-infrared band

R = Reflectance in the red band

Ideally, NDVI values should range from -1 to 1 but in practice, they quite often range from 0 to 1. Index value of zero indicates complete absence of any green vegetation at the site, whereas index value of 1 indicates that each unit area of the ground is completely covered by green vegetation. It is possible to use a multiplying factor to convert the 0 to 1 NDVI value range into the 0 to 255 range normally used in digital analysis of remotely sensed data.

In this work, the near-infrared and red radiometer readings were used to work out mean NDVI values for different land cover types. These are graphically presented in Figure 2.8. The NDVI graph indicates that the highest index value was recorded for thriving bracken fronds and young heather. Dead bracken stems had a mean NDVI value of around zero, indicating the complete absence of green leafy or other live plant structures.

Bidirectional reflectance values for the different land cover types were also plotted in a 2-D feature space with near-infrared and red bidirectional reflectance values on the opposite axes. This step was undertaken in order to discover if different land cover types can be discriminated using the radiometer data. The whole procedure is fully explained in the next chapter (section 3.4.1).

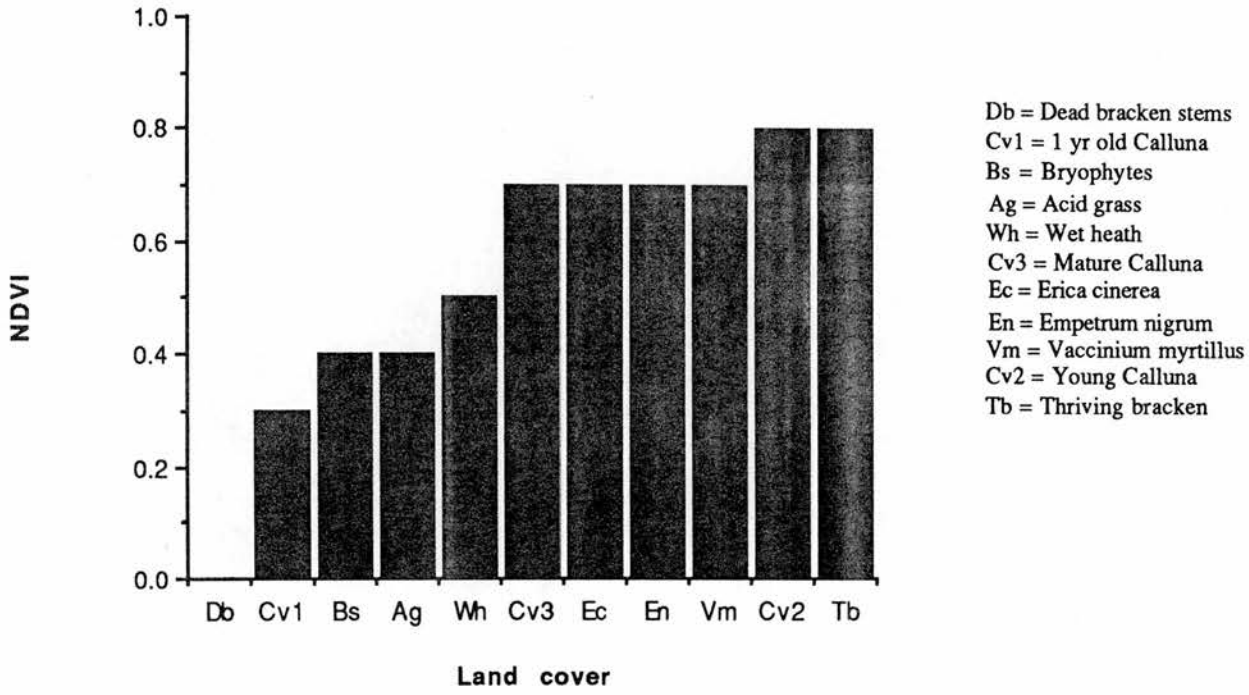


FIGURE 2.8 NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI) GRAPH

2.4.5 Analysis of Landsat TM Data

Landsat TM data were processed and analysed on an image processing system consisting of a host computer, colour monitor and text screen. The operation software used was version 4 of the Reading-Copenhagen Image Processing System (R-CHIPS).

R-CHIPS is an improved successor of the original Copenhagen Image Processing System (CHIPS) which was developed to satisfy an operational need for vegetation monitoring in Senegal, Africa. R-CHIPS was designed by the Department of Geography at the University of Reading initially as an educational software system for teaching principles of image processing at undergraduate level. But because of its user friendliness, the software has become equally popular outside the undergraduate teaching laboratories. It is now used as a research support system and as a low-cost work station system for operational users who had previously been unable to use image processing owing to the complexity and cost of other systems. Thus, in version 4 many functions have been incorporated to cater for research needs. R-CHIPS is copyrighted by I.S Limited (I.S Limited, 1991).

The image processing functions available on R-CHIPS version 4 are shown in Table 2.2. These functions are accessed either through a system of user menus that appear on the screen, or through some direct access commands. The menus are easy to use because they do not require the user to remember much about programme syntax. They also allow the user to see what is available through out the whole system. The R-CHIPS direct access user interface is intended for experienced users who find that the menus hinder them because of the hassle of moving between menus and selecting options (I.S Limited, 1991).

The user interacts with the system either through the keyboard or through a mouse. The colour monitor is able to display grey scale images; single colour blue, green or

IMAGE DISPLAY

Image Inspection Tool Box
Display Colour Composite
Display Grey Scale
Display Single Colour Band
Split Screen Display
Loop Display
Flick Display
Clear Colour Screen

IMAGE ENHANCE

Image Inspection Tool Box
Automatic Contrast Stretch
Histogram Equalize Stretch
Density Slice
Filter Image On Screen
Median Filter (Across)

IMAGE STATISTICS

Image Inspection Tool Box
Statistics Of Imager On Screen
Statistics Under Overlays
Multifile Display And Statistics
Histograms
Profile Across Data On Screen
Define Areas Under Overlays
Clear Overlays

IMAGE MATHEMATICS

Image Inspection Tool Box
Add Two Colour Guns
Subtract Two Colour Guns
Multiply Two Colour Guns
Ratio Two Colour Guns
Normalized Ratio Of Two Colour Guns

IMAGE CLASSIFICATION

Classify Data Shown On Screen
(Parallelepiped/Box Classification)
Classify Data Held In Files
(Maximum Likelihood and Minimum
Distance -To-Means Classifications)

IMAGE REGISTRATION

Image Inspect Routines
Select Ground Control Points
Edit Ground Control Points
Calculate Transform
View Transform Result File
Register (Warp) File
View Warp Results File

IMAGE TRANSFORMATION

Image Inspection Toolbox
Principal Components
Flip Screen Around Central Line
Flip Screen Around Central Pixel
Mirror Screen
Fix Colours And Overlays
Fix Split Look Up Tables
Fix Zoom Factor

DISK BASED TASKS

Filter Disk Files
Mosaic Disk Files
Contrast Stretch Disk Files
Mirror Disk File
Flip Disk File
Flip Disk Files
Import Disk Files

TABLE 2.2 R - CHIPS IMAGE PROCESSING FUNCTIONS (After LS Ltd.; 1991)

red images; and colour composites made up of blue, green and red colours. It can display any size of an image to the maximum of one with 512 pixels by 512 lines in dimensions. The text screen is where the menus and any other text appear. Image statistics and histograms can also be displayed on the text screen.

The system used in this work was also connected to a colour jet printer. Grey scale and colour image hard copies can be produced with the printer. The printer can print images displayed on the colour monitor or those held in files. Statistics and histograms can also be printed in a similar manner.

The analysis of the image data began with the selection and extraction of some subscenes as the image processor cannot display images larger than 512 pixels by 512 lines in size, and therefore the whole area cannot be studied as a single unit. It was intended that each of the subscenes should incorporate as much variety in landscape features as possible. This meant avoiding the northern parts of the park where the extensive Esk Valley is the single most dominant landscape feature, as well as the south where extensive parts in most areas are under one type of land cover, namely coniferous forest. On the 1985 data, the area west of Farndale had some cloud cover. Taking all these factors into consideration, the suitable area left was the central zone from Westerdale Moor eastwards to Fylingdales moor. This area was divided into three equal extracts each of which represented an area equivalent to 10Km x 8.89Km on the ground (i.e approximately 10Km x 9Km). The pixels on the imagery had been subsampled so that each represented approximately 22.22m x 22.22m on the ground. Therefore, the 10Km x 9Km extracts were 450pixels x 400 lines in dimensions on the imagery.

The 1985 imagery had been geometrically rectified to the British National Grid by the supplier so that the extracts selected on it corresponded geometrically with the available maps. The 1991 imagery had not been geometrically rectified by the supplier and therefore it had to be rectified to make it geometrically similar to the

1985 imagery and the available maps. This was accomplished by registering the 1991 imagery to the 1985 imagery. To register them, ground control points (GCPs) were identified and located on the extracts of the two image sets. The GCPs' *x, y* co-ordinate values on the 1985 imagery were regressed against corresponding ones on the 1991 imagery to produce some coefficients which were then fitted into transformation polynomials. The latter were used to determine new geometrically correct grid systems of cells (i.e "pixels" without spectral data). To complete the generation of new geometrically rectified image, brightness intensity (DN) values were transferred from the original 1991 (geometrically distorted) imagery to the newly created grid system of cells using nearest neighbour interpolation method.

In natural and/or semi-natural terrestrial environments, the structure of land cover is normally very complex and because of this, it is not easy to study and map vegetation at the species level. Land cover studies in such environments are therefore normally based on groups of species which are studied and mapped as single units. Different researchers may use different groupings of species as units of study and mapping depending on the purpose of study as well as the scale at which it is to be conducted. It is therefore essential preliminary to any land cover study, to clearly define the land cover categories (i.e groups of species) that are going to be used as units of study and mapping. Those that were to form the bases of the present study were therefore established and defined prior to analysis of the image data. The categories used in the *Monitoring Landscape Change in National Parks Project* (Silsoe College, 1991), were adopted with some slight modifications to suit some specific purposes of the present study and the resolution of the Landsat TM data. The categories are described and presented in chapter 3, section 3.2.

The starting point in the actual analysis of the Landsat TM data was to assess the extent to which different land cover categories could be visually identified on analogue displays of the data. Three colour composite images, one for each extract, were displayed using the 1985 image data by loading the red band (TM3) on to the

green gun of the R-CHIPS graphic card; the near-infrared (TM4) on to the red gun; and the mid-infrared band (TM5) on to the blue gun. These were then visually analysed using qualitative aerial photo interpretation methods to detect and identify different land cover categories. Similar procedures were followed to detect and identify land cover categories on three colour composite images displayed by loading TM3, TM4 and TM5 of the 1991 imagery on to R-CHIPS' green, red, and blue guns respectively.

The extent to which each land cover category was spectrally distinct from other categories was assessed by computing an index called Normalized Index of Spectral Separability. This index is worked out by dividing the difference in mean DN values of a pair of land cover types by the sum of their standard deviations in a specific data band (see equation 3.3 in chapter 3). An index value of more than 1 indicates that the pair of land cover is spectrally separable in that specific band. An index value of less than 1 indicates that the two land cover types are not spectrally separable in that specific band. In this work, these indices were computed for different pairs of land cover types in TM3, TM4 and TM5 in all three extracts of the 1985 data, and again in all three extracts of the 1991 data.

Multispectral image classification was carried out on colour composite displays for the 1985 data, and again on those for the 1991 data in all three study extracts. The classification process was carried out using minimum distance-to-means, maximum likelihood and parallelepiped decision rules. All three classifiers are supervised and therefore the classification process had to begin with the selection of training areas on the colour composite displays. The training areas consist of sample pixels of predefined land cover classes. The classifiers work out some parameter models from the training areas and they use such models to determine the land cover category to which each pixel in the imagery can be assigned. The effectiveness of supervised classification largely depends on success in selecting very representative training (sample) pixels. In this work, the representativeness of the training data was

statistically assessed and less representative training areas were revised. The three classifiers were run using the edited training data. The resulting classified images had a "salt and pepper" appearance. Post-classification filtering was therefore carried out to smooth them out. For parallelepiped classification, the results are output to overlays each of which is presented in a different colour. Thus, the resulting classified images are very impressive colour displays. For maximum likelihood and minimum distance classification strategies, the results are output to grey scale image files where the different land cover categories cannot be easily distinguished. In this work, the image outputs of these two strategies were therefore interactively colour-coded to produce visually impressive classified images.

All classifications were assessed for accuracy. The 1: 10 000 habitat maps were the main reference data used in the accuracy assessment work. In each extract, five 1Km x 1Km squares on the maps were randomly selected and manually registered to the appropriate parts of the image data with the help of ground control points. Each of the selected map squares was stratified into 45 equal divisions in west-east as well north-south directions to create a block of 45 x 45 small squares that corresponded with the 45 x 45 pixels representing 1Km x 1Km area on the imagery. The appropriate sections of the maps were enlarged by a factor of two, and the parts on the imagery were zoomed to level 4 and the zoom was made permanent using the Fix Zoom Factor function in the Image Transform menu on R-CHIPS. This was undertaken to bring the two data bases to the same scale. Then classified image pixels were compared with corresponding squares on the maps to identify those that had been correctly classified as well as those that had not been correctly classified. The statistics on correctly and incorrectly classified pixels were used in calculating some measures of accuracy and error. The accuracy measures calculated were class accuracy (%) and overall accuracy (%). Similar measures for errors of omission and commission were also computed. The confidence limits of the accuracy values obtained were also computed at 99% confidence level.

The 1985 and 1991 image data constituted a multi-temporal data set which was used in this work to assess if such data could provide information about land cover changes. A variety of digital change detection techniques were employed in analysing changes on the multi-temporal data set. One is post-classification comparison approach which simply involves overlaying results of good classifications of data acquired at times t_1 and t_2 and then viewing the overlay set to discover sections where the two classifications match or mismatch. It is the areas where the classifications mismatch that are said to have undergone change. The effectiveness of the method largely depends on high accuracy levels being achieved in the independent classification of each of the images in the multi-temporal set. In this work, the maximum likelihood classifier produced better results than either the minimum distance or the parallelepiped strategy in the classification of both the 1985 and 1991 data. Therefore, the image outputs of maximum likelihood classification for the 1985 and 1991 data were considered more suitable for use in the post-classification comparison change detection approach. These were overlaid and viewed to detect land cover changes.

An equivalent of direct multi-date classification approach was also undertaken. Under the conventional direct multi-date classification approach, all bands in a multi-temporal data set are displayed as a multi-band colour composite where areas that have undergone change appear in unique colours. These areas are then classified using the conventional image classification approaches. In this work, the technique would have involved displaying all six data bands (three for 1985 and three for 1991) as a multi-band colour composite and then carrying out classification on it. But because the image processor used in this work cannot display colour composite images comprising more than three bands, then the six data bands were together subjected to principal component transformation. In each extract, the first three principal components together accounted for more than 95% of the variance in the original data. It was therefore considered that the first three PCs could stand for the

original data bands. Therefore, in each extract, the first three PCs were displayed as colour composites and classified.

Image subtraction (differencing) technique was also followed in this work in trying to detect land cover change. Under this method, the brightness intensity (DN) values of pixels on an imagery acquired at time t_1 are subtracted from those of corresponding pixels on an imagery acquired at time t_2. This subtraction produces a new image file where pixels representing areas that have not undergone change will have DN values of around zero, and those that have undergone significant change will have values greater than zero (positive integers) or less than zero (negative integers). It is possible to rescale the difference/residual values into the normal 0 to 255 range using some constants. In this research project, the 1985 data bands were subtracted from the corresponding ones on the 1991 imagery and the resulting residual images were analysed to assess the extent to which the method was effective in portraying information about areas that had undergone change between 1985 and 1991.

Image ratioing is a method of change detection that works in quite the same way as image differencing only that instead of subtracting corresponding bands in images of times t_1 and t_2, they are divided/ratioed. In this work, corresponding bands on the 1985 and 1991 image data sets were divided and the resulting ratio images were analysed to discover if information about land cover change could be obtained from them.

Principal component analysis (PCA) is another approach used in this work to analyse land cover change. Change detection through PCA involves subjecting multi-temporal data bands to principal component transformation and then analysing the resulting principal component (PC) image files to identify areas of change. In this work, the 1985 and 1991 data bands were together subjected to the principal component transformation as already indicated above. The resulting PC images were visually analysed to detect areas that had undergone change between 1985 and 1991.

Attempts were also made to analyse change through methods incorporating image classification and image ratioing/image differencing/PCA. These integrated/"hybrid" approaches involved displaying three residual/ratio/PC image files as a colour composite where areas that had undergone change were expected to appear in unique colours. The areas appearing in such unique colours were then classified into different categories of change using the conventional image classification approaches.

The information about land cover changes obtained in this work was transferred on to copies of the 1: 10 000 maps. These were then taken to the area of study where checks were undertaken to verify the findings. The bracken control scheme map obtained from the North York Moors National Park Offices also gave reference information for verifying the findings about areas of bracken that had been treated. Similarly, the forestry map obtained from the Forestry Commission Offices in Pickering helped in verifying the findings about cleared woodland areas.

2.4.6 Illustrations and Presentation of Results

Different types of diagrams, tables, graphs and maps are used in the thesis to illustrate certain aspects of the work. Qualitative and numerical tables are extensively used to present results of most of the research operations. The tabulated information is further explained and/or interpreted in the main text. Hard copies were photographically produced for the unprocessed colour composite images, for classified images produced under maximum likelihood approach, and for land cover change "maps" produced under the classification of residual images approach. Cost prohibited the production of hard copies for the results of each and every image processing operation. Some data tables, diagrams and photographs are presented in the appendices.

"[Satellite]....remotely sensed recordings can be subjected to optical and numerical processing that increases the quantity of information that they otherwise furnish. Aerial photographs can be subjected only to densitometer analyses, which are delicate, relatively expensive, and of infrequent usage. The various bands [of satellite data], in contrast, can be subjected not only to equal treatments, but also to many others which depend only on the dexterity of the operator. There is here a veritable mine that remains to be prospected."

J. Tricart and C. KiewietdeJonge (1992) **p 160**

CHAPTER 3
IMAGE PREPROCESSING, LAND COVER IDENTIFICATION AND DISCRIMINATION

This chapter describes some operations undertaken prior to analysis of the image data. These include rectification of the 1991 imagery to the British National Grid, and formulation of an analytical land cover classification scheme specifically for use in this project. Some initial analyses carried out on the Landsat TM data sets are also reported in this chapter . These include visual analysis of colour composite displays to identify different land cover types; assessment of the spectral separability of land cover types; and analysis of spring-summer spectral changes for moorland and related cover.

3.1 IMAGE PREPROCESSING

The term preprocessing refers to operations that are carried out on image data preliminary to main analysis (Campbell, 1987). These operations are undertaken to correct image data for distortions and "noise" which are introduced during data scanning and transmission processes (Sabins, 1978). The distortions and "noise" come about as a result of sensor malfunctions, effect of adverse atmospheric conditions like haze, system noise, sensor motion and earth rotation (Sabins. 1978). Typical preprocessing operations therefore include radiometric correction to adjust digital values for the effect of hazy atmosphere and sensor malfunctions: and geometric rectification to bring an image into registration with a planimetric map or another image which is considered to be geometrically correct (Campbell, 1987).

Companies that supply satellite data normally undertake radiometric correction of the data. Quite often, they also undertake geometric correction to remove the more serious systematic geometric errors. However, the less serious non-systematic geometric errors are often left without being corrected (Gordon, 1981; Jensen, 1986).

These non-systematic errors are mainly caused by the departure of the satellite platform from the normal altitude, as well as the departure of the sensor from its normal look-angle (Jensen, 1986). Non-systematic geometric errors do not matter for most purposes of image analysis. However, some analyses require that these errors should also be corrected. For instance, where there is need to mosaic two or more adjacent image scenes, they have to be made planimetric by removing the non-systematic errors. Similarly, the analyses of multi-temporal data sets require that images in the sets should be geometrically registered to each other. Geometric registration may also be required when comparing data collected by different sensors but covering the same area (Gordon, 1981).

Of the two image data sets used in this project, the 1985 imagery was obtained from the National Remote Sensing Centre's own archive. The Centre has a policy of undertaking geometric rectification for image scenes in its possession. Scenes covering areas that are entirely within Britain are rectified to the British National Grid. Those scenes that include areas in Ireland are rectified to the Irish National Grid; whereas those that include parts of France are rectified to the Universal Transverse Mercator Grid (Gordon, 1981). The TM scene 203/22 used in this work covers areas that are entirely within Britain. The Centre had therefore geometrically rectified the 1985 imagery to the British National Grid before supplying it. The 1991 imagery came from the European Space Agency's archive and although it was supplied through the National Remote Sensing Centre, it had not been geometrically rectified to the British National Grid. It therefore had to be rectified in order to make it comparable to the 1985 imagery.

Because the image processor used in this project cannot display images larger than 512 pixels x 512 lines in size, registration and all the subsequent analytical operations were carried out on smaller subscenes. These were selected and extracted from the larger image files using the Loadsub direct access command on the R-CHIPS programme. In order to be representative, each of the subscenes to be selected and

extracted was expected to include a variety of landscape features and/or land cover types. This meant that the subscenes could not be selected to cover the northern and southern parts of the park because these parts lack variety in land cover types. In Esk Valley, which is the single most dominant landscape feature north of the park, the land cover is almost entirely of the agro-pastoral type. Similarly, coniferous plantations constitute the most extensive land cover type in most of the southern parts. This meant that the subscenes were to be selected and extracted from the central zone of the park. On the 1985 imagery, the area west of Farndale had some cloud cover. This factor reduced the suitable area to the stretch of land from Westerdale Moor eastwards to Fylingdales. It was necessary to have medium-sized extracts in order to avoid working with too many pixels at a time or with less meaningful tiny areas. Because of this, the central zone between Westerdale Moor and Fylingdales was divided into three study extracts each 450pixels x 400lines in dimensions. The pixels on the imagery had been subsampled so that each represented an area approximately 22.22m x 22.22m on the ground. Therefore, each 450pixels x 400lines study extract represented an area 10Km x 8.89Km on the ground (i.e approximately 10Km x 9Km). Figure 3.1 shows the location of the study extracts. The extract to the west encloses parts of Westerdale, Farndale, Blakey Ridge, Danby and Glaisdale; and was named "Rosedale Extract" for convenience sake. The one to the east encloses Fylingdales and eastern parts of Goathland; and was named "Fylingdales Extract". The one in the middle encloses Wheeldale, Egton and western parts of Goathland; and was named "Wheeldale Extract". Each of the three encloses plateau, ridge and valleys/dale zones.

With the 1985 imagery, it was possible to define extract boundaries that could match with the grid lines on Ordnance Survey Maps because the imagery had already been rectified to the British National Grid by the supplier. However, it was not possible to do so with the 1991 imagery which had some geometrical distortions on it. The process to correct these geometrical distortions involved two sets of operations, namely spatial interpolation and intensity interpolation. These are described below.

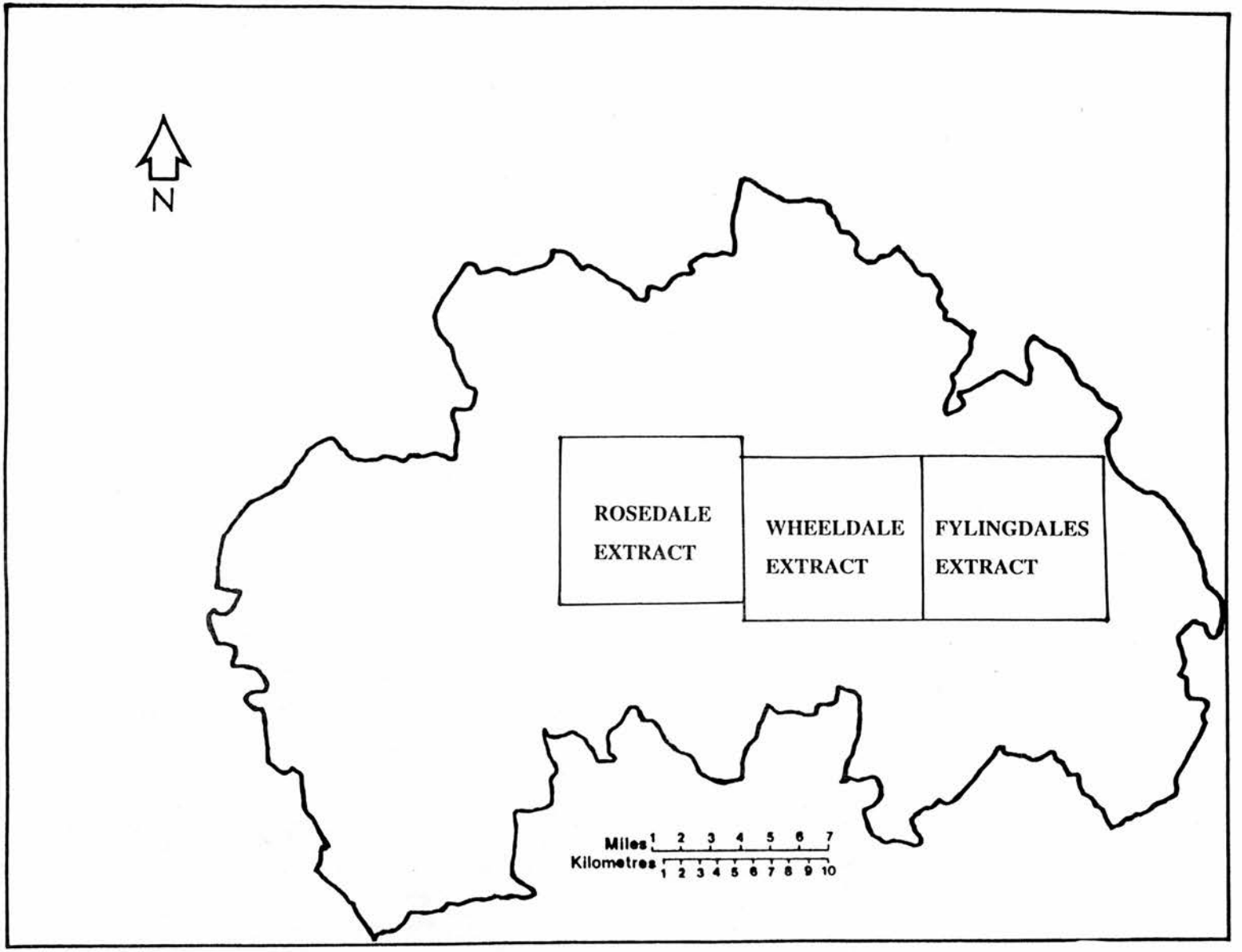


FIGURE 3.1 MAP SHOWING THE LOCATION OF THE STUDY EXTRACTS

3.1.1 Spatial Interpolation

The aim of spatial interpolation is to create a new geometrically correct grid of x,y co-ordinates that will represent the rectified image. The first step in spatial interpolation is to establish the geometric relationship between x,y co-ordinates of pixels in the input (source) image and that of corresponding pixels in the image that is used as the reference (target). To do this, ground control points (hereafter simply referred to as GCPs) should be identified and located on the input and reference images. GCPs are well-defined and easily recognizable features that can be accurately located on the two images (Mather, 1987a). Features that are normally used as GCPs include bends and junctions on roads/motorways, railways and rivers; islands and permanent features along sea/lake shores; runways on air fields and large areas of woodland (Gordon. 1981). For effective registration results, the GCPs should not be too few. They should also be well distributed all across the images. Good registration results cannot be achieved where too many GCPs are crowded around one place, while some parts are left without any or with only a few (Mather, 1987a; 1992).

Once the GCPs have been identified and located, their x,y co-ordinate values on the input image are regressed against the corresponding x,y co-ordinate values on the reference image. The least square regression produces coefficients that can be used to interrelate the source (input) image co-ordinates with the reference image co-ordinates. These coefficients are then fitted into a polynomial equation relating estimated $\boldsymbol{x,y}$ co-ordinate values of a yet non-existent grid to the x',y' co-ordinate values of the input image grid. The image processor then proceeds through each cell in the input image grid and uses the transformation polynomial equation to generate a new geometrically correct grid of $\boldsymbol{x,y}$ co-ordinates. For moderate distortions in a relatively small area of an image, like a quarter Landsat scene, at least six coefficients are required to make this type of transformation very effective (Jensen, 1986). Where

the six coefficients are used, the transformation polynomial can be expressed as follows :

$$x' = a_0 + a_1 x + a_2 y$$
$$y' = b_0 + b_1 x + b_2 y \qquad (3.1)$$

(After Jensen, 1986)

where x', y' = co-ordinate values in the input (distorted) image

x, y = co-ordinate values in a new correct grid which is being created

$a_0, a_1, a_2, b_0, b_1, b_2$ = the six transformation coefficients

In this work, the extracts from the 1985 imagery were used as the reference set whereas those from the 1991 imagery were used as the source (input) set. GCPs were identified and located on the reference and input extracts. Maps, aerial photographs and information from field work helped to identify and locate these GCPs. In most cases, they were major bends on dalesides; bends and junctions on roads; corners of large plantations; farmsteads; large woodlots on farms; and dams such as the Randy Mere in Egton. In all, 20 GCPs were identified and located on the Rosedale reference-input extract set; 30 on Wheeldale reference-input extract set; and 25 on Fylingdales reference-input extract set. The image processor then regressed the location (x,y co-ordinate) values of the GCPs in each reference extract against those of corresponding GCPs on each input extract to work out transformation coefficients. These coefficients were output to files that could be viewed and saved.

The R-CHIPS programme is able to use up to third-order polynomial to undertake the transformation task explained above. The first-order polynomial works when there are only a few GCPs and the third-order polynomial works only when there are about 20 or more GCPs. The second-order polynomial is the more robust one in that it can work with fewer as well as more numbers of GCPs. But in this study, it could not work when they were less than 10 in an extract. The higher order polynomials normally give better transformation results (Mather, 1987a). In this work the third-order polynomial was initially used in all three extracts. But after editing the GCPs as

explained below, only 16 GCPs remained in the Rosedale Extract and these were too few for the third-order polynomial to work on. Thus finally, the second-order polynomial was used in the Rosedale Extract and the third-order polynomial was still employed in the other two extracts.

How well a transformation polynomial succeeds in creating a new geometrically correct grid depends on the coefficients used. The use of coefficients derived from the least square regression of x,y co-ordinate values of GCPs that are correctly located in both the input and reference images tends to generate a new grid that is more geometrically correct. Conversely, the use of coefficients derived from the least square regression of x,y co-ordinate values of GCPs that are incorrectly located in either the input or reference images tends to generate a new grid that is less geometrically correct. It is therefore essential to evaluate the accuracy with which the GCPs have been located before accepting the new grid as being geometrically correct. The method that is often used to carry out such an evaluation involves the computation of the root mean square (RMS) error statistic.

If the newly created grid is actually geometrically correct, then its $\boldsymbol{x,y}$ co-ordinate values would be the same as those on the image which is being used as a reference. This means that if the co-ordinate values of the reference image (here presented as x_{ref}, y_{ref}) are fitted into the right hand side of the expressions in 3.1 above with all the coefficients in place, then the values produced (here presented as x'_{est}, y'_{est}) would be equivalent to x', y' values in the expressions in 3.1; i.e the expressions in 3.1 will have the same values as the following expressions:

$$x'_{est} = a_0 + a_1 x_{ref} + a_2 y_{ref}$$
$$y'_{est} = b_0 + b_1 x_{ref} + b_2 y_{ref} \qquad (3.2)$$

where x'_{est}, y'_{est} = estimated (computed) co-ordinate values

x_{ref}, y_{ref} = co-ordinate values on the reference image

$a_0, a_1, a_2, b_0, b_1, b_2$ = same coefficients as in 3.1

Any observed differences between the values of x', y' (in 3.1) and x'_{est}, y'_{est} (in 3.2) would indicate that the registration process has failed to bring the distorted image into perfect registration with the reference image, which would therefore imply that the coefficients used in the transformation process were derived from a least square regression of co-ordinate values of incorrectly located GCPs. Thus, the differences between x'_{est}, y'_{est} and x', y' values indicate error in the location of GCPs. The RMS error statistic is a measure of these differences, and therefore of error in location of GCPs. It is computed using estimated co-ordinate (x'_{est}, y'_{est}) values of GCPs and their corresponding trues co-ordinate (x', y') values on the distorted image. It is given by the following expression:

$$\text{RMS error} = \sqrt{(x'_{est} - x')^2 + (y'_{est} - y')^2} \tag{3.3}$$

(After Jensen, 1986 with modifications in notation)

where x'_{est}, y'_{est} = computed (estimated) co-ordinate values of a GCP

x', y' = true co-ordinate values of a GCP on the input image

It is clear from equation 3.3 above, that the RMS error statistic is essentially the square root of the squared deviations of the actual position of a GCP from its computed (estimated) position. When the RMS error statistic is computed for all GCPs in a scene or subscene, it is possible to see which ones of them exhibit the greatest error. The overall average RMS error can also be worked out. Better image registration results are achieved where the RMS error value is low for all GCPs. Normally, the analyst specifies a threshold value, and any GCP with an RMS error value greater than the threshold can be edited out. Sometimes, this editing process leaves too few GCPs for a transformation polynomial to work on. In which case, more GCPs have to be identified and subjected to the same evaluation process before using the data derived from them to generate the new image grid (Jensen, 1986).

In this work, RMS error values were computed for all GCPs in each extract. A value of 1.0 was chosen to be a threshold, and all GCPs with RMS error values of more than 1.0 were edited out. As a result of this editing, 16 GCPs in Rosedale Extract, 24 in Wheeldale Extract, and 19 in Fylingdales Extract qualified for use in the final transformation process out of the original 20, 30 and 25 GCPs identified and located in the three extracts respectively. The overall average RMS error values were 0.55 in Rosedale Extract; 0.54 in Wheeldale Extract and 0.49 in Fylingdales Extract. The RMS error values and other statistics for the GCPs are presented in Tables 3.1-3.3.

3.1.2 Intensity Interpolation

Spatial interpolation produces a new geometrically correct grid to represent the rectified image. Intensity interpolation determines the brightness intensity (DN) value to be assigned to each cell in the newly created grid. This involves the extraction of an intensity pixel (DN) value from an x',y' location in the original distorted input image, and the relocation of the value to the appropriate x,y location on the newly created output grid. This is accomplished pixel by pixel, line by line. It is this process that essentially completes the creation of the rectified image (Jensen, 1986).

There are three common ways to undertake intensity interpolation. One is known as nearest neighbour approach under which each cell in the newly created grid is assigned the intensity (DN) value of the nearest pixel in the input image. Thus, in Figure 3.2, the highlighted cell in the output grid would be assigned the DN value of pixel **a** from the input image simply because it is the one nearest to it. This approach is both simple and time-saving. It also ensures that the DN values in the output image are real ones in that they are copied directly from the input image. They are not "fabricated" by some averaging procedures as is the case in the two other approaches described below (Curran, 1985; Lillesand and Kiefer, 1987).

LOCATION OF GROUND CONTROL POINTS

GCP	SOURCE IMAGE		TARGET IMAGE		E R R O R		AVERAGE
NO.	X	Y	X	Y	X	Y	RMS
1	238	49	301	44	-0.69	-0.12	0.71
2	354	137	412	179	0.78	-0.24	0.81
3	376	118	441	163	-0.29	0.31	0.42
4	273	142	316	162	-0.44	-0.70	0.82
5	398	320	410	405	-0.19	-0.22	0.29
6	432	355	440	456	0.27	-0.30	0.41
7	328	314	330	378	0.24	0.73	0.76
8	405	262	435	341	-0.09	0.38	0.39
9	292	258	304	303	-0.48	0.42	0.64
10	321	294	328	353	0.34	0.61	0.69
11	232	284	227	315	0.21	-0.74	0.76
12	232	300	220	334	0.39	-0.02	0.39
13	175	389	125	418	-0.24	0.00	0.24
14	262	41	332	41	0.60	0.15	0.62
15	393	306	408	387	-0.50	-0.46	0.68
16	82	65	118	28	0.11	0.21	0.24

Transform level 2

RMS error : 0.56

TABLE3.1 GCP STATISTICS USED IN IMAGE REGISTRATION : ROSEDALE EXTRACT

LOCATION OF GROUND CONTROL POINTS

GCP	SOURCE IMAGE		TARGET IMAGE		E R R O R		AVERAGE
NO.	X	Y	X	Y	X	Y	RMS
1	174	374	140	410	0.18	-0.02	0.18
2	258	366	239	425	-0.10	0.09	0.14
3	128	325	92	372	0.39	-0.08	0.40
4	128	323	100	339	0.13	0.87	0.88
5	141	302	122	316	-0.19	-0.67	0.68
6	145	401	98	433	-0.22	-0.43	0.49
7	161	401	117	438	-0.08	0.29	0.30
8	95	242	85	234	-0.34	0.04	0.34
9	249	143	294	164	0.44	0.83	0.94
10	243	141	287	158	-0.44	-0.56	0.71
11	81	139	100	111	0.88	0.06	0.88
12	93	133	115	106	-0.12	-0.67	0.69
13	102	121	128	96	-0.57	0.70	0.90
14	89	168	101	146	0.41	-0.21	0.46
15	268	61	336	72	-0.14	0.03	0.14
16	302	120	362	150	0.48	-0.70	0.85
17	374	313	388	397	0.20	0.60	0.63
18	379	329	389	416	0.01	0.23	0.23
19	396	310	415	397	-0.01	-0.79	0.79
20	279	277	289	328	-0.06	-0.65	0.65
21	394	262	427	342	-0.15	0.18	0.23
22	205	243	214	267	-0.10	0.30	0.32
23	61	178	63	151	-0.43	0.04	0.44
24	327	142	384	184	-0.25	0.53	0.59

Transform level 3
RMS error : 0.54

TABLE 3.2 GCP STATISTICS USED IN IMAGE REGISTRATION : WHEELDALE EXTRACT

LOCATION OF GROUND CONTROL POINTS

GCP	SOURCE IMAGE		TARGET IMAGE		E R R O R		AVERAGE
NO	X	Y	X	Y	X	Y	RMS
1	258	348	210	420	-0.30	0.72	0.78
2	243	365	189	434	0.39	-0.65	0.75
3	254	299	221	362	0.57	0.33	0.66
4	312	337	276	421	0.02	-0.41	0.41
5	389	291	380	389	-0.02	0.21	0.21
6	376	33	436	87	-0.21	0.32	0.38
7	350	152	374	217	-0.75	-0.25	0.79
8	198	32	231	35	0.17	-0.44	0.47
9	217	18	256	23	-0.22	-0.56	0.60
10	258	104	281	136	0.19	0.27	0.33
11	355	114	392	175	0.78	0.03	0.79
12	383	82	433	145	0.09	-0.32	0.33
13	84	142	67	129	0.10	-0.30	0.31
14	158	107	165	110	0.25	-0.12	0.27
15	82	105	75	86	-0.15	0.29	0.33
16	185	324	134	370	0.38	-0.63	0.73
17	215	247	190	290	-0.56	0.24	0.61
18	148	355	81	396	-0.01	0.29	0.29
19	214	395	146	461	-0.36	0.15	0.39

Transform level 3

RMS error : 0.49

TABLE3.3 GCP STATISTICS USED IN IMAGE REGISTRATION : FYLINGDALES EXTRACT

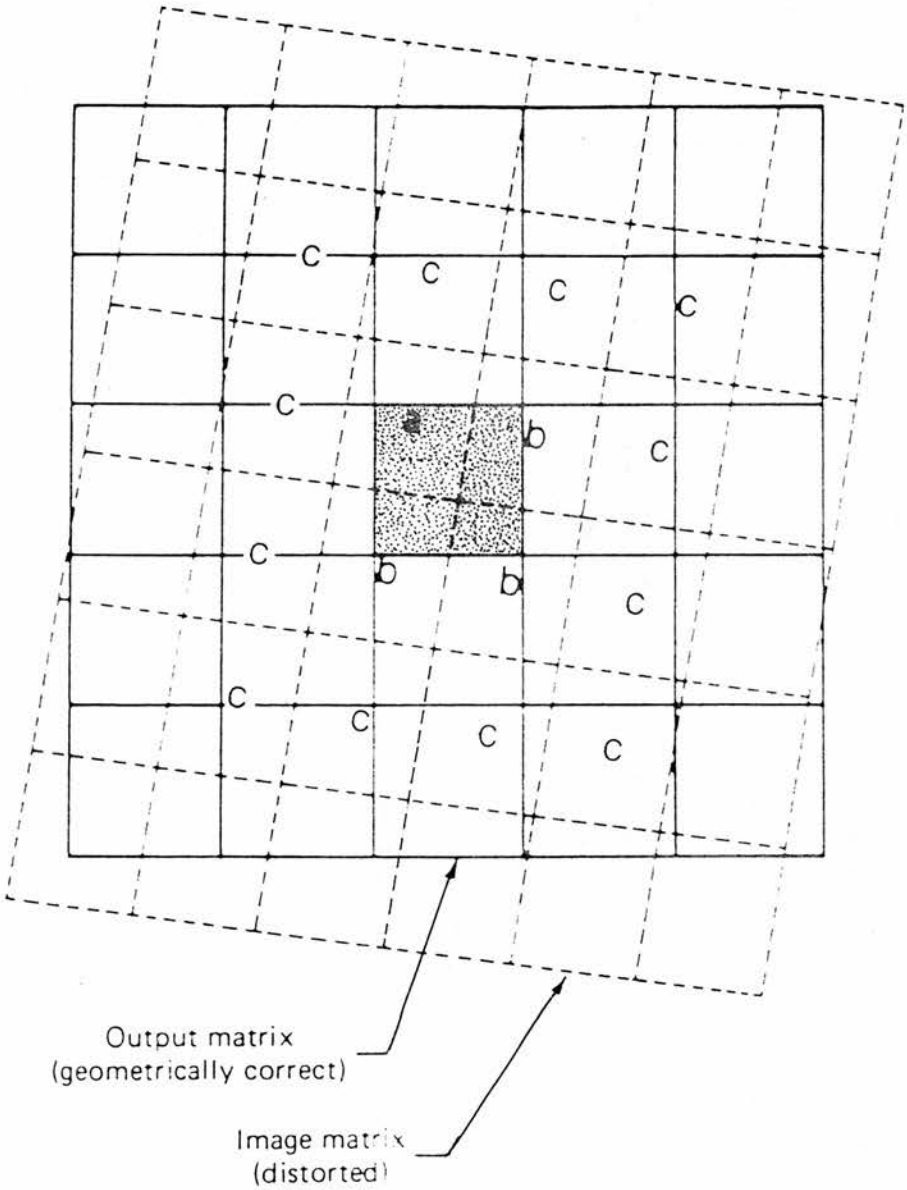


FIGURE 3.2 DIAGRAMMATIC REPRESENTATION OF INTENSITY INTERPOLATION PROCEDURES (After Lillesand and Kiefer, 1987)

The second approach is called bilinear interpolation under which the DN value to be assigned to each output cell is calculated as the weighted average of the four nearest pixels in the input image. Thus, in Figure 3.2, the highlighted output cell would be assigned a DN value calculated as the weighted average of the values of pixel **a**, and the three **b** pixels from the input image. This approach results in a smoother output image because it is basically an average filtering process. Loss of some spectral information is inevitable with such filtering process and the resulting output image may therefore contain less spectral information than the original distorted image (Campbell, 1987; Curran, 1985; Lillesand and Kiefer, 1987).

The third approach is cubic convolution which assigns DN values to output cells in much the same manner as bilinear interpolation, only that under this approach the DN value to be assigned to each output cell is calculated as the weighted average of the 16 nearest pixels from the input image. Thus, in Figure 3.2, the highlighted output cell would be assigned a value calculated as the weighted average of the DN values of pixel **a,** the three **b** pixels and the twelve **c** pixels. The process is more complex than the other two. The resulting output image is even smoother than the one generated under the bilinear interpolation method (Curran, 1985; Lillesand and Kiefer, 1987).

In this work, intensity interpolation was undertaken following the nearest neighbour strategy. This was preferred to the other two in order to allow the corrected imagery to retain more or less true spectral information. A land cover study like the present one needs high spectral variation across the scene in order to be able to identify and distinguish different land cover types. It would be difficult to identify and distinguish different land cover types on the smooth images that the other two approaches generate.

The results of the whole registration operation were very satisfactory. It is clear from the hard copies in Plates 3.1-3.6 that the extracts from the 1991 imagery had been made geometrically similar to those from the 1985 imagery. Note, however, that in

Fylingdales Extract, the 1991 imagery had some pixels missing at the far-right top corner. This was because of the way the quarter scene of the 1991 imagery was cut by the supplier. It had nothing to do with the image registration process.

3.2 ADOPTION OF ANALYTICAL LAND COVER CLASSIFICATION SCHEME

The structure and floristic composition of natural or semi-natural vegetation communities are often very complex. This complexity makes it difficult for one to understand, describe and map the communities very effectively. These problems are normally overcome by grouping species into classes based on some common characteristics. In this way, the complex distribution of communities is compressed into a fewer number of categories that we can describe, map and think about much more efficiently. Developing a classification scheme is therefore more than just a convenience, it is rather an essential aid in organizing facts and in promoting clear thinking (Hanson and Churchill, 1961).

Classification schemes normally show some analytical units formed by grouping together communities that have some common characteristics. These units form the bases for analysis, generalization of information, mapping and prediction of response to alternative management practices. In all resource surveys, one of the most important initial tasks is therefore to formulate or adopt a classification scheme (Mitchell, 1979). The ideal classification scheme is one that is based upon categories which are exhaustive (do not omit any phenomena) and mutually exclusive (do not have any categories which overlap). Equally important is that the scheme should be simple and easy to understand (Mitchell, 1979).

There are some standard land cover classification schemes that have very sound conceptual bases. One such scheme specifically developed for use in analyses based on remotely sensed data is the United States Geological Survey's Land Use and Land

Cover Classification Scheme developed by J. R. E. Anderson and colleagues in the 1970s. This scheme (Table 3.4) consists of a hierarchical structure of land cover units. Categories under the first and second levels of the hierarchy are specified. Level I categories are to be interpreted from small scale, coarse resolution imagery (Campbell, 1987; Lo, 1986). They are appropriate for mapping at the scale of 1: 250 000 (Lo, 1986). Level II categories are to be interpreted from large scale, fine resolution imagery (Campbell, 1987; Lo, 1986). They are appropriate for mapping at the scale of 1: 100 000 (Lo, 1986). The scheme does not specify land cover units at Levels III and IV. These are much smaller subdivisions of the higher order categories and are normally defined by the analyst to meet the specific requirements of a particular study (Campbell, 1987; Lo, 1986). The scheme was designed for applications in the USA, and while it has been used in other parts of the world, problems have often arisen when applying it in other countries which have landscapes different from those in the USA (Harris, 1987).

Of the schemes that have been developed and used in Britain, the one that came close to meeting the objectives of the present study is that used by Hunting Technical Services Limited in the *Monitoring Landscape Change Project* (Dean *et al*, 1987). The scheme consists mainly of land cover categories that have resource management implications. The same scheme was adopted with some slight modifications in the *Monitoring Landscape Change in National Parks Project* undertaken by researchers at Silsoe College (Silsoe College, 1991). It consists of a three-tiered structure of land cover categories. At the first level are very broad land cover categories like woodland, moorland, water, developed land and others. The second level specifies the land cover types within each broad category. The third level consists of even smaller subdivisions of the land cover types. The scheme is presented in Table 3.5. It was developed for use in studies that covered large areas which obviously had a greater variety of landscape features. It was also developed for survey work whose main source of data was not Landsat TM imagery. The scheme, therefore, could not be used in this project without some modifications because the area covered in this

LEVEL I	LEVEL II
(1) Urban or built-up land	(11) Residential (12) Commercial and services (13) Industrial (14) Transportation, communication and utilities (15) Industrial and commercial complexes (16) Mixed urban or built-up land (17) Other urban or built-up land
(2) Agricultural land	(21) Cropland and pasture (22) Orchards,groves,vineyards,nurseries and horticultural areas (23) Confined feeding operations (24) Other agricultural land
(3) Rangeland	(31) Herbaceous rangeland (32) Shrub-brushland rangeland (33) Mixed rangeland
(4) Forest Land	(41) Deciduous forest land (42) Evergreen forest land (43)Mixed forest land
(5) Water	(51) Streams and canals (52) Lakes (53) Reservoirs (54) Bays and estuaries
(6) Wetland	(61) Forested wetand (62) Non-forested wetand
(7) Barren land	(71) Dry salt flats (72) Beaches (73) Sandy areas other than beaches (74) Bare exposed rock (75) Strip mines, quarries and gravel pits (76) Transitional areas (77) Mixed barren land
(8) Tundra	(81) Shrub and brush tundra (83) Herbaceous tundra (84) Wet tundra (85) Mixed tundra
(9) Perennial snow or ice	(91) Perennial snowfields (92)Glaciers

TABLE 3. 4 USGS' LAND USE AND LAND COVER CLASSIFICATION SCHEME FOR USE WITH REMOTELY- SENSED DATA (After Anderson *et al;* 1976 through Harris, 1987)

MAIN CATEGORY	CODE	TYPE	SUBDIVISION
A Linear features	A1	Hedgerows	
	A2	Fences and insubstantial field boundaries	
	A3	Wall	
	A4	Banks	
	A5	Open ditches	
	A6	Woodland edge	
	A8	Strip woodland	
	A9	Grips	
B Small or isolated features	B1	Individual trees in linear features	
	B2	Individual trees outside linear features	
	B3	Groups of trees, all species	
	B6	Inland water	
C Wood and forest land	C1	Broadleaved high forest	
	C2	Coniferous high forest	
	C3	Mixed high forest	
	C4	Scrub	
	C5	Clear felled/newly planted areas	
D Moor and heath land	D1	Upland heath	
	D2	Upland grass moor	(b) grass moor (d) blanket peat grass moor
	D3	Bracken	
	D4	Unenclosed lowland areas	(a) rough grassland (b) heath
	D6	Upland mosaics	(a) heath/grass (b) heath/bracken (c) heath/blanket peat
	D7	Eroded areas	(a) peat (b) mineral soils
	D8	Coastal heath	
E Agro-pastoral land (enclosed farmland)	E1	Cultivated land	
	E2	Grassland	(a) improved pasture (b) rough pasture
F Water and wetland	F1	Open water, coastal	
	F2	Open water, inland	
	F3	Wetland vegetation	(a) peat bog (b) freshwater marsh (c) saltmarsh
G Rock and coastal land	G2	Bare rock	(a) inland (b) coastal
	G3	Other coastal features	(a) dunes (b) sand beach (c) shingle beach (d) mud flats
H Developed land	H1	Built-up land	(a) urban area (b) major transport routes
	H2	Quarries, mineral workings and derelict land	(a) quarries and mineral working (b)derelict land
	H3	Isolated rural development	(a) farmsteads (>0.25 ha) (b) other (>0.25 ha)
I Unclassified			

TABLE 3.5 SCHEME USED IN THE MONITORING LANDSCAPE CHANGE IN NATIONAL PARKS PROJECT (After Silsoe College, 1991)

project is relatively small and the main source of data is Landsat TM imagery whose resolution is relatively coarse. A modified scheme was therefore required for use in the present research project.

The field data on vegetation communities and the results of the aerial photo interpretation (see Table 2.2) were used to modify the classification scheme used in the *Monitoring Landscape Change in National Parks Project* (Table 3.5). Reference was also made to the habitat classification scheme used in the *Phase 1 Habitat Survey* (NCC, 1990). Two factors played a major role in determining the categories to be included in the modified scheme. One was the spatial resolution of Landsat TM imagery. This inhibited the disaggregation of land cover to the level of individual species except for species like bracken which may dominate over relatively large areas. The second factor was the consideration that the categories should fulfil the information needs for resource management purposes in the area.

The scheme that was finally adopted is presented in Table 3.6. It consists of two levels of generalization. At Level I there are six broad categories of land cover. These

LEVEL I	LEVEL II	CODE
Bracken		B1
Dry heath	Fire damaged moorland	D1
	Young heather moorland	D2
	Established heather canopy	D3
Forests/Woodland	Broadleaved, mixed and scrub	F1
	Coniferous	F2
Grass and crops	Grass moorland (unimproved)	G1
	Agro-pastoral	G2
Bare peat, bare cultivated fields		P1
Wet heath		W1

TABLE 3.6 LAND COVER CLASSIFICATION SCHEME ADOPTED FOR USE IN THIS STUDY

are **bracken,** referring to communities where bracken is the dominant species; **dry heath**, referring to communities of dwarf ericaceous shrubs on less wet areas; **forest/woodland**, referring to natural and planted woodland; **grass and crops**, referring to natural and cultivated grass and other crops; **bare ground/fields**, referring to non-vegetated areas and ploughed farmland; and **wet heath**, referring to mixed communities in permanently wet areas. Level II categories are subdivisions of the broad categories. Not all broad categories could be subdivided to Level II. But the dry heath category was subdivided into **fire damaged moorland,** referring to zones that had been damaged by uncontrolled fires in 1976 and later; **young heather moorland**, incorporating heather moorland communities that are in the pre-mature stage (approximately less than 10 years of age); and **established heather,** incorporating mature and old heather moorland communities. The broad category of forest/woodland was subdivided into **broadleaved and mixed** forests, and **coniferous** forests. The grass and crops group was subdivided into **grass moorland**, referring to all unimproved grass communities; and **agro-pastoral**, referring to improved and semi improved pasture, as well as other types of cultivated crops. The scheme also gave a code to each land cover category at Level II or at Level I where the category has no subdivisions. These codes (see Table 3.6) are used in place of the class names in many parts of the thesis particularly in the statistics tables.

3.3 IDENTIFICATION OF LAND COVER TYPES ON LANDSAT TM IMAGERY

It was necessary to assess whether or not the categories included in the adopted scheme could be detected and identified on the Landsat TM imagery. If they could be identified, then it would mean that it is possible to obtain more information about them from the imagery. If some could not be identified, then it would mean that it is difficult , if not impossible, to obtain more details about them from the imagery. In that case, it would require a revision of the classification scheme.

To assess whether the categories could be detected and identified on the imagery, a false colour composite display was prepared for each extract by loading TM3 (red band) on the green gun of the R-CHIPS graphics card, TM4 (near-infrared band) on the red gun, and TM5 (mid-infrared band) on the blue gun. Each study extract had two colour composite displays prepared in this way. One consisted of the three 1985 data bands, and the other consisted of the three 1991 data bands. In total, six colour composite displays were prepared. Hard copies of these are presented in Plates 3.1-3.6.

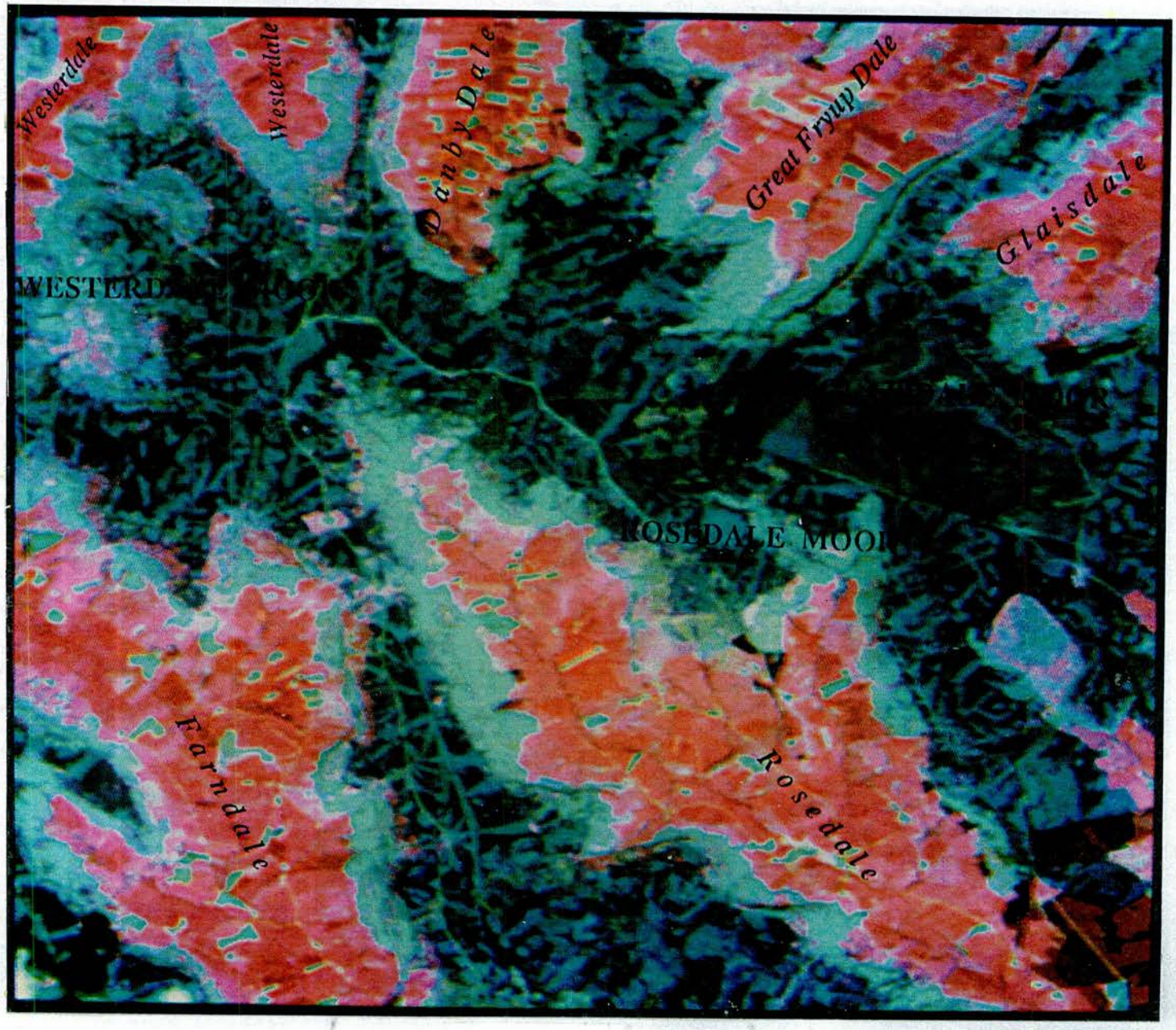
Once loaded on the screen, each colour composite display was enhanced using automatic contrast stretch option. The enhanced display was then visually interpreted using the qualitative elements of photo-interpretation namely, colour, pattern, texture, geometrical shape, site, situation and association. Colour proved to be the most outstanding factor in identifying the various categories as most of them appeared in more or less distinct colour (range of colours) on the composite displays. However, there were a few cases where the difference in colour between pairs of land cover categories was so subtle so that they could easily be confused. For instance, on the colour composite displays prepared with the spring 1985 image bands, there was confusion in colour between spring (largely dead) bracken and bare agricultural fields; between broadleaved woodland and stands of old heather; and between broadleaved woodland and grass moor. On the extracts prepared with summer 1991 image bands, the only big case of confusion was between the summer (largely live) bracken and green crops/pasture. Fortunately, the confused categories have different patterns of occurrence in the area. For instance, bracken occurs mostly along the slopes of the ridges whilst bare agricultural plots and improved pasture occur down in the valleys. In this way, it was possible to distinguish the different categories based on the ideas of site and association or context.

The exercise showed that all the categories in the adopted scheme could be identified on the analogue displays of the image data. This therefore suggested that the work

PLATE 3.1 COLOUR COMPOSITE IMAGE COMPRISING TM3, TM4 AND TM5 OF SPRING 1985 DATA : ROSEDALE EXTRACT

LAND COVER CATEGORY	COLOUR ON THE IMAGE*
B1: Bracken	Light blue
D1: Fire damaged moorland	Green to dark green
D2: Young heather moorland communities	Blue
D3: Established heather moorland communities	Dark blue
F1: Broadleaved and mixed woodland	Deep/rose pink
F2: Coniferous forest	Magenta to dark red
G1: Grass moor	Light pink
G2a: Fallow/semi improved pasture	Pink to rose pink
G2b: Improved pasture/crops	Magenta to true red
P1: Bare fields	Very pale green

* Because the plates are copies of the original photographs, the colours on them may not be exactly the same as indicated.

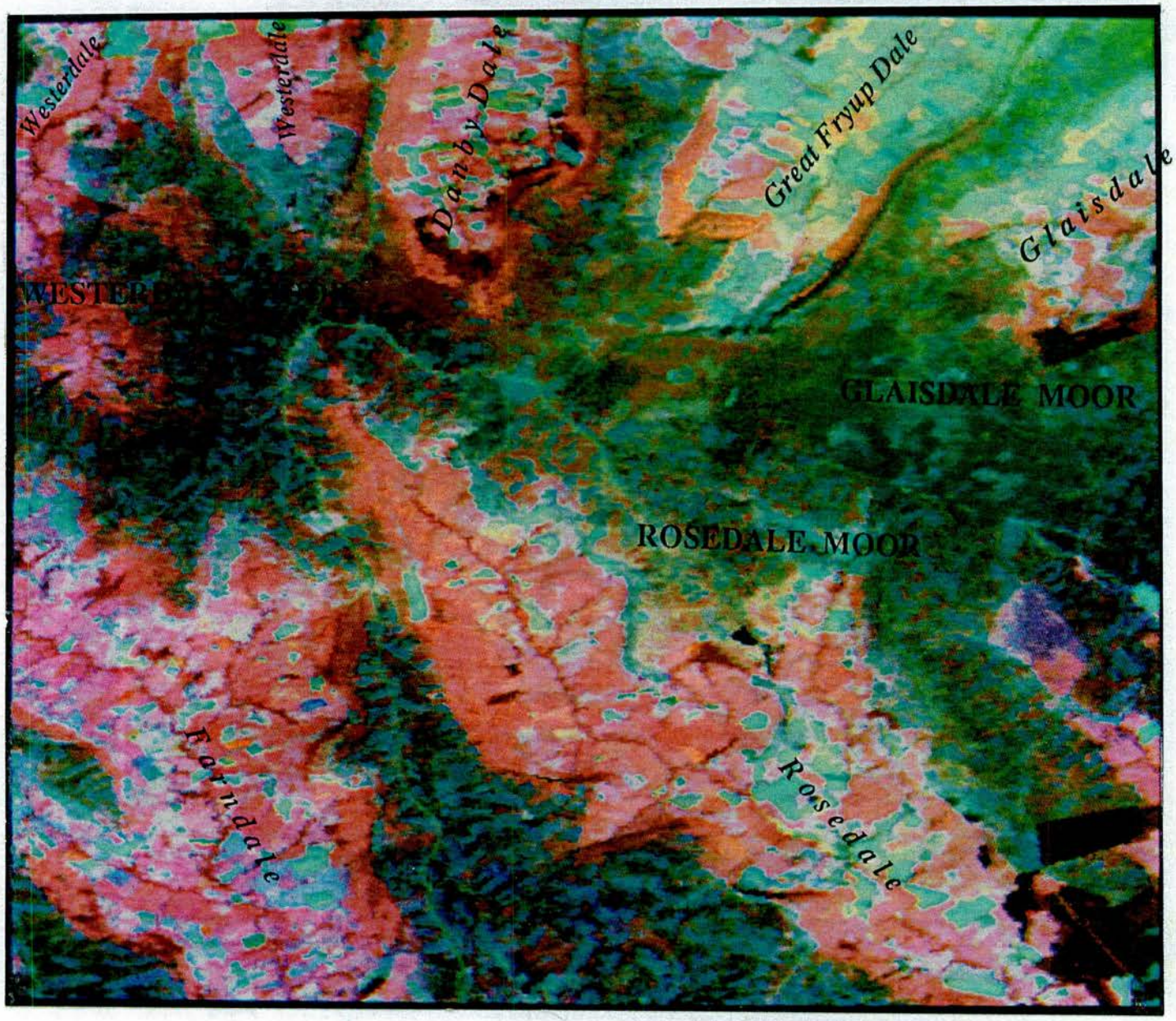

Westerdale
Westerdale
Danby Dale
Great Fryup Dale
Glaisdale
WESTERD
ROSEDALE MOOR
Farndale
Rosedale

N

0 1 2 Km

PLATE 3.2 : COLOUR COMPOSITE IMAGE COMPRISING TM3, TM4 AND TM5 OF SUMMER 1991 DATA: ROSEDALE EXTRACT

LAND COVER CATEGORY	COLOUR ON THE IMAGE
B1: Bracken	Scarlet red
D1: Fire damaged moorland	Green
D2: Young heather moorland communities	Blue
D3: Established heather moorland communities	Yellow, through purple to dark red
F1: Broadleaved and mixed woodland	Deep/rose pink
F2: Coniferous forest	Magenta, through dark red to black
G1: Grass moor	Blue-grey to light pink
G2a: Fallow/semi improved pasture	Blue-grey , through light pink to true pink
G2b: Improved pasture/crops	Pink, through rose pink to magenta
P1: Bare fields	Light blue to pale green

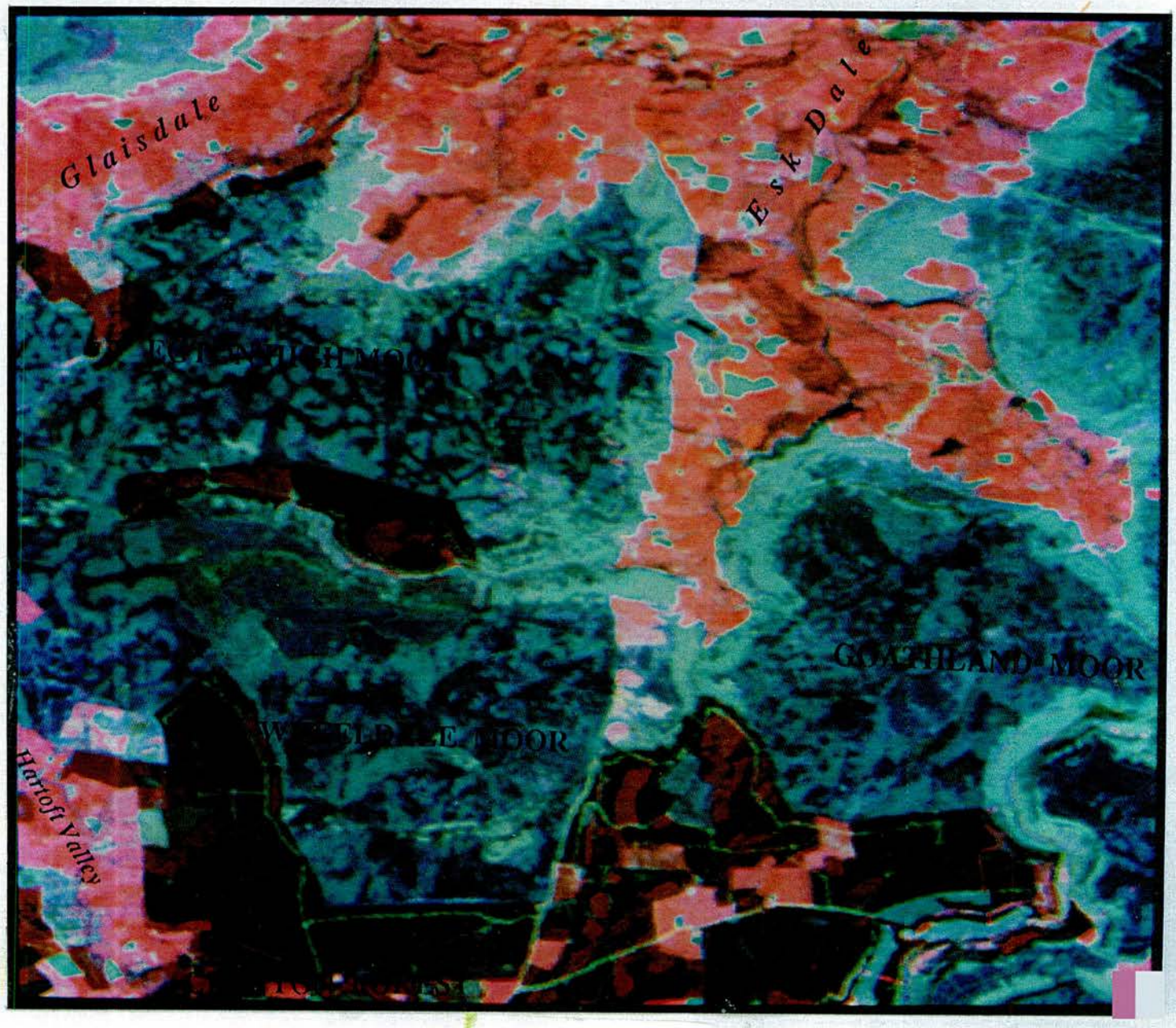

Westerdale
Westerdale
Danby Dale
Great Fryup Dale
Glaisdale
WESTER
GLAISDALE MOOR
ROSEDALE MOOR
Farndale
Rosedale

N

0 1 2 Km

PLATE 3.3 : COLOUR COMPOSITE IMAGE COMPRISING TM3, TM4 AND TM5 OF SPRING 1985 DATA : WHEELDALE EXTRACT

LAND COVER CATEGORY	COLOUR ON THE IMAGE
B1: Bracken	Light blue
D1: Fire damaged moorland	Green to dark green
D2: Young heather moorland communities	Blue
D3: Established heather moorland communities	Dark blue
F1: Broadleaved and mixed woodland	Deep/rose pink
F2: Coniferous forest	Magenta to dark red
G1: Grass moor	Light pink
G2a: Fallow/semi improved pasture	Pink to rose pink
G2b: Improved pasture/crops	Magenta to true red
P1: Bare fields	Very pale green
W1: Wet heath	Dark blue-green

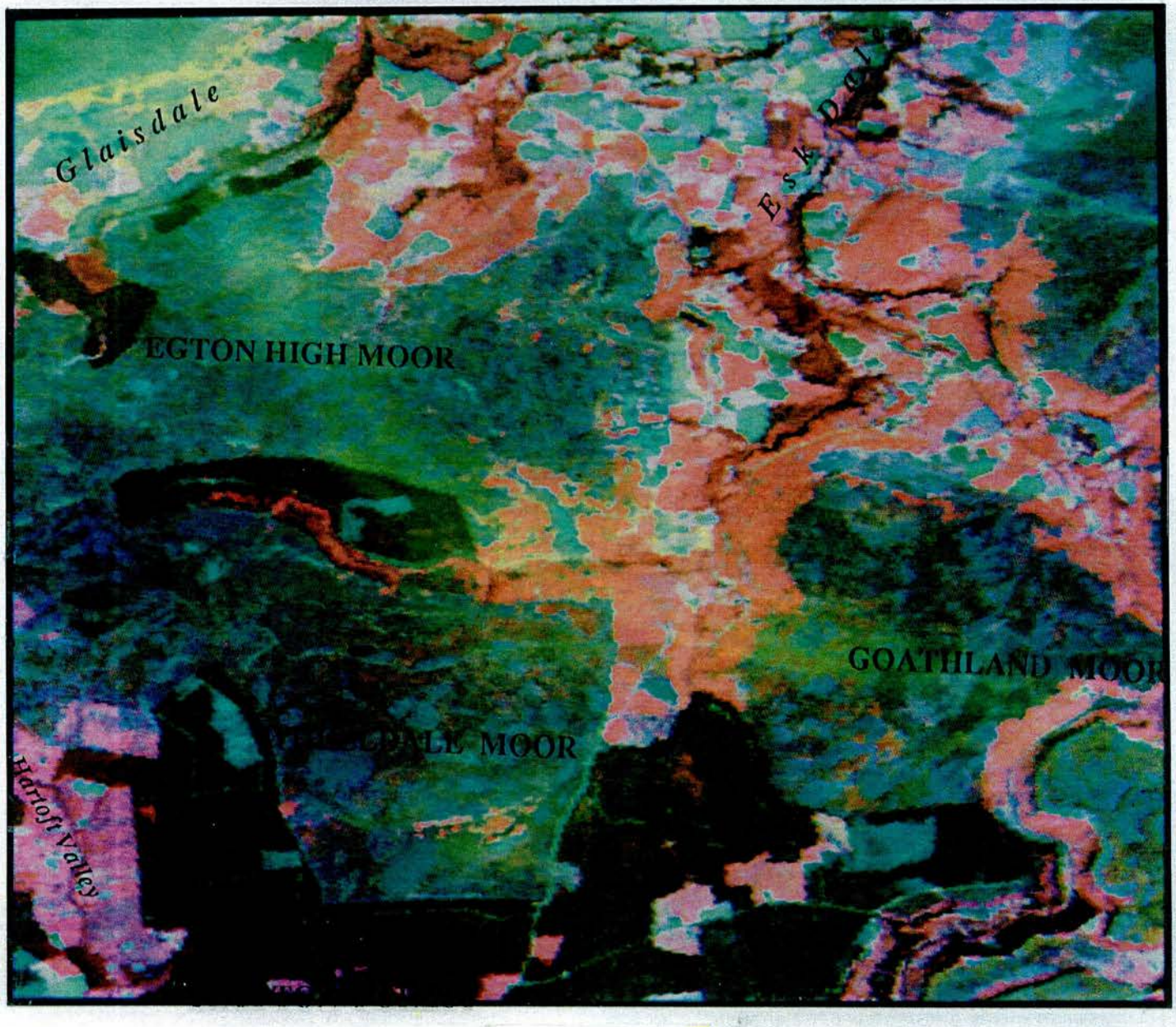


N

0 1 2 Km

PLATE 3.4: COLOUR COMPOSITE IMAGE COMPRISING TM3, TM4 AND TM5 OF SUMMER 1991 DATA: WHEELDALE EXTRACT

LAND COVER CATEGORY	COLOUR ON THE IMAGE
B1: Bracken	Scarlet red
D1: Fire damaged moorland	Green
D2: Young heather moorland communities	Blue
D3: Established heather moorland communities	Yellow, through purple to dark red
F1: Broadleaved and mixed woodland	Dark/rose pink
F2: Coniferous forest	Magenta, through dark red to black
G1: Grass moor	Blue-grey to light pink
G2a: Fallow/semi improved pasture	Blue-grey, through light pink to true pink
G2b: Improved pasture/crops	Pink, through light pink to true pink
P1: Improved pasture/crops	Pink, through rose pink to magenta
W1: Bare fields	Light blue to pale green

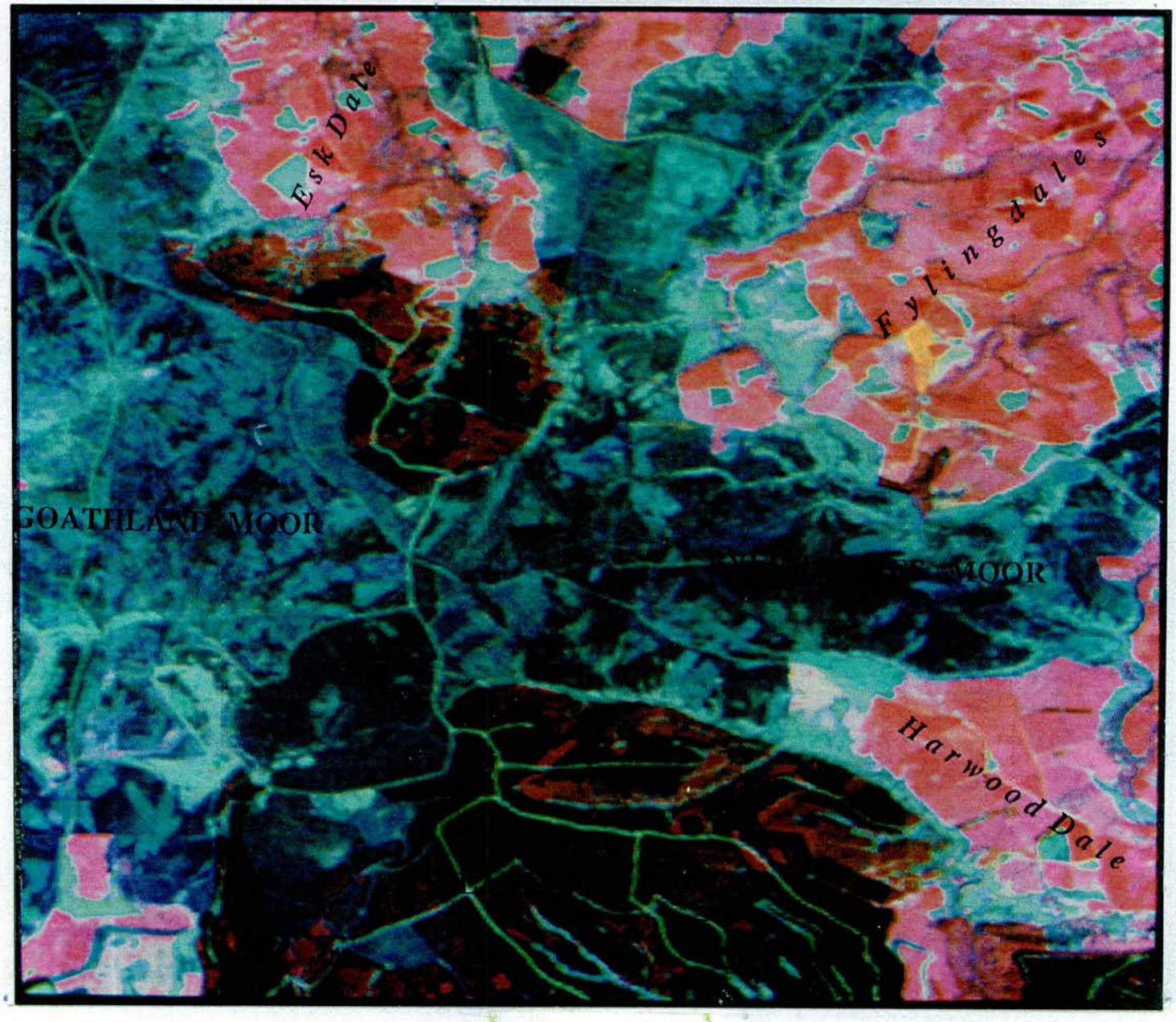

Glaisdale
Esk Dal
EGTON HIGH MOOR
GOATHLAND MOOR
MOOR
Harrioff Valley

N

0 1 2 Km

PLATE 3.5: COLOUR COMPOSITE IMAGE COMPRISING TM3, TM4 AND TM5 OF SPRING 1985 DATA : FYLINGDALES EXTRACT

LAND COVER CATEGORY	COLOUR ON THE IMAGE
B1: Bracken	Light blue
D2: Young heather moorland communities	Blue
D3: Established heather moorland communities	Dark blue
F1: Broadleaved and mixed woodland	Deep/rose pink
F2: Coniferous forest	Magenta to dark red
G1: Grass moor	Light pink
G2a: Fallow/semi improved pasture	Pink to rose pink
G2b: Improved pasture/crops	Magenta to true red
P1: Bare fields	Very pale green
Wet heath	Drak blue-green



N

0 1 2 Km

PLATE 3.6 : COLOUR COMPOSITE IMAGE COMPRISING TM3, TM4 AND TM5 OF SUMMER 1991 DATA : FYLINGDALES EXTRACT

LAND COVER CATEGORY	COLOUR ON THE IMAGE
B1: Bracken	Scarlet red
D2: Young heather moorland communities	Blue
D3: Established heather moorland communities	Yellow, through purple to dark red
F1: Broadleaved and mixed woodland	Dark/rose pink
F2: Coniferous forest	Magenta, through dark red to black
G1: Grass moor	Blue-grey to light pink
G2a: Fallow/semi improved pasture	Blue-grey, through light pink to true pink
G2b: Improved pasture/crops	Pink,through rose pink to magenta
P1: Bare fields	Light blue to pale green
W1: Wet heath	Dark blue-green


Esk Dale
Fylingdales
GOATHLAND MOOR
FYLINGDALES MOOR
Harwood Dale
AL

N

0 1 2 Km

could proceed with the analytical classification scheme presented in Table 3.6. The colours in which the different land cover types appeared on the analogue displays are given in the explanatory notes accompanying Plates 3.1-3.6.

3.4 LAND COVER DISCRIMINATION USING SPECTRAL PROPERTIES

The visual identification of land cover as described in the preceding section makes use of spatial properties of imagery. These include the pattern of image brightness (colour), site, association (context), shadow. size and geometrical shape. The full value of satellite data, however, cannot be obtained through the analysis based exclusively on these spatial properties (Townshend, 1981). Much more useful information is normally obtained through the manipulation of spectral properties of the data. These are represented by the brightness intensity (DN) values on an imagery, or by bidirectional reflectance (BDR) values in data sets collected using non-imaging sensors like ground radiometers.

The use of spectral properties to acquire information about features or land cover is based on the assumption that these have different spectral response patterns in different data bands. The differences in spectral response values give clues to the identity and condition of different types of features or land cover. In reality, however, it is not always the case that features/land cover types of interest to the analyst would have different spectral response patterns in all the data bands available. It is therefore almost customary to begin any spectral analysis of remotely sensed data by assessing whether or not the features of interest to the analyst are spectrally separable in the data bands being used.

In this work, spectral distinctiveness of different land cover categories in TM3, TM4 and TM5 was assessed by working out normalized difference index of spectral separability. The assessment was carried out on both 1985 and 1991 data bands. A 2-D feature space was also prepared using the *in situ* spectral data described under

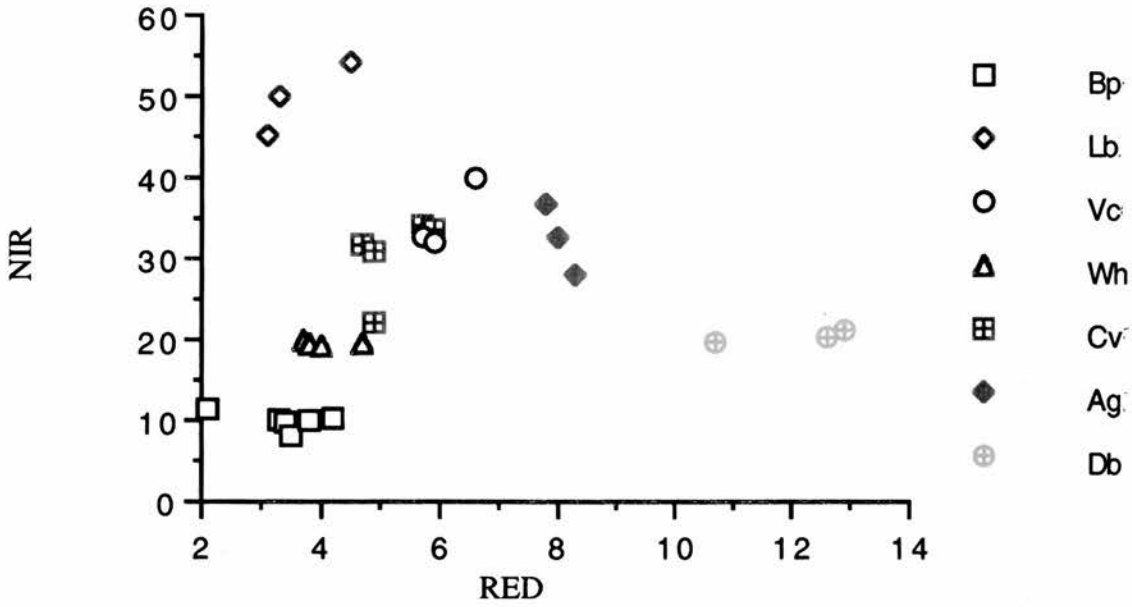
section 2.2.2.2. The aim was to discover if different land cover types could be spectrally discriminated using the radiometer data. Both the 2-D feature space and the index methods of assessing the spectral separability are described below.

3.4.1 2-Dimensional Feature Space Method

A common approach for evaluating the extent to which features are spectrally separable involves plotting their spectral reflectance values in one band against the corresponding values in other bands on axes that are orthogonal to each other. This creates a multi-dimensional Euclidean space that is normally known as a feature space (Mather, 1987a). The plotting points for land cover types that are spectrally separable would form more or less distinct clusters in different regions of such a feature space. Those for land cover types that are not spectrally separable would not show the clustering and regionalization tendencies. In practice, however, it is difficult to present diagrammatically any feature space that has more than two dimensions (Campbell, 1987). Further, many people face problems in trying to visualize the relationship between data points on more than two axes (Mather, 1987a). For these reasons therefore, it has become customary to use 2-dimensional (2-D) feature space diagrams in evaluating the spectral separability of features in bands of remotely sensed data (Mather, 1987a).

In this work, a 2-D feature space plot was prepared using red band and near-infrared band data recorded in the field using a radiometer. These data were recorded for a few land cover categories which do not exactly conform to the standard classification scheme (Table 3.6) in some respects. For instance, data were separately recorded for *Vaccinium myrtillus* and *Calluna vulgaris* , both of which fall in the same dry heath category in the standard classification scheme.

In the feature space (Figure 3.3) near-infrared reflectance values were set on the x (vertical) axis and the red reflectance values were set on the y (horizontal) axis. It is



Bp = Bare peat

Lb = Live bracken

Vc = Vaccinium myrtillus

Wh = Wet heath

Cv = Calluna vulgaris

Ag = Acid grass

Db = Dead bracken

FIGURE 3.3 BIVARIATE (2-D) FEATURE SPACE PLOT BASED ON RADIOMETER DATA

evident from Figure 3.3 that, by and large, the plots for different land cover types occupy more or less distinct regions of the feature space. This is an indication that they are largely separable in the two bands. However, this is not true for all land cover categories. It is clear from the diagram that around the point where $x = 34$ and $y = 6$, *Calluna vulgaris* and *Vaccinium myrtillus* are not clearly separable. This may justify the placement of these two species into one category for an analysis based on high altitude and relatively coarser resolution data like Landsat TM.

3.4.2 Normalized Difference Index Method

The normalized difference index of spectral separability is a simple measure of the degree to which land cover types are spectrally separable in a given data band. It is computed by dividing the difference in the mean reflectance values of two land cover classes by the sum of their standard deviations in a specified data band (Campbell, 1987; Weaver, 1986; 1987a). It can be mathematically expressed in the following terms:

$$NDIa,b_j = \frac{\bar{X}a_j - \bar{X}b_j}{Sa_j + Sb_j} \qquad (3.4)$$

(After Campbell, 1987; Weaver, 1986; 1987a
with some modifications in notation)

where NDI = normalized difference index of spectral separability

a,b = two land cover classes

j = specific data band

$\bar{X}$ = mean DN value

S = standard deviation

Where any two land cover classes are spectrally separable in a given data band, the index worked out for them would have the value of 1 or more. Index values of less than 1 indicate that the pairs of land cover classes are not spectrally separable in that specific band.

In this work, normalized difference indices of spectral separability were worked out for different pairs of land cover categories in TM3, TM4 and TM5 of the 1985 data, and again on corresponding bands of the 1991 data. Before the indices could be computed, mean reflectance values and standard deviations for each land cover category in each spectral band had to be determined. To determine these, in each study extract sixty pixels of each land cover category were randomly selected on the false colour composite displays using the zoom/roam function in the Image Inspection Tool Box of the R-CHIPS programme. This function also gives DN values of the selected pixels in all three bands comprising the colour composite. These values were read off the text screen and recorded, and were used to determine the pixel value range, mean and standard deviation for each land cover category in each band. These procedures were followed on colour composite displays of the 1985 data, and again on similar displays of the 1991 data. The pixel value range, mean and standard deviation statistics that were obtained are presented in the tables in Appendix III. The mean values and standard deviations were then used to calculate the normalized indices of spectral separability following formula 3.4. The indices worked out in this way are presented in Tables 3.7-3.12.

From the indices calculated, it was discovered that on average, 73% of the pairs of land cover categories in each extract were spectrally separable in TM3 of the spring 1985 data; but only 64% in TM3 of the summer 1991 data. On average, 80% of the pairs of land cover categories in each extract were spectrally distinct in TM4 of the spring 1985 data, as opposed to only 72% in TM4 of the summer 1991 data. Similarly, on average, 75% of the pairs of land cover categories in each extract were spectrally separable in TM5 of the spring 1985 data , as opposed to only 70% in TM5 of the summer 1991 data.

It is clear from the statistics in the preceding paragraph that more pairs of land cover categories were spectrally distinct in the spring 1985 data bands than in the corresponding summer 1991 data bands. This suggests that imagery acquired in

spring contain much more valuable information about moorland and related land cover than one acquired in summer. The visual appearance of the colour composite displays comprising spring 1985 data bands, *vis-à-vis* that of those comprising summer 1991 data bands, seems to support this suggestion. The former appeared much more colourful, with most of the features on the imagery coming out in distinct colours. The latter were less colourful. [Compare Plates 3.1 and 3.2; 3.3 and 3.4; and 3.5 and 3.6].

Whilst in general more pairs of land cover categories appeared to be spectrally distinct in the spring data bands, the indices also indicate that there are some that were more spectrally separable in the summer 1991 data bands than in the spring 1985 data bands. These include broadleaved woodland and bare fields; as well as bare fields and bracken. In the visual identification exercise (section 3.3) it was equally very difficult to distinguish these categories on the colour composite displays comprising spring 1985 data bands but not so on those comprising summer 1991 data bands. This shows that the data acquired in spring may provide information for discriminating more but not all land cover types in the area. Neither summer nor spring can therefore be regarded as the optimum data acquisition period for the purposes of discriminating moorland and related land cover types.

Another observation that comes from the indices is that with both spring 1985 and summer 1991 data, more pairs of land cover categories were spectrally separable in either of the two infrared bands (TM4 and TM5) than in the visible red band (TM3). This is true in all extracts. This observation suggests that the infrared bands contain more information about moorland and related land cover types than the red band. Between the two infrared bands, the indices indicate that more pairs of land cover categories were spectrally separable in TM4 than in TM5. This was true in both the spring 1985 and summer 1991 data. One implication of this would be that where there is need to work with only one band, then TM4 would be the most suitable since much more information can be obtained from it than from either of the other two bands.

TM3

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b
D1	3.9								
D2	2.9	1.8							
D3	5.8	0.0	3.0						
F1	4.6	0.7	1.7	1.3					
F2	6.3	0.5	3.7	1.1	2.2				
G1	3.7	0.8	1.7	1.3	0.3	1.9			
G2a	3.7	1.3	0.8	2.3	1.0	3.1	0.5		
G2b	5.7	0.0	2.9	0.0	1.3	1.1	1.2	2.2	
P1	0.2	0.3	2.9	6.2	5.5	6.7	3.8	3.8	6.0

SEPARABLE : 34 OUT OF 45 PAIRS = 76%

TM4

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b
D1	4.8								
D2	2.3	1.8							
D3	5.3	1.9	0.4						
F1	0.4	3.4	1.9	2.5					
F2	1.3	1.8	0.4	0.8	1.3				
G1	1.0	4.8	2.8	3.8	0.4	1.9			
G2a	4.6	14	7.5	12	2.1	4.7	1.9		
G2b	4.0	7.4	5.4	6.6	2.7	0.1	2.7	2.4	
P1	1.1	5.0	2.7	3.1	1.1	0.8	2.0	8.1	5.2

SEPARABLE : 38 OUT OF 45 PAIRS = 84%

TM5

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b
D1	5.5								
D2	2.0	3.5							
D3	8.7	1.2	5.3						
F1	3.6	1.6	1.7	1.7					
F2	6.5	0.4	4.3	2.0	2.8				
G1	2.3	2.0	0.7	0.7	0.1	2.4			
G2a	2.0	4.2	0.2	2.1	1.4	5.1	1.0		
G2b	2.8	1.9	1.1	0.4	0.2	2.3	0.3	1.4	
P1	2.0	3.8	0.1	1.8	1.1	4.6	0.8	0.1	1.2

SEPARABLE : 34 OUT OF 45 PAIRS = 76%

TABLE 3.7 NORMALIZED DIFFERENCE INDICES OF SPECTRAL SEPARABILITY : **ROSEDALE EXTRACT: 1985 DATA BANDS**

TM3

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b
D1	1.5								
D2	2.0	0.3							
D3	0.7	0.6	0.9						
F1	0.5	2.0	2.5	1.1					
F2	0.4	0.8	2.1	0.9	0.0				
G1	0.8	0.7	1.0	0.0	1.3	1.1			
G2a	2.4	0.3	0.0	1.0	2.9	2.3	1.2		
G2b	0.8	0.7	1.0	0.0	1.3	1.0	0.0	1.1	
P1	3.7	2.3	2.1	2.6	4.1	3.6	2.9	2.3	2.8

SEPARABLE : 27 OUT OF 45 PAIRS = 60%

TM4

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b
D1	3.9								
D2	4.9	1.1							
D3	3.5	0.8	1.9						
F1	3.5	0.2	0.8	0.8					
F2	4.1	0.4	0.7	1.1	0.2				
G1	1.7	1.8	2.8	1.3	1.7	2.1			
G2a	1.8	2.5	3.6	1.9	2.2	2.7	0.3		
G2b	0.1	3.6	3.9	3.2	3.2	3.8	1.6	1.6	
P1	2.6	0.5	1.4	0.0	3.6	0.8	1.0	1.4	2.4

SEPARABLE : 32 OUT OF 45 PAIRS = 73%

TM5

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b
D1	0.1								
D2	0.5	0.7							
D3	1.3	1.5	2.3						
F1	1.7	1.9	2.5	0.7					
F2	2.4	2.7	3.5	1.4	0.3				
G1	0.7	0.9	0.4	2.2	2.3	3.1			
G2a	1.4	0.9	1.2	3.2	3.1	4.1	0.6		
G2b	0.7	0.9	0.2	2.5	2.6	3.7	0.2	1.0	
P1	1.8	2.2	1.7	3.7	3.5	4.6	1.0	0.5	1.5

SEPARABLE : 30 OUT OF 45 PAIRS = 67%

TABLE 3.8 : NORMALIZED DIFFERENCE INDICES OF SPECTRAL SEPARABILITY : **ROSEDALE EXTRACT : 1991 DATA BANDS**

TM3

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b	P1
D1	3.8									
D2	3.2	0.3								
D3	6.8	4.6	4.3							
F1	5.7	3.2	3.1	0.8						
F2	7.1	5.0	4.6	0.5	1.2					
G1	3.7	0.9	1.0	2.4	1.6	2.7				
G2a	2.8	0.0	0.2	2.9	2.1	3.2	0.6			
G2b	4.1	1.9	1.9	0.8	0.2	2.2	1.0	1.4		
P1	0.0	2.9	2.5	5.3	4.5	5.5	3.0	2.3	3.4	
W1	2.6	0.0	0.2	2.6	1.9	2.9	0.6	0.0	1.3	2.2

SEPARABLE : 41 OUT OF 55 PAIRS = 75%

TM4

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b	P1
D1	4.4									
D2	3.5	1.4								
D3	3.3	0.9	0.2							
F1	0.1	3.9	7.7	2.9						
F2	2.2	1.0	0.3	0.4	2.1					
G1	2.4	10	8.5	7.6	2.4	5.2				
G2a	3.7	15	12	13	4.2	6.8	1.2			
G2b	3.9	7.6	6.9	6.6	3.9	5.4	2.9	2.6		
P1	1.5	2.8	1.8	1.8	1.3	1.0	4.6	1.2	5.2	
W1	2.1	0.3	0.2	0.1	2.0	0.3	4.5	2.5	5.0	1.1

SEPARABLE : 46 OUT OF 55 PAIRS = 84%

TM5

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b	P1
D1	5.0									
D2	1.9	3.9								
D3	5.0	1.4	4.1							
F1	4.3	0.3	3.2	0.8						
F2	6.0	3.4	5.5	1.7	2.5					
G1	2.9	1.8	1.5	2.5	1.7	3.9				
G2a	4.1	4.9	0.4	5.0	3.9	6.2	2.0			
G2b	2.2	1.7	0.9	2.2	1.6	3.3	0.3	1.2		
P1	1.9	2.7	0.4	3.1	2.3	3.9	0.9	0.8	0.5	
W1	4.1	1.6	2.6	2.5	1.4	4.3	0.7	3.4	0.9	1.7

SEPARABLE : 44 OUT OF 55 PAIRS = 80%

TABLE 3.9 : NORMALIZED INDICES OF SPECTRAL SEPARABILITY : **WHEELDALE EXTRACT: 1985 DATA**

TM3

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b	P1
D1	4.3									
D2	2.2	2.0								
D3	0.0	4.1	2.1							
F1	0.6	4.3	2.4	0.5						
F2	0.3	2.8	1.4	0.0	0.0					
G1	1.6	2.2	0.3	1.5	1.9	1.1				
G2a	2.5	0.2	1.4	2.5	2.6	1.9	1.5			
G2b	1.1	3.3	1.2	1.1	1.5	0.8	0.7	2.0		
P1	0.2	1.6	0.6	0.2	0.4	0.3	0.5	1.3	0.2	
W1	3.4	0.2	1.5	3.3	3.5	3.4	1.7	0.3	2.6	1.4

SEPARABLE : 36 OUT OF 55 PAIRS = 65%

TM4

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b	P1
D1	4.9									
D2	4.1	0.5								
D3	3.6	1.9	1.2							
F1	3.8	1.3	0.8	0.3						
F2	3.1	1.1	0.6	0.4	0.1					
G1	1.0	4.5	3.6	2.9	2.6	2.5				
G2a	1.7	2.5	1.9	1.1	1.2	1.2	1.0			
G2b	0.5	3.9	3.2	2.6	2.4	2.4	0.3	1.1		
P1	3.0	0.8	0.4	0.6	0.1	0.2	2.5	1.3	2.4	
W1	4.8	0.1	0.4	1.9	1.2	1.0	3.1	4.3	3.8	0.7

SEPARABLE : 39 OUT OF 55 PAIRS = 71%

TM5

	B1	D1	D2	D3	F1	F2	G1	G2a	G2b	P1
D1	0.3									
D2	0.5	0.2								
D3	2.0	2.0	2.2							
F1	2.1	2.1	2.3	0.5						
F2	2.8	2.7	2.9	0.8	0.2					
G1	1.5	1.1	0.8	3.2	3.1	3.8				
G2a	2.0	1.6	1.4	3.5	3.3	4.0	0.7			
G2b	1.1	0.7	0.4	3.4	3.2	4.3	0.7	1.4		
P1	1.0	0.7	0.5	2.3	2.3	2.8	0.2	0.8	0.3	
W1	1.1	1.2	1.5	1.0	0.9	1.3	2.3	2.7	2.2	1.7

SEPARABLE : 39 OUT OF 55 PAIRS = 69%

TABLE 3.10 : NORMALIZED DIFFERENCE INDICES OF SPECTRAL SEPARABILITY : **WHEELDALE EXTRACT : 1991 DATA BANDS**

TM3

	B1	D2	D3	F1	F2	G1	G2a	G2b	P1
D2	2.4								
D3	4.6	2.2							
F1	4.7	2.1	0.3						
F2	4.1	1.9	0.0	0.2					
G1	1.7	0.1	1.3	1.2	0.9				
G2a	2.4	0.0	2.3	2.2	2.0	0.1			
G2b	5.6	2.9	0.3	0.7	0.3	1.6	2.9		
P1	0.1	1.2	2.3	2.3	2.2	1.0	1.2	2.6	
W1	3.0	0.8	1.3	1.2	1.2	0.4	0.8	1.8	1.6

SEPARABLE : 31 OUT OF 45 PAIRS = 69%

TM4

	B1	D2	D3	F1	F2	G1	G2a	G2b	P1
D2	2.3								
D3	3.5	0.9							
F1	0.3	2.1	2.9						
F2	1.5	0.1	0.7	1.5					
G1	1.3	2.8	3.5	0.8	2.1				
G2a	2.7	4.7	5.7	1.8	3.2	0.7			
G2b	8.6	12	15	5.3	6.9	3.2	3.0		
P1	0.5	1.2	1.9	0.7	0.8	1.3	2.4	1.5	
W1	1.9	0.1	0.9	1.8	0.0	2.5	4.1	9.8	1.0

SEPARABLE : 33 OUT OF 45 PAIRS = 73%

TM5

	B1	D2	D3	F1	F2	G1	G2a	G2b	P1
D2	1.1								
D3	4.3	3.1							
F1	2.9	1.8	1.0						
F2	5.6	3.9	1.2	1.9					
G1	1.2	0.1	3.0	1.8	3.9				
G2a	1.0	0.3	3.8	2.3	4.8	0.3			
G2b	1.8	0.8	1.8	0.8	2.7	0.8	1.1		
P1	1.2	0.0	3.2	1.9	4.2	0.1	0.3	0.8	
W1	2.5	1.4	1.5	0.5	2.5	1.3	1.8	0.5	1.4

SEPARABLE : 33 OUT OF 45 PAIRS = 73%

TABLE 3.11 : NORMALIZED DIFFERENCE INDICES OF SPECTRAL SEPARABILITY : **FLYINGDALES EXTRACT : 1985 DATA BANDS**

TM3

	B1	D2	D3	F1	F2	G1	G2a	G2b	P1
D2	1.8								
D3	0.0	1.7							
F1	1.1	3.2	1.0						
F2	1.6	3.2	1.5	0.9					
G1	1.8	0.0	1.7	3.2	3.2				
G2a	0.0	1.3	0.0	0.8	1.3	1.4			
G2b	0.4	1.8	0.3	0.4	1.0	1.8	0.3		
P1	2.7	1.8	2.7	3.4	3.4	1.8	2.4	2.6	
W1	0.5	2.5	0.9	0.6	1.3	2.5	0.4	0.0	3.1

SEPARABLE : 30 OUT OF 45 PAIRS = 67%

TM4

	B1	D2	D3	F1	F2	G1	G2a	G2b	P1
D2	4.5								
D3	3.1	1.5							
F1	2.6	1.8	0.4						
F2	3.8	0.5	1.0	1.3					
G1	1.6	2.9	1.5	0.9	2.3				
G2a	1.3	3.6	2.0	1.4	2.8	0.4			
G2b	0.4	4.4	3.2	2.5	3.8	1.8	1.6		
P1	3.3	0.8	0.6	0.9	0.4	1.8	2.3	3.3	
W1	5.0	0.2	1.6	1.9	0.3	3.2	4.0	4.9	0.8

SEPARABLE : 33 OUT OF 45 PAIRS = 73%

TM5

	B1	D2	D3	F1	F2	G1	G2a	G2b	P1
D2	1.0								
D3	1.8	2.5							
F1	1.4	2.1	0.2						
F2	4.3	4.6	2.4	2.4					
G1	1.7	0.7	3.3	2.8	5.5				
G2a	1.8	0.7	3.4	2.9	5.8	0.0			
G2b	0.9	0.1	2.5	2.1	4.9	0.8	0.8		
P1	0.3	1.0	1.6	0.9	3.1	1.7	1.8	1.0	
W1	1.9	2.7	0.0	0.2	2.7	3.5	3.7	2.8	1.3

SEPARABLE : 32 OUT OF 45 PAIRS = 71%

TABLE 3.12 : NORMALIZED DIFFERENCE INDICES OF SPECTRAL SEPARABILITY : **FLYINGDALES EXTRACT : 1991 DATA BANDS**

The indices also show that some pairs of land cover categories were spectrally separable in TM3 but not in one or both of the infrared bands. For instance, the indices indicate that in TM4, young heather and established heather were largely inseparable in most of the cases. However, these two categories were clearly separable in TM3. Similarly, in TM5, bare fields and deciduous woodland were spectrally inseparable in most of the cases. However, they were largely separable in TM3 in all the cases. This shows that while the infrared bands might have more information about the land cover categories, they are, however, not the optima in terms of providing information about moorland and related land cover types. An analysis of all the three bands together (multispectral analysis), would certainly provide more information than an analysis based on only one of the three bands.

3.5 DIFFERENCES IN SPECTRAL VALUES OF LAND COVER ON SPRING AND SUMMER IMAGE DATA

Phenology, the seasonal changes in vegetative growth, causes the spectral characteristics of many vegetation communities to be in a continuous state of change (Hoffer, 1978). The two sets of Landsat TM data that were used in this work were acquired during two different seasons. It was therefore expected that land cover categories would have different spectral values on each of the two sets of data owing to the effect of phenology. The spectral data in the tables in Appendix III show that for many land cover categories, their mean reflectance values were actually different in the two data sets. This section looks at these differences and attempts to explain the phenological changes that might have caused them. A brief factual description of the phenological changes that moorland communities undergo is given first.

3.5.1 Major Phenological Changes in Moorland Communities

Moorland communities normally show distinct sequence of phenological changes that correspond with seasons. The major changes are dormancy, growth and flowering

(Woolhouse and Kwolek, 1981). Dormancy occurs in winter. *Calluna vulgaris* and most of its associates become dormant when average temperature is less than 5°C for anything longer than a couple of days (Grace and Woolhouse, 1970; 1974). In the sub-montane uplands where moorland communities are commonly found, average temperatures in winter may be lower than 5°C. For instance, it has already been indicated under section 2.1.4 that the heather-clad plateau zones in the North York Moors have mean temperatures of around 1.7°C in winter. The chilly winter conditions inhibit growth of the ericaceous shrubs. They therefore stay dormant in winter during which they have a dark-red and brown appearance most probably because of higher concentration levels of accessory pigments like anthocyanin in the plants' structures (Woolhouse and Kwolek, 1981).

The plants emerge from their dormancy at the beginning of spring in March when average temperatures normally exceed 5°C. During spring, new shoots appear and over-wintered shoots elongate into leading shoots. For *Calluna vulgaris*, this growing season may start as early as February or as late as May depending on local conditions. *Erica cinerea, E. tetralix, Empetrum nigrum* and *Vaccinium vitis ideae* normally start the growth process in April and May. *Vaccinium myrtillus* is actually a deciduous plant whose new leafy shoots also emerge in March and April. With the growth processes, the appearance of moorland communities changes from brown to dull green in spring (Woolhouse and Kwolek, 1981).

For most of the species, the growth processes culminate in flowering and fruition. Species like *Vaccinium myrtillus*, *V.vitis ideae*, *Empetrum nigrum*, and *Arctostaphylos urva-ursi* start flowering during the same spring season . But for most of the other species, the main flowering season is summer from June to September. *Calluna vulgaris* produce flowers mainly during the months of August and September. *Erica cinerea* and *E. tetralix* produce flowers mainly from June to August (Reader, 1984). The two species of *Vaccinium* have two flowering seasons: in spring and early summer (Woolhouse and Kwolek, 1981). During summer, which

is the main flowering season, the moorland communities appear in purple and pink colours (Woolhouse and Kwolek, 1981).

Pteridium aquilinum (bracken) has its own seasonal growth patterns . It is a deciduous species that dies completely in winter. New fronds normally begin to emerge in May and June, and continue to grow until July and early August when the bracken plants thrive vigorously. Normally, the fronds begin to wither during September, and by the end of that month, many fronds are dead. The dead stems then decompose into litter (Nilchoson and Paterson, 1976; Watt, 1976). Accordingly, areas of bracken are more likely to appear brownish-grey in spring, green in summer, pale green to yellow in autumn, and yellow to brownish-grey in winter.

3.5.2 Spring-Summer Changes in Spectral Values of Land Cover

The phenological changes described above cause the spectral behaviour of moorland communities to change from season to season. Data on the range of pixel values, mean pixel values and standard deviations for each land cover category in each band of the spring 1985 and summer 1991 imagery are presented in Appendix III. The data on mean values were extracted from the appendix and presented here in Tables 3.13-3.15 to highlight the differences in the mean values of each land cover category between spring and summer. The general trends in spring-summer changes that emerge from the data in those tables are now described.

3.5.2.1 *Changes in the Red Band (TM3)*

The data in Table 3.13 reveal some general trends of spring-summer changes in the reflectance patterns of different land cover categories in the red band (TM3). One general trend is that reflectances for established heather (D3), crops and pasture (G2), broadleaved woodland (F1) and coniferous forests (F2) were higher on the summer imagery than on the spring imagery. For heathland communities, reflectances in the

	ROSEDALE EXTRACT			WHEELDALE EXTRACT			FYLINGDALES EXTRACT		
LAND COVER	SPRING '85	SUMMER '91	**DIFFERENCE**	SPRING '85	SUMMER '91	**DIFFERENCE**	SPRING '85	SUMMER '91	**DIFFERENCE**
B1	43	22	**-21**	43	22	**-21**	41	23	**-18**
D1	18	26	**8**	28	34	**6**	-	-	**-**
D2	27	27	**0**	29	27	**-2**	28	27	**-1**
D3	18	24	**6**	17	22	**5**	18	23	**5**
F1	21	21	**0**	19	21	**2**	19	21	**2**
F2	16	21	**5**	16	21	**5**	18	19	**1**
G1	22	24	**2**	25	26	**1**	27	27	**0**
G2a	24	27	**3**	28	35	**7**	28	23	**-5**
G2b	18	42	**24**	20	24	**4**	17	22	**5**
P1	42	36	**-6**	43	23	**-20**	40	35	**-5**
W1	-	-	-	28	33	**5**	24	22	**-2**

TABLE 3.13 SPRING-SUMMER DIFFERENCES IN SPECTRAL VALUES IN THE RED BAND (TM3)

red band are normally high in summer because of the contribution of flowers (Milton and Rollin, 1988; 1990). The flowers reflect higher proportions of red radiation and since reflected red band radiation is perceptible to the human eyes, heathlands therefore appear in reddish or purple colours during the flowering summer season. The only other time that heathland communities have relatively higher reflectance levels in the red band is in winter as Figure 3.4 illustrates. This winter peak is believed to be the result of the higher concentration of accessory pigments such as anthocyanin in the plants' shoots (Milton and Rollin, 1988; 1990). These pigments give moorland communities a dark-red brownish appearance during winter (Woolhouse and Kwolek, 1981).

Similarly, crops planted in spring would be producing flowers and/or seeds during summer. The effect of flowers may therefore also be responsible in making reflectance of these canopies higher in summer than in spring. The summer higher reflectance for crops might have also been caused by lower chlorophyll concentration levels in crops planted in winter (like winter wheat) which would normally be in post-maturity stage by summer. Crop reflectance levels in the red band increases as their chlorophyll content drops (Myers, 1975).

The trend for bracken (B1) was that it had lower reflectance levels on the summer imagery than on the spring imagery. In spring, bracken is mostly in the form of senescent stems or even litter, with only a few isolated plants beginning to produce fronds. As already stated above, senescent plants reflect higher proportions of the red band radiation than green plants (Myers, 1975). Growth of bracken reaches its peak in July and August (Nicholson and Paterson, 1976). Thus, by 20th August, the date on which the summer 1991 imagery was acquired, bracken might have been still thriving vigorously. Higher concentration levels of chlorophyll in such vigorously growing plants result in higher absorption levels in red band with consequent low reflectance levels.

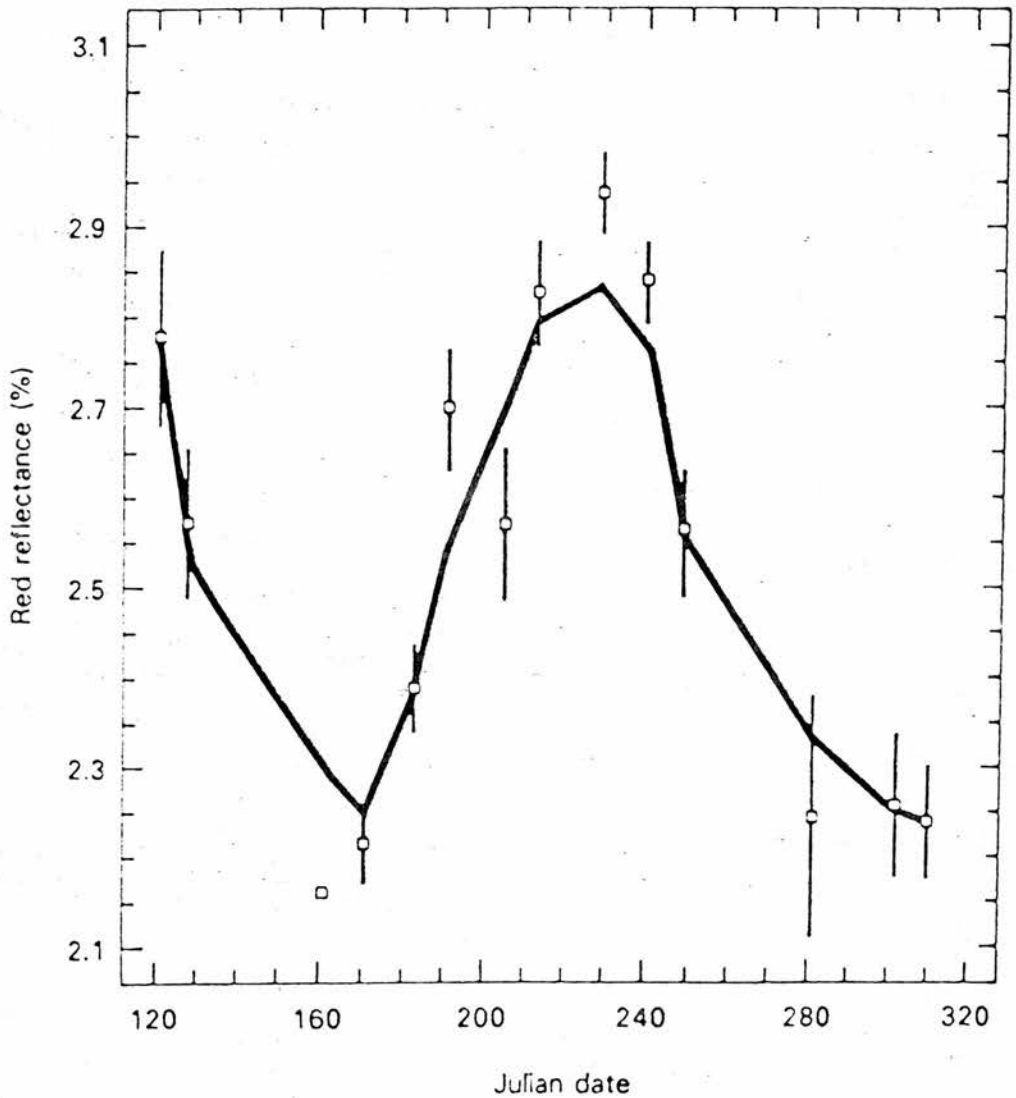


FIGURE 3.4 SEASONAL TREND IN HEATHLAND REFLECTANCE IN RED WAVELENGTHS

(After Milton and Rollin, 1990)

3.5.2.2 *Changes in the Near-Infrared Band (TM4)*

The data in Table 3.14 show that in TM4, the reflectance values for all categories of dry heath (D1, D2, and D3) as well as wet heath (W1) were higher on the summer imagery than on the spring imagery. Other studies (Milton and Rollin, 1988; 1990) similarly found that the reflectance of heathland canopies in the near-infrared tends to be higher in summer and lower in spring as Figure 3.5 illustrates. The higher reflectance levels in summer are believed to be the result of the increase in the area of green leaves and the reduction of intra-canopy shadows as the solar elevation angles increase (Milton and Rollin, 1990). The same may possibly explain why bracken also had higher infrared reflectance levels in summer than in spring, since bracken similarly has higher amounts of green leaves in summer.

A study showed that for annual crop canopies, their highest reflectance levels in the near-infrared tend to occur during the middle of the growth cycle (Kanemasu, 1974). For most annual crops in Britain, the middle of their growing season would probably be late spring to early summer. We would therefore expect the annual crops to record higher near-infrared reflectance on an imagery acquired late spring than on one acquired late summer. In the data in Table 3.14, the crops category (G2) had higher near-infrared reflectance on the May 31, 1985 imagery than on the August 20, 1991 imagery.

3.5.2.3 *Changes in the Mid-Infrared Band (TM5)*

In the mid-infrared (TM5) the general trend that emerges from the data in Table 3.15 is that most of the canopies had lower reflectance values in summer than in spring. In the first chapter, under 1.3.4.3.1, it was explained that the mid-infrared radiation is highly absorbed by moisture in leaves and other plant structures. Normally, it is turgid leaves and shoots that give plants a green and healthy appearance. Since summer is normally regarded as the season of growth for most species of vegetation, it would be

	ROSEDALE EXTRACT			WHEELDALE EXTRACT			FYLINGDALES EXTRACT		
LAND COVER	SPRING '85	SUMMER '91	**DIFFERENCE**	SPRING '85	SUMMER '91	**DIFFERENCE**	SPRING '85	SUMMER '91	**DIFFERENCE**
B1	66	102	**36**	65	100	**35**	62	100	**38**
D1	25	59	**34**	33	46	**13**	-	-	**-**
D2	41	48	**7**	38	51	**13**	41	47	**6**
D3	37	66	**29**	37	63	**26**	33	64	**31**
F1	73	57	**-16**	64	60	**-4**	66	69	**3**
F2	47	55	**8**	40	59	**19**	42	52	**10**
G1	80	80	**0**	88	89	**1**	79	81	**2**
G2a	100	83	**-17**	96	76	**-20**	90	85	**-5**
G2b	133	101	**-32**	132	93	**-39**	113	105	**-8**
P1	57	66	**9**	50	56	**6**	56	57	**1**
W1	-	-	**-**	36	47	**11**	42	49	**7**

TABLE 3.14 SPRING-SUMMER DIFFERENCES IN SPECTRAL VALUES IN THE NEAR-INFRARED BAND (TM4)

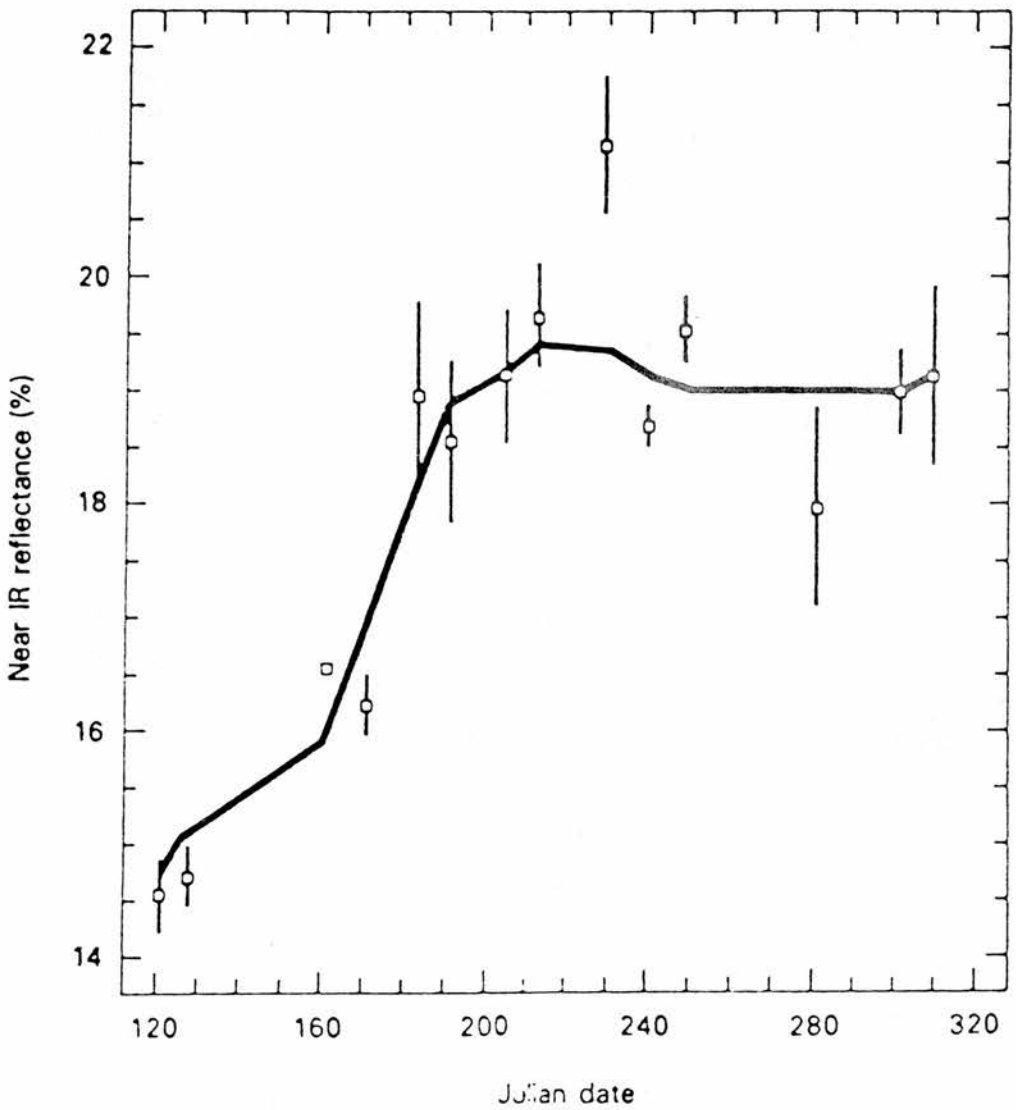


FIGURE 3.5 SEASONAL TREND IN HEATHLAND REFLECTANCE IN NEAR-INFRARED WAVELENGTHS (After Milton and Rollin, 1990)

	ROSEDALE EXTRACT			WHEELDALE EXTRACT			FYLINGDALES EXTRACT		
LAND COVER	SPRING '85	SUMMER '91	**DIFFERENCE**	SPRING '85	SUMMER '91	**DIFFERENCE**	SPRING '85	SUMMER '91	**DIFFERENCE**
B1	116	63	**-53**	114	61	**-53**	104	59	**-45**
D1	40	62	**22**	57	64	**7**	-	-	**-**
D2	87	69	**-18**	88	67	**-22**	85	70	**-15**
D3	48	46	**-2**	47	43	**-4**	45	43	**-2**
F1	62	36	**-26**	55	38	**-17**	57	45	**-12**
F2	36	31	**-5**	30	36	**6**	33	25	**-8**
G1	74	74	**0**	72	78	**6**	84	79	**-5**
G2a	90	82	**-8**	92	89	**-3**	89	79	**-10**
G2b	69	71	**2**	76	71	**-5**	71	69	**-2**
P1	88	88	**0**	83	75	**-8**	85	56	**-29**
W1	-	-	**-**	66	49	**-17**	64	43	**-21**

TABLE 3.15 SPRING-SUMMER DIFFERENCES IN SPECTRAL VALUES IN THE MID-INFRARED BAND (TM5)

expected that much of the mid-infrared radiation would be absorbed by the moisture in the plants' turgid shoot and leaf cells, resulting in generally low levels of reflectance in that band.

"The aim of any scientific activity is to understand; once we can explain why certain events occur (and when, and where) then we might be in a position to control them, so as to produce a better world. Thus science involves the development of predictive methodologies, which produce generalisations, theories and laws. These apply not to particular instances or events but to classes of phenomena.

"The philosophy of science is based on an acceptance of the classification axiom, that there are groups of like phenomena/objects which can be treated as a single unit for the purpose of making valid generalisations about aspects of their behaviour.....The purpose of classification procedures is to provide a grouping which is valid for the scientific activity being undertaken.....".

R. J. Johnston (1976) **p 3**

CHAPTER 4
EXTRACTING LAND COVER INFORMATION FROM MULTISPECTRAL DATA USING CLASSIFICATION APPROACHES

This chapter describes the work undertaken to assess the effectiveness of image classification approaches in extracting and presenting information about land cover from sets of remotely sensed data. It begins with a discussion of classification as a method of extracting information from complex spatial data sets including remotely sensed imagery, and goes on to describe the classification approaches used in this work. The actual procedures followed in classifying the 1985 and 1991 image data sets, in assessing accuracy of the classifications, and in determining confidence limits for the classification accuracy levels achieved are also outlined. The final results obtained are presented and discussed. The chapter ends with a discussion on what the results obtained suggest about the potential of image classification as a technique for generating thematic data bases from raw satellite imagery.

4.1 CLASSIFICATION AS A TECHNIQUE FOR EXTRACTING INFORMATION FROM RAW SPATIAL DATA

In geographical research, the extraction of information from raw spatial data basically involves resolving them into patterns that can be understood, described and mapped more efficiently. Raw spatial data normally contain too much information and therefore present "a situation in which we cannot see the forest because there are so many trees in the way" (Abler *et al*, 1977). But by resolving elements in raw data into a number of pattern categories, we essentially summarise them and thus render them into a form in which it becomes relatively easy to discern and describe relationships among them (Abler *et al*, 1977). Similarly, it is more practicable to map a number of pattern categories but not the extremely large number of individual elements in a set of raw data. Pattern recognition is therefore the means by which significant features

or attributes of spatial data can be extracted from a background of very complex and often irrelevant detail (Harris, 1987).

What constitutes a pattern in spatial data is essentially an aggregation of elements that have some common functional relationships. Resolving data into patterns therefore involves identifying and recognising these functional groupings. Sometimes, the "natural" patterns inherent in spatial data may not satisfy the information needs of the analyst. In which case, the analyst may consider to introduce "exotic" patterns into the raw data by grouping the elements into some categories based on some predetermined criteria. The identification, recognition and interpretation of "natural" groupings among phenomena; and the use of predetermined criteria to categorise phenomena into some "artificial" groups, constitute the scientific process of classification. The former is *a posteriori* classification where the analyst tries to identify some "natural" groupings among elements in raw data and thereafter works out what information categories (features or land cover classes of interest to the analyst) the groupings represent. The latter is *a priori* classification where the analyst uses some predetermined criteria to aggregate elements in raw data into some "artificial" groups which satisfy his information needs.

Classification, whether *a priori* or *a posteriori* is a powerful "scaling factor" because it reduces a large number of individual elements to a relatively small number of groups that can be understood, described and mapped much more easily (Johnston, 1976). It is therefore regarded as an effective tool for extracting information from complex raw spatial data including remotely sensed imagery. In fact, classification is the most commonly used approach for extracting information from sets of multispectral remotely sensed data (Jensen, 1986).

The classification of remotely sensed data has the same basis as that of any other set of raw spatial data. One aim is to reduce the large numbers of pixel values in n bands of the multispectral data set to relatively fewer numbers of groups that the analyst

can easily handle and on the basis of which he can make inference about features or land cover categories of interest to him. Another aim is to produce the equivalent of choropleth maps from the raw image data. Choropleth maps show areas of equal or nearly equal values in terms of certain quantitative spatial attributes like population density, landform gradient and air pollution levels; or of similar or nearly similar qualitative attributes like land use and soil types (Burrough, 1986). They are produced by grouping data elements into classes and drawing boundaries around them. Choropleth maps convey information much more efficiently and clearly than the plotting of the extremely large numbers of individual elements comprising raw spatial data. Results of spatial surveys like soil, land systems (integrated), and land use surveys, are therefore normally classified into some nearly homogeneous groupings which are then delineated to produce choropleth maps like soil, land use and land systems maps. Similarly, pixels in n bands of multispectral image data can be classified into a number of categories based on similarities and differences in their brightness intensity (DN) values. The equivalents of choropleth maps are produced by presenting the various spectral classes in different colours and photographing or printing the classified colour image outputs, or by presenting the classes in different character symbols that form different patterns on paper when printed out using line printers or plotters. Where these equivalents of choropleth maps are produced on the basis of *a priori* classification of remotely sensed data, then the regions presented in different colours or character patterns on the outputs represent features or land cover classes of interest to the analyst. Thus, they may represent different land systems, land use types, soil types, vegetation types, water quality zones, or geological units. Classification is therefore the means by which thematic maps can be produced from remotely sensed data (Mather, 1987a; Schowengerdt, 1983; Thomas *et al*, 1987).

In the classification of remotely sensed data, *a priori* classification is known as supervised classification and *a posteriori* classification is known as unsupervised classification. In supervised classification, the identity and location of some of the features or land cover types are known *a priori* through a combination of fieldwork,

analysis of aerial photographs and maps, and personal experience. This information enables the analyst to decide upon the categories into which the image pixels are to be classified. The analyst then attempts to locate, on the imagery, specific sites that represent homogeneous samples of the known features or land cover types. Multivariate statistical parameters like mean values, standard deviations, and variance-covariance matrices are calculated for each sample class. The sample sites are commonly known as training areas because the classifier is trained on their spectral data and it uses the statistics obtained to classify the whole data set (Jensen, 1986).

Since classes are decided upon *a priori*, the problem in supervised classification is actually that of allocating individual pixels to the pre-determined classes. There are a number of decision rules or strategies that can be used to accomplish this. The commonest ones are parallelepiped, minimum distance-to-means, and maximum likelihood strategies. These are described later in section 4.2.1.

In unsupervised classification, the image processor identifies some "natural" pixel groupings or clusters in the image data and presents them to the analyst. It then remains to the analyst to relate the "natural" clusters to features or land cover classes of interest to him. But quite often, these clusters fail to match land cover classes that are of interest to resource managers. Unsupervised classification, therefore, may not be a better option where the aim is to produce thematic maps. However, it has special value where the identities of features or land cover types are generally not known *a priori* because ground truth is lacking or surface features are not well defined (Jensen, 1986; Mather, 1987a).

Common to the conventional supervised and unsupervised classification approaches is that each pixel is considered individually and is then assigned to a class or a cluster based on its spectral values in the n bands of the multispectral data set. It is entirely the spectral values and nothing else that determine to which class would a pixel be

assigned. Thus, these pixel-by-pixel spectral classification approaches do not consider spatial properties of image data like texture and association /context (Campbell, 1987) which, however, are essential elements used in visual pattern recognition (Townshend, 1981).

Less common approaches consider both spectral properties as well as spatial relationships between pixels. Such relationships are normally expressed as texture and association or context. As stated already, these are the elements that play a very significant role in visual pattern recognition like in the qualitative interpretation of aerial photographs (Townshend, 1981). These approaches attempt to incorporate textural and contextual information from neighbourhoods of pixels into the classification process so as to replicate the kind of spatial synthesis that is normally done by human eyes during visual interpretation of analogue images. Such approaches, commonly known as textural and contextual classifiers (Campbell, 1987), therefore tend to be much more complex and computationally intensive (Campbell, 1987; Lillesand and Kiefer, 1987). At the present, they are still unconventional (Campbell, 1987; Mather, 1987a).

4.2 CLASSIFICATION OF THE 1985 AND 1991 IMAGE DATA SETS

The 1985 and 1991 image data sets were independently classified to assess the degree to which multispectral classification approaches could be effective in converting raw image data into thematic data bases that resource managers can use in planning the rational use or conservation of land resources. This part describes the strategies (decision rules) followed in assigning pixels to different classes, and outlines the actual steps undertaken to accomplish the classification process.

4.2.1 Classification Strategies

R-CHIPS supports three supervised classification algorithms. These are minimum distance-to-means, maximum likelihood and parallelepiped (box) classifiers. All three algorithms were used in this work. The results obtained under the three classification strategies were compared in order to discover which approach was more effective in extracting land cover information from the sets of Landsat TM data. The ways in which these strategies operate are explained below.

4.2.1.1 *Minimum Distance Strategy*

This decision rule is computationally simple and commonly used (Jensen, 1986). The classifier computes mean pixel values for the different training classes and plots them as centroids in n-dimensional feature space. It then determines the direct distances between each of the centroids and each and every other data point (pixel) in the feature space. The distances between a pixel and the centroids are compared, and a pixel is then assigned to a class whose centroid is closest to it. For instance, to assign a pixel at point **1** to one of the classes in Figure 4.1, the direct distances between the point and the various centroids would be worked out. These are illustrated by the dashed lines. After evaluating these distances, the unknown pixel would be assigned to the class whose centroid is closest to it, in this case to **C** class (Lillesand and Kiefer, 1987).

The direct distance which the minimum distance classifier computes can take two forms. It can be the Euclidean distance based on the Pythagorean theorem. In a multidimensional space, the Euclidean distance is given by the following formula:

$$Dab = \sqrt{[\sum_{i=1}^{n} (a_i - b_i)]^2} \qquad (4.1)$$

[After Burrough, 1986; Jensen, 1986
with some modifications in notation]

where a & b = two data points (pixels)

n = total number of dimensions (bands) in the multivariate data

i = one of the n dimensions (data bands)

Dab = distance between two points (pixels) a & b

The Euclidean distance is more computationally intensive than the second form of distance which is known as "Around The Block " distance (Jensen, 1986) or "City Block Metric" distance (Burrough, 1986). This one is given by the following formula where all symbols have the same meaning as in (4.1) above

$$\mathrm{Dab} = \sum_{i=1}^{n} | a_i - b_i | \qquad (4.2)$$

[After Burrough, 1986; Jensen, 1986 with some modifications in notation]

Applied in its original form as explained above, the minimum distance classifier would leave no unclassified pixels in an image since any pixel would be closest (even in relative terms only) to one of the centroids, except in the unusual case where a pixel may lie at equal distance between centroids (Mather, 1987a). But in this original form, the classifier is totally insensitive to the variance within classes. It puts the dividing line between two classes at a point half-way between the centroids without any regard for the way the data points are spread around their respective centroids. In reality, there are some less pure classes whose data points would therefore show the tendency to disperse to greater distances around mean values (centroids); and relatively pure classes whose data points would show a tendency to cluster just around the mean values (centroids). Where the two types of classes are in proximity in a feature space as is illustrated by classes **U** and **S** in Figure 4.1, drawing the dividing line at a point half-way between the two centroids would result in some pixels of the class with greater dispersion or variance value (**U** in Figure 4.1) being classified into the class with lower dispersion or variance value (**S** in Figure 4.1). Thus in Figure 4.1, while the greater dispersion of **U** data points around their centroid

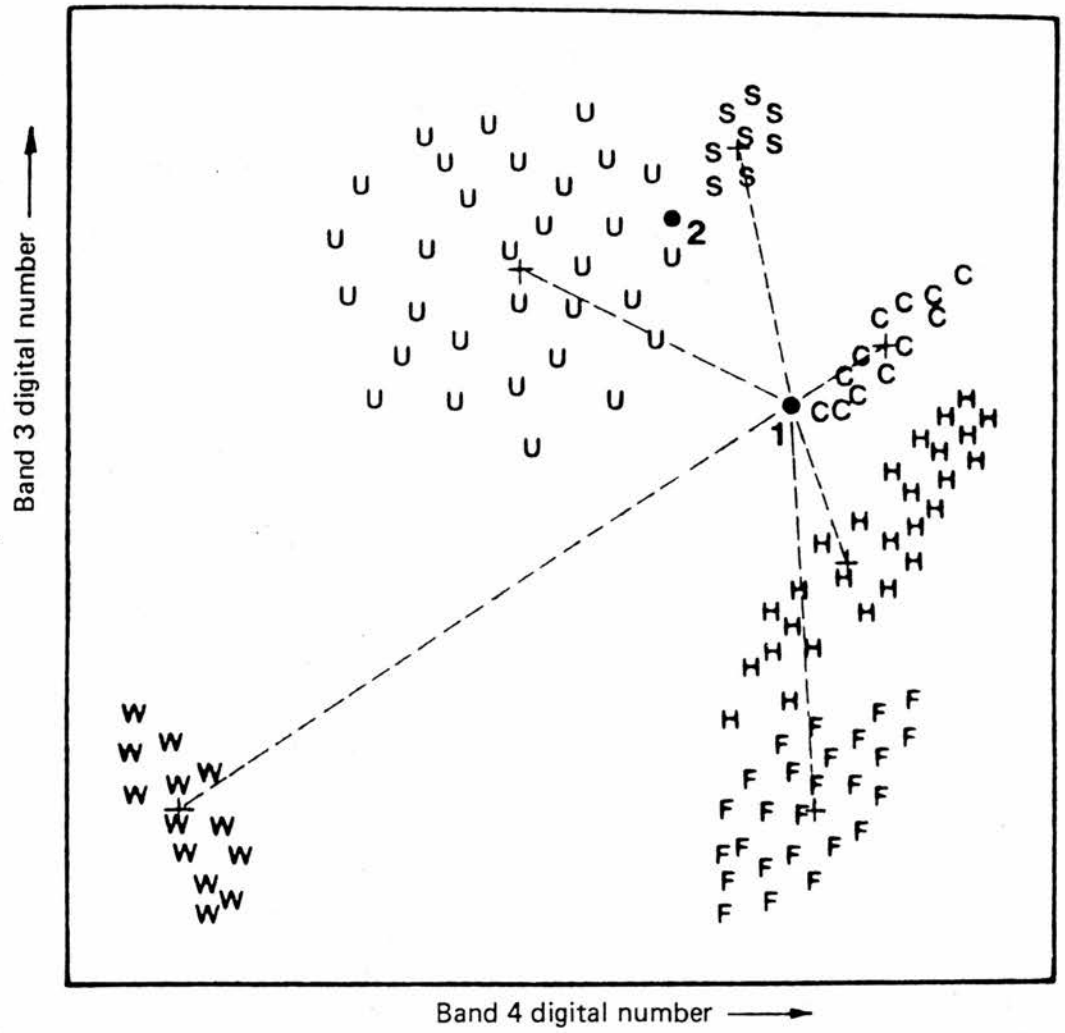


FIGURE 4.1 : THE MINIMUM DISTANCE CLASSIFICATION STRATEGY IN A 2-D FEATURE SPACE (After Lillesand And Kiefer, 1987).

makes it more likely that a pixel at point **2** would belong to that class, the minimum distance classifier would assign it to class **S** just because the point is closer to the centroid of the **S** class than to that of the **U** class. This in fact would be assigning the pixel to a wrong class.

Many minimum distance algorithms have now been developed that require the analyst to specify a distance threshold point away from the centroid. A pixel at a point beyond the threshold distance cannot be assigned to the class of the centroid in question even though in relative terms it might be the nearest to the pixel. The threshold is normally a standard deviation value above the class mean. The use of the threshold strengthens the classifier by making it sensitive to class variance. The minimum distance classifier on R-CHIPS is of the modified type. It requires the user to specify a threshold in form of a standard deviation value above the mean before starting to assign pixels into different classes.

4.2.1.2 *Parallelepiped Strategy*

The parallelepiped strategy, also known as box classifier, is probably the simplest of all classification strategies and it uses the least computer resources (Thomas *et al.* 1987). It operates as a simultaneous density slice in *n* bands of multispectral data (Curran, 1985). The minimum and maximum pixel values for a training class in a given data band form a "slice" on the 0 to 255 brightness intensity (DN) value range in that specific band. The lower and upper limits of the "slice" would be two parallel lines in a one-dimensional plane. The minimum and maximum pixel values for the same training class but in a different band, would form another "slice" on the 0 to 255 DN value range in that band. Two parallel lines would, similarly, represent the lower and upper limits of the "slice". If this slicing is undertaken simultaneously on the two data bands, then the two pairs of parallel lines marking the lower and upper limits of the two "slices" would form a square or rectangular box in the two-dimensional plane. If similar slicing operation is simultaneously undertaken in more

than two data bands, then the pairs of parallel lines marking the lower and upper limits of the n "slices" would form a polygon with more than four sides in the n-dimensional space. Because the lower and upper limits of a slice in each plane are marked by two parallel lines, then the polygon in the n-dimensional space would always have parallel opposite sides. Such a polygon is known as a parallelepiped (Mather, 1987a).

The parallelepiped classifier considers minimum and maximum pixel values in each training class and uses the simultaneous density slice principle to define, for each training class, a parallelepiped in an n-dimensional feature space, or a square/rectangular box in a two-dimensional feature space. All data points (pixels) that fall in a parallelepiped/box for a given land cover class are then classified into that specific class. It is the occurrence within or outside a parallelepiped/box for a given class that would determine whether or not a pixel would be assigned to that class.

Some parallelepiped algorithms do not use actual minimum and maximum pixel values for training classes in defining the boxes/parallelepipeds. Instead, they require the analyst to specify threshold values (normally standard deviation values) above and below the mean pixel values for the training classes, and they use these to mark the lower and upper limits of the slices. The automatic mode of the parallelepiped algorithm on R-CHIPS works in that way, whilst the "manual feed" mode of the same algorithm uses actual minimum and maximum values supplied to it by the analyst (I.S. Ltd., 1992). The use of the actual minimum and maximum values often produces unsatisfactory classification results because those two values rarely reflect the spectral properties of the majority of pixels in a class. The use of some standard deviation values above and below the mean helps to exclude the untypical pixels from the classes and, therefore, has the potential of giving better classification results. In this work therefore, the option of using standard deviation thresholds was preferred.

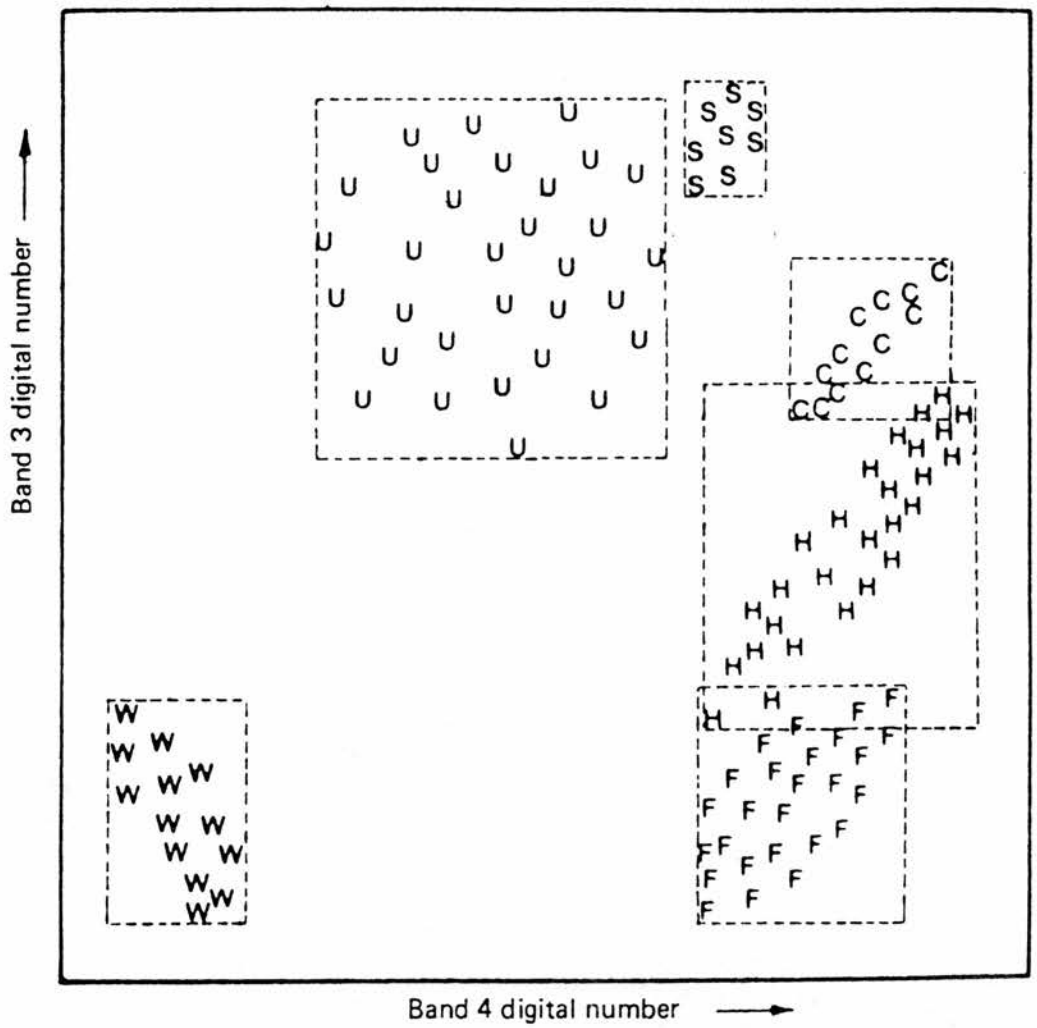


FIGURE 4.2 THE PARALLELEPIPED CLASSIFICATION STRATEGY IN A 2-D FEATURE SPACE

(After Lillesand and Kiefer, 1987)

Whilst the parallelepiped strategy might be fast and computationally efficient, its main problem is that the parallelepipeds/boxes tend to overlap in some regions of the feature space. Thus, some data points (pixels) may fall in two or more parallelepipeds/boxes. For instance, in Figure 4.2, the boxes enclosing **C** and **H** pixels overlap. Similarly, boxes enclosing **H** and **F** pixels overlap. The pixels in the overlapping regions have properties that make them qualified to be assigned to either of the classes. However, in classification, each pixel has to be assigned to one class only. Therefore, any pixel falling in the overlapping region is normally assigned to the first class for which it meets all criteria (Jensen, 1986). But quite often, this results in misclassification.

A better solution to the problem would be to use a parallelepiped classifier that incorporates some principles of minimum distance classification. With such a "hybrid" classifier, the parallelepiped classification principles would apply to pixels falling in the non-overlapping regions of the parallelepipeds/boxes. The minimum distance rule explained earlier (see 4.2.1.1 above) would apply to pixels in the overlapping regions. Thus, any pixel in the overlapping regions would be assigned to the class whose mean value is closest to it as judged by the measure of direct distance (Jensen, 1986). The parallelepiped algorithm on R-CHIPS belongs to the "hybrid" category and operates in the way just described (I.S. Ltd., 1992).

4.2.1.3 *Maximum Likelihood Strategy*

The maximum likelihood classifier requires mean, variance and covariance statistics from training data. It plots the mean values as centroids in n-dimensional feature space in the same way as the minimum distance classifier does. It then uses the variance-covariance data to determine distances of the data points (pixels) away from the centroids. These are essentially modified Euclidean distances and are known in statistics as Mahalanobis distances, after the Indian statistician, P.C. Mahalanobis (King, 1969). The Mahalanobis distance (M^2) is the square of the simple Euclidean

distance modified by dividing it by the variance of the distribution (class) in the appropriate *n*-dimensional (point-to-mean) direction. Whereas the square of the Euclidean distance (D^2) is expressed in the following terms:

$$D^2 = (X_k - U_i)\ (X_k - U_i) \tag{4.3}$$

[After Thomas *et al*, 1987)

the Mahalanobis distance (M^2) can be expressed as follows

$$M^2 = (X_k - U_i)\ V_i^{-1} (X_k - U_i) \tag{4.4}$$

[After Thomas *et al* , 1987]

In both equations, X_k = vector representing point (pixel) k

U_i = mean vector for class i

And in equation 4.4, V_i = variance-covariance matrix for class i

V_i^{-1} = Inverse of variance-covariance matrix for class i

The Mahalanobis distance measures the remoteness of a point (pixel) from a centroid in *n*-dimensional space. In this case it is like the measures of distance used in the minimum distance strategy. But it differs from them in that its computation takes into account the correlation among values of pixels in *n* data bands. In acquiring data, satellite sensors detect continuous signals that are then sampled a couple of times (7 times for Landsat TM and 4 times for Landsat MSS) to produce multispectral data bands. As such, values of a pixel in the different bands are not entirely independent of each other. There is normally a degree of correlation among them (Thomas *et al*, 1987). The variance-covariance data which the maximum likelihood classifier uses in calculating Mahalanobis distance reflect the actual correlation that exists within multispectral data. Classifiers like parallelepiped and minimum distance do not consider the correlation aspect of the spectral data and therefore they draw straight line boundaries between classes in a feature space. By contrast, because the maximum likelihood strategy recognises the correlation among data points, the boundaries

between correlated clusters of pixels are marked by ellipsoidal isolines in 2-dimensional feature space, or by elliptical isolines in a features space with more than 2 dimensions. The boundaries around uncorrelated clusters of pixels are marked by circular isolines. The position of each isoline in the feature space is determined by a Mahalanobis distance value away from a centroid; and since different data points will occur at locations with different Mahalanobis distance values, then a family of concentric elliptical (ellipsoidal) or circular isolines can be envisaged around each centroid in a feature space (Mather, 1987a).

In image classification, the Mahalanobis distances from a point (pixel) to the centroids of different classes are normally multiplied by the multivariate normal distribution probability density function which essentially converts the elliptical (ellipsoidal) or circular isolines of Mahalanobis distance values into equiprobability contours. For instance, the equiprobablity contour $p\,(X_k)$ computed using the mean (centroid) value of class i as the point of reference would be calculated using the following formula:

$$p\,(X_k \mid i) = \frac{1}{(2\pi)^{n/2}\,|V_i|^{1/2}} \exp\left[-1/2\,(\mathbf{X}_k - \mathbf{U}_i)\,\mathbf{V}_i^{-1}\,(\mathbf{X}_k - \mathbf{U}_i)\right] \qquad (4.5)$$

[After Thomas *et al* 1987. Same equation appear with different notations in Mather, 1987b and Jensen, 1986]

where the expression in bold type at the far right is the Mahalanobis distance formula with all symbols as previously described in equation (4.4); and the rest on the right hand side of the equation is the usual multivariate normal distribution probability density function. Figure 4.3 demonstrates equiprobability contours in a 2-D feature space. Each equiprobability contour gives a measure of the degree to which the pixels enclosed within it are likely or less likely to belong to a class. Thus, in essence, expression 4.5 above gives the likelihood (probability) value p that pixels enclosed within the original isoline X_k would belong to class i. The classifier assigns pixels to

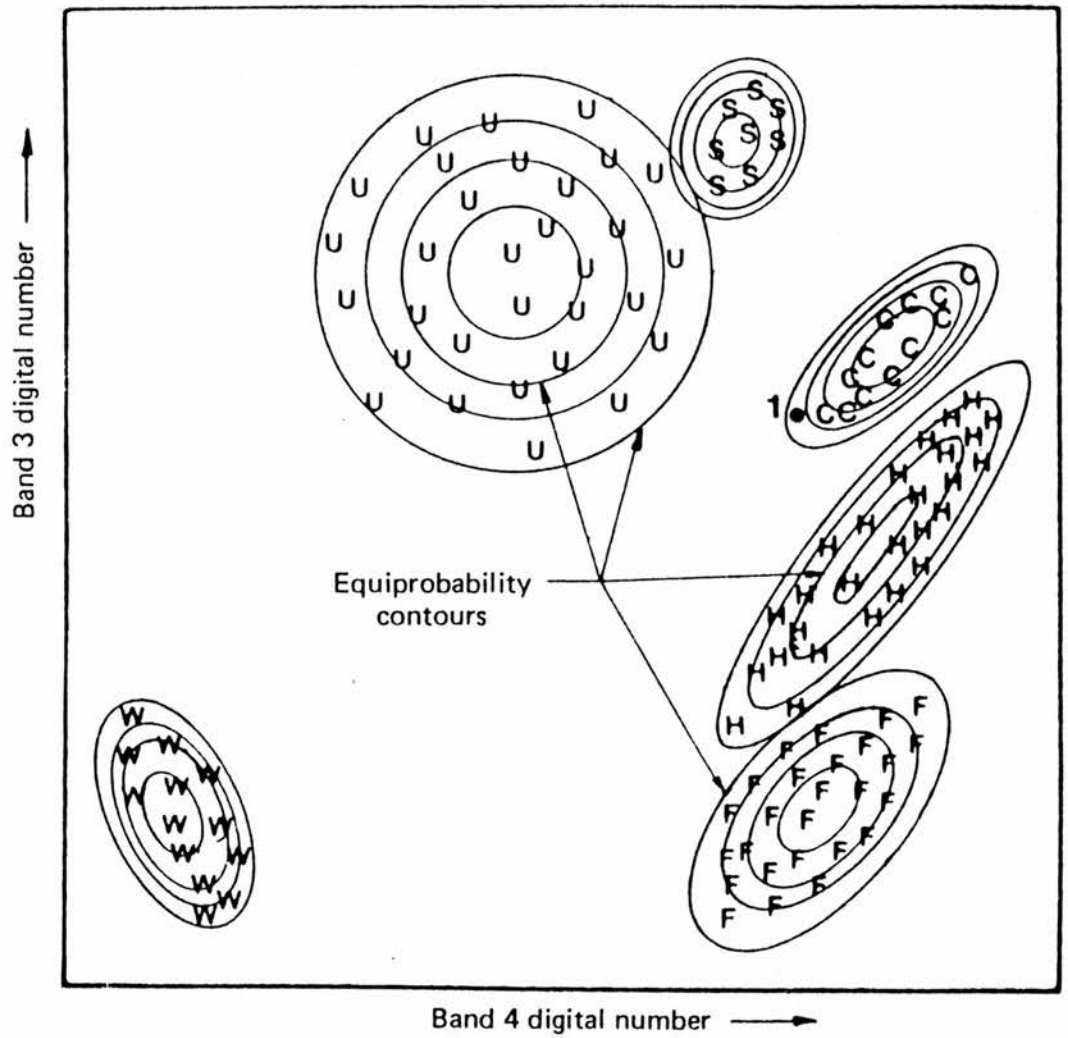


FIGURE 4.3 : EQUIPROBABILITY CONTOURS DEFINED BY A MAXIMUM LIKELIHOOD CLASSIFIER IN A 2-D FEATURE SPACE (After Lillesand And Kiefer, 1987).

a class in which their likelihood (probability) value of belonging is highest (Jensen, 1986; Mather, 1987a; 1987b; Thomas *et al,* 1987).

The maximum likelihood classification involves intensive calculation so that it has the disadvantage of requiring more computer resources than the other simpler techniques (Campbell, 1987; Lillesand and Kiefer, 1987).

4.2.2 Procedure of the Classification Process

Classification was undertaken on each of the study extracts. First, the 1985 data were classified and the same steps were repeated to classify the 1991 data. Since all three classifiers used in this work are supervised, then the classification process began with the selection of training areas on the study extracts. These were then edited to make sure that only correct training data were used in the classification. The classifiers were run using the edited training data. Post-classification filtering was performed in order to suppress some specks of "alien" pixels within the categories on the classified data. The image outputs of maximum likelihood and minimum distance were then colour-coded. These steps are now briefly described.

4.2.2.1 *Selection of Training Areas*

The aim of the training stage in supervised classification is to identify sample pixels for each class. The classifier uses the statistics from the sample pixels to work out classification model parameters like size of parallelepipeds and their location in *n*-dimensional space (for parallelepiped classification); location of centroids in *n*-dimensional space (for minimum distance classification); and location, shape and sizes of concentric ellipsoids of equiprobability (for maximum likelihood classification). The classifiers then use these model parameters to assign each and every pixel in the image to a class.

The sample pixels have to be correctly identified and each training class should have not less than a statistically significant minimum number of sample pixels. Training a classifier on wrongly selected training areas and/or on too few training pixels would give it wrong information which would result in misclassification. Good supervised classification results depend on correct selection of a good number of training sites.

In this work, the selection of training areas was undertaken on colour composite displays for each study extract. Colour composite displays comprising the 1985 data bands were used to select training areas for use in the classification of the 1985 data. Colour composite displays comprising the 1991 data bands were used to select training areas for use in the classification of the 1991 data.

The appearance of pixels of different land cover categories on colour composite displays had already been established earlier in this work (see section 3.3, chapter 3). It was therefore possible to identify groups of contiguous pixels representing a given land cover class. Each area identified as a potential training site was checked on the maps and aerial photographs. Where information from these secondary data confirmed that the land cover in the potential training area has been correctly identified, then the area was selected as a valid training site. But where the maps and aerial photographs gave information quite different from that on the colour composite displays, then the area was not selected as a valid training site. To select a group of contiguous pixels as a training site, a polygon was drawn around them on the screen. The training areas for all classes in an extract were selected in this way.

There is no consensus yet on what may constitute the statistically significant minimum number of sample pixels for each training class. Some like Harris (1987) put the acceptable minimum number of pixels in each training class at ten times the number of data bands used in the classification. This is a minimum of 30 pixels for each training class where three bands are used like in the present work. Jensen (1986) and Lillesand and Kiefer (1987) put the acceptable minimum number of pixels in

each training class at $n + 1$, where n is the number of data bands used in the classification. This would be a minimum of 4 pixels in each training class where three bands are used. However, they further state that ideally people choose at least ten times the number of data bands, which is what Harris (1987) regards as the acceptable minimum. Campbell (1987) regards 100 as the acceptable number of pixels in each training class. But it is not clear whether this would apply to any number of bands used in the classification. Mather (1987a) stated that the minimum number of pixels in each training class should be $30p$ where p is the number of bands used in the classification.

In this work, Mather's $30p$ rule was adopted and since $p = 3$ in the present work, then not less than 90 pixels were selected for each training class in each extract, except where the class had fewer typical pixels that could be clearly recognised on the screen. However, the classes with less than 90 training pixels were few. The majority had training pixels in excess of 100. The numbers of pixels for the training classes in each of the study extracts are presented in Tables 4.2-4.4.

Once the training areas for all classes in a study extract had been selected, the image processor then worked out statistics from the training pixels. For the minimum distance classification strategy, these statistics were mean values and standard deviations. For the maximum likelihood classification strategy, these were mean values, standard deviations, variance-covariance matrices, and the inverse of those matrices. For parallelepiped classification strategy, the statistics included minimum and maximum pixel values, mean values and standard deviations.

4.2.2.2 *Evaluation of Training Data*

Once the training areas have been selected and the statistics have been obtained, it is essential to assess how representative they are with respect to their parent classes. This evaluation enables the analyst to identify classes which do not have the correct

sample statistics. Once identified, these can be revised in order to ensure that the classifier is given the right statistics.

One simple way to evaluate training data is to compare the mean value of a training class with the mean value of the respective parent class, with the assumption that where the training data are actually representative of the entire class, then the training class mean value would be close to the mean value (μ) of the parent class. This assumption is valid only where the parent class is relatively pure and therefore with very low value of variance.

It was decided in this work that the training data should be evaluated by comparing the mean values for the training classes with those for the parent classes. Estimates of the latter were worked out under section 3.4.2 (chapter 3) and are presented in the tables in Appendix III. However, these values were estimated from samples of 60 pixels for each class. While they might be realistic estimates, they are, however, not the exact mean values (μ_s) for the parent classes. The exact mean values (μ_s) would be slightly higher or lower than the mean values calculated from samples. It is the true class mean values (μ_s) that are compared with the mean values for training classes in order to assess how representative the training data are. However, when the parent classes contain very large numbers of individual elements (pixels), then the calculation of exact values (μ_s) is time-consuming. Nevertheless, it is possible to use the sample mean value ($\bar{x}$) to determine a range which would certainly bracket the exact mean value (μ) for a given class. Where the sample mean values ($\bar{x}_s$) are derived from small samples, then the limits of the ranges that would certainly enclose the exact mean values (μ_s) are calculated using the following formula:

$$\bar{x} - (t_{n-1,\,100-\alpha\%}) \times \frac{s}{\sqrt{(n-1)}} < \mu > \bar{x} + (t_{n-1,\,100-\alpha\%}) \times \frac{s}{\sqrt{(n-1)}} \qquad (4.6)$$

[Simplified from Miller, 1986)

where $\bar{x}$ = mean value for the small sample

μ = true population mean

s = standard deviation for the small sample

t = Student's t -distribution

n -1 = v (degree of freedom)

t_{n-1} = value of Student's t -distribution at a given degree of freedom. This value is given in statistical tables

α = percentage level of confidence required

The above formula was used in this work to calculate the limits of a range within which the exact mean value (μ) for a class would occur. The sample mean values ($\bar{x}_s$) used are those presented in Appendix III. These limits were worked out at 99.9% confidence level and are presented in Table 4.1. After these had been calculated, it was then checked to discover whether the mean value for each training class fell within or outside the limits of μ for that class in each of the three bands. Those that fell within the limits in two or all three bands were partially accepted as valid training data. Training classes with mean values that were 2 points less than the lower limits, or 2 points greater than the upper limits in two or all three bands were also partially accepted. All training classes with mean values that fell completely outside the limits were rejected and had to be revised.

In order to get fully accepted as valid, the training classes whose mean values fell within the acceptable limits were also expected to have low values of standard deviations in at least two of the three bands. A class with low standard deviation is relatively pure and tends to have one distinct peak when its distribution is plotted in a histogram form. Those with large standard deviations are less pure classes and they tend to display bimodal or multimodal histograms. The use of less pure training class data produces poor classification results (Campbell, 1987; Mather, 1987b). In this work, training classes with large standard deviation values in two or all three bands had to be revised even if their mean values were within the acceptable limits.

	ROSEDALE EXTRACT						WHEELDALE EXTRACT						FYLINGDALES EXTRACT					
	LIMITS OF CLASS μ ON 1985 IMAGERY			LIMITS OF CLASS μ ON 1991 IMAGERY			LIMITS OF CLASS μ ON 1985 IMAGERY			LIMITS OF CLASS μ ON 1991 IMAGERY			LIMITS OF CLASS μ ON 1985 IMAGERY			LIMITS OF CLASS μ ON 1991 IMAGERY		
LAND COVER	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
B1	41-44	63-68	112-119	21-22	99-104	59-66	41-44	62-67	110-117	21-22	97-102	59-63	39-42	60-63	100-107	22-23	97-102	56-61
D1	16-19	23-26	37-42	25-27	56-61	59-64	27-28	32-33	55-58	33-34	43-48	61-66						
D2	26-27	38-43	83-90	26-27	45-50	66-71	28-29	37-38	85-90	26-27	48-53	64-69	26-29	38-43	81-88	26-27	43-49	67-72
D3	17-18	35-38	47-48	23-24	64-67	43-48	16-17	35-38	44-49	21-22	61-64	41-44	17-18	31-34	42-47	22-33	61-66	41-44
F1	20-21	67-78	58-65	20-21	53-60	32-39	18-19	61-66	52-57	20-21	57-62	35-40	18-19	62-65	53-60	20-21	65-71	42-47
F2	15-16	42-51	33-38	20-21	52-57	28-33	15-16	37-42	27-32	19-22	55-62	34-37	16-19	38-45	30-35	18-20	49-54	23-26
G1	20-23	76-83	69-78	23-24	76-83	70-77	24-26	86-89	69-74	25-26	86-91	74-81	24-29	74-83	80-87	26-27	78-83	75-82
G2a	23-24	99-100	87-92	26-27	80-85	80-85	26-29	94-97	89-94	33-36	72-79	84-93	26-29	87-92	86-91	22-23	82-87	76-79
G2b	17-18	127-138	64-73	23-24	97-104	68-73	18-21	126-137	72-79	23-24	89-96	69-72	16-17	112-113	66-75	21-22	101-108	66-71
P1	40-43	50-58	85-90	35-37	62-69	85-90	41-44	47-52	79-86	20-25	52-59	70-79	36-43	52-59	81-88	33-36	53-60	52-59
W1							26-29	32-39	64-67	31-34	44-49	46-51	22-25	39-44	60-67	21-22	47-50	41-44

TABLE 4.1 LIMITS OF MEAN PIXEL VALUES AT 99.9% CONFIDENCE LEVEL

LAND COVER CATEGORIES	TRAINING DATA STATISTICS FROM 1985 IMAGERY							TRAINING DATA STATISTICS FROM THE 1991 IMAGERY						
		MEAN PIXEL VALUES			STANDARD DEVIATION				MEAN PIXEL VALUES			STANDARD DEVIATION		
	PIXELS	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**PIXELS**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
B1	1533	41	66	114	3.4	5.3	9.1	4104	23	102	63	1.5	13.8	7.1
D1	369	20	25	42	1.6	5.1	4.2	186	28	59	64	0.5	5.8	4.0
D2	1047	27	39	86	2.0	4.5	5.8	756	27	47	70	1.3	5.5	3.9
D3	1956	17	37	49	1.2	4.0	4.3	3480	23	64	44	1.8	4.2	4.1
F1	75	20	74	59	2.3	9.4	10.6	162	21	57	36	0.7	3.6	4.6
F2	777	16	47	35	0.8	8.4	4.0	864	21	55	32	1.1	5.4	4.1
G1	105	22	81	73	2.0	8.5	10.0	78	26	82	73	0.7	2.3	2.1
G2a	639	24	98	90	1.6	6.6	8.0	711	29	81	85	1.7	8.2	6.4
G2b	1473	19	134	70	1.4	10.7	6.2	3396	24	99	71	1.7	8.2	6.6
P1	321	44	54	87	3.8	4.7	7.8	702	36	66	87	2.2	7.2	6.9

TABLE 4.2 SUMMARY STATISTICS FOR TRAINING DATA IN ROSEDALE EXTRACT

LAND COVER CATEGORIES	TRAINING DATA STATISTICS FROM THE 1985 IMAGERY							TRAINING DATA STATISTICS FROM THE 1991 IMAGERY						
		MEAN PIXEL VALUES			STANDARD DEVIATION				MEAN PIXEL VALUES			STANDARD DEVIATION		
	PIXELS	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**PIXELS**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
B1	1200	41	63	111	3.7	8.1	10.6	4845	24	99	62	2.3	11.6	9.3
D1	12	30	31	59	1.3	1.1	2.1	24	36	43	62	1.6	1.6	5.9
D2	393	27	39	87	2.4	3.5	6.2	3000	29	53	65	3.6	11.7	7.6
D3	1371	17	36	46	1.1	2.9	3.3	5145	23	63	45	2.2	5.4	6.0
F1	54	18	65	53	0.5	6.6	2.9	225	21	59	36	0.9	5.5	5.3
F2	1692	16	43	30	1.0	9.0	4.3	5775	21	53	29	1.7	7.5	4.1
G1	24	26	87	92	2.2	1.5	5.4	45	27	87	77	1.1	2.7	1.7
G2a	351	28	96	102	1.6	6.3	4.8	2787	33	78	86	4.4	8.8	10.0
G2b	960	20	135	76	1.6	12.6	9.5	3123	25	91	72	2.2	7.6	7.3
P1	186	41	47	80	4.4	6.3	12.5	897	25	59	77	4.4	8.8	17.4
W1	285	27	37	68	2.6	10.1	5.7	1650	35	49	46	1.1	4.6	5.6

TABLE 4.3 SUMMARY STATISTICS FOR TRAINING DATA IN WHEELDALE EXTRACT

LAND COVER CATEGORY	TRAINING DATA STATISTICS FROM THE 1985 IMAGERY							TRAINING DATA STATISTICS FROM THE 1991 IMAGERY						
		MEAN PIXEL VALUES			STANDARD DEVIATION				MEAN PIXEL VALUE			STANDARD DEVIATION		
	PIXELS	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**PIXELS**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
B1	1884	40	62	104	5.7	7.7	13.1	2227	23	96	60	1.4	13.0	7.7
D2	465	27	43	87	1.9	4.4	6.8	681	27	48	72	1.3	4.3	4.9
D3	1983	17	33	43	0.9	2.9	3.0	6120	24	61	43	1.6	5.3	4.3
F1	81	18	64	54	0.9	4.1	6.6	225	21	67	43	1.0	5.0	3.9
F2	2418	16	44	31	1.1	7.7	5.2	4218	20	55	26	1.3	8.1	3.6
G1	54	29	79	82	1.4	7.7	7.8	54	21	64	46	0.8	1.6	5.9
G2a	1335	26	93	88	2.0	6.2	6.5	5535	23	80	80	3.4	6.3	11.0
G2b	2439	19	113	69	1.6	15.2	9.3	3651	23	105	71	1.7	10.5	6.6
P1	819	39	56	85	4.3	10.9	7.2	1470	37	56	76	4.5	8.0	19.6
W1	585	25	43	60	2.0	6.0	6.4	978	22	41	41	0.9	5.0	3.9

TABLE 4.4 SUMMARY STATISTICS FOR TRAINING DATA IN FYLINGDALES EXTRACT

The two steps for evaluating training data were undertaken for each and every training class in each extract. They were undertaken to evaluate the training data extracted from the 1985 imagery, and were also repeated to evaluate the training data extracted from the 1991 data bands. The evaluation made it possible to identify unrepresentative and/or impure training classes which were then edited out. Fresh training areas were selected to replace those that were edited out. The fresh training areas were also evaluated in the same way before accepting them as satisfactory. Summary statistics for the training data that were finally accepted are presented in Tables 4.2-4.4. Variance-covariance statistics and their inverse are not included in the tables.

4.2.2.3 *Running the Classifiers*

After all the necessary revisions had been made to the training areas, each study extract was then independently classified using minimum distance, maximum likelihood and parallelepiped strategies. In classifying the 1985 image data extracts, the classifiers used the training data derived from the 1985 image data bands. In classifying the 1991 image data extracts, the classifiers used the training data derived from the 1991 image data bands. In all, 6 classifications were undertaken for each study extract. These were as follows:

(1) Maximum likelihood classification of 1985 data bands

(2) Minimum distance classification of 1985 data bands

(3) Parallelepiped classification of 1985 data bands

(4) Maximum likelihood classification of 1991 data bands

(5) Minimum distance classification of 1991 data bands

(6) Parallelepiped classification of the 1991 data bands

The parallelepiped algorithm on R-CHIPS classifies an imagery displayed on the screen. The results are output to overlays, with different classes shown in different colours (I.S. Ltd., 1992). The maximum number of overlays that the programme can

display at any particular time is 8. Consequently, this type of classification where results are output to overlays, is possible to the maximum of 8 classes. The 9th, 10th.....*n*th classes would have no overlays to which the classification results might be displayed. Given more than 8 training classes, the classifier would simply use the data for the first 8 to classify the imagery into 8 classes only. In this work, this meant that pixels represented by the other training classes shown in Table 4.1 were left unclassified by the parallelepiped classifier.

The maximum likelihood and minimum distance classifiers on R-CHIPS operate on data held in files and they output the results to new files that have names with the suffix .CLA. Both classifiers can use data for as many as 20 classes to classify image data held in files into an equivalent number of land cover classes (I.S. Ltd., 1992). In this work, these two classifiers therefore used data for all the training classes to assign pixels into all the pre-determined land cover categories.

At the training stage, the broad agro-pastoral category (G2) was subdivided into semi-improved pasture and/or fallow land (G2a); and improved pasture and/or crops (G2b). This subdivision was made in order to reduce the diversity in spectral values that was evident in the broad category. The algorithms classified G2a and G2b as independent classes, but these were later interactively integrated into the original broad agro-pastoral category (G2) when displaying the classification results. The practice of disaggregating broad categories at the training stage and aggregating them again when displaying the classification results was recommended by Williams (1987a; 1987b; 1988) who discovered that it increased classification accuracy.

A problem at the stage of running the classifiers was that of choosing the most effective threshold values for the classifications. For minimum distance and parallelepiped classifications, the threshold is a standard deviation value above and below the class mean as already explained under 4.2.1.1 and 4.2.1.2. For maximum likelihood classification, the threshold is a Mahalanobis distance value (I.S Ltd,

1992). After a series of trials with a wide ranging values, it was discovered that a threshold standard deviation value of 3 gave minimum distance and parallelepiped classification results that were visually considered to be good enough. Similarly, the use of a Mahalanobis distance value of 100 as a threshold gave maximum likelihood classification results that were visually considered to be very satisfactory. These were therefore adopted as standard threshold values for use in all minimum distance/parallelepiped and maximum likelihood classifications respectively.

After completing a classification, the image processor gave summary statistics of the completed classification. Such statistics included absolute number as well as percentage of pixels assigned to each class. These statistics are presented in Tables 4.5-4.7.

4.2.2.4 *Post-classification Smoothing*

As explained under section 4.1, conventional classification approaches including minimum distance, parallelepiped and maximum likelihood classifiers use only the per-point/per-pixel spectral information as the basis for assigning a pixel to a class. These methods vary in their complexity and effectiveness, but even the most elaborate ones do not satisfactorily segment digital images into regions of homogeneous land cover classes. Instead, all conventional classifiers tend to produce classified images that have "salt-and-pepper" appearance (Gilmour, 1987; Lillesand and Kiefer, 1987; van Genderen and Uiterwijik, 1987). This is mostly because of "noise" resulting from the non-uniform response of satellite sensors (van Genderen and Uiterwijik, 1987); problems posed by mixed pixels; as well as genuine variation within specific land cover objects, such as variation in stages of development of a crop within a field (Gilmour, 1987).

Once classification has been performed on the image, it is therefore essential to smooth out the image output in order to suppress the pixels that cause the "salt-and-

pepper" appearance. This post-classification smoothing does not simply improve the appearance of the classified imagery, but it also increases classification accuracy (Williams, 1987a; 1987b; 1988). The common technique for smoothing out the classified images is to undertake post-classification filtering.

In this work, post-classification filtering was undertaken on all classified images to smooth them . On R-CHIPS programme, post-classification smoothing can be performed using the median filter (across) function (I.S. Ltd, 1992) which is in the image enhance menu (see Table 2.2). On classified images, this function operates by passing a moving window through the classified data set. As it does so, it changes the class labels (1, 2, 3, 4 .....) of the pixels within it to the class label of the central (median) pixel in the window.

4.2.2.5 *Colour -coding Classified Images.*

As already stated earlier in section 4.2.2.3, the parallelepiped classifier outputs the results to overlays, with classes automatically shown in different colours. The results of parallelepiped classification are therefore visually impressive colour overlay displays. By contrast, the output of minimum distance and maximum likelihood classifications are grey scale image files. These show less contrast between classes when displayed on the screen or when hard copies are produced. In order to make each class visually distinctive, it was therefore decided to interactively assign a distinct colour to each class on the classified grey scale images. To do this, the classified and smoothed grey scale images were loaded on the screen, one at a time. A colour palette was also loaded with each grey scale image . Then a colour was chosen from the palette and assigned to a given class. This was repeated until all classes had been assigned distinctive colours. The resulting colour-coded classified images had a very good visual impression. Plates 4.1-4.6 show some displays which were colour-coded in the way explained above.

LAND COVER CLASS	CLASSIFICATION OF THE SPRING 1985 IMAGERY						CLASSIFICATION OF THE SUMMER 1991 IMAGERY					
	MAXIMUM LIKELIHO.		MINIMUM DISTANCE		PARALLELEPIPED		MAXIMUM LIKELIHO.		MINIMUM DISTANCE		PARALLELEPIPED	
	PIXELS	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**
Unclassified	121	0.07	51195	28.44	23993	13.33	0	0.00	38429	21.35	51108	28.39
B1	23012	12.78	9093	5.05	39298	21.83	28943	16.08	35830	19.91	16287	9.05
D1	10696	5.94	4021	2.23	18937	10.52	9127	5.07	5156	2.86	5254	2.92
D2	29067	16.15	11282	6.27	8741	4.86	18634	10.35	8036	4.46	17829	9.91
D3	36410	20.23	24599	13.67	47031	26.13	54672	30.37	39997	22.22	25003	13.89
F1	7689	4.27	25965	14.43	1920	1.07	3021	1.68	1782	0.99	24448	13.58
F2	2390	1.33	2027	1.13	1607	0.89	1904	1.06	2402	1.33	1975	1.10
G1	10832	6.01	13792	7.66	7024	3.90	7311	4.06	2660	1.48	16495	9.16
G2	46394	25.78	33986	18.88	31449	17.47	47248	26.25	39740	22.08	21601	12.00
P1	13389	7.44	4040	2.24			9140	5.08	5968	3.32		
TOTAL	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**

TABLE 4.5 CLASSIFICATION STATISTICS FOR ROSEDALE EXTRACT

LAND COVER CLASS	CLASSIFICATION OF THE SPRING 1985 IMAGERY						CLASSIFICATION OF THE SUMMER 1991 IMAGERY					
	MAXIMUM LIKELIHO.		MINIMUM DISTANCE		PARALLELEPIPED		MAXIMUM LIKELIHO.		MINIMUM DISTANCE		PARALLELEPIPED	
	PIXELS	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**
Unclassified	26	0.02	55585	30.88	24239	13.47	0	0.00	1766	0.98	732	0.41
B1	22795	12.66	10722	5.96	17818	9.90	24645	13.69	35035	19.46	36521	20.29
D1	21	0.01	21	0.01	9126	5.07	40	0.02	14	0.01	5295	2.94
D2	27535	15.30	6857	3.80	37634	20.90	21092	11.72	30507	16.95	26252	14.58
D3	33171	18.43	19443	10.80	22194	12.33	40539	22.52	40850	22.69	58064	32.26
F1	8441	4.69	3117	1.73	12559	6.98	10667	5.93	7737	4.29	11683	6.49
F2	26117	14.51	20027	11.13	17424	9.68	22115	12.29	22799	12.67	22371	12.43
G1	2231	1.24	1894	1.05	7823	4.35	1888	1.05	298	0.17	680	0.38
G2	38526	21.40	19525	10.85	31183	17.32	34291	19.05	23560	13.09	18402	10.22
P1	2988	1.66	7443	4.14			5076	2.82	5254	2.92		
W1	18149	10.08	35366	19.65			19647	10.91	12180	6.77		
TOTAL	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**

TABLE 4.6 CLASSIFICATION STATISTICS FOR WHEELDALE EXTRACT

LAND COVER CLASS	CLASSIFICATION OF THE SPRING 1985 IMAGERY						CLASSIFICATION OF THE SUMMER 1991 IMAGERY					
	MAXIMUM LIKELIHO.		MINIMUM DISTANCE		PARALLELEPIPED		MAXIMUM LIKELIHO.		MINIMUM DISTANCE		PARALLELEPIPED	
	PIXELS	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**	**PIXELS**	**% IMAGE**
Unclassified	49	0.03	33760	18.76	32434	18.02	1717	0.96	11215	6.23	12992	7.22
B1	14605	8.11	9851	5.47	20066	11.15	16591	9.22	22810	12.67	18974	10.54
D2	17429	9.68	9606	5.34	21131	11.74	10280	5.71	3999	2.22	8548	4.75
D3	27358	15.20	19423	10.79	31631	17.57	38849	21.58	41363	22.98	58803	32.67
F1	7022	3.90	4863	2.70	10139	5.63	9141	5.08	7319	4.07	9347	5.19
F2	27802	15.44	25107	13.95	24226	13.46	30803	17.11	30616	17.01	30586	16.99
G1	1269	0.71	1793	1.00	15425	8.57	3424	1.90	1256	0.70	3029	1.68
G2	38910	21.62	30631	17.01	24948	13.86	38950	21.64	32527	18.07	37721	20.96
P1	8980	4.99	7811	4.34			7469	4.15	13678	7.60		
W1	36576	20.32	37155	20.64			22776	12.65	15217	8.45		
TOTAL	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**	**180000**	**100.00**

TABLE 4.7 CLASSIFICATION STATISTICS FOR FYLINGDALES EXTRACT

4.3 ASSESSMENT OF THE ACCURACY OF CLASSIFICATION

The accuracy levels of the classifications were quantitatively assessed in order to determine the degrees to which the different approaches had been effective in extracting and presenting information about land cover from the sets of remotely sensed data. This part describes the procedures followed in assessing the accuracy of the classifications, the measures of accuracy and error that were calculated, and the presentation of the accuracy and error statistics.

4.3.1 Accuracy Assessment Procedure

The conventional way to assess the accuracy of a classification is to compare the classified image with a set of reference data which is assumed to be correct. The reference data may consist of existing maps and aerial photographs (Jensen, 1986). Ground checks may also be necessary for some sites where more details are required.

The main set of reference data used in this work consisted 1:10 000 habitat maps of 1989. These were the most detailed land cover maps that were available, and were supplemented for some sites by 1:10 000 colour aerial photographs acquired in 1991 and 1: 20 000 colour aerial photographs acquired in 1988. Ground checks were also undertaken in some areas to acquire more detailed information. In general, however, the reference data used were not ideal for the purpose of assessing the accuracy of the classifications. The same set of reference data was used to assess the accuracy of the classifications for the 1985 imagery as well as that for the 1991 imagery. Ideally, the reference maps were supposed to have been compiled quite close to the time the remotely sensed data were acquired by the satellite (Campbell, 1987). Thus in this case, the ideal reference data required for assessing the accuracy of the classifications for the 1985 imagery should have consisted of maps compiled in 1985 or aerial photographs taken in 1985. Similarly, the ideal reference data required for assessing the accuracy of the classifications for the 1991 imagery should have consisted of

maps compiled in 1991 or aerial photographs taken in 1991. But no detailed 1985 and 1991 land cover maps for the North York Moors were available ; and only a few prints of the 1991 1:10 000 aerial photo acquisition were of good quality. Non-availability of the ideal reference data meant that the available single set of reference data, which was less ideal, had to be used in assessing the accuracy of the classifications for both the 1985 and 1991 imagery (Soulsby, Pers. comm.). But because the reference data were not ideal, it means that only rough estimates of classification accuracy could be obtained from the accuracy assessment undertaken in this work.

On the 1:10 000 habitat maps, the dry moorland category was not subdivided into young and mature subcategories as is the case in the scheme followed in this work. In the accuracy assessment exercise, young heather and mature heather categories (D2 and D3) were therefore considered together as a broad category of dry heather moorland in order to match the presentation made on the 1:10 000 maps.

Image pixels are the basis of any quantitative assessment of the accuracy of a classification. The reference map is therefore also required to be stratified into a grid of cells that should be equivalent in size with the image pixels. Comparison can then be made between a pixel on the classified image and its corresponding cell on the reference map (Campbell, 1987; Rosenfield *et al*, 1982). An image pixel is said to be correctly classified if the land cover category it represents is the same as that represented by the corresponding cell on the reference map. Conversely, an image pixel is said to be incorrectly classified if the land cover category it represents is different from that represented by the corresponding cell on the reference map.

Normally, it would not be possible to compare each and every pixel on the classified image with corresponding cells on the reference map. The assessment of classification accuracy is therefore normally undertaken on sample test sites (Schowengerdt, 1983).

Thus, only image pixels in the sample areas are compared with corresponding cells on the reference map.

In order to obtain statistically valid estimates of classification accuracy, the sample sites to be used in the assessment should be chosen based on sound sampling procedure (Quirk and Scarpace, 1980). There is , however, no consensus on what may be regarded as the optimum sampling procedure for assessing the accuracy of a classification. van Genderen *et al* (1978) regard a stratified random sampling as the most appropriate method for sampling in resource studies using remotely sensed data, and they therefore recommend it for use in sampling pixels for the assessment of classification accuracy. Berry and Baker (cited in Quirk and Scarpace, 1980; and in Rosenfield *et al*, 1982) consider a stratified systematic non-aligned sampling procedure as the ideal for verifying the accuracy of land use maps produced from remotely sensed data; and Matern (also cited in Rosenfield *et al*, 1982) actually proposed that this strategy should be adopted as the model for sampling natural populations for forestry and land use surveys. Schowengerdt (1983) recommends a pragmatic approach where each case should be considered separately and the sampling strategy to be adopted should depend on the nature of the study area and the classes being mapped. He, however, emphasises that whatever strategy is used, sampling should be based on groups of contiguous pixels and not on single pixels because of the practical difficulty in accurately locating single pixels on reference maps, aerial photographs and on the ground when conducting field checks. Further, where the structure of the land cover is complex, any single pixel picked up in the per-pixel sampling strategies would rarely be representative of the other pixels within the neighbourhood. But where sampling is based on fields consisting of groups of contiguous pixels, then the diversity on the ground is, to some extent, also reflected in the sampled group of pixels. In this way, sampling based on fields and not points (individual pixels) is seen as the better strategy that can lead to more realistic estimates of classification accuracy (Bradbury and Macdonald, 1986).

In this work, the test sites were selected using a random sampling strategy based on fields. The fields in this case were 1Km x 1Km squares on 1:10 000 habitat maps. On the habitat maps, the area equivalent to each study extract consisted of 10 columns by 9 rows of 1Km x 1Km squares. The co-ordinates of the squares were labelled 00 to 10 from west to east and again 00 to 09 from north to south. Each 1Km x 1Km square could therefore be identified using a four-figure grid reference like 0000 to refer to the square at the top left corner of the study extract. Random numbers from statistical tables were then used to select five 1Km x 1Km squares .

Each of the selected 1Km x 1Km squares was then stratified into 45 equal divisions in the West-East direction, and 45 equal divisions in the North-South direction. This created an array of 45 cells by 45 lines which corresponded with the 45 pixels by 45 lines per 1Km x 1Km area on the image data.

Using ground control points, it was possible to identify on the screen the x, y co-ordinates of the 45 x 45 pixel blocks that corresponded with the 45 x 45 array of cells on the selected 1Km x 1Km map squares. In essence, this was manual registration of the image data to the reference maps. Manual registration is conceptually valid and popular in most remote sensing applications (Schowengerdt, 1983).

Enlarging the squares on the map by a factor of 2, and zooming the appropriate parts of the imagery to level 4 brought the reference data and the image data almost to the same scale where the relationship between the pixels and the corresponding cells became clearer. The zoom was made permanent through the fix zoom factor option on the image transform menu on R-CHIPS (see Table 2.2).

Each pixel in the target 45 x 45 pixel block was checked to find to which land cover it had been assigned to in the classification. Since this exercise was undertaken on the colour-coded classified images, the class of a pixel was therefore readily identified by colour. Each time a pixel was checked to identify its class, the corresponding cell on

the reference map was also checked, so that there was a one-to-one cross-referencing of an image pixel with a corresponding cell on the map. A total of 10125 pixels in each extract were cross-referenced in this way i.e 5 times (45 x 45). These constituted 5.6% of the 180 000 pixels in each study extract.

The 5.6% sample was taken with the assumption that out of the 10125 there would be about 50 sample pixels for each class. 50 is the minimum number of sample pixels required to make a valid estimate of the classification accuracy level for a class (Hay, 1979). Accuracy estimates derived from samples with less than 50 pixels can be accepted only where the specific land cover class is thinly represented in the study area. The assumption stated above worked in all but one case. The fire damaged moorland category (D1) in Wheeldale extract had only 46 sample pixels and this was understandable given that this category was thinly spread in the area. With this exception, the other classes had more than 50 sample pixels in each study extract.

The comparison of the classified images and reference maps was undertaken on extract by extract basis. Each of the six classifications (3 for 1985 data and 3 for 1991 data) in each extract was compared with the reference map for that extract. This made it possible for correctly and incorrectly classified pixels in each class sample to be identified.

4.3.2 Computation of Measures of Accuracy and Error

The numbers of correctly and incorrectly classified pixels that were obtained from the comparison of classified images with reference maps were used in calculating some measures of classification accuracy and error. One of the accuracy measures worked out was class accuracy level. This was calculated for each class in an extract by dividing the number of correctly classified pixels in the class sample by the total number of pixels in the class sample. The values were expressed as percentages. Thus, the class accuracy level (%) could be expressed as follows:

$$A_i(\%) = \frac{c_i}{n_i} \times 100 \qquad (4.7)$$

where c = number of correctly classified pixels in a class sample

n = total number of pixels in a class sample

i = specific class sample

$A_i(\%)$ = Classification accuracy level of class i expressed as %

Another measure of accuracy that was worked out was overall accuracy level. This is an estimate of the combined accuracy for all the classes in an extract . It was computed by adding up the numbers of correctly classified pixels for all classes and then dividing the sum by the total number of pixels sampled in each extract, which was 10125. The overall accuracy values were also expressed as percentages. Thus, the overall accuracy level (%) could be expressed as follows:

$$OA(\%) = \frac{\sum_{i=1}^{n} c_i}{N} \times 100 \qquad (4.8)$$

where c & i are as in (4.7) above

n = total number of classes in the extract

N = total number of pixels in all class samples, i.e $N = \sum n_i$

where n is the number of pixels in each class sample

OA(%) = Overall classification accuracy level expressed as %

The overall accuracy is the most widely used measure of classification accuracy (Foody, 1987). For practical purposes, a classification is normally considered useful if its overall accuracy exceeds a specified threshold. A classification is considered not useful if its overall accuracy is below the specified threshold. But there is a practical problem in judging the utility of a classification solely on the basis of overall accuracy level. A classification with overall accuracy level that exceeds the specified

threshold may have some very low individual class accuracy levels. It would be misleading to think that the data for those classes with low individual accuracy levels are quite useful just because the overall accuracy level is high. Conversely, a classification whose overall accuracy level does not exceed a specified threshold may have a few very high individual class accuracy levels. It would similarly be misleading to think that the data for the few classes with high individual accuracy levels are worthless just because the overall accuracy level is low (Foody, 1987). The individual class accuracy level in this case offers a better guide about the utility value of specific class data derived from the classification. Thus, one concerned with bracken, for instance, would go forward to use the bracken class data if its individual class accuracy level is very high even though the overall accuracy of the entire classification might be low. Conversely, the bracken class data would not be used if its accuracy level is very low even if the overall accuracy level for the entire classification is very high.

In addition to calculating class and overall accuracy levels, similar measures for errors of omission and commission were also worked out. What constitute error of omission are pixels belonging to class x on the reference map, that are however, not classified as x on the image. They are omitted out of class x on the classified image. Error of omission can be calculated on class by class basis in much the same way as the class accuracy level is calculated. The expression for the level of error of omission in a class therefore has the same structure as equation 4.7 above. It can be represented as follows:

$$O_i\,(\%) = \frac{(n_i - c_i)}{n_i} \times 100 \qquad (4.9)$$

where c, n & i are as in equation 4.7

$(n_i - c_i)$ = number of pixels constituting omission error in class i

$O_i\,(\%)$ = level of omission error in class i expressed as %

Overall error of omission was also worked out in much the same way as overall classification accuracy. The formula for calculating overall omission error had the same structure as equation 4.8 and could be expressed as follows:

$$OO(\%) = \frac{\sum_{i=1}^{n} (n_i - c_i)}{N} \times 100 \qquad (4.10)$$

where c, n & i are as in equations 4.7 and 4.9

N & n are as in equation 4.8

OO(%) = overall error of omission expressed as %

What constitute error of commission are pixels belonging to classes *w, y,* .....etc on the reference map, that are however, classified as x on the image. They are pixels belonging to other classes, that are wrongly assigned to a given class. Error of commission in a class was computed in much the same way as error of omission in each class. Its expression therefore had the same structure as equation 4.9 and could be represented as follows:

$$K_i(\%) = \frac{(m_i - c_i)}{n_i} \times 100 \qquad (4.11)$$

where c, n & i are as in equations 4.7 and 4.9 above

m = total number of pixels classified into class i (both correctly and incorrectly classified into class i)

$(m_i - c_i)$ = number of pixels constituting commission error to class i

K_i (%) = level of commission error in class i expressed as %

Overall error of commission was similarly worked out in much the same way as the overall error of omission. It was computed using an equation which has the same structure as equation 4.10 above and is represented as follows:

$$OK\,(\%) = \frac{\sum_{i=1}^{n} (m_i - c_i)}{N} \times 100 \qquad (4.12)$$

where OK(%) = level of overall error of commission expressed as %

c, m, N, & i are as in equation 4.11 above

n is as in equation 4.10 above

The total number of pixels correctly and incorrectly classified into all the classes in an extract ($\sum m_i$) would certainly be the total number of pixels sampled for all classes in the extract ($\sum n_i$) or N. This means equations 4.10 and 4.12 would have the same value. Thus, overall error of omission does have the same value as overall error of commission .

These measures of accuracy and error were worked out on each classification in each extract. This means they were computed six times in each study extract : for the three classifications for the 1985 imagery; and for the other three classifications for the 1991 imagery.

4.3.3 Presentation of Accuracy and Error Statistics

After the classification accuracy and error levels had been determined in the way described above, the resulting statistics were cross-tabulated in a form of contingency tables. These are sometimes called confusion matrices (Schowengerdt, 1983) because they take the form of m x m matrices , where m is the number of classes under investigation. In this work, the rows in the accuracy-error contingency tables represented the classes on the classified images, whilst the columns represented the classes on the reference maps (See Tables 4. 8-4.25).

4.4 DETERMINING CONFIDENCE LIMITS OF CLASSIFICATION ACCURACY LEVELS

The classification accuracy levels were estimated from samples. They therefore cannot be exactly the same as the accuracy values one would obtain if it were possible to include entire class populations (all pixels in each class) in the accuracy assessment exercise. But if the samples were well taken and of statistically significant size, then the true classification accuracy levels would be values either slightly higher or slightly lower than those obtained from the samples. Using probability statistics, it is possible to calculate limits of a range of values that would most certainly enclose the true classification accuracy value. The width of the interval between the values at the end points of the range is determined by the degree of certainty attached to the likelihood of it enclosing the exact/true accuracy level; hence the values at the end points of the range are conventionally known as confidence limits.

Because a pixel can only be either correctly or wrongly classified, then the probability of having pixels correctly classified out of a given sample is essentially a binomial function (Schowengerdt, 1983; Thomas and Allcock, 1984; Thomas *et al,* 1987). This means that confidence limits for a classification accuracy level have to be determined following procedures used in calculating confidence limits for binomial distributions. At 99% confidence level, the confidence limits for a binomial distribution are determined using the following expression:

$$p - 2.58 \sqrt{[p\ (1 - p)/n]} < \pi > p + 2.58 \sqrt{[p\ (1 - p)/n]} \qquad (4.13)$$

[After Clarke and Cooke, 1978; Miller, 1986. 2.58 replaces 1.96, the z value at 95% confidence level. Large brackets added to make the formula clearer]

where p = sample probability of success (e.g probability of pixels being correctly

classified)

1- p = sample probability of failure (e.g probability of misclassification)

n = size of sample (e.g number of pixels in the sample)

π = true population probability of success (e.g true accuracy of the classification)

In image classification, p in the above formula would be the number of correctly classified pixels divided by the total number of pixels sampled. Thus, where individual class accuracy is concerned, then p would be found by an equivalent of equation 4.7 without the multiplying factor of 100. Similarly, where overall accuracy is concerned, then p would be found by an equivalent of equation 4.8 without the multiplying factor of 100.

Formula 4.13 was used in this work to determine the confidence limits of the classification accuracy levels calculated earlier (see section 4.3.2). The lower and upper limits that were worked out in this way for overall accuracy levels are presented below the accuracy-error statistics tables (Tables 4.8-4.25). Looking at the values of the lower and upper confidence limits of overall accuracy levels, it was discovered that all the calculated limits were respectively a point value lower than the accuracy level determined from the samples, and a point value greater than the same. Thus, if α% is the accuracy value determined from the sample, in each and every case, the lower limit was (α–1)% and upper limit was (α+1)%. It was therefore assumed that the limits of the accuracy levels of individual classes would also be (α-1)% to (α+1)% in all cases; where α% is the individual accuracy level worked out from the class sample.

4.5 DISCUSSION OF CLASSIFICATION RESULTS

This part discusses the successes and failures of the classification approaches in extracting and presenting information about the different land cover classes from the

sets of image data. The discussion is based on the classification summary statistics presented in Tables 4.5-4.7; and on the accuracy-error statistics determined earlier (section 4.3.2) and presented in Tables 4.8-4.25. The discussion begins with a brief appraisal of each classifier's successes or failures in assigning pixels to their true classes. The general patterns in the occurrence of classification error are also discussed. The final part considers what the classification results imply as regards the potential of image classification as a tool for resource inventorying.

4.5.1 Performance of the Classifiers

4.5.1.1 *Maximum Likelihood Classification, 1985 Data*

The data in Tables 4.5-4.7 show that the maximum likelihood classifier left negligible amounts of unclassified pixels in each extract. Only 0.07%, 0.02% and 0.03% of the pixels were left unclassified in the Rosedale, Wheeldale and Fylingdales extracts respectively.

The classification accuracy statistics in Tables 4.8-4.10 indicate that the maximum likelihood classifier gave overall classification accuracy of 89% in Rosedale and Wheeldale, and 91% in Fylingdales. It also gave individual class accuracy levels of 70% and above in the Rosedale extract. The classifier gave similar good class accuracy levels for all but one class in Wheeldale. The exception was the fire damaged moorland class (D1) with an accuracy level of only 56%. On the 1:10 000 reference maps, the D1 land cover class covered only a narrow belt of land just south of the Wheeldale plantation (approximately from SE 765985 to SE 791986). Narrow features are often represented by mixed pixels which always cause problems in classification (Campbell, 1987). The classifier also gave encouraging individual class accuracy levels in Fylingdales where all but one class had accuracy levels of over 80%. The exception was grass moor (G1) which was classified with an accuracy level of only 58%.The grass moor category occupies narrow belts of land on the edges of

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**TOTAL**	**% Correct**	**% Commi**
B1	400		34	41		29		21	**525**	**85**	**27**
D1	4	1242	66	3					**1315**	**88**	**5**
D2+D3		158	3252		32	44	11		**3497**	**92**	**7**
F1	20		115	351	36	71		11	**604**	**71**	**51**
F2			7	27	264				**298**	**80**	**10**
G1	2		38	21		633	104		**798**	**73**	**19**
G2			34	20		88	2777		**2919**	**96**	**5**
P1	44	9		32		7		77	**169**	**70**	**84**
TOTAL	**470**	**1409**	**3546**	**495**	**332**	**872**	**2892**	**109**	**10125**		
% Omiss.	**15**	**12**	**8**	**29**	**20**	**27**	**4**	**30**			

OVERALL CLASSIFICATION ACCURACY = 8996/10125 = 89%
OVERALL COMMISSION/OMISSION ERROR = 1129/10125 = 11%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 88% - 90%

TABLE 4.8 ACCURACY-ERROR STATISTICS FOR MAXIMUM LIKELIHOOD CLASSIFICATION OF 1985 IMAGERY : ROSEDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS											
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	751	6						74	10	**841**	**86**	**10**
D1		26								**26**	**56**	**0**
D2+D3	10		2305	39	47	9	21		138	**2569**	**90**	**10**
F1	36		10	1144	27	3	18	11	11	**1260**	**86**	**9**
F2			16	33	1570	2	21			**1642**	**94**	**4**
G1			3	12		223	19		3	**260**	**84**	**14**
G2			25	34	23	26	1590		7	**1705**	**90**	**6**
P1	66			27			70	235		**398**	**73**	**51**
W1	15	14	199	41		3	33		1119	**1424**	**87**	**24**
TOTAL	**878**	**46**	**2558**	**1330**	**1667**	**266**	**1772**	**320**	**1288**	**10125**		
% OMIS.	**14**	**44**	**10**	**14**	**6**	**16**	**10**	**27**	**13**			

OVERALL CLASSIFICATION ACCURACY = 8963/10125 = 89%
OVERALL COMMISSION/OMISSION ERROR = 1162/10125 = 11%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 88% - 90%

TABLE 4.9 ACCURACY-ERROR STATISTICS FOR MAXIMUM LIKELIHOOD CLASSIFICATION OF 1985 IMAGERY : WHEELDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	383	27					12		**422**	**84**	**9**
D2+D3	17	1513				21		161	**1712**	**88**	**12**
F1			787	5		10		10	**812**	**89**	**3**
F2		3	34	278				12	**327**	**97**	**17**
G1					217	19			**236**	**58**	**5**
G2	44	29	23		90	3824	11		**4021**	**97**	**5**
P1			36			77	112		**225**	**83**	**83**
W1	11	158		3	65			2133	**2370**	**92**	**10**
TOTAL	**455**	**1730**	**880**	**286**	**372**	**3951**	**135**	**2316**	**10125**		
% Omiss.	**16**	**12**	**11**	**3**	**42**	**3**	**17**	**8**			

OVERALL CLASSIFICATION ACCURACY = 9247/10125 = 91%
OVERALL COMMISSION/OMISSION ERROR = 878/10125 = 9%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 90% - 92%

TABLE 4.10 ACCURACY-ERROR STATISTICS FOR MAXIMUM LIKELIHOOD CLASSIFICATION OF 1985 IMAGERY : FYLINGDALES EXTRACT

the heather moorland. It also occurs in the acid flushes which are also narrow features. As it has already been stated above, narrow features present classification problems.

In general, the classifier produced very encouraging results for those land cover classes that are of particular importance for the purpose of making resource management decisions in the North York Moors National Park. Bracken, for instance, had accuracy levels of 85%, 86% and 84% in the Rosedale, Wheeldale and Fylingdales extracts respectively. Thus, on average, bracken had a classification accuracy level of 85% which is regarded as the acceptable minimum accuracy level for effective land cover mapping using remotely sensed data (Lo, 1986; Jensen, 1986; Lindgren, 1985; Robinove, 1981).

Another important land cover class, heather moorland (D2+D3) had accuracy levels of 92%, 90% and 88% in the Rosedale, Wheeldale and Fylingdales extracts respectively. These translate into an average class accuracy of 90% which is well above the acceptable minimum accuracy level for effective mapping. Similarly, wet heath (W1) had an average class accuracy of 90%. The coniferous forest class (F2) had accuracy levels of 80%, 94% and 97% in the three extracts respectively, giving an average of 90%. Agro-pastoral land (G2) had accuracy levels of 96%, 90% and 97% in the three extracts respectively, giving an average of 94%. Even for broadleaved/mixed woodland, the average classification accuracy level was only three percentage points lower than the required minimum of 85%.

The facts that the maximum likelihood classification of the spring 1985 imagery left negligible amounts of unclassified pixels, and that at the same time it gave very satisfactory class and overall accuracy levels, implies that the classifier succeeded in extracting information about the important moorland and related land cover types. In particular, those categories that are considered important for making resource management decisions were classified very satisfactorily. These include bracken, dry

heather moorland, wet heath, agro-pastoral land and coniferous forests. Although the average classification accuracy levels for broadleaved woodland (82%) and grass moor (72%) were below the acceptable minimum for effective mapping, they were nevertheless satisfactory results too.

4.5.1.2 *Minimum Distance Classification, 1985 Data*

Whilst the maximum likelihood classifier left negligible amounts of unclassified pixels in each extract, the data in Tables 4.5-4.7 show that the minimum distance classifier left as much as 28.44%, 30.88% and 18.76% unclassified pixels in the Rosedale, Wheeldale and Fylingdales extracts respectively. The large numbers of unclassified pixels indicate that the classifier failed to extract information from large sections of the imagery.

For those pixels the minimum distance classifier managed to assign to classes, it did so less correctly than the maximum likelihood classifier. The statistics in Tables 4.11-4.13 show that it gave overall accuracy levels of 74%, 79% and 87% in Rosedale, Wheeldale and Fylingdales extracts respectively. These accuracy levels were respectively 15, 10 and 4 percentage points lower than those obtained under the maximum likelihood classification for the same extracts.

In terms of individual class accuracy, the classifier produced encouraging results for only two classes, namely agro-pastoral land (G2) and wet heath (W1) which had average accuracy levels of 85% and 92% respectively. For the coniferous forest class (F2), its average class accuracy was just 3 percentage points lower than the 85% required minimum. Most of the land cover classes that are very important in making resource management decisions were just satisfactorily classified, but their accuracy levels did not reach the 85% required minimum. These include bracken, dry heather moorland, broadleaved woodland and grass moor. Their average classification accuracy levels were 77%, 79%, 75% and 71% respectively.

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**TOTAL**	**% Correct**	**% Commi**
B1	344		61	27	7	58	150		**647**	**73**	**64**
D1		618						5	**623**	**44**	**0**
D2+D3	18	316	3260	33	50	70	38	7	**3792**	**92**	**15**
F1	8	6	46	330	45	69	71		**575**	**67**	**49**
F2	5		18	18	209	4	3		**257**	**63**	**15**
G1	10		45	23	3	510	190		**781**	**58**	**31**
G2	60		42	54	15	135	2172	19	**2497**	**75**	**11**
P1	12		13			16	206	74	**321**	**68**	**227**
Unclassif.	13	469	61	10	3	10	62	4	**632**		
TOTAL	**470**	**1409**	**3546**	**495**	**332**	**872**	**2892**	**109**	**10125**		
% Omiss.	**27**	**56**	**8**	**33**	**37**	**42**	**25**	**32**			

OVERALL CLASSIFICATION ACCURACY = 7517/10125 = 74%
OVERALL COMMISSION/OMISSION ERROR = 2608/10125 = 26%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 73% - 75%

TABLE 4.11 ACCURACY-ERROR STATISTICS FOR MINIMUM DISTANCE CLASSIFICATION OF 1985 IMAGERY : ROSEDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS											
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	696	2		36						**734**	**79**	**4**
D1	12	35								**47**	**76**	**27**
D2+D3			1469		36				37	**1542**	**57**	**3**
F1				1027	21		50	3		**1101**	**77**	**6**
F2	25			56	1502					**1583**	**90**	**5**
G1	5			18		255	24			**302**	**96**	**17**
G2						10	1563	91		**1664**	**88**	**6**
P1	87	9		36				206		**338**	**64**	**41**
W1	40		1042	35	43				1226	**2386**	**95**	**90**
Unclassi.	13		47	122	65	1	135	20	25	**428**		
TOTAL	**878**	**46**	**2558**	**1330**	**1667**	**266**	**1772**	**320**	**1288**	**10125**		
% Omiss.	**21**	**24**	**43**	**23**	**10**	**4**	**12**	**36**	**5**			

OVERALL CLASSIFICATION ACCURACY = 7979/10125 = 79%
OVERALL COMMISSION/OMISSION ERROR = 2146/10125 = 21%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 78% - 80%

TABLE 4.12 ACCURACY-ERROR STATISTICS FOR MINIMUM DISTANCE CLASSIFICATION OF 1985 IMAGERY : WHEELDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	355	16	15			53	12	42	**493**	**78**	**30**
D2+D3	7	1510		1		15		135	**1668**	**87**	**9**
F1	4	7	715	5	7	46		7	**791**	**81**	**9**
F2		9		262		26			**297**	**92**	**12**
G1					220	41		5	**266**	**59**	**12**
G2		39	46	1	103	3599	21	18	**3827**	**91**	**6**
P1	57		43			86	92		**278**	**68**	**138**
W1	14	107	19	17	27	11		2094	**2289**	**90**	**8**
Unclassi.	18	42	42		15	74	10	15	**216**		
TOTAL	**455**	**1730**	**880**	**286**	**372**	**3951**	**135**	**2316**	**10125**		
% Omiss.	**22**	**13**	**19**	**8**	**41**	**9**	**32**	**10**			

OVERALL CLASSIFICATION ACCURACY = 8847/10125 = 87%
OVERALL COMMISSION/OMISSION ERROR = 1278/10125 = 13%
ACCURACY LIMITS AT 99% CONFIDENCE LIMITS : 86% - 88%

TABLE 4.13 ACCURACY-ERROR STATISTICS FOR MINIMUM DISTANCE CLASSIFICATION OF 1985 IMAGERY : FYLINGDALES EXTRACT

4.5.1.3 *Parallelepiped (Box) Classification, 1985 Data*

The statistics in Tables 4.5-4.7 show that the classifier left significant amounts of unclassified pixels in each extract. This was expected because the classifier did not use data for all the training classes. It has already been stated in section 4.2.2.3 that this classifier uses data for a maximum of 8 training classes to classify images into an equivalent number of land cover classes. The pixels represented by the 9th, 10th, or 11th training classes were therefore left unclassified. Not withstanding this, the statistics in Tables 4.5-4.7 indicate that in the Rosedale and Wheeldale extracts, the parallelepiped classifier left relatively less amounts of unclassified pixels than the minimum distance classifier. It left 13.33% and 13.47% unclassified pixels in the two extracts respectively, while the minimum distance classifier left 28.44% and 30.88% unclassified pixels in the same two extracts respectively. In the Fylingdales extract, the two classifiers left almost the same amounts of unclassified pixels. This may suggest that, if the parallelepiped classifier had used all the training classes, then it would have probably left much less amounts of unclassified pixels than the minimum distance classifier.

Since a number of land cover categories were not classified, it was expected that the classifier would give lower overall classification accuracy levels. Less lower overall accuracy levels were expected where the unclassified categories were less extensive. Thus, in the Rosedale extract, for instance, there was only one less extensive unclassified category, bare fields (P1). The overall accuracy in the Rosedale extract was therefore relatively less affected by the fact that this small category was not classified. The overall accuracy achieved was 75% which was even 1 percentage point higher than the accuracy level given by the minimum distance classifier in the same extract. Much lower overall accuracy levels were expected where the unclassified categories were relatively more extensive. For instance, in the Wheeldale and Fylingdales extracts, in addition to the bare fields (P1) category, there was a more

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**TOTAL**	**% Correct**	**% Commi**
B1	355		75	47	5			21	**503**	**76**	**32**
D1		1282	102						**1384**	**91**	**7**
D2+D3	9	109	2872	14	21	54	60		**3139**	**81**	**8**
F1	43		353	362	83	157	108	15	**1121**	**73**	**153**
F2			50	62	223	3	4		**342**	**67**	**36**
G1	19		44			604	202		**869**	**69**	**30**
G2	7					54	1888		**1949**	**65**	**2**
Unclassif.	37	18	50	10			630	73	**818**		
TOTAL	**470**	**1409**	**3546**	**495**	**332**	**872**	**2892**	**109**	**10125**		
% Omiss.	**24**	**9**	**19**	**17**	**33**	**31**	**35**	**100**			

OVERALL CLASSIFICATION ACCURACY = 7586/10125 = 75%
OVERALL COMMISSION/OMISSION ERROR = 2539/10125 = 25%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 74% - 76%

TABLE 4.14 ACCURACY-ERROR STATISTICS FOR PARALLELEPIPED CLASSIFICATION OF 1985 IMAGERY : ROSEDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS											
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	780	4	30	54		20		14		**902**	**89**	**14**
D1	14	40	9							**63**	**87**	**50**
D2+D3		2	1766		60				64	**1892**	**69**	**5**
F1	38		62	1141	432	26	47	20	15	**1781**	**86**	**48**
F2			34	71	1124		36		10	**1275**	**67**	**10**
G1	29		51	30	16	173	69	13		**381**	**65**	**78**
G2			13		35	36	1297	9		**1390**	**73**	**5**
Unclassif.	17		593	34		11	323	264	1199	**2441**		
TOTAL	**878**	**46**	**2558**	**1330**	**1667**	**266**	**1772**	**320**	**1288**	**10125**		
% Omiss.	**11**	**13**	**19**	**24**	**33**	**35**	**27**	**100**	**100**			

OVERALL CLASSIFICATION ACCURACY = 6321/10125 = 62%
OVERALL COMMISSION/OMISSION ERROR = 3804/10125 = 38%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 61% - 63%

TABLE 4.15 ACCURACY-ERROR STATISTICS FOR PARALLELEPIPED CLASSIFICATION OF 1985 IMAGERY : WHEELDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% correct**	**% Commi**
B1	322	27	69		27	47	45	37	**574**	**71**	**55**
D2+D3	8	1367		5	5	26		135	**1546**	**79**	**10**
F1	77	23	623	11	31	57	25	9	**856**	**71**	**27**
F2		5	45	260		25			**335**	**91**	**26**
G1	48	14	110	2	210	461		12	**857**	**56**	**174**
G2			17	8	99	2993			**3117**	**76**	**3**
Unclassif.		294	16			342	65	2123	**2840**		
TOTAL	**455**	**1730**	**880**	**286**	**372**	**3951**	**135**	**2316**	**10125**		
% Omiss.	**29**	**31**	**19**	**9**	**44**	**24**	**100**	**100**			

OVERALL CLASSIFICATION ACCURACY = 5775/10125 = 57%
OVERALL COMMISSION/OMISSION ERROR = 4350/10125 = 43%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 56% - 57%

TABLE 4.16 ACCURACY-ERROR STATISTICS FOR PARALLELEPIPED CLASSIFICATION OF 1985 IMAGERY : FYLINGDALES EXTRACT

extensive wet heath (W1) category which was equally not classified. The overall accuracy levels in the two extracts were therefore considerably affected by the fact that such an extensive category was not classified. The statistics in Tables 4.15-4.16 show that the overall accuracy levels in the Wheeldale and Fylingdales extracts were only 62% and 57% respectively.

The individual class accuracy values did not present any clear pattern in relation to the results obtained under the other two strategies. For instance, in the Rosedale extract, the accuracy value for bracken (76%) was 9 percentage points lower than that obtained under the maximum likelihood classification, but 3 percentage points higher than that obtained under the minimum distance classification for the same extract. In the Wheeldale extract, the accuracy value for bracken (89%) was 3 and 10 percentage points higher than the accuracy values given by the maximum likelihood and minimum distance classifiers respectively. In the Fylingdales extract, the accuracy value for bracken (71%) was 13 percentage points lower than that achieved under the maximum likelihood classification, and 6 percentage points lower than that achieved under the minimum distance classification for the same extract. These inconsistencies in the relationships between class accuracy values obtained under the parallelepiped classification and those obtained under the other two were not only observed for bracken, but also for the other classes.

In general, however, the classifier gave fair accuracy levels of between 60% and 80% for most of the classes. But there was no class whose average accuracy level in the three extracts was 85% or above.

4.5.1.4 *Maximum Likelihood Classification, 1991 Data.*

The data in Tables 4.5-4.7 also show that with the 1991 image data, the maximum likelihood classifier left no unclassified pixels in the Rosedale and Wheeldale extracts. In Fylingdales, it left 1917 unclassified pixels. But these were actually the

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**TOTAL**	**% Correct**	**% Commi**
B1	382		114	19	9	3	110	12	**649**	**81**	**57**
D1		860							**860**	**61**	**0**
D2+D3	28	451	3288	15	7	28		2	**3819**	**93**	**15**
F1	15	33	92	405	15	17	3		**580**	**82**	**35**
F2	9	48	4	29	300	8	4		**402**	**91**	**30**
G1	23		19	14	1	745	55		**857**	**85**	**13**
G2	13		29	13		71	2603	24	**2753**	**90**	**5**
P1		17					117	71	**205**	**65**	**123**
TOTAL	**470**	**1409**	**3546**	**495**	**332**	**872**	**2892**	**109**	**10125**		
% Omiss.	**19**	**39**	**7**	**18**	**9**	**15**	**10**	**35**			

OVERALL CLASSIFICATION ACCURACY = 8654/10125 = 86%
OVERALL COMMISSION/OMISSION ERROR = 1471/10125 = 14%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL = 85% - 87%

TABLE 4.17 ACCURACY-ERROR STATISTICS FOR MAXIMUM LIKELIHOOD CLASSIFICATION OF 1991 IMAGERY : ROSEDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS											
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	713		9	26	7		52			**807**	**81**	**11**
D1		20								**20**	**44**	**0**
D2+D3	46	26	2390	43	28				178	**2711**	**93**	**13**
F1	8		44	1085	86	10			49	**1282**	**82**	**15**
F2	12			72	1483					**1567**	**89**	**5**
G1	9					159	15			**183**	**60**	**9**
G2	80		16	64	8	88	1671	70		**1997**	**94**	**18**
P1							11	244		**255**	**76**	**4**
W1	10		99	40	55	9	23	6	1061	**1303**	**82**	**19**
TOTAL	**878**	**46**	**2558**	**1330**	**1667**	**266**	**1772**	**320**	**1288**	**10125**		
% Omiss.	**19**	**56**	**7**	**18**	**11**	**40**	**6**	**24**	**18**			

OVERALL CLASSIFICATION ACCURACY = 8826/10125 = 87%
OVERALL COMMISSION/OMISSION ERROR = 1299/10125 = 13%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 86% - 88%

TABLE 4.18 ACCURACY-ERROR STATISTICS FOR MAXIMUM LIKELIHOOD CLASSIFICATION OF 1991 IMAGERY : WHEELDALE EXTRACT

IMAGE DATA CLASS	CLASSES ON REFERENCE MAPS										
	B1	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	369	34			16	153		24	**596**	**81**	**50**
D2+D3	15	1598	27			10		142	**1792**	**92**	**11**
F1		29	789	9		12		42	**881**	**90**	**11**
F2			35	274		23			**332**	**96**	**20**
G1	6				288	24			**318**	**77**	**8**
G2	59	6			64	3716	40		**3885**	**94**	**4**
P1						13	95		**108**	**70**	**10**
W1	6	63	29	3	4			2108	**2213**	**91**	**5**
TOTAL	**455**	**1730**	**880**	**286**	**372**	**3951**	**135**	**2316**	**10125**		
% Omiss.	**19**	**8**	**10**	**4**	**23**	**6**	**30**	**9**			

OVERALL CLASSIFICATION ACCURACY = 9237/10125 = 91%
OVERALL COMMISSION/OMISSION ERROR = 888/10125 = 9%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 90% - 92%

TABLE 4.19 ACCURACY-ERROR STATISTICS FOR MAXIMUM LIKELIHOOD CLASSIFICATION OF 1991 IMAGERY : FYLINGDALES EXTRACT

"no data pixels" in the areas that were missing from the quadrant as a result of problems of extracting the 1991 quarter scene from the full scene image. This means that all data pixels in all three extracts were classified.

The statistics in Tables 4.17-4.19 show that the maximum likelihood classifier performed quite as well with the 1991 data as it did with the 1985 data. It gave overall accuracy of 86% in the Rosedale extract, 87% in the Wheeldale extract and 91% in the Fylingdales extract. In the first two extracts, the overall accuracy levels were 3 and 2 percentage points lower than the corresponding overall accuracy levels achieved in classifying the 1985 imagery. In the Fylingdales extract, the classifier gave the same overall accuracy level in the classification of both the 1985 and 1991 data.

The classifier also gave very satisfactory individual class accuracy levels. In the Rosedale extract, the least correctly classified class was the fire damaged moorland (D1) with an accuracy of only 61%. The bare field class (P1) had a slightly higher accuracy of 65%. All the other categories had accuracy levels of more than 80%. In the Wheeldale extract, as with the 1985 data, the fire damaged moorland class (D1) was once again the least correctly classified with an accuracy level of only 44%. Grass moor was poorly classified too. It had an accuracy level of only 60%. The other classes had accuracy levels of over 70%. In the Fylingdales extract, all classes had accuracy levels of more than 70%.

Bracken had a classification accuracy of 81% in each of the three extracts. This is just 4 percentage points lower than the acceptable minimum accuracy level for effective land cover mapping. Dry heather moorland class (D2+D3) had accuracy levels of 93% in Rosedale, 93% in Wheeldale and 92% in Fylingdales . These translate into an average accuracy level of about 93%. The average classification accuracy level for wet heath was 87%. For the agro-pastoral land (G2), the accuracy levels obtained were 90% in Rosedale, 94% in Wheeldale and 94% in Fylingdales. These therefore

translate into an average accuracy level of 93%. The average accuracy levels for broadleaved woodland and coniferous forests were 85% and 92% respectively.

The statistics presented above indicate that the maximum likelihood classifier proved effective in extracting information about moorland and related cover types from the summer 1991 imagery, just as it did in classifying the spring 1985 imagery. The classifier left no unclassified data pixels in all the extracts. It gave very satisfactory overall accuracy levels in all the extracts. It also gave individual class accuracy levels of around or above 85% for those land cover types that are important in making decisions about resource management. However, it still failed to produce more than just satisfactory results for the grass moor class which had an average accuracy of 74%.

In all three extracts, some individual classes were much more correctly classified on the 1991 imagery than on the 1985 imagery, and *vice versa* for other classes. For instance, in all the extracts, bracken (B1), fire damaged moorland (D1) and wet heath (W1) were generally much more correctly classified on the spring 1985 imagery than on the summer 1991 imagery. By contrast, dry heather moorland (D2+D3) was generally better classified on the summer imagery than on the spring 1985 imagery.

4.5.1.5 *Minimum Distance Classification, 1991 Data*

The minimum distance classifier left more unclassified pixels than the maximum likelihood classifier. But compared with the minimum distance classification of the 1985 data, that of the 1991 data left relatively fewer unclassified pixels. Tables 4.5-4.7 show that 21.35% pixels were left unclassified in the Rosedale extract; just under 1% in the Wheeldale extract, and 5% (excluding the "no data pixels") in the Fylingdales extract. These compare to the 28.44%, 30.88% and 18.76% unclassified pixels left in the minimum distance classification of the 1985 data in the three extracts respectively.

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**TOTAL**	**% Correct**	**% Commi**
B1	312			43		2	14	19	**390**	**66**	**17**
D1		1173	23				7		**1203**	**83**	**2**
D2+D3	12	101	2876	35	18	47	43		**3132**	**81**	**7**
F1	77		282	282	33		56	11	**741**	**57**	**93**
F2			11	10	262				**283**	**79**	**6**
G1	11		51	60	7	595	308	3	**1035**	**68**	**50**
G2		62	141	22		203	2407		**2835**	**83**	**15**
P1	50	2	11	34			29	71	**197**	**65**	**118**
Unclassi.	8	71	151	9	12	25	28	5	**309**		
TOTAL	**470**	**1409**	**3546**	**495**	**332**	**872**	**2892**	**109**	**10125**		
% Omiss.	**34**	**17**	**19**	**43**	**21**	**32**	**17**	**35**			

OVERALL CLASSIFICATION ACCURACY = 7978/10125 = 79%
OVERALL COMMISSION/OMISSION ERROR = 2147/10125 = 21%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 78% - 80%

TABLE4.20 ACCURACY-ERROR STATISTICS FOR MINIMUM DISTANCE CLASSIFICATION OF 1991 IMAGERY : ROSEDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS											
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	742		9	87	47	12	162		24	**1083**	**85**	**39**
D1		10								**10**	**22**	**0**
D2+D3	21	29	2254	220	41		33		345	**2943**	**88**	**27**
F1	11		123	978	62		11		52	**1237**	**74**	**20**
F2				45	1454					**1499**	**87**	**3**
G1						104				**104**	**39**	**0**
G2	57					127	1554	96		**1834**	**88**	**16**
P1	29		47				12	216		**304**	**67**	**28**
W1	10	7	125		54	23			867	**1086**	**67**	**17**
Unclassif.	8				9			8		**25**		
TOTAL	**878**	**46**	**2558**	**1330**	**1667**	**266**	**1772**	**320**	**1288**	**10125**		
% Omiss.	**15**	**78**	**12**	**26**	**13**	**61**	**12**	**33**	**33**			

OVERALL CLASSIFICATION ACCURACY = 8179/10125 = 81%
OVERALL COMMISSION/OMISSION ERROR = 1946/10125 = 19%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 80% - 82%

TABLE 4.21 ACCURACY-ERROR STATISTICS FOR MINIMUM DISTANCE CLASSIFICATION OF 1991 IMAGERY : WHEELDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	341	32	15			81		37	**506**	**75**	**36**
D2+D3	10	1478	26			7		189	**1710**	**85**	**13**
F1	10	41	681	7	18	20			**777**	**77**	**11**
F2		15	48	256				47	**366**	**89**	**39**
G1					205	35			**240**	**55**	**9**
G2	80	30	74	3	128	3668	15		**3998**	**93**	**8**
P1						76	97		**173**	**72**	**57**
W1		114	24	20	21	5		2016	**2200**	**87**	**8**
Unclassif.	14	20	12			59	23	27	**155**		
TOTAL	**455**	**1730**	**880**	**286**	**372**	**3951**	**135**	**2316**	**10125**		
% Omiss.	**25**	**15**	**23**	**11**	**45**	**7**	**28**	**13**			

OVERALL CLASSIFICATION ACCURACY = 8742/10125 = 86%
OVERALL COMMISSION/OMISSION ERROR = 1383/10125 = 14%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL: 85% - 87%

TABLE4.22 ACCURACY-ERROR STATISTICS FOR MINIMUM DISTANCE CLASSIFICATION OF 1991 IMAGERY : FYLINGDALES EXTRACT

The minimum distance classifier gave lower levels of overall classification accuracy than the maximum likelihood classifier. The statistics in Tables 4.20-4.22 show that the overall accuracy levels were 79% in Rosedale, 81% in Wheeldale and 86% in Fylingdales. These levels were respectively 6, 6 and 5 percentage points lower than the overall accuracy levels obtained under the maximum likelihood classification in those three extracts.

In terms of individual class accuracy, the classifier did well for only a few classes. For instance, heather moorland (D2+D3) had an average accuracy of 85% and so too the coniferous forest (F2) class. The average accuracy levels for wet heath and agro-pastoral land were 86% and 88% respectively. But bracken, which is one of those land cover types that have great impact on resource management decisions was less correctly classified by the minimum distance classifier. It had an average accuracy level of 75%. The classifier gave even less encouraging results for broadleaved woodland (F1) and grass moor (G1) whose average classification accuracy levels were only 69% and 62% respectively.

The minimum distance classifier had therefore only modest successes in extracting information from the image data compared to the maximum likelihood classifier. It left more unclassified pixels, and gave lower class accuracy levels to more classes than the maximum likelihood classifier. The overall accuracy levels and most of the individual class accuracy levels were, however, very close to those given by the classifier for the 1985 data.

4.5.1.6 *Parallelepiped (Box) Classification, 1991 Data*

The parallelepiped classifier left significant numbers of unclassified pixels in classifying the 1991 imagery, just as it did in classifying the 1985 imagery. The probable reasons for this have already been discussed in section 4.5.1.3. In the Rosedale and Fylingdales extracts, it left more unclassified pixels than either of the

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**TOTAL**	**% Correct**	**% Commi**
B1	346			43	7	5	171	5	**577**	**74**	**49**
D1	25	978	36					7	**1046**	**69**	**5**
D2+D3		244	3264	33	41	71	16		**3669**	**92**	**11**
F1	7	11	109	299	20		32		**478**	**60**	**36**
F2			33	75	248		13		**369**	**75**	**37**
G1	32		29	28		546	115		**750**	**63**	**23**
G2	52		19	8		217	1858	14	**2168**	**64**	**11**
Unclassif.	8	176	56	9	16	33	687	83	**1068**		
TOTAL	**470**	**1409**	**3546**	**495**	**332**	**872**	**2892**	**109**	**10125**		
% Omiss.	**26**	**31**	**8**	**40**	**25**	**37**	**36**	**100**			

OVERALL CLASSIFICATION ACCURACY = 7622/10125 = 75%
OVERALL COMMISSION/OMISSION ERROR = 2503/10125 = 25%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 74% - 76%

TABLE 4.23 ACCURACY-ERROR STATISTICS FOR PARALLELEPIPED CLASSIFICATION OF 1991 IMAGERY : ROSEDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS											
	B1	**D1**	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	753		34	17		18	236	98		**1156**	**86**	**46**
D1		40	48							**88**	**87**	**104**
D2+D3		6	2290	98	43		44	38	819	**3338**	**90**	**41**
F1	23		163	897	91		23		112	**1309**	**67**	**31**
F2			14	236	1448		29		214	**1941**	**87**	**30**
G1	29		9	66	30	151	2			**287**	**57**	**52**
G2	73			16	55	97	1357	113		**1711**	**77**	**20**
Unclassif							81	71	143	**295**		
TOTAL	**878**	**46**	**2558**	**1330**	**1667**	**266**	**1772**	**320**	**1288**	**10125**		
% Omiss.	**14**	**13**	**10**	**37**	**13**	**43**	**37**	**100**	**100**			

OVERALL CLASSIFICATION ACCURACY = 6936/10125 = 69%
OVERALL COMMISSION/OMISSION ERROR = 3189/10125 = 31%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 68% - 70%

TABLE 4.24 ACCURACY-ERROR STATISTICS FOR PARALLELEPIPED CLASSIFICATION OF 1991 IMAGERY : WHEELDALE EXTRACT

IMAGE DATA CLASSES	CLASSES ON REFERENCE MAPS										
	B1	**D2+D3**	**F1**	**F2**	**G1**	**G2**	**P1**	**W1**	**TOTAL**	**% Correct**	**% Commi**
B1	276	18	17		29	39	5	51	**435**	**61**	**35**
D2+D3	5	1537	36		8	37		407	**2030**	**89**	**28**
F1	7	48	661	11	20	36	2	55	**840**	**75**	**20**
F2			105	270	6	43		19	**443**	**94**	**60**
G1	46	11			264	424	9		**754**	**71**	**132**
G2	121	35	61	5	45	3015	19		**3301**	**76**	**7**
Unclassif.		81				357	100	1784	**2322**		
TOTAL	**455**	**1730**	**880**	**286**	**372**	**3951**	**135**	**2316**	**10125**		
% Omiss.	**39**	**11**	**25**	**6**	**29**	**24**	**100**	**100**			

OVERALL CLASSIFICATION ACCURACY = 6023/10125 = 60%
OVERALL COMMISSION/OMISSION ERROR = 4102/10125 = 40%
ACCURACY LIMITS AT 99% CONFIDENCE LEVEL : 59% - 61%

TABLE 4.25 ACCURACY-ERROR STATISTICS FOR PARALLELEPIPED CLASSIFICATION OF 1991 IMAGERY : FYLINGDALES EXTRACT

other two classifiers. In the Wheeldale extract, the parallelepiped and minimum distance classifiers left just about the same amounts of unclassified pixels.

The accuracy statistics in Tables 4.23-4.25 indicate that the classifier had modest successes in terms of overall accuracy levels. As already stated in section 5.5.1.3, this was expected because the classifier works with a maximum of only 8 classes and therefore some of the categories were not classified. The overall accuracy level in the Rosedale extract was 75%, in the Wheeldale extract it was 69% and in the Fylingdales extract it was 60%. There was only one small unclassified category in the Rosedale extract, the bare fields (P1) category. It therefore did not have much influence in reducing the overall accuracy in that extract. By contrast, in the Wheeldale and Fylingdales extracts, in addition to the bare fields (P1) category, there was the extensive wet heath (W1) category which was equally not classified. The overall accuracy levels were therefore considerably reduced by the fact that such an extensive category was not classified. Tables 4.21-4.22 show that the overall accuracy levels in the two extracts were only 69% and 60% respectively.

However, the classifier produced very encouraging results for some individual classes. The dry heather moorland category (D2+D3), for instance, had accuracy of 92% in the Rosedale extract; 90% in the Wheeldale extract; and 89% in the Fylingdales extract. These values translate into an average accuracy level of 90% which is really very satisfactory. Similarly, the coniferous forest category (F2) had accuracy of 75% in the Rosedale extract; 87% in the Wheeldale extract; and 94% in the Fylingdales extract, giving an average of 85% which is the minimum required for effective resource mapping. Most of the remaining classes had average accuracy levels of around 70%.

The performance of the parallelepiped classifier, just as that of the other two, appeared to have been influenced by the season of data acquisition. For instance, in all the extracts, the strategy classified the spring bracken on the 1985 imagery with

higher levels of accuracy than it did with the summer bracken on the 1991 imagery. The same is true for the broadleaved woodland category (F1). Conversely, in all the extracts, the strategy classified the dry moorland category much more correctly on the summer 1991 imagery than it did on the spring 1991 imagery. The same is true for the coniferous forest category (F1).

4.5.2 Patterns of Classification Error

It has been noted in the preceding discussion that the three classifiers performed differently. In general, the maximum likelihood classifier yielded more satisfactory results than the other two strategies. It gave fairly consistent high overall and individual class accuracy levels for both 1985 and 1991 data sets in all the three extracts. The minimum distance and parallelepiped classifiers gave relatively lower and less consistent overall and individual class accuracy levels. The two classifiers (parallelepiped and minimum distance) gave class accuracy levels that, in most cases, were within close ranges. The reason for this might have been the fact that the parallelepiped classifier on R-CHIPS is a "hybrid" which incorporates minimum distance principles in its operation, and therefore, to some extent it works like a minimum distance classifier.

Whilst the maximum likelihood classifier produced more satisfactory results, and the other two produced more omission and/or commission errors, a closer examination of the colour-coded and accuracy-tested classified images revealed that the spatial distribution pattern of the erroneously classified pixels was similar in all three types of classification. Thus, while the magnitude of error differed among the three classifications, the pattern of error was nevertheless similar in all of them.

The accuracy-tested image outputs of the three classifications showed that in all of them errors in classification were not randomly distributed. Instead, the incorrectly classified pixels tended to occur more in some locations than in others; and as groups

of contiguous pixels and not as isolated single pixels. Similarly, it was discovered that misclassification tended to occur more in areas of land cover of particular sizes. Finally, the season of data acquisition seemed to have an effect on the degree of misclassification for some land cover types.

As for the location of classification error, the classified and accuracy-tested images revealed that most incorrectly classified pixels occurred in the transitional zones between different land cover types. All three classifiers did not do well in the transitional zones. The minimum distance and parallelepiped classifiers either misclassified or failed to classify pixels in such zones. Similarly, 8 in 10 pixels misclassified by the maximum likelihood classifier occurred in similar zones.

The occurrence of much classification error in the transitional zones results most probably from the unsatisfactory assumption on which the whole concept of classification is based. The concept of land cover classification is based on the assumption that ground surface components, mainly vegetation, comprise discrete and mutually exclusive categories that can be identified and discriminated (Foody and Trodd, 1990). All conventional classification strategies like minimum distance, parallelepiped and maximum likelihood classifiers therefore seek to identify discrete and recurring patterns of land cover, and to draw boundaries around them. These classifiers have therefore worked more successfully in agricultural lowlands where sharp boundaries can be recognised on the ground and on remotely sensed images (McMorrow and Hume, 1986). They have, however, been less successful in areas like the moorlands where communities tend to form the end points of continua (Wood and Foody, 1989) and where the transition from one land cover type to another is therefore gradual. In the gradual zones of transition, pixels display properties of two or more land cover types. Since a classifier has to allocate each pixel to one class only, then the mixed pixels in such transitional zones are therefore expected to be misclassified (Foody and Trodd, 1990; 1993) or not classified at all.

As regards relationship between classification error and particular sizes and spatial distribution pattern of land cover, it was discovered that the classifiers performed less well for narrow, linear features and/or small and isolated features. These included acid flushes (wet peat grass moor); upland grass moor on moorland edge; hedge rows and broadleaved/mixed woodland plots on farms, along streams and along the sides of roads. Misclassification of such narrow, linear features and/or small isolated patches of different land cover types results most probably from the coarseness of the spatial resolution of the TM sensor. Most of the acid flushes, for instance, are less than 30m wide (Soulsby, Pers. Comm.). It means therefore that such features cannot register signals that would fill whole 30m x 30m pixels on the imagery; and as a result, they tend to be represented by mixed pixels which, as stated above, are a great source of classification error.

The results also showed that the season of data acquisition may affect levels of classification accuracy achieved for some land cover types. Spring bracken on the 1985 imagery, for instance, was relatively more correctly classified by all the classifiers than summer bracken on the 1991 imagery. Similarly, wet heath was more correctly classified on the spring 1985 imagery than on the summer 1991 imagery where it tended to be confused with dry heather moorland probably owing to the effect of flowers. Dry heather moorland, on the other hand, was more correctly classified on the summer 1991 imagery than on the spring 1985 imagery. The results also showed that there was much confusion between broadleaved woodland and dry heather moorland on the summer imagery than on the spring imagery. These are all examples of how the season of image data acquisition may affect classification results.

PLATE 4.1: MAXIMUM LIKELIHOOD CLASSIFICATION FOR THE 1985 DATA : ROSEDALE EXTRACT

LAND COVER CLASS	COLOUR ON THE IMAGE
1. Bracken	Brown
2. Fire damaged moorland	Pink
3. Young heather moorland communities	Green
4. Established heather moorland communities	Dark blue
5. Broadleaved and mixed woodland	Black
6. Coniferous forest	Dark green
7. Grass moor	Red
8 & 9. Agro-pastoral	Orange
10. Bare ground	White

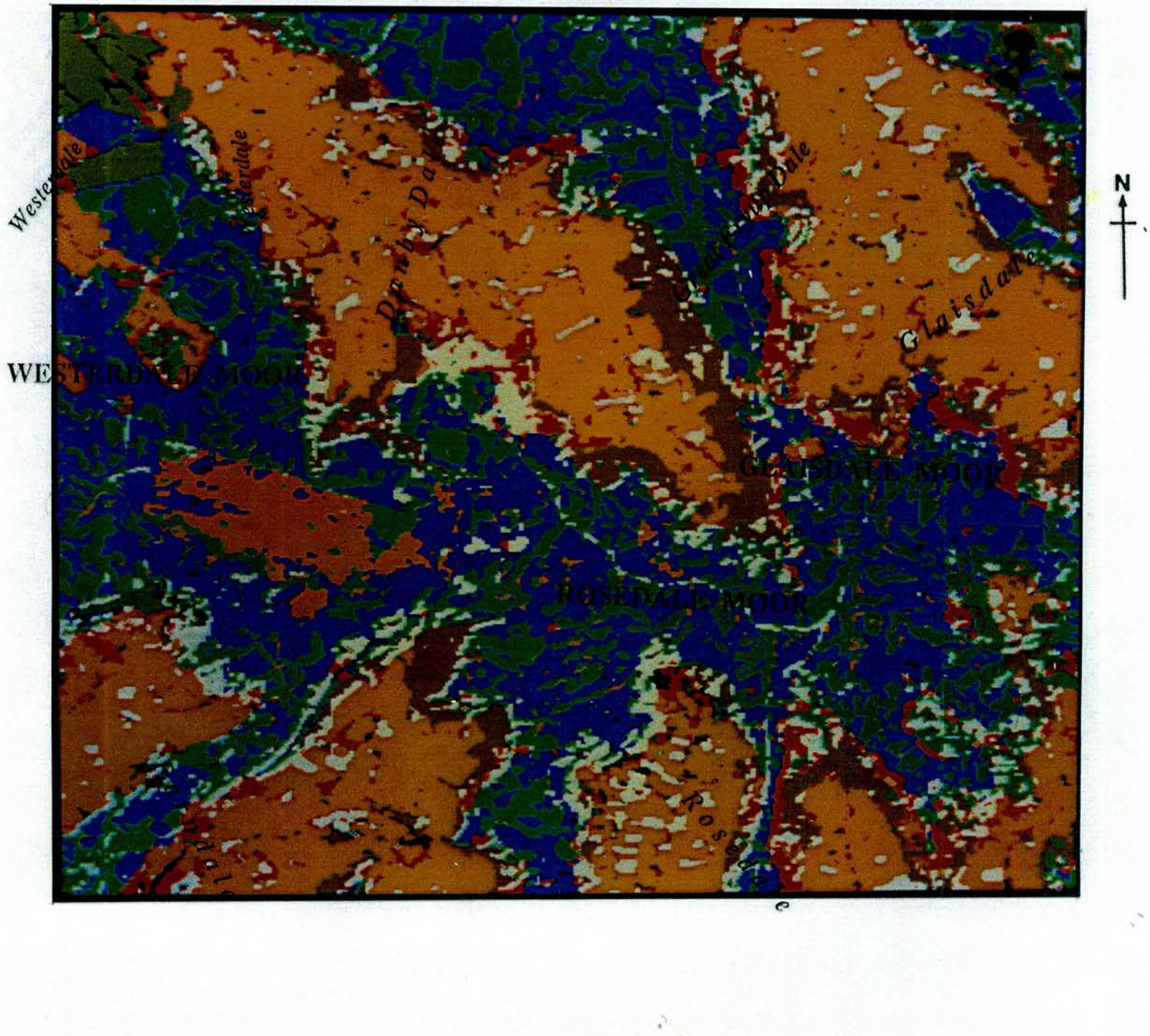
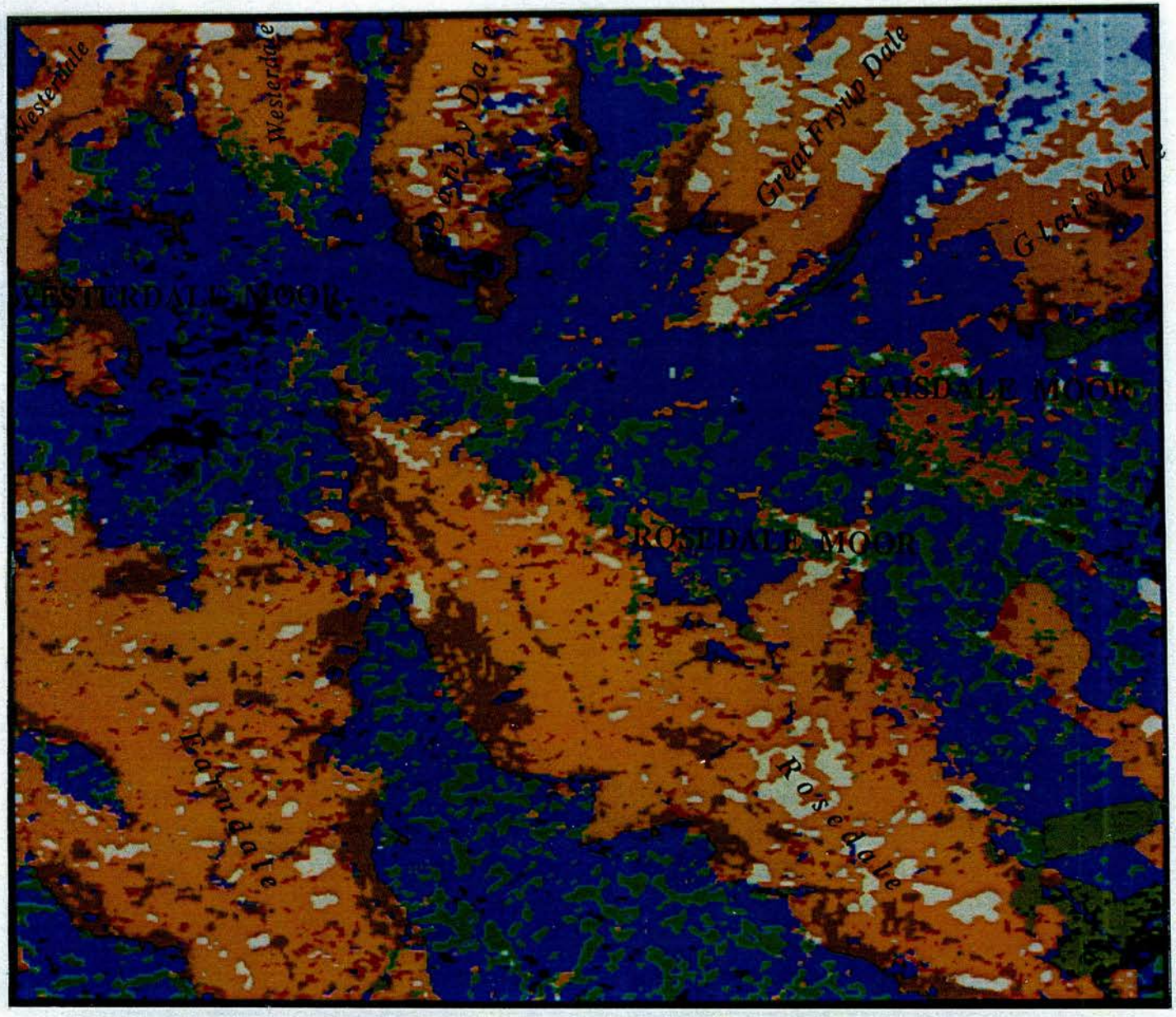

Westerdale
Westerdale
Danby Dale
Glaisdale
WESTERDALE MOOR
GLAISDALE MOOR
ROSEDALE MOOR
N
0
1
2 Km

PLATE 4.2 : MAXIMUM LIKELIHOOD CLASSIFICATION FOR THE 1991 DATA : ROSEDALE EXTRACT

LAND COVER CLASS	COLOUR ON THE IMAGE
1. Bracken	Brown
2. Fire damaged moorland	Pink
3. Young heather moorland communities	Green
4. Established heather moorland communities	Dark blue
5. Broadleaved and mixed woodland	Black
6. Coniferous forest	Dark green
7. Grass moor	Red
8 & 9 Agro-pastoral	Orange
10. Bare ground	White


Westerdale
Westerdale
Great Fryup Dale
Glaisdale
WESTERDALE MOOR
GLAISDALE MOOR
ROSEDALE MOOR
Rosedale
Eskdale

N

0 1 2 Km

PLATE 4.3: MAXIMUM LIKELIHOOD CLASSIFICATION FOR THE 1985 DATA: WHEELDALE EXTRACT

LAND COVER CLASS	COLOUR ON THE IMAGE
1. Bracken	Brown
2. Fire damaged moorland	Pink (post-classification smoothing made the 21 pixels for this class less visible on the image)
3. Young heather moorland communities	Green
4. Established heather moorland communities	Dark blue
5. Broadleaved and mixed woodland	Blue
6. Coniferous forest	Dark green
7. Grass moor	Red
8 & 9. Agro-pastoral	Orange
10. Bare ground	White
11. Wet heath	Yellow

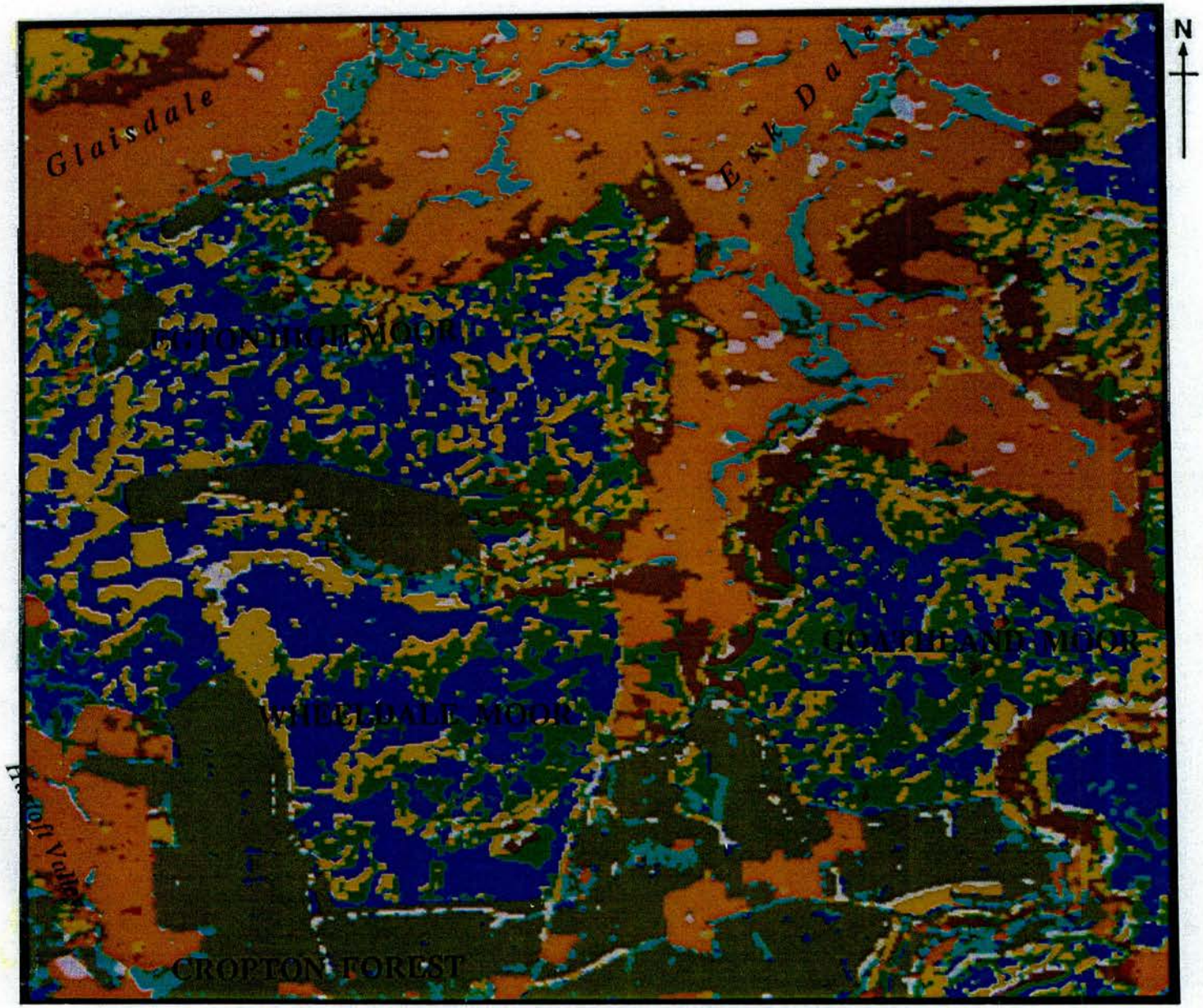

Glaisdale
Esk Dale
CROPTON HIGH MOOR
COAT LEAND MOOR
WHEELDALE MOOR
CROPTON FOREST
N
1
2 Km

PLATE 4.4: MAXIMUM LIKELIHOOD CLASSIFICATION FOR THE 1991 DATA: WHEELDALE EXTRACT

LAND COVER CLASS	COLOUR ON THE IMAGE
1. Bracken	Brown
2. Fire damaged moorland	Pink (post-classification smoothing made the 40 pixels for this class less visible)
3. Young heather moorland communities	Green
4. Established heather moorland communities	Dark blue
5. Broadleaved and mixed woodland	Blue
6. Coniferous forest	Dark green
7. Grass moor	Red
8 & 9. Agro-pastoral	Orange
10. Bare ground	White
11. Wet heath	Yellow

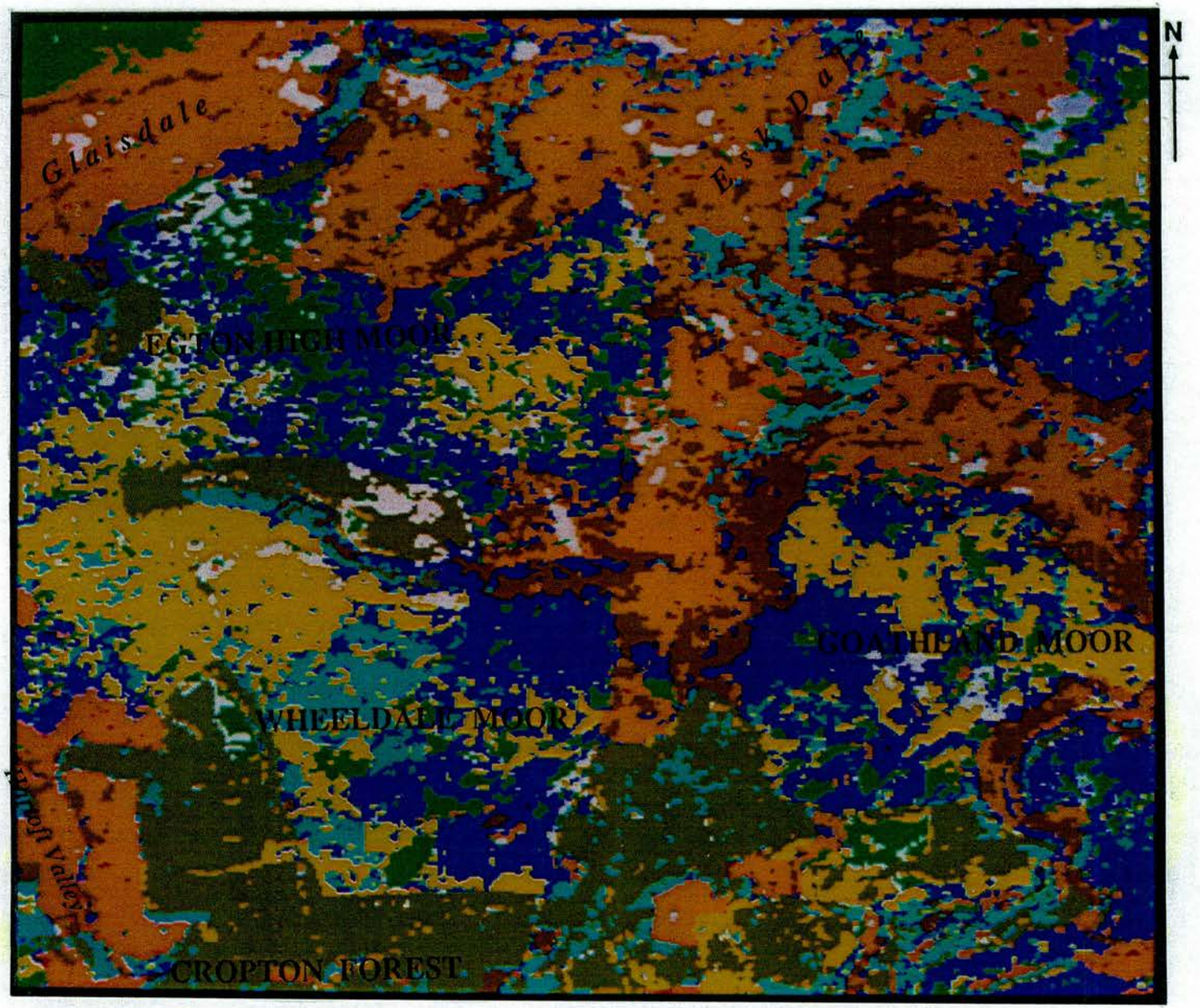

N
Glaisdale
Esk Dale
EGTON HIGH MOOR
GOATHLAND MOOR
WHEELDALE MOOR
Lockton Valley
CROPTON FOREST
1
2 Km

PLATE 4.5 MAXIMUM LIKELIHOOD CLASSIFICATION FOR THE 1985 DATA: FYLINGDALES EXTRACT

LAND COVER CLASS	COLOUR ON THE IMAGE
1. Bracken	Brown
2. Young heather moorland communities	Green
3. Established heather moorland communities	Dark blue
4. Broadleaved and mixed woodland	Blue
5. Coniferous forest	Dark green
6. Grass moor	Red
7 & 8. Agro-pastoral	Orange
9.Bare ground	White
10. Wet heath	Yellow

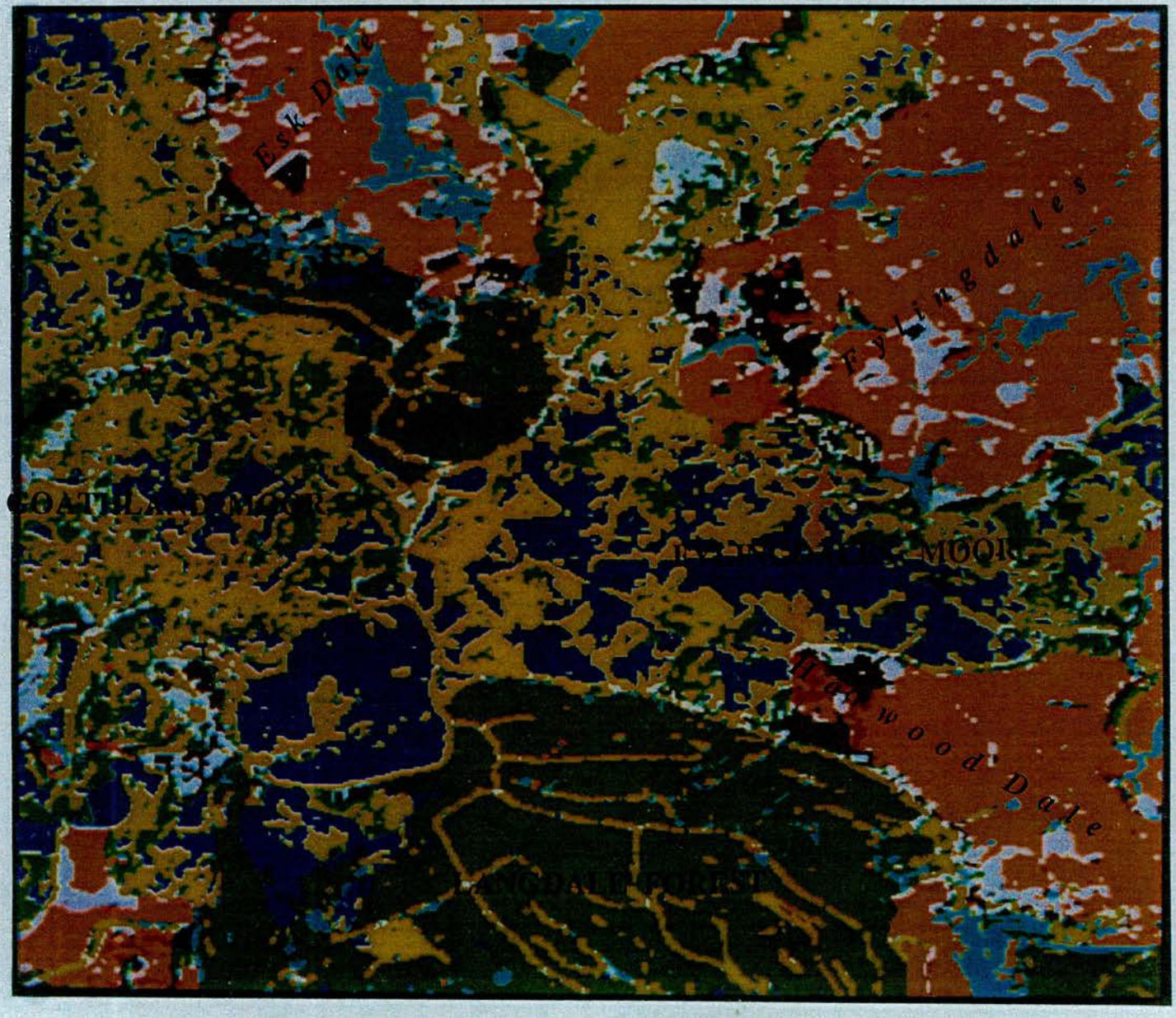
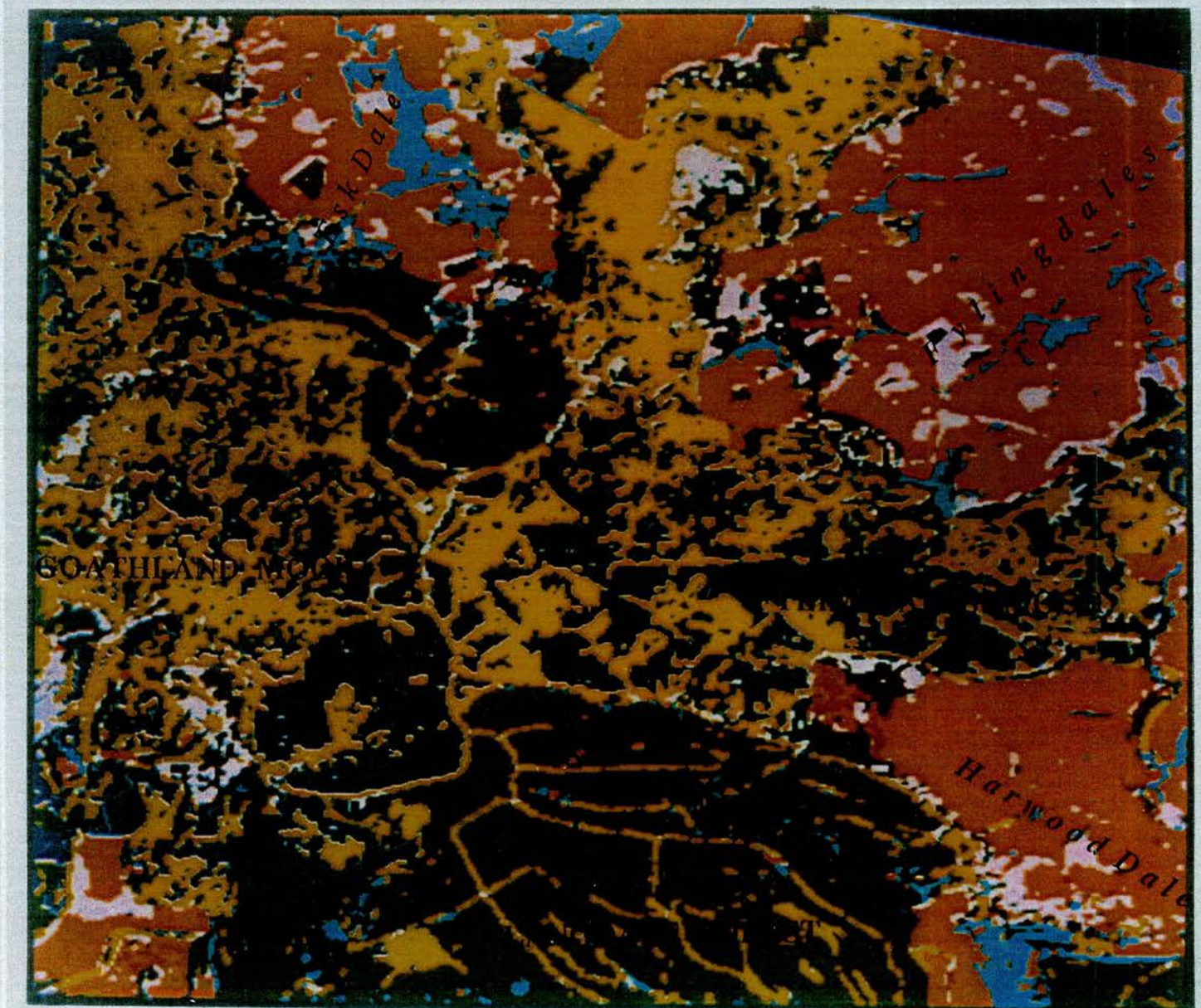

Esk Dale
Eskingdales
COATHLAND MOOR
MOOR
Hawood Dale
N
0
1
2 Km

PLATE 4.6: MAXIMUM LIKELIHOOD CLASSIFICATION FOR THE 1991 DATA: FYLINGDALES EXTRACT

LAND COVER CLASS	COLOUR ON THE IMAGE
1. Bracken	Brown
2. Young heather moorland communities	Green
3. Established heather moorland communities	Dark blue
4. Broadleaved and mixed woodland	Blue
5. Coniferous forest	Dark green
6. Grass moor	Red
7 & 8. Agro-pastoral	Orange
9. Bare ground	White
10. Wet heath	Yellow



N

0 1 2 Km

4.5.3 Implications of Classification Results for Resource Surveys

The results of image classification showed the extent to which the three methods of classification could extract information about land cover from sets of remotely sensed data. Considering the results of the classifications of both the 1985 and 1991 data together, it was discovered that the maximum likelihood classifier gave an average overall accuracy level of 89%. This is 4 percentage points higher than the minimum accuracy level required for effective resource mapping. The classifier also yielded high class accuracy levels for those categories that are particularly important in making resource management decisions. The image outputs of the maximum likelihood classification could therefore be regarded as reliable data bases for making resource management decisions. Besides, the classifier left no or negligible amounts of unclassified pixels, which means that it tried to extract information from each and every section of the imagery. Thus, information was made available for all parts of the area, and not only parts of it, as would normally happen when information were to be collected exclusively through ground survey (Robinove, 1981). Hard copies of the outputs of maximum likelihood classification are presented here in Plates 4.1-4.6.

The maximum likelihood classifier, however, did not do well in the transitional zones between land cover classes so that the boundaries between the classes as shown on Plates 4.1-4.6 are not reliable. But the problem of boundaries is not only encountered when producing maps through the classification of remotely sensed data. It is rather a common problem in all types of mapping, especially where the phenomena being mapped change very gradually over space. Thus, the dilemma regarding where to place a boundary between one category and another is always faced in all types of mapping where the phenomena being mapped form a continuum with gradual transition from one category to another. The normal tendency is to choose a point within a continuum, whether arbitrarily or through some calculations of distance, and then draw a line through it to divide the categories (Robinove, 1981). This is basically the same as the method used by the maximum likelihood classifier in determining

boundaries between the different land cover categories. Thus, either through conventional mapping or maximum likelihood classification, boundaries defined between categories that do not have clear-cut discontinuities between them are not realistic. It might therefore be argued that the products of maximum likelihood classification should not be considered as invalid data bases because of the problem of class boundaries just as the outputs of conventional resource mapping are normally not rejected despite the fact that they also have the same problem.

As stated earlier (section 4.5.2), the classification problem in the transitional zones originates from the assumption on which the very idea of image classification is based. Thus, in order to overcome this problem, one has to go beyond the realms of classification. In basic biogeography, dissatisfaction with classification led to the popularisation of ordination as an alternative analytical approach. Ordination, like classification, stresses orderly tendencies in data, but instead of segregating data into clusters, it produces clines which reflect the continuous nature of vegetation change over space and the absence of discrete associations (Randall, 1978). Parallel developments are taking place in the remote sensing of environments with complex structure of land cover. With reference to moorland areas, for instance, Morton (1986) and Wood and Foody (1989) attempted to incorporate ordination principles in classification algorithms in order to effectively extract information about moorland cover types and their spatial patterns from remotely sensed data. Similarly, Foody and Trodd (1990; 1993) tried to use probability surface mapping techniques to model the continuous nature of heathland communities on remotely sensed data.

Where the continuous nature of moorland and related land cover has to be reproduced, then integrated classification-ordination algorithms such as those used by Morton (1986) and Wood and Foody (1989); or alternatively classification algorithms with modelling functions such as the one used by Foody and Trodd (1990; 1993), have to be acquired and used in the analysis of image data. However, boundaries do not matter for most purposes of thematic data bases. It is further argued that the

importance of land cover classes is not in their boundaries but in the fact that they are functional entities that simplify reality and therefore help people to understand the structure and distribution pattern of vegetation resources (Randall, 1978).

The image outputs of the minimum distance and parallelepiped classifications cannot be directly regarded as valid resource maps because, in most of the cases, the two classifiers gave average overall accuracy levels, and average class accuracy levels of less than the 85% required minimum. The two classifiers also left significant amounts of unclassified pixels, which is an indication that they failed to extract information from all parts of the imagery. However, this does not mean that the image outputs of the two classification strategies are completely worthless. Accuracy levels for most of the classes in both types of classification were in the region of 60-80%. It is possible to build on this 60-80% correct information in order to produce more reliable resource maps. This can be accomplished by undertaking ground survey covering the 20-40% misclassified and/or unclassified areas. The data collected from the ground would be used to fill in the "information gaps". Alternatively, reliable maps and aerial photographs can be consulted to provide accurate information about the misclassified and/or unclassified areas.

The ancillary information collected either by supplementary ground survey or by referring to aerial photographs and maps, can be cartographically integrated with the outputs of image classification to produce resource maps. The resulting resource maps may even be more reliable than those produced based exclusively on ground survey. In ground-based resource surveys, the maps are produced by extrapolating the information acquired from some sample areas (Justice and Townshend, 1981; Robinove, 1981). The resulting maps may therefore have relatively larger margins of error than those compiled through an approach that involves gathering correct information from image data where possible, and supplementing it with ground survey where image classification fails to extract correct information.

The fact that the parallelepiped algorithm on R-CHIPS can classify data into not more than 8 classes might be a drawback where the strategy is used in classifying imagery for areas with a greater diversity in land cover types. One possible way to avoid the classifier leaving many land cover categories unclassified would be to work on extremely small extracts. But this increases the time and cost of analysis particularly where the resource information is required for a larger area.

".....survey was what we have all been doing for years; it is an inventory; it is static in its background philosophy and it is usually done once only. On the other hand monitoring is purpose orientated; it tells us how something(s) is/are changing; it is repeated at regular intervals and it often provides the baseline for recording possible change in the future. Thus it is dynamic in philosophy....."

B. Goldsmith, *Preface* in Goldsmith, F. B (ed) 1992 **p x**

"Implicit in the rationale for most monitoring activities is a recognition of the potential for change. One is concerned, therefore, to secure a means of detecting that change has occurred, of establishing its direction and of measuring its extent or intensity."

J. M. Hellawell (1992) **p 1**

CHAPTER 5
DETECTING LAND COVER CHANGES USING MULTI-TEMPORAL LANDSAT TM DATA

This chapter describes the work undertaken to discover whether land cover changes could be effectively detected using multi-temporal satellite data. It begins with general discussions on the importance of change detection in resource planning and the methods that are normally employed in detecting change. The types of change that are under investigation in this project are also described. The procedures followed in trying to detect the changes, and in assessing change detection accuracy are outlined. The results obtained are presented and discussed. The chapter ends with an assessment of what the results obtained suggest as regards the potential of using multi-temporal satellite data for monitoring land cover.

5.1 SIGNIFICANCE OF CHANGE DETECTION IN RESOURCE PLANNING

Just like many things in nature, a resource base can never be completely static over any long period of time. The quantity and/or condition of resources are bound to change over time as a result of management practices; developmental pressures such as the spread of urban development into hitherto rural areas; natural cycles like succession in vegetation; and episodic events such as floods, drought, uncontrolled fires, epidemics like the Dutch elm, and other damage by pests.

Changes brought about by management practices are normally intended and are therefore deliberately induced. In moorland management, an example of deliberately induced change is the clearing of old heather through burning or cutting. Management practices may also bring about some unintended changes. For instance, the management practice of heather burning may encourage the spread of bracken or leave areas more susceptible to erosion.

Successional changes can be desirable or undesirable depending on the nature of the resource management programme. Where the main management objective is nature conservation, then successional changes are normally desirable and management is mainly oriented towards promoting such changes. Such is normally the case in the management of nature reserves, for instance. But where nature conservation is not the over-riding objective, then successional changes are normally reversed or halted by appropriate management practices. For instance, the management practice of heather burning is normally undertaken to prevent heather developing into the final phase of its life cycle, the degenerate stage.

Developmental pressures often have the effect of reducing the spatial extent of the available resources . Similarly, episodic events may reduce the quantity of resources, or they may cause deterioration in their condition.

Effective resource planning requires timely and accurate information about both the intended and unintended changes in the resource base. If change is a policy goal, then the information would help the planner to assess the extent to which the intended changes are being realised. Similarly, timely and accurate information about unintended changes would help the planner to assess the extent to which these might have resulted from some deficiencies in the existing management policies. Information about change therefore provides the basis for assessing the effectiveness or failures of existing resource management policies (Hellawell, 1992).

Where information about change suggests deficiencies in existing policies, it then provides the basis for redefining them or for formulating completely new management strategies. Information about change acquired after the implementation of the redefined or newly formulated policies would similarly provide the basis for judging their effectiveness. Where it is discovered that the redefined policies are not as effective as they were supposed to be, then new policies can be formulated again. Thus, after each policy evaluation exercise, information about change often leads

planning into new directions. In this case, resource planning can be envisaged not as a one-time event, but rather as an on-going process where change in the resource base is the major determinant of the direction into which the process is likely to proceed. The detection and monitoring of change is therefore basic to any effective resource management programme (Michalak, 1993).

5.2 COMMON METHODS FOR DETECTING LAND COVER CHANGE

Traditionally, changes in land cover have been analysed through manual comparison of maps or aerial photographs produced or acquired at different times, but covering the very same areas. However, developments in computer hardware and software technologies, coupled with declining costs of computer hardware in recent years, have revolutionised digital methods of change detection (Michalak, 1993). Multi-temporal satellite data are normally used in the computer-based digital change detection methods because they have the advantage of being in digital form already. Maps and aerial photographs have to be digitised first before they can be used in computer-based digital change detection methods. Both manual and digital methods of change detection are briefly described below.

5.2.1 Manual Methods

Before digital analysis of geographical data became common, researchers used manual methods for detecting change. Although digital methods of change detection are now more popular because they are time-saving and cost-effective, manual methods may still be very useful where the necessary equipment or expertise for digital change analysis may not be available.

Manual methods essentially involve visual comparison of maps or aerial photographs of different times but covering the same area(s). This comparison requires that the aerial photographs should have the same scale, and should have been acquired during

a similar season (Lindgren, 1985). Similarly, the maps should have the same scale, same projection and preferably the same land cover classification scheme.

There are many ways in which the visual comparison of maps or aerial photographs can be made. One way is to take the maps or aerial photographs from different times and lay them side-by-side. These are then viewed alternatively to identify areas where the features/ land cover on corresponding locations match or mismatch (Lindgren, 1985). Where they match, it would mean that no change had taken place. Where they do not match, it would mean that change had taken place.

An alternative way is to photocopy the maps or aerial photographs on to transparencies. These can be overlaid, preferably on a light table, in a way that would allow corresponding grid lines on maps or photo margins on aerial photographs to be perfectly registered to each other. The changes are detected by viewing the overlaid transparencies (Crapper and Hynson, 1983). Where the information on them match, then probably no change has taken place. But where the information on them do not match, then change may well have taken place.

Another approach involves the manipulation of positive and negative films to produce positive transparencies for photos of a given date, and negative transparencies for photos of another date (Crapper and Hynson, 1983; Milne, 1988). These can also be overlaid in a similar way as stated above. Once overlaid, areas on which no change has taken place would appear in uniform neutral tone. Those on which change has occurred would appear in darker or lighter tones (Crapper and Hynson, 1983).

Comparison may also be undertaken using a Zoom Transfer Scope. A photograph can be placed on the photo easel; another photograph or a map would be placed on the table below. The zoom magnification and anamorphic controls would then be adjusted in order to visually match the scales of the two photos or of the photo and the map. These can then be viewed simultaneously through the eye pieces of the Zoom

Transfer Scope to detect areas where the information on the two photos or on the photo and the map match or mismatch. A plain sheet of acetate or tracing paper can be spread over the photo or map on the table below the viewer, and the changes detected can be traced on it (Lindgren, 1985).

5.2.2 Digital Methods

Digital change detection involves the comparison of DN values of corresponding pixels in spatially registered multi-temporal data sets. Change is said to have taken place if the value of a pixel at time t_2 is different from its value at time t_1.

The underlying assumption of this digital concept of change is that differences in the DN values of corresponding pixels in spatially registered multi-temporal sets of data, indicate that changes in land cover had taken place. In reality, however, such differences can occur even when the land cover has not actually changed. For instance, in chapter 3 (section 3.5.2) it was discovered that for most land cover types their spectral values on the spring imagery were different from their values on the summer imagery. These differences were caused by seasonal growth changes in the communities as well as seasonal changes in atmospheric conditions and solar illumination angles. They did not result from actual change in land cover, where land cover change is in this case defined as an alteration in the surface components of landscape (Milne, 1988). In this way, the digital concept of change is realistically valid only where the spectral differences caused by extraneous factors, other than the actual alteration in the surface components of landscape, are identified and accounted for, or completely removed from the data set if possible (Milne, 1988).

The brightness intensity changes caused by phenology and seasonal variations in atmospheric conditions and solar illumination angles can be removed from the multi-temporal data sets by some computer modelling techniques (Berger, 1989; Milne, 1988; Vogelmann, 1988). These changes are, however, very minimal in multi-

temporal data sets comprising images acquired during the same time of the year. There is normally no significant variation in these conditions within the same month or season in different years unless there is a major climatic change or there is a major episodic event like drought. The use of anniversary or nearly-anniversary images is therefore the simplest way to exclude spectral changes caused by other factors as than the actual alteration in the components of landscape (Chuvieco, 1989; Jensen, 1986; Milne, 1988).

One prerequisite for effective digital change detection is perfect or nearly-perfect spatial registration of the multi-temporal data sets. If the multi-temporal data sets are unregistered or misregistered, then the differences in DN values that would be recorded would most probably result from the fact that the comparison is being made between pixels that do not represent the same areas on the ground. In order to avoid the recording of such spurious changes, the images need to be registered to within an accuracy of one pixel or less (Milne, 1988; Townshend and Justice, 1988) which is equivalent to a root mean square (RMS) error of less than 1.

There are a number of approaches that can be followed in undertaking digital change detection. These approaches fall into two broad categories, namely multispectral classification techniques and image enhancement techniques (Michalak, 1993; Wang and Newkirk, 1987). The main multispectral classification technique involves carrying out independent classification of each of the images in the multi-temporal data set. These classifications are then compared at the end to detect the changes as is illustrated in Figure 5.1a. The comparison can be undertaken through the overlay operation function available on many image processing systems. Alternatively, hard copies of the image outputs of the independent classifications can be produced and compared in much the same ways as aerial photographs (see section 5.2.1). A less common multispectral classification approach is the direct classification of multi-temporal data (Jensen, 1986; Singh, 1986) illustrated in Figure 5.1b. It involves taking all the *n* bands in the images of the different times, and displaying them

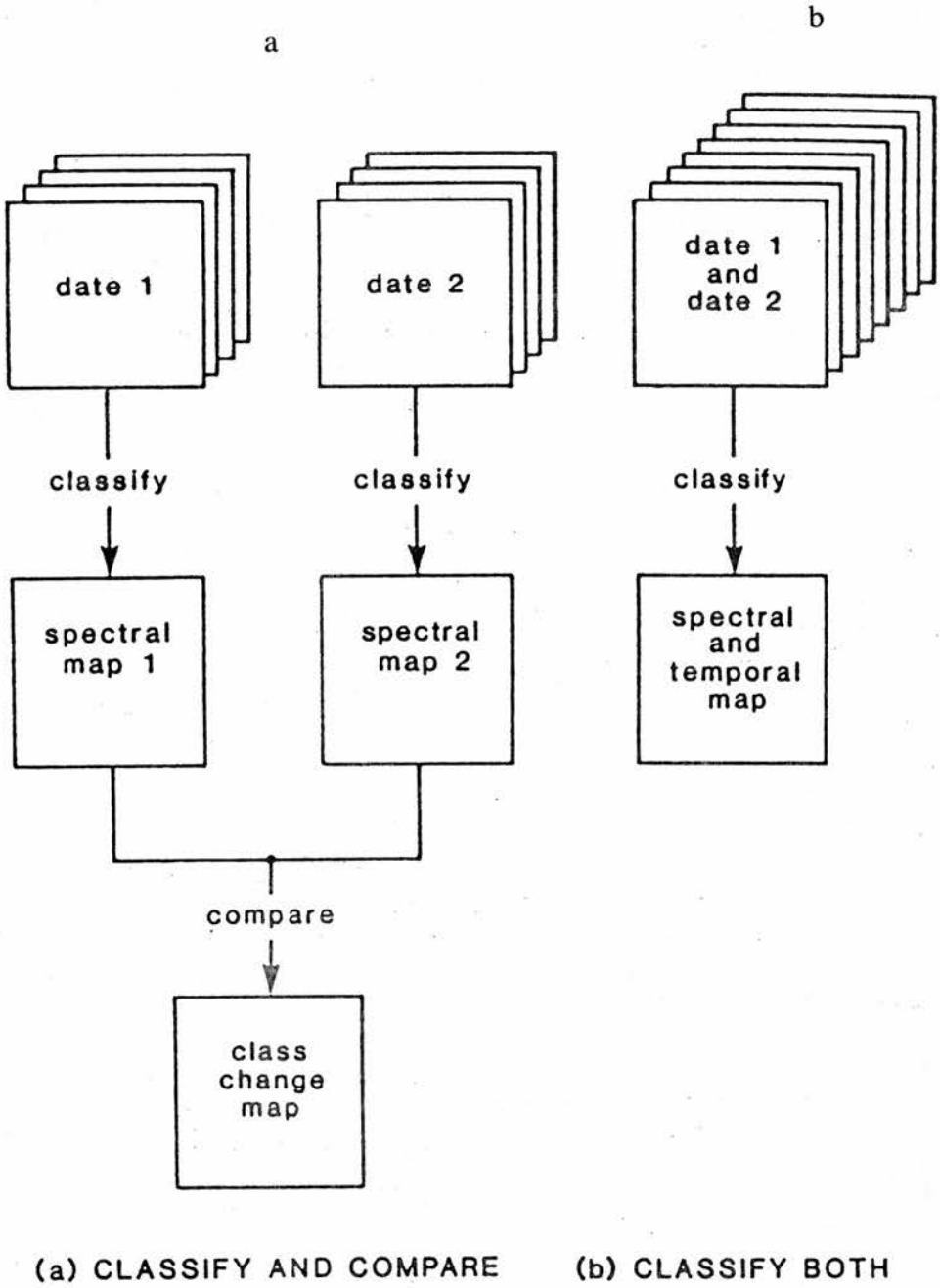


FIGURE 5.1 DIAGRAMS ILLUSTRATING THE MULTI-SPECTRAL CLASSIFICATION APPROACHES
(After Schowengerdt, 1983)

together as a single multi-band colour composite. Changed pixels appear in unique colours on the multi-band colour composite and these are then classified.

Image enhancement techniques involve mathematical combinations of data bands from different dates. These combinations result in areas of change and those of no change appearing in distinct tones on grey scale images, or in unique colours on colour composite displays (Michalak, 1993; Pilon *et al*, 1988). Common enhancement approaches include image differencing, image ratioing and principal component analysis (Michalak, 1993).

Both multispectral classification and enhancement groups of techniques were used in the present work. They are therefore described in more detail in section 5.4.3.

5.3 CHANGES THAT AFFECT RESOURCE MANAGEMENT POLICIES IN THE NORTH YORK MOORS

Concern about land cover changes brought about by episodic events like the uncontrolled summer fires of 1976; developmental pressures like improvement in agriculture, afforestation and tourism; and rapid spread of bracken, led to the inception of the moorland management programme in 1976 (NYMNP, 1986). The programme aims at reversing much of the undesirable changes by promoting regeneration on fire damaged areas and encouraging the re-establishment of moorland vegetation on previously reclaimed land; as well as protecting the existing areas of moorland from any possible causes of degradation or actual loss (NYMNP, 1991a).

The strategies being followed at present in the management of moorland and related land cover are intended to bring about some desirable changes and to prevent the occurrence of some undesirable changes. The desirable changes include rotational burning of moorland; enhanced regeneration on fire damaged areas; clearing of bracken from moorland areas; and leaving sections of farmland fallow. The

undesirable changes that management strategies intend to prevent include loss of moorland to bracken encroachment; and wanton felling of woodland (NYMNP, 1991a; 1991b). Timely and accurate information about these changes is essential for making resource management decisions in the area. The present work seeks to discover whether it would be possible to obtain information about these changes through digital manipulation of multi-temporal Landsat TM data. But first, the background, nature and significance of these changes are explained below. Each category of change is also assigned a code which is used from time to time in this research project in lieu of the full name of a category. These codes are presented below in brackets just after the full names of the categories.

5.3.1 Bracken encroachment or re-development (C1)

Bracken (*Pteridium aquilinum*) occurs naturally on the steeper, well-drained slopes of upland heath areas. A combination of factors has led it to spread rapidly into areas of open moorland and agricultural land. One such factor is the relatively more frequent uncontrolled fires particularly where bracken and heather are in competition. These fires give bracken a competitive advantage because it has rhizomes which, unlike the roots of heather or grasses, are hardly damaged by even the more intense fires. Thus, bracken starts to grow more rapidly from its charred rhizomes and succeeds to inhibit the growth of other plant species (Brown, 1986; NYMNP, 1986). This leads to its eventual dominance.

The unprecedented spread of bracken has also resulted from the reduction in intensity of cutting. Bracken used to be extensively cut for cattle bedding but with the reduction in availability of labour, this is no longer economically feasible. There is therefore little check on its growth and spread (Brown, 1986; NYMNP, 1986).

The spread of bracken has also been promoted by the clearing of woodland in some areas. Bracken is often a natural constituent of the undergrowth in woodland areas,

and when the trees are felled, it is able to spread widely since the increased availability of light makes it grow vigorously and extend its rhizomes over wider areas (Brown, 1986; NYMNP, 1986). Undermanagement of enclosed farmland on the plateau edges may also encourage the spread of bracken especially where the slopes of the plateau are already infested (Brown, 1986; NYMNP, 1986).

In 1988, approximately 140 Km^2 or 28% of the total moorland area were encroached by bracken (NYMNP, 1991a; 1991b). Bracken is spreading into the open moorland at a rate of about 1% per annum (Barber, 1986; NYMNP, 1986; Weaver, 1986). This situation is of much concern to land owners and the national park authority because bracken has limited ecological value and it is directly toxic to animals if they graze it. It can also harbour sheep ticks which can carry a virus to sheep and grouse (Brown, 1986; NYMNP, 1986). In some areas, bracken is already indirectly proving to be the primary cause of the decline in sheep and particularly grouse populations on the moor (NYMNP, 1986).

The control of bracken is expensive and often not very effective (NYMNP, 1986) as the bracken fronds keep on re-emerging after treatment. It requires a number of follow-up treatments in order to succeed in preventing bracken re-development (Rees, Pers. Comm.).

Timely and accurate information about bracken encroachment or re-development is necessary to help in planning control activities.

5.3.2 Dead bracken [post-treatment] (C2)

The control of bracken encroachment is one of the top resource management priorities in the North York Moors. The National Park Committee in conjunction with moorland land owners launched the Integrated Bracken Control Programme in 1988. Under the programme, infested areas are sprayed with chemicals to kill bracken

(NYMNP, 1991a). However, it may not die out completely until after a number of follow-up treatments (Rees, Pers. Comm.). The target in the control programme is to reduce the area under bracken to less than 10% of the moorland area by the year 2000 (NYMNP, 1991a; 1991b).

The effectiveness of the control programme can be judged by monitoring changes in the condition of bracken within the treated areas. The treatment can be considered effective where it results in complete death of bracken. Areas where treated bracken is not dying need follow-up control operations. Where it dies out completely as a result of the treatment, there is need to carry out some vegetation restoration activities to prevent its re-development. Such activities include re-establishment of heather moorland, development of broadleaved woodland through planting and natural regeneration, and re-establishment of traditional pasture (NYMNP, 1991a; 1991b). There is therefore much need for timely and accurate identification of treated areas on which bracken is dying out in order to be able to carry out these preventative measures before re-encroachment begins.

5.3.3 Moorland regeneration (C3)

One of the top resource management priorities in the North York Moors is the promotion of moorland regeneration on areas damaged by the 1976 summer fires. The National Park Committee has since 1984 supported a restoration scheme on the fire damaged area on Glaisdale Moor. About 202 hectares of eroding peat were enclosed in a fence to keep out sheep and thereby reducing grazing and trampling pressures. This has encouraged natural regeneration. In addition, bare peat is being treated with heather brash containing heather seed. This is regarded as a very effective method of promoting regeneration. Re-instatement of moorland vegetation on areas treated in this way can be achieved within four years (NYMNP, 1991a).

One of the very basic objectives of the moorland management programme is to monitor the progress of recovery on the fire damaged areas (NYMNP, 1979; 1986; 1991c). Areas where regeneration is taking place have to be identified. Similarly, those where regeneration is failing to take root have to be identified so that efforts should be concentrated on them.

5.3.4 Rotational burning (C4)

Traditionally, the moorland had been managed through a pattern of rotational burning which helps to maintain the heather in its most competitive and productive stage of growth. The rotational burning creates a patchwork landscape with canopies at different stages of regeneration and development (Ward *et al*, 1987; 1989).

The practice of rotational burning was, however, neglected in the middle part of this century resulting in the existence of a large area of overaged heather (NYMNP, 1991a).The stands of over-aged heather are a fire hazard since the woody and relatively dry, old heather stems burn fiercely when they catch fire. The fierce fires may not only clear the plants above the ground, but may also destroy the roots and ignite the underlying peat, thereby jeopardising chances of post-fire plant re-colonisation. The burnt peat may also be very susceptible to soil erosion (Ward *et al*, 1987; 1989).

Since 1983, rotational burning as well as mechanical cutting of over-aged heather have been encouraged under the Moorland Management Programme (NYMNP, 1991a). To ensure that this management priority is being followed, there is need to monitor the rotational burning of heather so that areas that have stayed unburnt for more than the required term should be identified.

5.3.5 Neglected/Fallow farmland (C5)

The upland margins traditionally experience fluctuations in land use in response to socio-economic factors. At times, they tend to be reclaimed for improved agriculture, but under adverse socio-economic conditions, they tend to be under-managed or completely neglected so that reversion to rough pasture takes place (Ball *et al*, 1982; Parry *et al*, 1982). Bracken also tends to spread rapidly into the neglected plots on the upland margins (Brown, 1986; NYMNP, 1986). Timely identification of the neglected farmland will not only allow resource managers to know how much land is being under-utilised at any given point in time, but it will also enable them to take action to prevent the spread of bracken into those areas.

At present, the management priority concerning agriculture is to encourage conservation-oriented farming. This is undertaken through a number of projects. One of these is the Alternative Land Use Project which incorporates, among other things, the national set aside policy. Under the project, farmers are expected to withdraw portions of their land from traditional farming and leave them fallow to provide habitat for wildlife. Alternatively, the grass growing naturally on the fallow plots can be managed for amenity purposes. Heather can also be introduced to create or re-create moorland on farms. Another option is to plant deciduous or coniferous trees on the fallow plots (NYMNP, 1991a; 1991b). The project is expected to bring significant amounts of agricultural land out of the traditional farming systems. It would be of interest from a resource management point of view to have information about land use changes brought about by these conservation-oriented farming policies.

5.3.6 Clearing of woodland (C6)

A major priority in the management of existing broad-leaved and coniferous woodland is to protect them against damage including inappropriate felling or pruning. It is the national park's policy that felling, for instance, should always follow

good forest design principles like the practice of selective felling as opposed to clear felling (NYMNP, 1991; 1991b). The National Park Committee can use Tree Preservation Orders to protect some areas of woodland from inappropriate felling. When an order is imposed, the owner would be encouraged to take active steps to manage the woodland so that its survival would be guaranteed. The Committee can also attach conditions to planning permissions requiring the retention of existing trees and the provision of additional landscaping measures. In extreme cases, the Committee would use its development control powers to resist any felling plans where the felling of trees is intended to give way to some kind of development (NYMNP, 1991a; 1991b).

The planners need information about conditions of the existing woodland, as well as location and extent of areas where woodland has or is being cleared. Felling that does not conform to management priorities has to be detected in time so that attempts can be made to stop it before much damage is done to the landscape and wildlife. Similarly, planners need timely information about the location and extent of areas where woodland has been damaged by natural hazards like strong winds.

5.4 DIGITAL DETECTION OF LAND COVER CHANGES USING 1985 AND 1991 LANDSAT TM DATA

This part describes the work undertaken to discover whether change categories C1 to C6 discussed earlier (section 5.3 above) could be detected on the multi-temporal Landsat TM data. The problems faced in trying to obtain the most suitable sets of data for this type of work are presented; the approaches followed in detecting the land cover changes are outlined; and the results obtained are discussed.

5.4.1 Problems of Data Acquisition

Northern England is often under cloud cover at the time of the satellite passes. This makes it difficult to find good quality imagery to work with. For instance, there were only two relatively cloud-free sets of image data for Landsat TM scene 203/22 at the time this project started in 1992. These were for May 31, 1985 and February 25, 1991. An image acquired on August 20, 1991 had zero cloud cover in the fourth (south-east) quadrant although the other three had heavy cloud cover (Thomas, Pers. Comm.).

The 1985 imagery was chosen to constitute the time t_1 data set. Ideally, time t_2 data set was supposed to be of the same month of May in order to avoid dealing with differences in spectral values caused by phenological changes and seasonal variations in atmospheric conditions and solar illumination angles. However, from 1986 to 1991, all acquisitions for the month of May had cloud problems (Thomas, Pers. Comm.).

The cloud-free February 25, 1991 imagery was not considered suitable for use because in February, much of the vegetation cover in upland areas is normally still dormant and covered by snow (Soulsby, Pers. Comm.). The summer 1991 quadrant was considered the better option for use as time t_2 data because summer and spring atmospheric conditions and solar illumination angles are not extremely different.

There were also ways of dealing with spectral differences caused by phenological changes between spring and summer. For instance, in the post-classification comparison method, there is no direct concern with DN values. The independent classification of the original images converts the DN values into pixel class labels and it is these class labels and not the actual DN values that are compared. In this way, the post-classification method can be used for classified images of different seasons without any fear of the influence of seasonal changes because these are normalized by

the independent classification (Schowengerdt, 1983). In image enhancement procedures like image ratioing and differencing, the thresholds of pixels of change and no change are empirically determined (Jensen, 1986; Lindgren, 1985). It is therefore possible to set the thresholds in a way that would exclude changes caused by phenology. Details of this are given under the description of the enhancement procedures in section 5.4.3.2.

5.4.2 Preparation of the 1985 and 1991 Data for Change Analysis

The two data sets were prepared for change analysis in two main ways. One way was to register them spatially/geometrically. The way in which the registration was undertaken has been described earlier in chapter 3, sections 3.1.1-3.1.2. The images were registered with an RMS error of less than 1 in all three extracts, which means that the recommended accuracy of registration to less than 1 pixel was achieved.

The two data sets were also independently classified in preparation for the post-classification comparison approach. As described in chapter 4, the data were classified using three approaches, namely maximum likelihood, minimum distance, and parallelepiped classification strategies. Of these, the maximum likelihood strategy produced the more satisfactory results. It gave relatively consistent high overall and individual class accuracy levels. High accuracy in the original classifications is a preprequisite for effective change detection using the post-classification comparison approach. The maximum likelihood classifications of the 1985 and 1991 image data sets were therefore considered the most suitable for use in the post-classification comparison method.

5.4.3 Change Detection Methods

Both multispectral classification and image enhancement groups of digital change detection methods were followed in this work. In addition, some "hybrid" approaches

integrating the principles of both multispectral classification and image enhancement procedures were also tested. All these are described briefly.

5.4.3.1 *Multispectral Classification Approaches*

As already stated earlier (section 5.2.2), there are two multispectral classification approaches to change detection. One is the post-classification comparison approach, and the other is the direct multi-date classification method. Both were undertaken in this work and are described below.

5.4.3.1.1 Post-classification Comparison

Under this approach, multispectral image data for times t_1 and t_2 are classified independently. If the classification is supervised, training data are independently obtained from each data set. Each image is then classified using its own training statistics. The two classified images are then compared to identify areas of agreement and disagreement in land cover (Figure 5.1a). Those areas that have different land cover types on the classified images of times t_2 and t_1 are considered to have had experienced land cover change. The approach allows the analyst to identify areas of change and their extent, as well as the direction or nature of the change that had taken place at each site (Howarth and Wickware, 1981).

The effectiveness of the method, however, depends on the accuracy of the initial classifications. Any errors in the original classifications are compounded when detecting the changes (Jensen, 1986). Stow *et al* (cited in Singh, 1986) established that the level of accuracy one would expect to obtain from the post-classification comparison approach can be estimated by the expression $[p_{t1} \times p_{t2}]$ where p_{t1} is the proportion of pixels correctly classified on the imagery of time t_1 and p_{t2} is the proportion of pixels correctly classified on the imagery of time t_2. In this work, for instance, this means that the expected accuracy of the method in detecting changes in the Rosedale extract would be around .89 x .86 = 77%, since the overall classification

accuracy for the 1985 data was 89% and that for the 1991 data was 86%. This implies that the method can give very reliable change data only when each of the initial classifications has an accuracy of close to 100% which, as seen in the last chapter, is almost unattainable in the uplands given the limitations of conventional classifiers.

Another drawback of the method is that the amount of effort and computation required are directly proportional to the number of images available in the multi-temporal data set (Schowengerdt, 1983). If there are images of two dates, two independent classifications have to be undertaken. If there are images for three, four, five, ...*n* dates, the number of independent classifications that have to be undertaken rises proportionally to three, four, five, ...*n*.. This may lead to inefficiency when data for many dates are to be employed in the analysis.

Not withstanding its limitations, the post-classification comparison method has been widely used to detect changes of different types in different parts of the world. For instance, it has been used in Alaska to monitor the regeneration of burnt tundra vegetation (Hall *et al*, 1980); in Sadbury for mapping areas of vegetation losses and gains (Allum and Dreisinger, 1986); in Toronto in detecting land use change in the rural-urban fringe (Martin and Howarth, 1989); in Botswana for detecting changes in rangeland conditions (Ringrose *et al*, 1990); in Guinea for monitoring forest clearing (Gilruth *et al* , 1990); in Spain for mapping fire damaged mediterranean forest land (Chuvieco, 1989); and in France for monitoring change in heathland region of Cause du Larzac (Csaplovics, 1992), to mention a few.

In this work, the colour-coded image outputs of the maximum likelihood classifications for the 1985 and 1991 imagery were photographed off the screen to produce hard copies. Colour transparencies were then generated from the hard copies. The transparencies for the 1985 and 1991 classifications in each extract were overlaid and the areas of agreement or disagreement between them were analysed. Those of disagreement represented areas of change. When the changed areas had been

identified, it was possible to refer to the 1985 classification to discover what land cover types were there at that time, and to refer to the 1991 classification to discover what they had changed into after the six-year period. It was therefore possible not only to detect the areas of change, but also to determine the nature or direction of change. Only the types of change fitting into categories C1 to C6, described earlier, were sought in the analysis. All other areas of disagreements between the classifications which did not represent change categories C1 to C6 were not considered.

The detected areas of change in each extract were delineated on a fresh transparency spread over the overlay set. The delineation exercise produced sketch change maps presented in Figures 5.2-5.4. The delineations show where the changes took place. They also give idea about the sizes of the areas involved in each type of change. It is impossible, however, to obtain information about the actual numbers of pixels involved in each type of change since the analysis was carried out on transparencies produced from photographically generated hard copies. The boundaries between pixels disappear when hard copies are generated photographically.

In the Rosedale extract, four types of change were detected and delineated. These were bracken encroachment (C1); bracken litter [post-treatment] (C2); moorland regeneration (C3) ; and neglected/fallow farmland (C5). Bracken encroachment or re-development was detected on the edges of the moorland around Esklets crag (NZ 655015); between the two arms of Westerdale; along the western and eastern dalesides of Danby Dale; and around SE670980 on the slopes linking Blakey Ridge and eastern Farndale. Areas of dead bracken were detected mainly around Crossley Side; on the eastern slopes of Danby Rigg; around the head of Great Fryup Dale; around the heads of River Severn and Northdale Beck; and around West Gill head. Moorland regeneration was detected on the fire-damaged site on Glaisdale Moor. Neglected/fallow farmland plots were detected in all the agro-pastoral zones in the dales. No forest clearing was detected in the Rosedale extract.

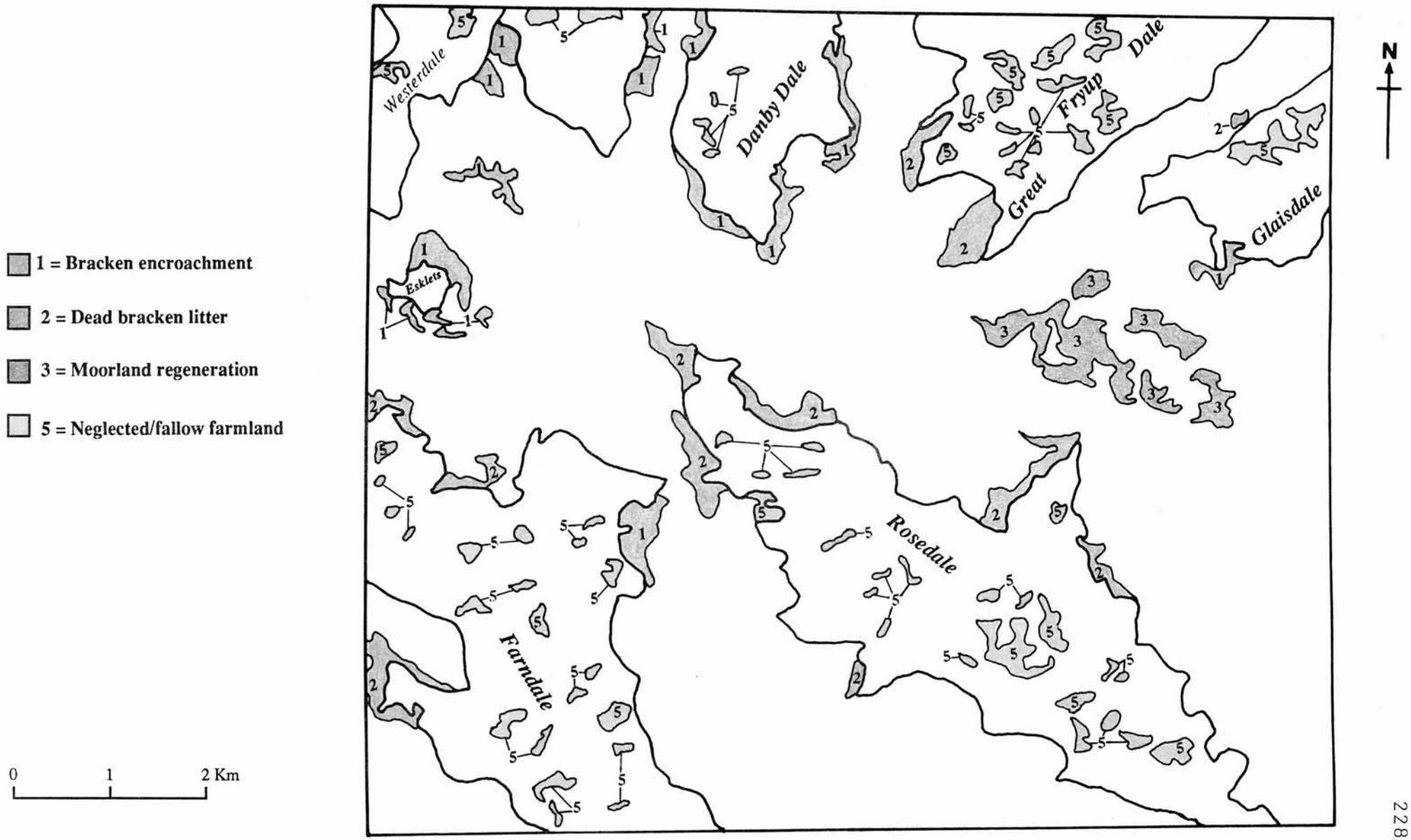


FIGURE 5.2 RESULTS OF POST-CLASSIFICATION COMPARISON IN A MAP FORM : ROSEDALE EXTRACT

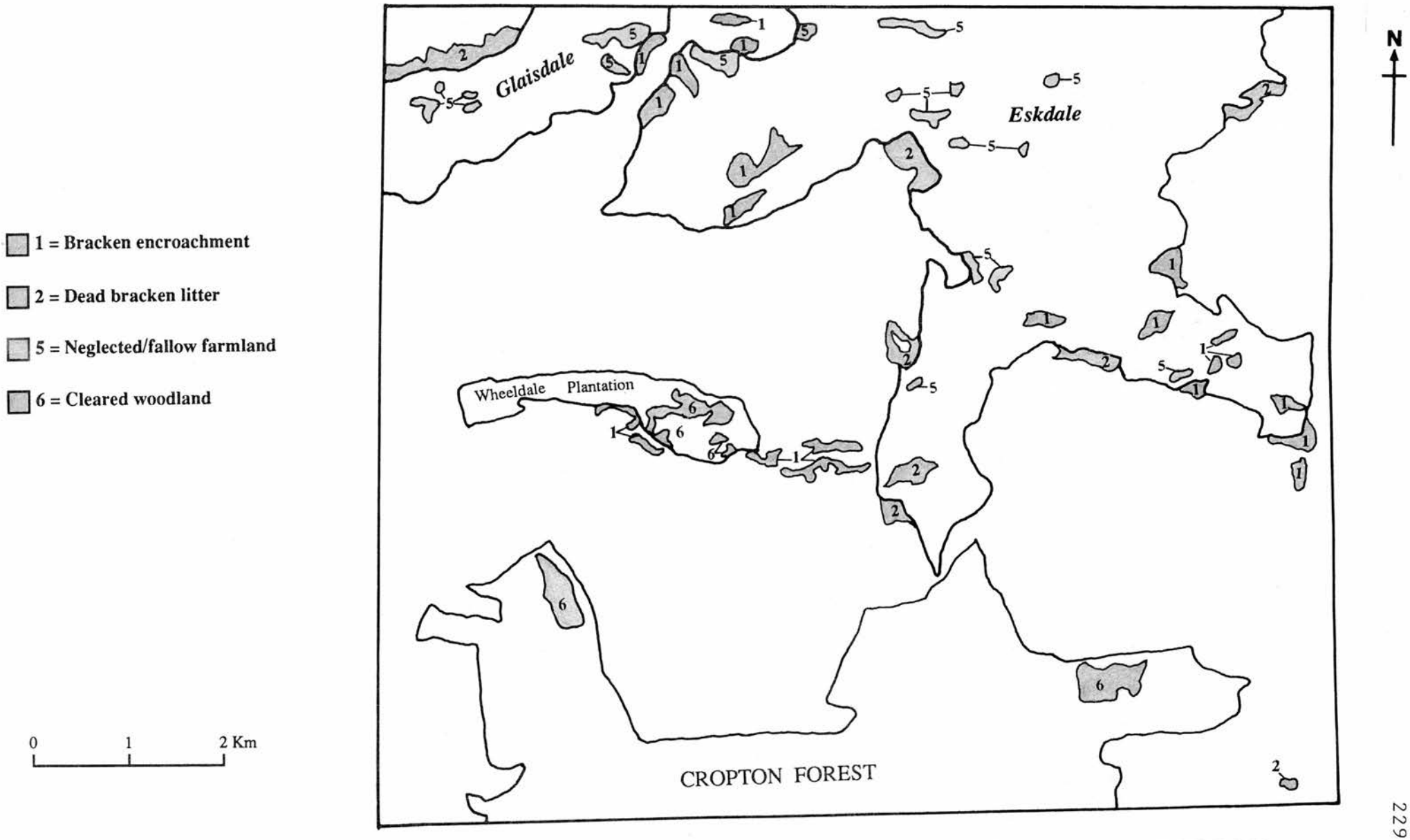


FIGURE 5.3 RESULTS OF POST-CLASSIFICATION COMPARISON IN A MAP FORM : WHEELDALE EXTRACT

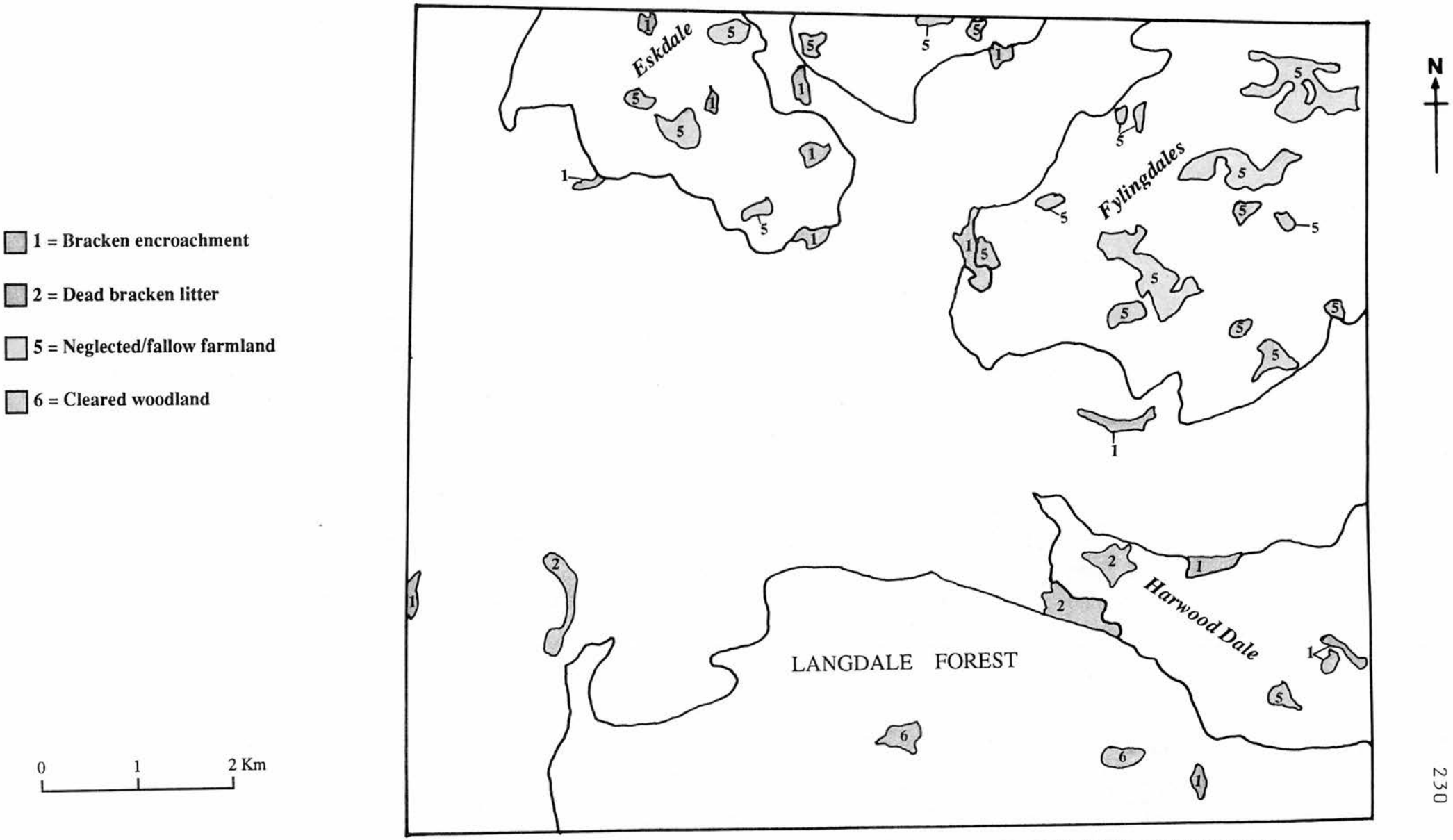


FIGURE 5.4 RESULTS OF POST-CLASSIFICATION COMPARISON IN A MAP FORM : FYLINGDALES EXTRACT

The changes detected and delineated in the Wheeldale and Fylingdales extracts were bracken encroachment (C1); bracken litter [post-treatment] (C2); fallow farmland (C5); and clearing of woodland (C6). In the Wheeldale extract, bracken encroachment or re-development was mainly detected around Egton Grange; along Wheeldale Gill; and in Eskdale around Goathland. Areas of dead bracken were detected around Hazel Head and around NZ 807040. Fallow farmland plots were detected in Eskdale and Glaisdale. Sections where forests had been cleared were detected in the central-eastern parts of Wheeldale Plantation; around White Mires in the Cropton Forest; and around Wilden Moor (approximately SE 835959) on the eastern end of Cropton Forest. In the Wheeldale extract, the stretch of fire damaged moorland was grossly underestimated by the classifier on the 1985 imagery. Consequently, the change from fire damaged moorland to moorland vegetation (i.e moorland regeneration) could not be effectively detected in comparing the two classifications.

In the Fylingdales extract, bracken encroachment or re-development was mainly detected around Grey Heugh Head and along Bloody Beck. Areas of dead bracken were detected along Eller Beck and River Derwent. Plots of neglected/fallow farmland were detected in Eskdale, Fylingdales and Harwood Dale. Sections of cleared forests were detected in areas around SE 905950 and SE 925949.

Rotational burning was not detected in any of the three extracts. This was because on the time t_2 (1991) imagery, freshly burnt areas were not distinct from those burnt two years earlier owing to the very similar nature of their spectral response patterns.

5.4.3.1.2 Direct Multi-date Classification

This approach, also known as spectral-temporal classification (Jensen, 1986; Weismiller *et al*, 1977) involves stacking together all the bands in the multi-temporal data set, and carrying out a single classification process on them. Thus, if the multi-temporal data set consists of four MSS bands of time t_1 and another four bands of

time t_2, the total eight bands are stacked and classified in a single classification process as illustrated in Figure 5.1b.

The classification can be supervised or unsupervised. If it is supervised classification, all the bands in the multi-temporal data set are displayed as a multi-band colour composite on which pixels of change appear in distinct colours. Some of these would be selected as training areas and the classifier would be run using the training data extracted from those pixels. If the classification is unsupervised, the classifier would simply identify and display the spectral-temporal clusters. It would then remain to the analyst to determine which of the spectral-temporal clusters represent changed pixels.

Because some image processors may not be able to stack or display up to 8 or more bands at any single time, then it is possible to carry out principal component transformation of the original 8 or more bands and then use the first two or three principal components in the classification. Normally, the first two or three principal components would contain a very high proportion of the total variance in the original bands. They may therefore be regarded as effective representatives of the original bands. Singh (1986), for instance, used PC1 and PC2 of the original 8-band multi-temporal data set to carry out a "direct" multi-date classification as a method of detecting change.

Among those who have used this approach in detecting change are Weismiller *et al* (1977). They used it, among other methods, in analysing changes in the coastal environment of Texas and discovered that it yielded very unsatisfactory results. The method was also among those tested by Singh (1986) in detecting tropical forest clearing and regeneration in India. It similarly gave unsatisfactory results.

The R-CHIPS programme used in this work displays colour composite images comprising not more than three bands. It was therefore not possible to display the six bands (3 for 1985 imagery, and the other three for 1991 imagery) as multi-band

colour composite. In this case, it was decided that the original six bands had to be subjected to the principal component transformation and that the first three principal components could be used as representatives of the original bands. In the Rosedale extract, the first three PCs accounted for 98.4% of the variance in the original bands; in the Wheeldale extract, they accounted for 97.27% of the variance in original bands; and in the Fylingdales extract, they accounted for 97.38% of the variance in the original bands. The first three PCs were therefore actually good representatives of the original six bands.

Colour composite displays comprising PC1, PC2 and PC3 were loaded for each extract. It was discovered that some of the zones that were identified as areas of change under the post-classification comparison approach, appeared in unique colours on such colour composite displays. However, the problem was that, at each site, the pixels appearing in such unique colours were often few so that it was difficult to define training areas. Classifying the supposedly changed pixels into change classes C1 to C6 failed because of insufficient training areas. All in all, the spectral-temporal (direct multi-date) classification proved a failure in the present project.

5.4.3.2 *Image Enhancement Approaches*

Three image enhancement approaches to change detection were tested in this work. These are the subtraction of multi-temporal bands; the division of multi-temporal bands; and the use of some principal components to display the areas of change. These are described below.

5.4.3.2.1 Image Subtraction

Image subtraction, commonly known as image differencing, involves calculating the difference in DN values between corresponding pixels in similar bands of images acquired at different dates. This subtraction process results in positive and negative

values in areas of change, and values of around zero where no change took place. Normally, the negative values are rescaled into positive range of values by an addition of a constant. When the difference values are rescaled into the positive range of 0 to 255, the areas originally with zero difference values take the new value of 127. The image differencing operation can be mathematically expressed as follows:

$$D_{i,j_k} = V_{i,j_k}(t_2) - V_{i,j_k}(t_1) + c \qquad (5.1)$$

(After Jensen, 1986; Jensen and Toll, 1982 with some modifications in notations)

where D = difference value of a pixel

V = actual value of pixel in a data band

i,j = x,y co-ordinate values used in identifying a specific pixel in imagery

k = specific data band

(t_1) = imagery for the first date

(t_2) = imagery for the second date

c = a constant used to rescale difference values into a positive range, normally 0 to 255

The procedure normally produces difference values that display an approximately Gaussian distribution pattern. Pixels of no radiance change are distributed around the mean, while pixels of very significant radiance change are concentrated in the tails of the normal distribution (Jensen, 1986; Jensen and Toll, 1982) as Figure 5.5 illustrates.

The critical task in using this method is that of determining where to place the boundary to separate pixels that had changed significantly and those that had undergone insignificant change. Normally, a number of standard deviation values are selected and empirically tested to see which one among them effectively separates the pixels of change from those of no change (Jensen, 1986; Lindgren, 1985).

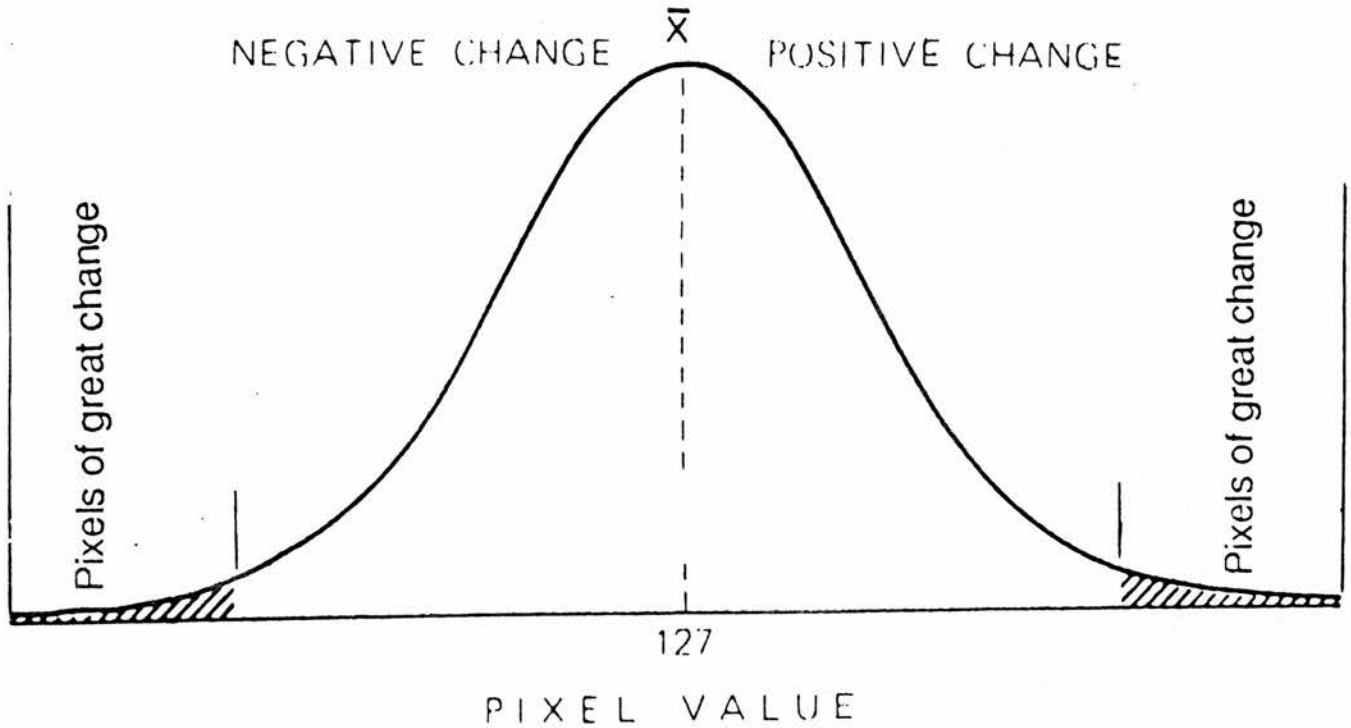


FIGURE 5.5 THE CHARACTERISTIC NORMAL DISTRIBUTION SHAPE OF THE HISTOGRAMS OF DIFFERENCE/RESIDUAL IMAGES (Modified from Jensen, 1986; Jensen and Toll, 1982)

The subtraction of image bands produces grey scale images where areas of no change appear in medium grey tones; those of positive change (i.e where pixels gained values between the two dates) appear in progressively lighter tones; and those of negative change (i.e where pixels lost values between the two dates) appear in progressively darker tones (Mather, 1987a). Three difference image files can be displayed as a colour composite (Lindgren, 1985).

The method has been used in detecting land cover and land use changes in different parts of the world. A few cases include for monitoring of urban change in Essex (Griffiths, 1988); for monitoring of water levels in Rutland Water reservoir in Leicestershire (Mather, 1987a); for detecting residential land use development at the urban fringe in Colorado (Jensen and Toll, 1982); for monitoring tropical forest clearance and regeneration in India (Singh, 1983; 1986); and for detecting forest change in the uplands of north-eastern United States of America (Vogelmann, 1988; Vogelmann and Rock, 1989).

Common to the studies in which the method has been used is that the changes sought to be detected were those caused by two contradictory processes such as forest clearing and forest regeneration; land development and abandonment; increase and decrease in water levels; rural-to-urban and urban-to-rural land use changes; and the emergence and disappearance of geographical features in general. In each case, one of the two contradictory processes results in the increase in pixel values between the two dates, and the other results in the decrease in the pixel values between the two dates. Positive change on the difference/residual image would represent the first type of process, and negative change would represent the second type of process. Thus, where changes are caused by two contradictory processes, it is possible to know the actual land cover conversions that are represented by pixels of radiance gain or radiance loss. But where there are more than one type of processes bringing about gain in pixel values and a number of other processes causing loss in pixel values, then

it is difficult to know exactly what type of land cover conversion is represented by each pixel that had experienced gain or loss in DN value.

In this work, DN values for pixels in TM3, TM4 and TM5 of the 1985 imagery were respectively subtracted from those for corresponding pixels in TM3, TM4 and TM5 of the 1991 imagery in each of the three extracts. The value 127 was used as the constant for rescaling the difference/residual values into the positive range of 0 to 255. In the resulting difference/residual images, pixels that had had experienced no change at all had values of around 127. Those that had experienced positive change (gain in DN values) between times t_1 and t_2 had values greater than 127; whereas those that had experienced negative change (loss in DN values) had values lower than 127.

Not the whole of 0 - 126 and 128 - 255 value ranges on the difference/residual images represented significant land cover changes. Some values within those ranges represented radiance change caused by seasonal factors since the two images were of different seasons. It was therefore necessary to determine thresholds of pixel values representing significant change. To determine the thresholds, histograms of the residual images were produced with difference/residual values on the y axis and number of pixels on the x axis as shown in Figures 5.6-5.8a,b,c . Then, using the density slicing function, different slices from the lower limit of 0 to the upper limit of 126 were tried to show areas of negative change. Similarly, different slices from the lower limit of 128 to the upper limit of 255 were also tried to show areas of positive change. From this type of trials, it was discovered that on TM4 and TM5 residual images, slices 0-64 and 192-255 presented areas of change whose spatial extent and distribution pattern were not very different from those of the areas of change detected under the post-classification comparison method (see Figures 5.2-5.4). These two slices were therefore considered to be the most suitable in highlighting areas of significant change.

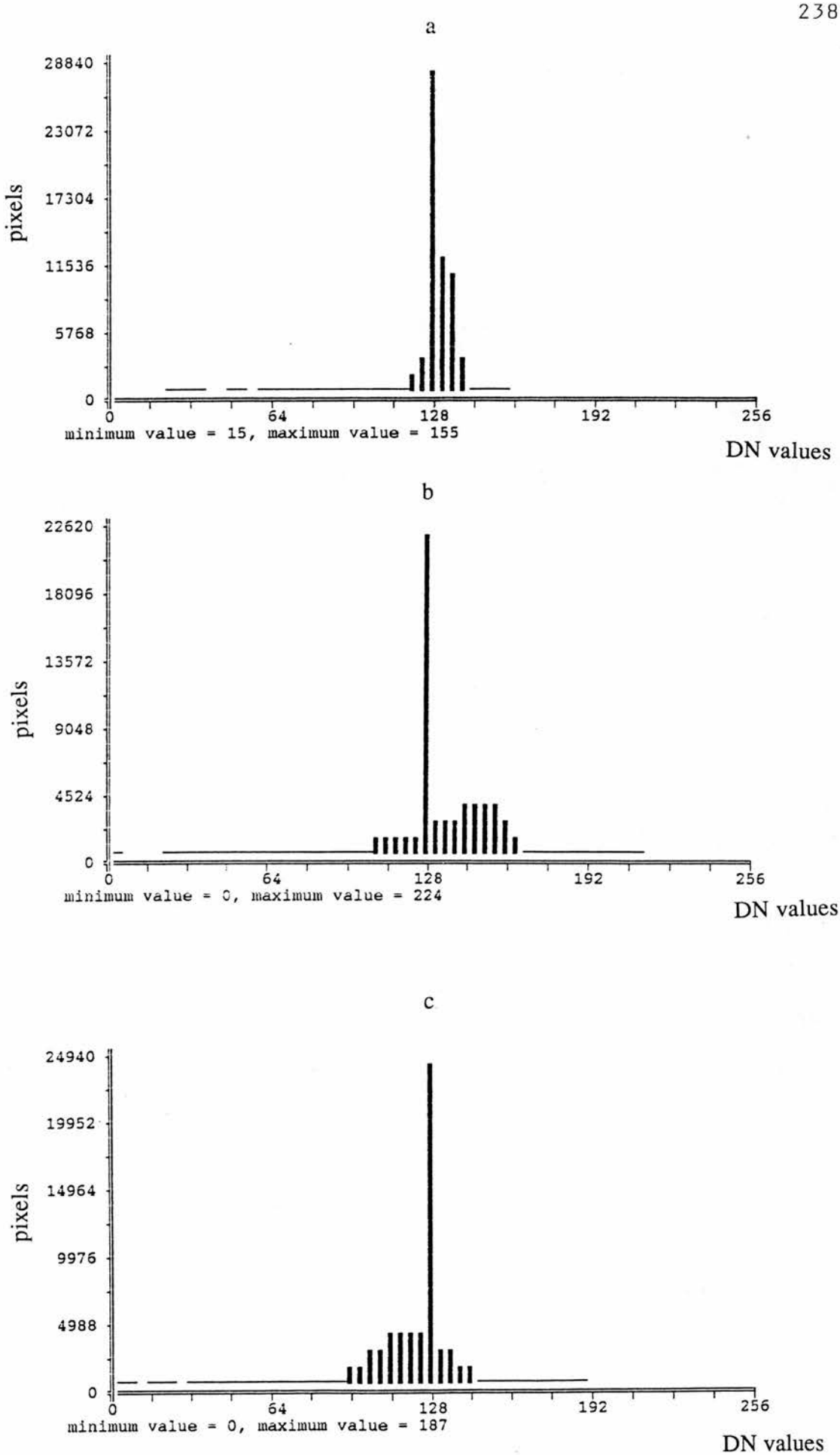
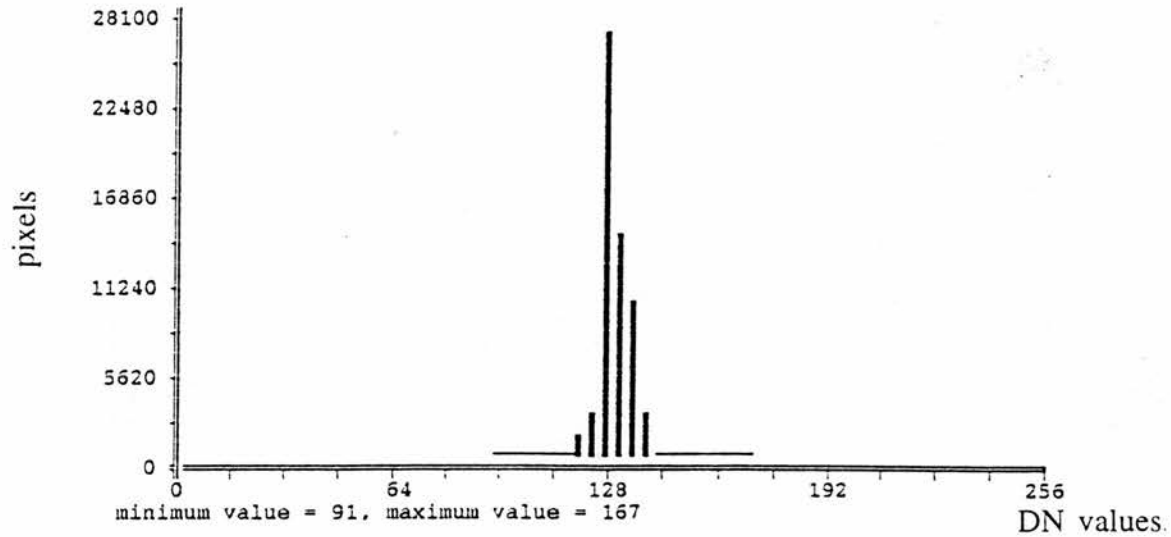
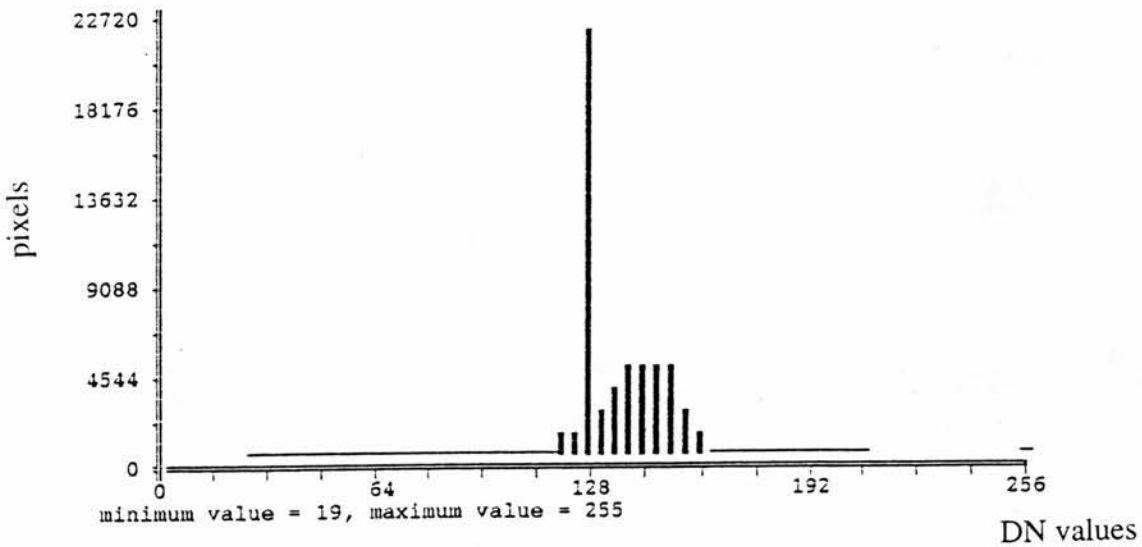


FIGURE 5.6 HISTOGRAMS OF RESIDUAL IMAGES IN ROSEDALE EXTRACT : (a) = TM3; (b) = TM4; (c) = TM5

a



b



c

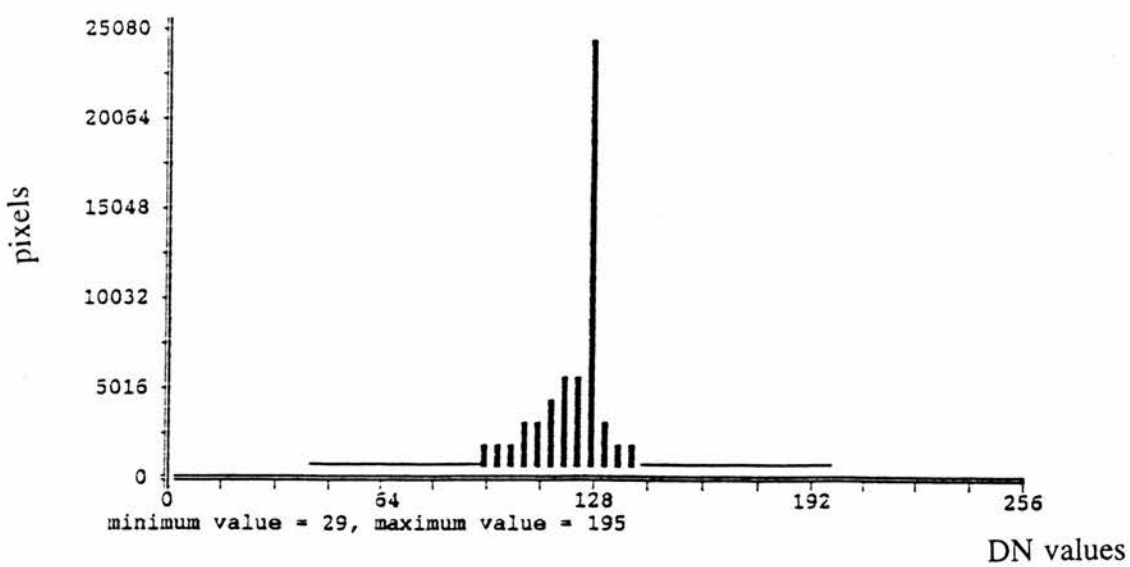
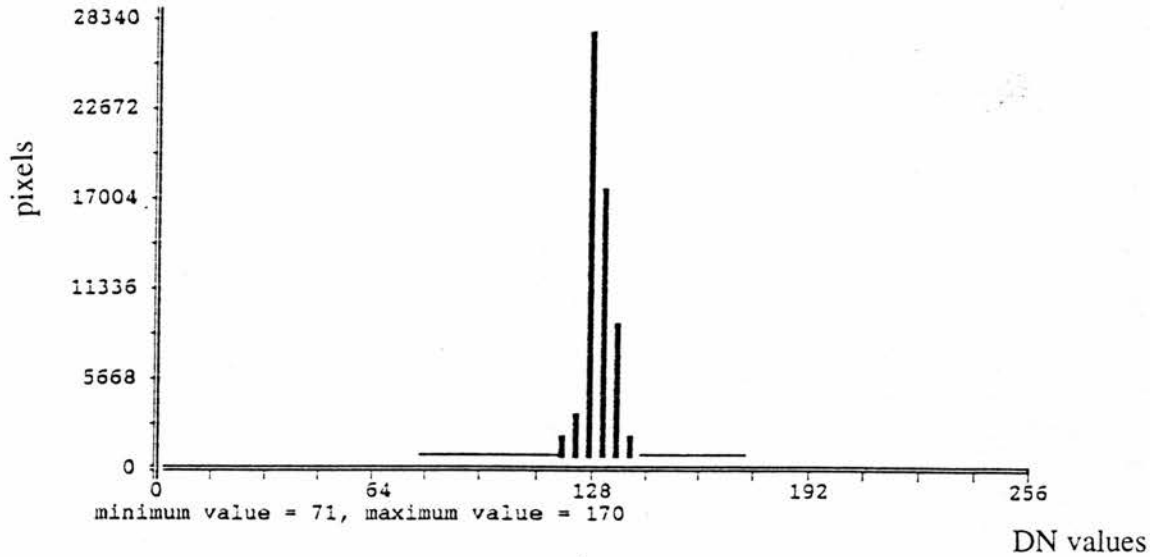
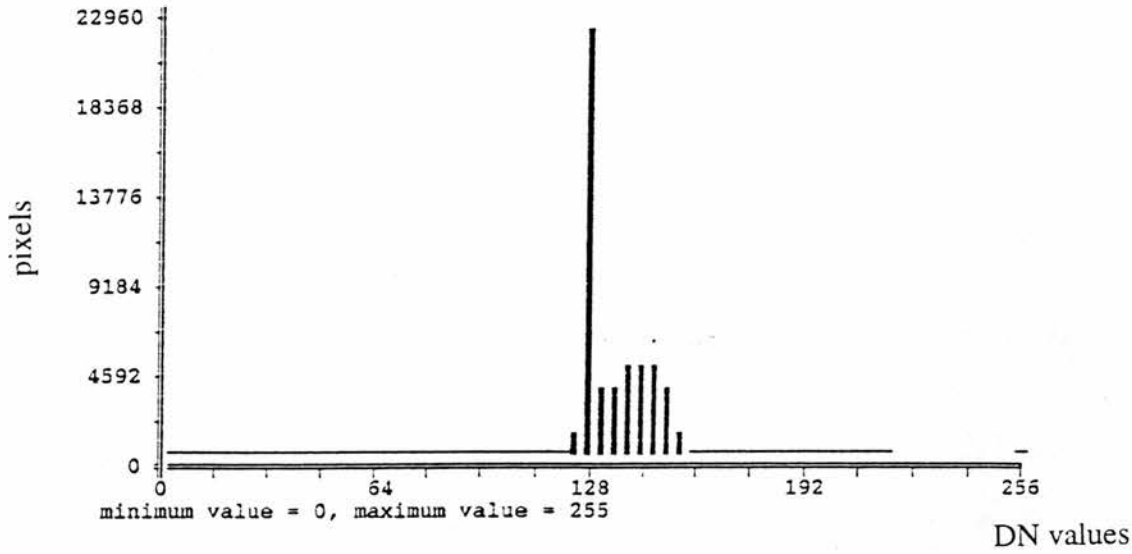


FIGURE 5.7 HISTOGRAMS OF RESIDUAL IMAGES IN WHEELDALE EXTRACT : (a) = TM3; (b) = TM4; (c) = TM5

a



b



c

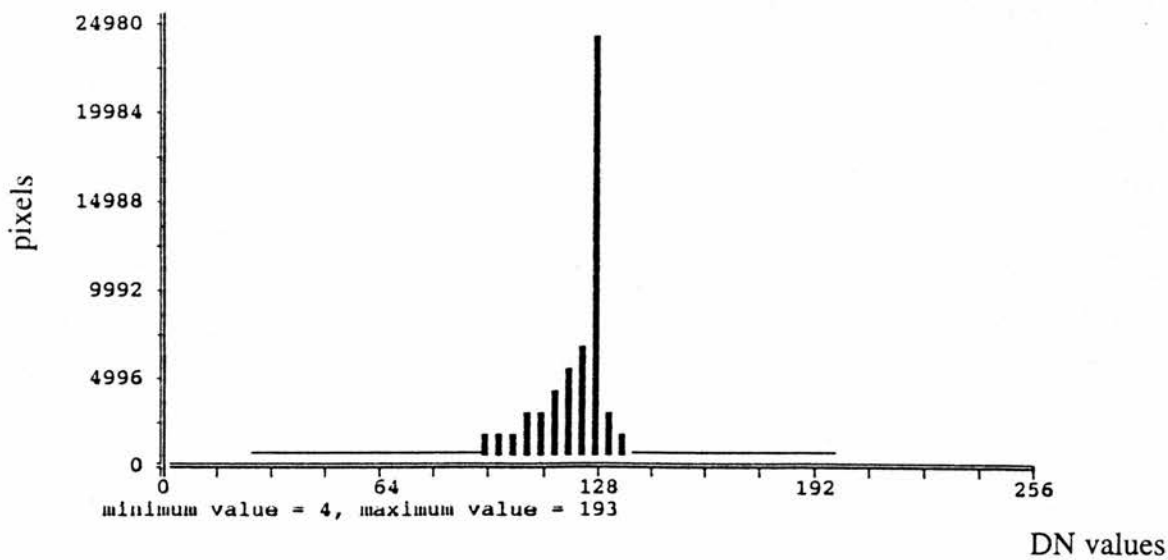


FIGURE 5.8 HISTOGRAMS OF RESIDUAL IMAGES IN FYLINGDALES EXTRACT : (a) = TM3; (b) = TM4; (c) = TM5

On the residual images, the pixels in the 0-64 slice were assigned blue colour and those in the slice 192-255 were assigned red colour. The former represented areas of negative change, and the latter represented those of positive change. There were a few pixels in the two slices on residual images of TM3 implying that not many areas of change could be detected in the subtraction of DN values for pixels in TM3 bands. Residual images of TM4 and TM5 showed more pixels of change in each extract. Between residual images of TM4 and TM5, the former showed more areas of change than the latter.

Although the residual images of TM4 and TM5 showed more areas of positive and negative change, there was no way one could tell what type of land cover conversion was represented by each pixel of radiance gain or loss. The pixels of positive change could represent changes like bracken encroachment, moorland regeneration and agricultural improvement. Similarly, pixels of negative change could represent changes like the clearing of forests, moorland burning, death of bracken on sprayed areas, or neglected/fallow farmland. However, the method gave no information to suggest whether a pixel of positive change at any specified x, y location was either bracken encroachment or moorland regeneration. Similarly, there was no information to suggest whether a pixel of negative change at any specified x,y location represented areas of dead bracken, areas of cleared forests, or fallow plots on farms. Because of this problem, it was therefore not possible to distinguish change categories C1 to C6 on the residual images.

5.4.3.2.2 Image Ratioing

In image ratioing, DN values of pixels in a data band are divided by the DN values of corresponding pixels in a similar data band but of a different date. This division gives ratio values of around 1.0 where the corresponding pixels had the same values on images of times t_1 and t_2. The ratio values would be more than 1.0 where the DN values of the pixels had increased between the two dates; and less than 1.0 where the

DN values of the pixels had decreased between the two dates. It is the ratio values greater and/or less than 1.0 that represent change (Howarth and Wickware, 1981).

Theoretically, the ratio values can range from zero to infinity, but in practice they tend to range from 0.3 to 3 (Lindgren, 1985). These can be rescaled to the usual range of 0 to 255 using an appropriate multiplying factor. Thus, the process of image ratioing can be mathematically expressed as follows:

$$R_{i,j_k} = \frac{V_{i,j_k}(t_2)}{V_{i,j_k}(t_1)} \cdot c \qquad (5.2)$$

[After Jensen, 1986 with some modifications in notations]

where R = Ratio value

All other symbols as in equation 5.1

The ratio values normally display a more or less Gaussian distribution pattern just like the difference/residual values obtained through the image subtraction process described above. The pixels of no change are represented by values around the mean and those of significant change are represented by values at the extremes of the normal distribution. Just like under image differencing, here too there is need to determine thresholds of ratio values that represent significant change (Jensen, 1986; Lindgren, 1985).

The ratioing procedure described above produces grey scale images where areas of no change appear in medium grey tones, and those of change appear in either darker or lighter tones. The darker tones represent areas of negative change and the lighter tones represent areas of positive change (Howarth and Wickware, 1981). Three ratio grey scale files can be displayed as colour composite.

It is also possible to ratio different bands of the same image and then compare the resulting ratios with corresponding ones for images of different dates. For instance, the near-infrared-to-red ratio (for example MSS7/MSS5 or TM4/TM3), which is a good indicator of vegetation vigour and abundance, can be separately calculated from the MSS or TM bands of images of times $t_1, t_2, \ldots\ldots t_n$. The resulting ratios can then be compared to detect changes in vegetation vigour and abundance over the period between the different image acquisition dates. Much research effort in digital change detection has actually been concentrated on the use of the near-infrared-to-red ratio and other transformed ratios in monitoring temporal vegetation changes, particularly at the global/continental scale where the ratio images are generated from NOAA's Advanced Very High Resolution Radiometer (AVHRR) data bands. Good examples on the use of these ratios, conventionally known as vegetation indices, are given in a special publication of the International Journal of Remote Sensing on monitoring the grasslands of semi-arid Africa (Int. J. Remote Sensing, Vol.7, No. 11, 1986).

In this work, the ratioing procedure expressed in equation 5.2 was undertaken by dividing DN values for pixels in TM3, TM4 and TM5 of the 1985 imagery by those for corresponding pixels in TM3, TM4 and TM5 of the 1991 imagery. The resulting ratios were multiplied by a constant 127 to rescale them into the 0 to 255 range. Just like under the image subtraction approach, here too slices 0-64 and 192-255 appeared to be the most suitable in presenting significant change. The ratio images were therefore density sliced using the 0-64 slice to present areas of negative change, and the 192-255 slice to present areas of positive change.

The approach produced results that were quite similar to those obtained under the image subtraction method. TM3 ratio images showed the least number of areas of change. TM4 and TM5 ratio images showed more areas of change. But the results simply showed areas of positive and negative change without any clues to suggest what actual type of land cover conversion was represented by each pixel that had experienced the gain or loss in DN values. Specific categories of land cover change

like bracken encroachment, dead bracken litter, moorland regeneration, neglected/fallow farmland and cleared woodland could not be identified on the image output results of this approach.

5.4.3.2.3 Principal Component Analysis

Principal component analysis, also known as Karhunen-Loeve analysis (Jensen, 1986; Mather, 1987a), is a data transformation technique. Each variable in a set of data is essentially an axis, or a dimension of variability. In principal component analysis, the data are transformed to describe the total variability (variance) with the same number of axes or dimensions, but in such a way that,

- the first axis accounts for as much of the total variance as possible;
- the second axis accounts for as much of the remaining variance as possible, whilst being uncorrelated with the first axis;
- the third axis accounts for as much of the variance remaining after that accounted for by the first two axes, whilst being uncorrelated with either;
- and so on (Daultrey, 1976).

Thus, the principal component transformation generates new data axes or dimensions that are uncorrelated with each other, and are weighted according to the total amount of variance they portray (Daultrey, 1976).

Data bands in an imagery are normally correlated to some varying degrees (Thomas *et al*, 1987). The correlation indicates that there is some information that is commonly found in the different data bands in a given imagery. Similarly, corresponding bands in images of different dates may also have some degrees of correlation. In this case, the correlation indicates information that has not changed between the two or more dates. Information about change is represented by the uncorrelated parts of the multi-temporal data bands (Bryne *et al*, 1980).

Since principal component analysis can transform highly correlated data axes into uncorrelated data components, it might render itself useful in change analysis. Multi-temporal data bands can be subjected to the principal component transformation to generate uncorrelated data bands, the principal components. The lower-order components would together account for the largest proportion of the total variance in the original bands. These would more likely portray information about no change in land cover because land cover changes quite often involve lesser proportions of land in any given area. It is the higher-order principal components that would, therefore, portray information about change (Bryne *et al*, 1980; Richards, 1984).

Bryne *et al* (1980) undertook principal component transformation on two sets of Landsat MSS data covering the Batemans Bay area of New South Wales, Australia. Each of the two sets comprised all the four MSS bands. They analysed land cover changes on the resulting 8 principal components and discovered that PC1 represented primarily unchanged land cover information in the infrared bands; PC2 represented unchanged land cover information in the visible bands; PC3-PC5 portrayed information about land cover changes; and PC6-PC8 contained random noise. Richards (1980) carried out a similar analysis on data covering an area north of Sydney, Australia. He also arrived at the same conclusion that it was the higher-order rather than the lower-order PCs that portrayed information about land cover changes. He also showed that a number of PCs could be combined to form colour composites that could be classified to make the information about change more readily available.

In this work, the1985 and 1991 data bands were subjected to the principal component transformation which produced six principal components representing the total variance in the original six bands (three 1985 plus three 1991 data bands). The percentages of the total variance contained in each component in the three extracts were as follows; with PC6 displaying the least variance, probably representing random noise.

COMPONENT	PERCENTAGE OF TOTAL VARIANCE ACCOUNTED		
	ROSEDALE	WHEELDALE	FYLINGDALES
PC1	90.78	88.34	87.80
PC2	6.14	7.28	7.55
PC3	1.48	1.65	2.03
PC4	1.31	1.53	1.80
PC5	0.18	0.97	0.57
PC6	0.09	0.23	0.25

TABLE 5.1 PERCENTAGES OF TOTAL VARIANCE CONTAINED IN EACH PC

The principal component transformation produced grey scale image files. These files were displayed one at a time and analysed to see if areas of change could be detected on each display. It was discovered that in all three extracts, displays for PC1 were almost smooth with minimal contrast across them. Displays for PC2 were relatively less smooth but it was still difficult to recognise features on them. However, there was distinctive tonal contrast between different sections on the displays for the higher-order components starting with PC3. Areas that had undergone change appeared in either darker or lighter tones, whereas those that did not undergo change appeared in medium grey tones. These displays were then density sliced using the 0-64 and 192-255 slices employed earlier in image subtraction and image ratioing. The 0-64 slice highlighted areas of negative change, whereas the 192-255 slice highlighted areas of positive change. The results showed that PC3 and PC4 portrayed more information about change than the other higher-order PCs. This was consistently observed in all three extracts.

Whilst areas of change could be identified on the displays for the higher-order PCs, the method showed that it had the same limitation as the image subtraction and image ratioing approaches. The approach simply highlighted the areas of negative and positive change without giving any clue to suggest what actual land cover conversion had taken place at each site of negative or positive change. It was therefore not

possible to distinguish various categories of change like bracken encroachment, moorland regeneration, clearing of forest, neglected farmland and others.

5.4.3.3 *Integrated Approaches*

The work with the different multispectral classification and image enhancement procedures for detecting change revealed their limitations. Post-classification comparison is very effective only when the original classifications have accuracy levels of close to 100% which is very difficult to achieve in reality, particularly in areas with complex land cover structure like the moorlands. Direct multi-date classification proved a failure in this work. Other researchers like Weismiller *et al* (1973) and Singh (1986) also judged the method as an unsatisfactory. Image differencing, image ratioing and principal component analysis approaches showed the location and extent of the areas where pixels had experienced either gain or loss in values between the two dates. The methods would therefore be very useful where changes might have been caused by two contradictory processes, one of which would be responsible for the gain and the other for the loss in pixel values. But in this case where there were quite a number of processes causing either gain or loss in pixel values, it was not possible to know which process was responsible for the radiance gain or loss experienced at a specific point. Consequently, it was not possible to categorise the changed areas into change classes C1 to C6.

Given the limitations of the conventional change detection approaches, suggestions have therefore been put forward that "hybrid" methods that integrate both classification and enhancement principles might be able to give better results (Pilon *et al*, 1988). Common integrated methods involve the classification of difference/residual and ratioed images (Howarth and Boasson, 1983); and the classification of colour composite images comprising higher-order principal components (Richards, 1980). These methods were tested in the present work and are described below.

5.4.3.3.1 Classification of Difference/Residual Images.

Difference/residual images were produced by subtracting DN values for pixels in TM3, TM4 and TM5 of the 1985 data from those for corresponding pixels in TM3, TM4 and TM5 of the 1991 imagery as already described in section 5.4.3.2.1. In each extract, the resulting three residual image files were displayed as colour composite. Areas that had undergone different types of change appeared in distinct colours on the colour composite display. By referring to ground data and the information about change obtained under the post-classification comparison method (section 5.4.1.1), it was possible to identify the type of land cover change represented by the pixels that appeared in those distinct colours. In the Rosedale extract, four categories of change were identified in that way. These were bracken encroachment (C1), bracken litter [post-treatment] (C2), moorland regeneration (C3), and neglected/fallow farmland (C5). Four categories of change were also identified in the Wheeldale and Fylingdales extracts. These were bracken encroachment (C1), bracken litter [post- treatment] (C2), moorland regeneration (C3), neglected/fallow farmland (C5), and clearing of woodland (C6). These were exactly the same categories identified under the post-classification comparison method.

Among the pixels representing each of the change categories, some were selected as training areas. Image classification was carried out using the training data. This classification produced change class "maps". The method is illustrated in Figure 5.9

Three classifiers were employed in the classification of the residual images. These were maximum likelihood, minimum distance and parallelepiped classifiers. In all three extracts, the maximum likelihood classifier greatly exaggerated the areas of change. In the last chapter, it was discovered that this classifier tends to leave fewer unclassified pixels because ideally each pixel in the feature space would have, even in relative terms only, one class to which its likelihood of membership would be higher. In this case, therefore, each pixel in the feature spaces had in relative terms, a class of

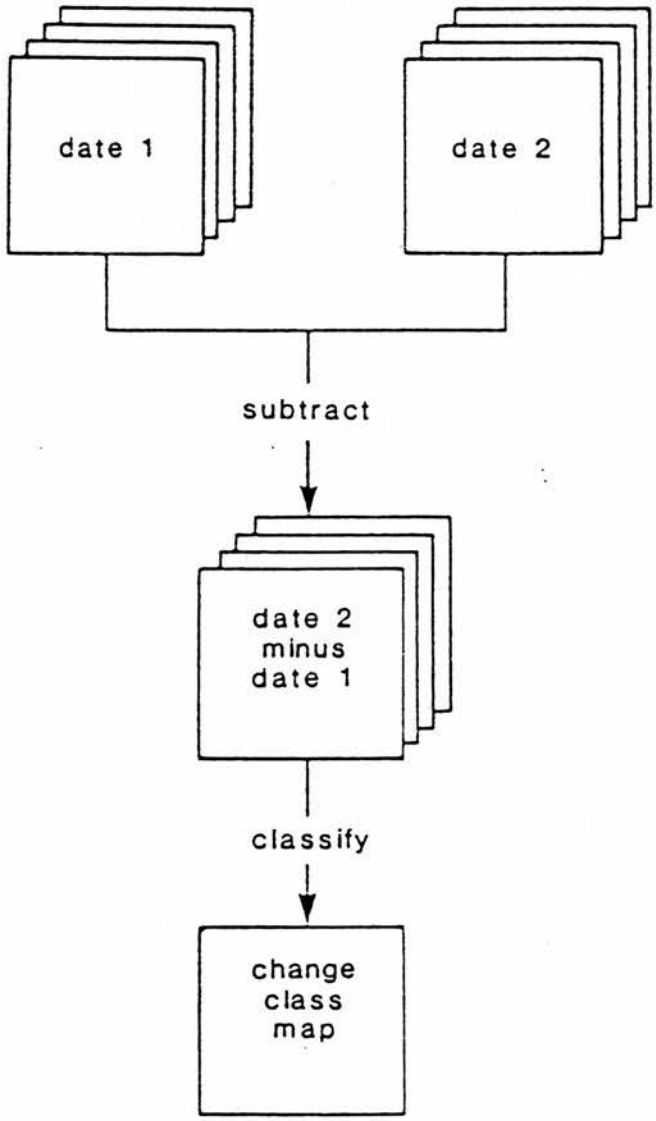


FIGURE 5.9 DIAGRAM ILLUSTRATING THE CLASSIFICATION OF RESIDUAL IMAGES APPROACH

(After Schowengerdt, 1983)

change to which its likelihood of membership was higher and into which it had to be classified. The expected result was therefore few unclassified pixels. This resulted in the gross exaggeration of the areas of change. The parallelepiped and minimum distance classifiers produced quite similar results, but the minimum distance classifier showed relatively larger areas of change than the box classifier. The results of the minimum distance classification were therefore considered more suitable for further analysis.

The numbers of pixels in each change category as determined by the minimum distance classification are presented in Table 5.2. A total of 7629 pixels had changed over the 6-year period in the Rosedale extract. These represented 4.2% of the total area in the extract. 1402 pixels represented the total area that had come under bracken. This represented a bracken encroachment rate of 6% over that 6-year period, which translates into an average annual encroachment rate of 1%. Official National Park statistics (NYMNP, 1986) and other researchers (Barber, 1986; Weaver, 1986) also put the annual bracken encroachment rate at 1%. The image output of the method showed that the main areas in which bracken encroachment and/or re-development had taken place in the Rosedale extract were around Esklets Crag (NZ 657015); and on some zones along the valley sides of Westerdale, Danby Dale, West Gill, Farndale and Rosedale.

A total of 1730 pixels represented areas on which bracken had died after treatment. This constituted 7.5% of the area classified as bracken on the 1985 imagery. The image output of the method showed that the main areas on which this type of change took place included the eastern slopes around the head of the Great Fryup Dale, around the head of Northdale and around the head of Rosedale.

Moorland regeneration was detected over an area equivalent to 2170 pixels which constituted 20.3% of the area classified as burnt/fire damaged moorland on the 1985 imagery. Expectedly, most of these pixels were in the area previously damaged by the

CATEGORY OF CHANGE	NUMBER OF CHANGED PIXELS DETECTED		
	ROSEDALE EXTRACT	WHEELDALE EXCT.	FYLINGDALES EXCT.
C1. Bracken encroachmen or re-devpt.	1402	1510	927
C2. Dead bracken litter (post-treatment)	1730	1187	268
C3. Moorland regeneration	2170	-	-
C4. Rotational burning	-	-	-
C5. Neglected/fallow farmland	2149	573	1432
C6. Clearing of woodland	-	1049	230
TOTAL	**7629**	**4319**	**2857**
% of the whole extract	**4.2**	**2.4**	**1.6**

TABLE 5.2 CHANGE DETECTION STATISTICS OBTAINED UNDER THE CLASSIFICATION OF RESIDUAL IMAGES APPROACH

1976 summer fires on Glaisdale Moor. Outside this area, there were also relatively small and scattered clusters of pixels belonging to the moorland regeneration category of change. These were on sites that had been classified as burnt/fire damaged moorland on the 1985 imagery.

2149 pixels in the dales were categorised as neglected/fallow farmland. These constituted 4.7% of the agro-pastoral land as classified on the 1985 imagery.

In the Wheeldale extract, the method identified a total of 4319 changed pixels constituting 2.4% of the total area in the extract. Of these, 1510 pixels represented areas on which bracken had encroached and/or re-developed. This represented an encroachment rate of 6.6% over that 6-year period, which translates into an average annual encroachment rate of around 1%. This tallies with official statistics on the rate of bracken encroachment. The spread of bracken was mostly detected on some zones along the slopes around Glaisdale, Egton Grange, Eskdale, Wheeldale Gill and Newton Dale. 1187 pixels represented areas on which bracken had died after treatment. These constituted 5% of the area classified as bracken on the 1985 imagery. These were also mostly detected on the slopes around the valleys.

The method also detected 573 pixels of neglected/fallow farmland constituting 1.5% of the area classified as agro-pastoral land on the 1985 imagery. These were detected mainly in the Glaisdale and Eskdale agricultural zones.

A total of 1049 pixels were detected as representing areas where woodland, mainly coniferous, had been cleared between 1985 and 1991. These constituted 4% of the total area classified as coniferous forest on the 1985 imagery. The largest "scar" left after the clearing of woodland was detected in the forest area north of Pickering. Other significant "scars" were detected at Grange Wood (NZ 7885028); around the central-eastern parts of the Wheeldale Plantation; and in an area between approximately SE 768978 and SE 7749969.

In the Flyingdales extract, the method identified a total of 2857 changed pixels constituting 1.6% of the total area in the extract. Of these, 927 pixels represented areas on which bracken had encroached or re-developed. This represented a bracken encroachment rate of 6.3% over the 6-year period, which in turn translates into an average annual encroachment rate of 1%. Once again, this tallies with official statistics on bracken encroachment. The image output of the method revealed that much of the bracken encroachment took place on the edges of the moorland. Some patches of dead bracken litter were also detected along the dale sides. These comprised a total of 268 pixels which constituted 2% of the area that was classified as bracken on the 1985 imagery.

Neglected/fallow plots of farmland were detected mainly in the Little Beck Valley, Harwood Dale, Eskdale and Fylingdales. A total of 1432 pixels represented this category of change, and these constituted 3.7% of the area classified as agro-pastoral land on the 1985 imagery.

"Scars" of cleared forests were detected in the Langdale Forest area. The total area of cleared forest was equivalent to 239 pixels which represented 0.7% of the total area classified as coniferous forest on the 1985 imagery.

5.4.3.3.2 Classification of Ratio Images

Ratio images were produced by dividing DN values for pixels in TM3, TM4 and TM5 of the 1991 imagery by those for corresponding pixels in TM3, TM4 and TM5 of the 1985 imagery. In each extract, the resulting three ratio image files were then displayed as colour composite on which pixels that had experienced different types of change appeared in distinct colours. By referring to ground data and the information about change obtained under the post-classification comparison approach (section 5.4.1.1), it was possible to determine what type of land cover changes were represented by the pixels appearing in those distinct colours. This allowed for the

categorisation of the changed pixels into classes of change similar to those detected under the post-classification and the classification of residual images approaches. In the Rosedale extract, the changed pixels could be categorised into four classes of change namely, bracken encroachment (C1); bracken litter [after treatment] (C2); moorland regeneration (C3); and neglected/fallow farmland (C5). In the Wheeldale and Fylingdales extracts, the changed pixels could be categorised into the following classes of change: bracken encroachment (C1); bracken litter [post- treatment] (C2); neglected/fallow farmland (C5); and cleared woodland areas (C6).

Training areas were selected among the pixels representing each type of change. Maximum likelihood, minimum distance and parallelepiped classifiers were run using the training data. Just like under the classification of residual images, here too it was the minimum distance classifier that gave more plausible results. The maximum likelihood classifier grossly exaggerated the extent of the areas of change. The probable cause for this has already been discussed under 5.4.3.3.1 above. The parallelepiped classifier gave results which were quite similar to those of minimum distance classification, but on the whole it underestimated most of the areas of change. Only the results of the minimum distance classification were therefore considered for further analysis.

The numbers of pixels in each category of change as determined by the minimum distance classifier are presented in Table 5.3. In the Rosedale extract, the method identified a total of 7600 changed pixels, just 29 less than the total number of changed pixels detected under the classification of residual images approach. The classification of ratio images approach underestimated the area on which bracken encroachment and/or re-development had taken place. Only 244 pixels were detected for this type of change as against the 1402 detected under the classification of residual images approach. The method detected more pixels for the moorland regeneration class than the classification of residual images. The two methods, however, detected quite similar amounts of dead bracken and neglected/fallow farmland pixels.

CATEGORY OF CHANGE	NUMBER OF CHANGED PIXELS DETECTED		
	ROSEDALE EXTRACT	WHEELDALE EXCT.	FYLINGDALES EXCT.
C1. Bracken encroachment/re-devpt.	244	877	265
C2. Dead bracken litter (post-treatment)	1720	291	1290
C3. Moorland regeneration	3044	-	-
C4. Rotational burning	-	-	-
C5. Neglected/fallow farmland	2346	437	745
C6. Clearing of woodland	-	1035	99
TOTAL	**7600**	**2640**	**2399**
% of the whole extract	**4.2**	**1.5**	**1.3**

TABLE 5.3 CHANGE DETECTION STATISTICS OBTAINED UNDER THE CLASSIFICATION OF RATIO IMAGES APPROACH

In the Wheeldale extract, the extent of the areas of all categories of change was underestimated by the classification of ratio images approach compared to the results obtained under the classification of residual images. The same was true for all but one class of change in the Fylingdales extract. The exception was the dead bracken category. The classification of ratio images detected more pixels of this class than the classification of difference/residual images.

The image outputs of the two approaches were flick-displayed to examine similarities and/or differences in the location of the changed pixels. It was discovered that the locations of the areas of change were basically the same on the image outputs of the two methods.

5.4.3.3.3 Classification of Higher-order Principal Components

Under the principal component analysis (section 5.4.3.2.3), it was indicated that in each extract, more areas of change could be identified on the displays for the higher-order principal components mainly PC3, PC4 and PC5. In each extract, the image files for these three PCs were displayed as colour composite on which areas of change appeared in distinct colours. The type of changes represented by the pixels could be determined by referring to ground data and the information about change obtained under the post-classification comparison method.

Training areas were selected among the pixels representing each type of change. Maximum likelihood, minimum distance and parallelepiped classifiers were run using the training data. Just like under the classification of residual and ratio images, here too it was the minimum distance classifier that gave the most plausible results. The number of pixels in each category of change as determined by the classifier are presented in Table 5.4. These statistics indicate that the method detected fewer changed pixels in the Rosedale and Fylingdales extracts than the classification of residual and ratio images. In the Wheeldale extract, the total number of changed

CATEGORY OF CHANGE	NUMBER OF CHANGED PIXELS DETECTED		
	ROSEDALE EXTRACT	WHEELDALE EXCT.	FYLINGDALES EXCT.
C1. Bracken encroachment/re-devept.	1439	311	1116
C2. Dead bracken litter (post-treatment)	1931	889	122
C3. Moorland regeneration	646	-	-
C4. Rotational burning	-	-	-
C5. Neglected/fallow farmland	977	1147	109
C6. Clearing of woodland	-	1127	374
TOTAL	**4993**	**3474**	**1721**
% of the whole extract	**2.8**	**1.9**	**1.0**

TABLE 5.4 CHANGE DETECTION STATISTICS OBTAINED UNDER THE CLASSIFICATION OF HIGHER-ORDER PCs

pixels detected under this method were slightly higher than that detected under the classification of ratio images. The numbers of pixels in most of the individual categories of change were underestimated.

The image outputs of the three methods were flick-displayed to examine similarities and/or differences in the locations of areas of change. It was discovered that the locations of the areas of change were basically the same in all three. It was only the extent of the areas of change that varied from one image output to another. Since the locations of the areas of change were basically the same in all three methods, it was therefore considered that the results of one of them could be taken as the representative of the integrated approaches in further analyses. In this case, it was the classification of the residual images that was chosen because this approach detected more changed pixels in each extract than either of the other two. Hard copies of the image outputs of the method are presented in Plates 5.1-5.3.

5.5 ASSESSMENT OF THE ACCURACY OF CHANGE DETECTION

The post-classification comparison approach gave information on the locations and extent of areas of change, as well as on the nature/direction of change experienced at each site. Image subtraction, image ratioing and direct analysis of principal components simply highlighted pixels that had gained or lost DN values between the two dates. The methods were therefore unable to give information about the change categories C1 to C6. The integrated methods gave information on the locations of areas of change, the direction/nature of the changes, and the extent of the areas affected. However, the methods detected different numbers of pixels for each category of change. Among them, the classification of residual images detected the largest numbers of changed pixels in each extract. Because the project aimed at detecting as much areas of change as possible, then the results of the classification of residual images were considered more meaningful and therefore suitable for further analysis.

PLATE 5.1 RESULTS OF THE CLASSIFICATION OF RESIDUAL IMAGES ROSEDALE EXTRACT

TYPE OF LAND COVER CHANGE	COLOUR ON THE IMAGE
1. Bracken encroachment	Red
2. Dead bracken litter	Dark Blue
3. Moorland regeneration	Green
5. Neglected/fallow farmland	Yellow

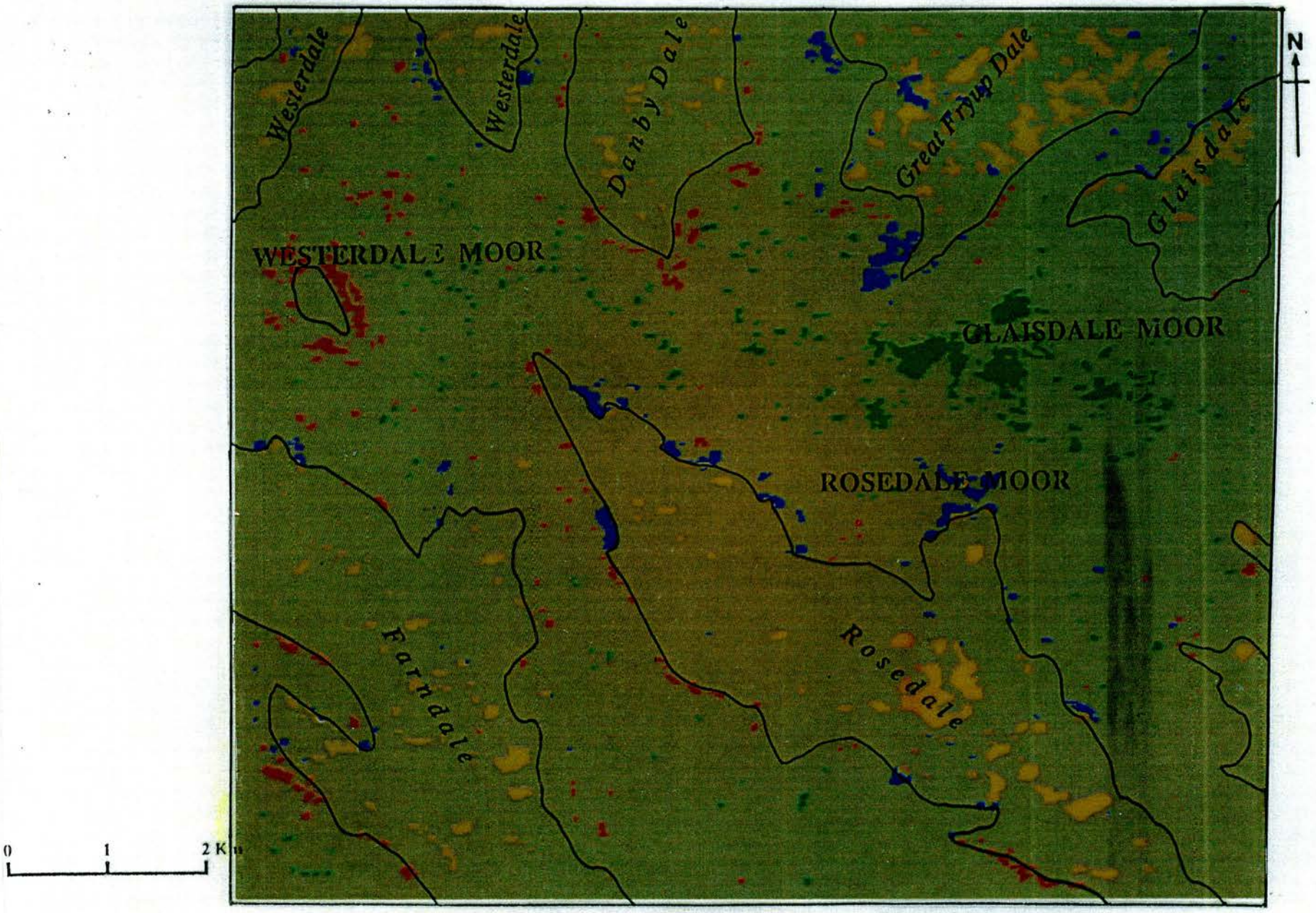

Westerdale
Westerdale
Danby Dale
Great Fryup Dale
Glaisdale
N
WESTERDALE MOOR
GLAISDALE MOOR
ROSEDALE MOOR
Farndale
Rosedale
0
1
2 Km

PLATE 5.2: RESULTS OF THE CLASSIFICATION OF RESIDUAL IMAGES WHEELDALE EXTRACT

TYPE OF LAND COVER CHANGE	COLOUR ON THE IMAGE
1. Bracken encroachment	Red
2. Dead bracken litter	Dark blue
5. Neglected/fallow farmland	Yellow
6. Cleared woodland	Purple

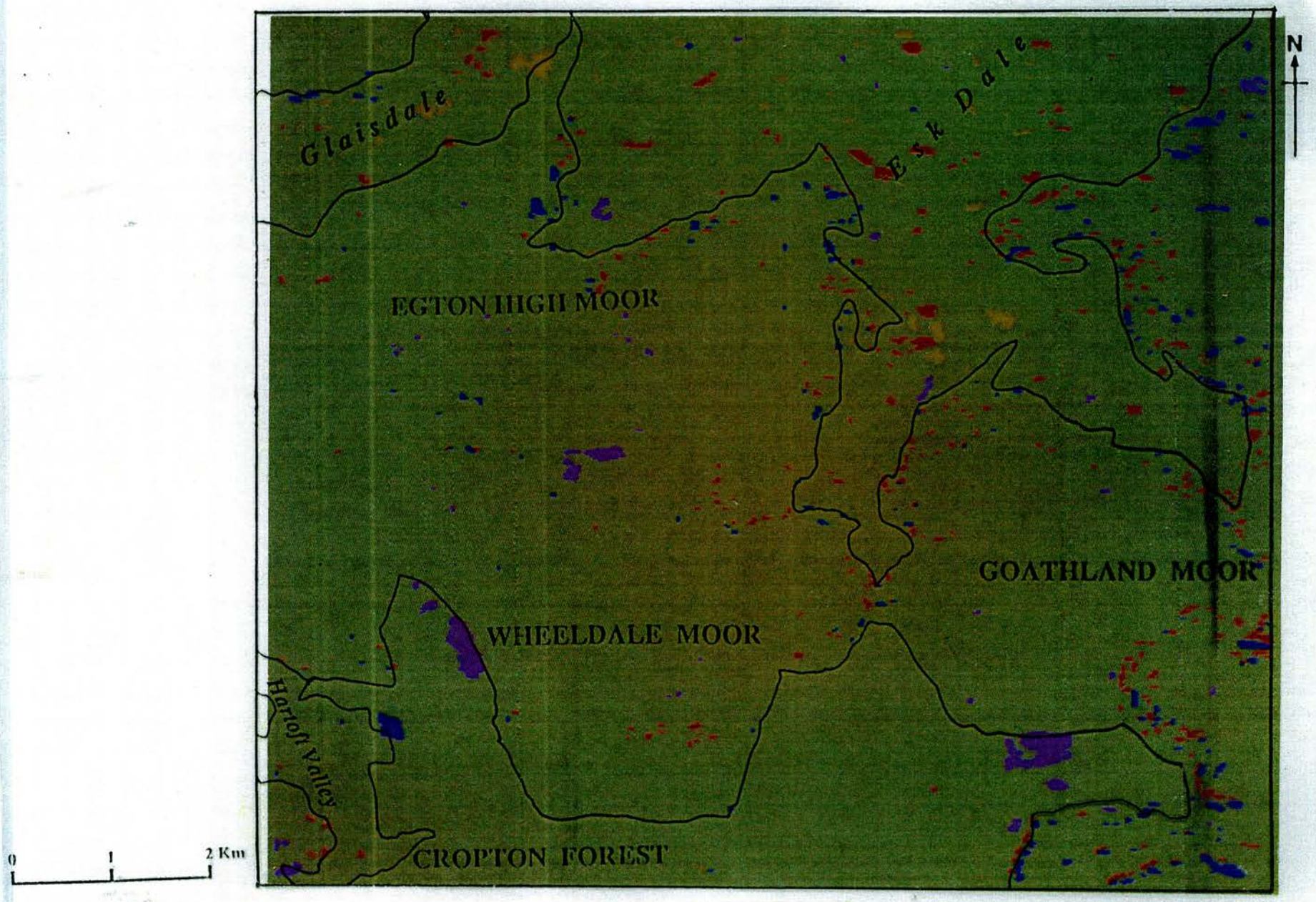
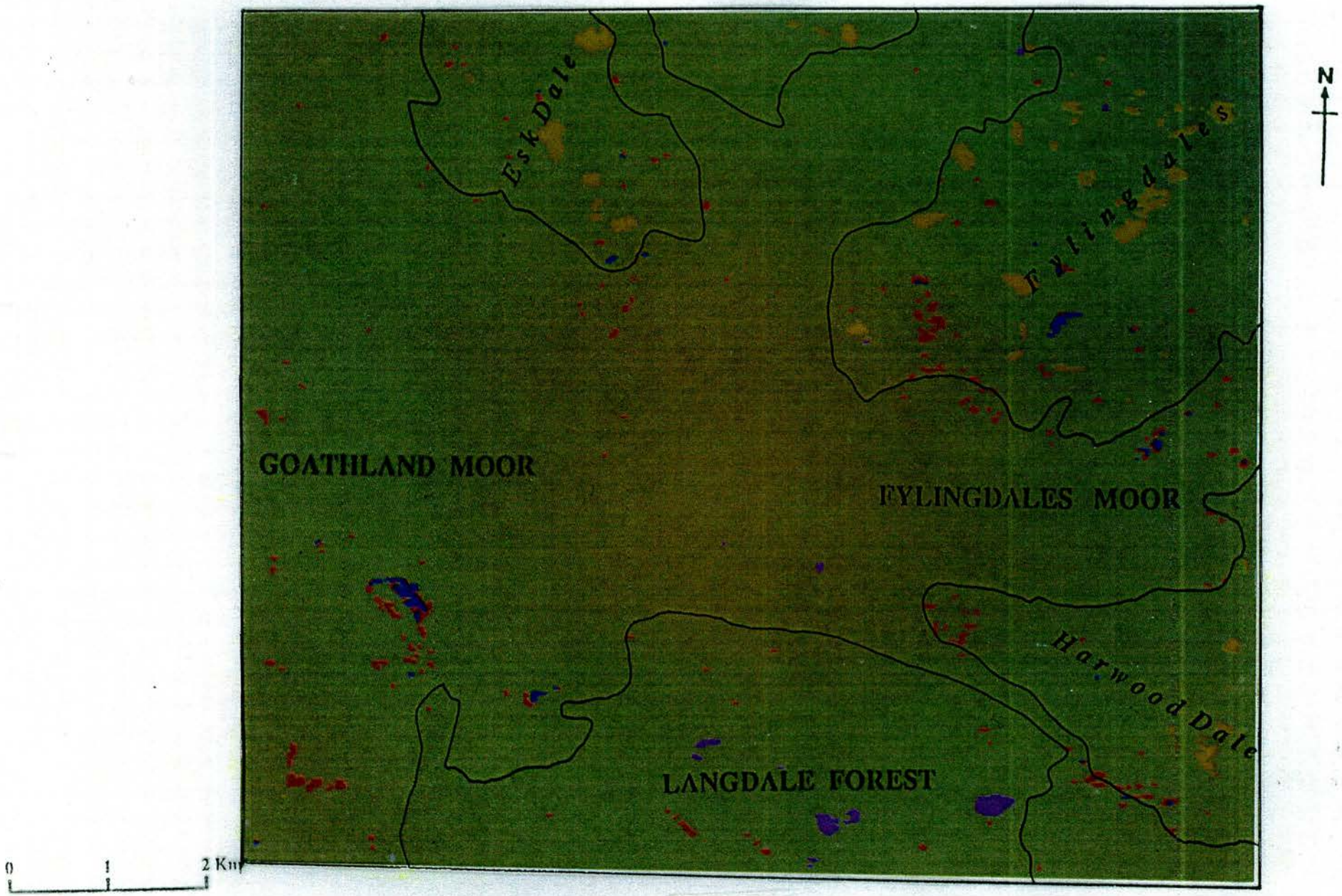

Glaisdale
Esk Dale
EGTON HIGH MOOR
GOATHLAND MOOR
WHEELDALE MOOR
Harlot Valley
CROPTON FOREST
N
0
1
2 Km

PLATE 5.3: RESULTS OF THE CLASSIFICATION OF RESIDUAL IMAGES FYLINGDALES EXTRACT

TYPE OF LAND COVER CHANGE	COLOUR ON THE IMAGE
1. Bracken encroachment	Red
2. Dead bracken litter	Dark blue
5. Neglected/fallow farmland	Yellow
6. Cleared woodland	Purple


Esk Dale
Fylingdales
GOATHLAND MOOR
FYLINGDALES MOOR
Harwood Dale
LANGDALE FOREST
N
0
1
2 Km

The accuracy of the results of the classification of residual images and the post-classification comparison approaches was evaluated. The areas of change, as detected by these two methods, were checked on the ground and on some unpublished official reference maps to assess how accurate had the changes been detected. The procedures followed in carrying out these checks are briefly described below.

5.5.1 Field Checks

The areas of change detected by the two methods were marked on photocopies of the 1:10 000 habitat maps. Ground control points helped in determining the locations of these areas on the habitat maps. However, only the larger areas of change were marked in that way. The corresponding positions of small groups of changed pixels could not be properly located on the maps.

The maps were taken to the field and the marked sites were then visited to check what was actually on the ground. The result of this checking was either acceptance that the particular type of change detected had really taken place at the site if there was evidence of it on the ground; or rejection that the change had not taken place if there was no evidence of it on the ground. Where it was confirmed that change had taken place, the extent of the areas affected were estimated.

Where the detected sites of change occurred in areas that had been visited during the field trips undertaken prior to change analysis, then the field data acquired during those trips were used to check the accuracy of the detected changes without actually re-visiting the sites.

There was one major limitation in assessing the accuracy of the detected changes through the field checks. The problem was that all field work for this project was carried out after 1991 whilst the changes detected on the images were for the period 1985-91. This meant that the reliability of the information acquired from the field

checks was highly dependent on whether there had or there had not been any further changes at the sites in the period after 1991. This problem affected mostly the neglected/fallow farmland category of change since once a neglected/fallow plot is brought back into use, it is difficult to establish whether it was neglected/fallow three years earlier. Otherwise, it was possible in areas outside the agricultural land to imply what type of land cover existed at a site a few years before the ground check. For instance, if the change analysis had indicated that bracken was establishing itself at site *A* in the 1985-91 period; and if during the field check in 1994 it was discovered that site *A* was an area of dead bracken, it would still be possible to conclude that the area had been under active bracken 3 to 4 years earlier, since bracken takes 3 to 4 years to die out completely after treatment (Rees, Pers. Comm).

5.5.2 Checks on Unpublished Official Reference Maps

Two sets of unpublished official maps were obtained for use as reference data in assessing how accurate had the changes been detected. One was a 1:63 360 map showing areas covered under the bracken control project. Bracken areas treated at different dates were shown in different colours. This map was obtained from the National Park offices at Helmsley and was used mainly to check areas that had been detected as dead bracken litter. Since it takes 3 to 4 years after treatment for bracken to die out completely, then the areas of dead bracken were considered to have been correctly detected if the map showed that those sites had been sprayed in 1989 or earlier. Areas of dead bracken were considered to have been incorrectly detected if the map showed that those sites had been sprayed after 1989 or never sprayed at all. This checking was used as a supplement to the field checks in assessing how accurate had the areas of dead bracken been detected.

The second set of official maps were 1:25 000 sheets of forestry management maps obtained from the Forestry Commission offices in Pickering. These were mainly used as sources of reference information on areas of cleared woodland and the dates on

which the felling was undertaken. Only information on areas cleared before 1991 was useful in this project. Areas detected as cleared woodland zones in the change analysis were checked on these maps. An area of cleared woodland was considered to have been correctly detected if on the maps it was shown that the woodland in the area had actually been felled before August 1991. Conversely, an area of cleared woodland was considered to have been incorrectly detected if on the maps it was shown that the woodland had not been felled before August 1991.

After making the checks in the way described above, the number of sites checked for each category of change in each extract were recorded. The number of sites where the change had been correctly detected were also noted down. The accuracy with which each category of change had been detected was calculated using the equivalent of equation 4.7 (i.e c_i/n_i x 100) where the numerator was the number of sites that had been correctly detected for that particular type of change; and the denominator was the total number of sites checked for that particular category of change. Similarly, the overall accuracy with which all types of changes in an extract had been detected was calculated using the equivalent of equation 4.8 (i.e $\sum[c_i/n_i]$ x 100) where the numerator and denominator are as stated above. The resulting statistics are presented in Tables 5.5-5.7.

5.6 DISCUSSION OF RESULTS

This part discusses how successful were the post-classification comparison and the classification of residual images approaches in detecting the different categories of change. The discussion is based on the information in Figures 5.2-5.4, Plates 5.1-5.3 and on the statistics presented in Tables 5.5-5.7. It begins with an appraisal of the performance of the post-classification comparison approach before giving a similar appraisal for the classification of residual images approach.

CATEGORY OF CHANGE	NUMBER OF SITES CHECKED	SITES WHERE CHANGES WERE CONFIRMED			
		POST-CLASSIF. COMPARISON		CLASSIF. OF RESIDUAL IMAGES	
		NUMBER	PERCENTAGE	NUMBER	PERCENTAGE
C1. Bracken encroachment/re-devpt.	12	9	75	10	83
C2. Dead bracken litter (post-treatment)	11	8	73	8	73
C3. Moorland regeneration	6	5	83	5	83
C4. Rotational burning	-	-	-	-	-
C5. Neglected/fallow farmland	4	4	100	4	100
C6. Clearing of forests	-	-	-	-	-
TOTAL	**33**	**26**	**79**	**27**	**82**

TABLE 5.5 CHANGE DETECTION ACCURACY STATISTICS : ROSEDALE EXTRACT

CATEGORY OF CHANGE	NUMBER OF SITES CHECKED	SITES WHERE CHANGES WERE CONFIRMED			
		POST-CLASSIF. COMPARISON		CLASSIF. OF RESIDUAL IMAGES	
		NUMBER	PERCENTAGE	NUMBER	PERCENTAGE
C1. Bracken encroachment/re-devpt.	8	7	88	7	88
C2. Dead bracken litter (post-treatment)	5	4	80	4	80
C3. Moorland regeneration	-	-	-	-	-
C4. Rotational burning	-	-	-	-	-
C5. Neglected/fallow farmland	5	5	100	4	80
C6. Clearing of forests	7	4	57	6	86
TOTAL	**25**	**20**	**80**	**21**	**84**

TABLE 5.6 CHANGE DETECTION ACCURACY STATISTICS : WHEELDALE EXTRACT

CATEGORY OF CHANGE	NUMBER OF SITES CHECKED	SITES WHERE CHANGES WERE CONFIRMED			
		POST-CLASSIF. COMPARISON		CLASSIF. OF RESIDUAL IMAGES	
		NUMBER	PERCENTAGE	NUMBER	PERCENTAGE
C1. Bracken encroachment/re-devpt.	7	5	83	6	86
C2. Dead bracken litter (post-treatment)	4	4	100	3	75
C3. Moorland regeneration	-	-	-	-	-
C4. Rotational burning	-	-	-	-	-
C5. Neglected/fallow farmland	4	3	75	2	50
C6. Clearing of forests	6	4	67	5	83
TOTAL	**21**	**16**	**76**	**16**	**76**

TABLE 5.7 CHANGE DETECTION ACCURACY STATISTICS : FYLINGDALES EXTRACT

5.6.1 Post-classification Comparison Approach

The areas of change detected under the post-classification comparison approach are presented in Figures 5.2-5.4 These areas were identified by visual comparison of the classified 1985 and 1991 data. They were then delineated manually. The identification and delineation of the areas of change were undertaken on transparencies of hard copies produced at an approximate scale of 1:56 000. At this relatively small scale, only the large scale changes involving more than just few contiguous pixels could be visually identified. Thus, the method had the disadvantage of being unable to identify changed areas that were of the size of one or two pixels.

The statistics in Tables 5.5-5.7 indicate that in the Rosedale extract, the post-classification comparison approach detected changes correctly in 79% of the total sites checked for all categories of change. The corresponding overall accuracy level in the Wheeldale extract was 80%; and in the Fylingdales extract it was 76%. The method therefore gave an average overall accuracy of 78%. This can be considered as a satisfactory accuracy level because it is stated that most digital analyses of change on multi-temporal satellite data tend to give overall accuracy levels that lie within the range of 70 to 75% (Lindgren, 1985). However, the 78% accuracy level is still 7 percentage points lower than the 85% minimum accuracy level required in resource evaluation projects carried out using remotely sensed data (Jensen, 1986; Lindgren, 1985; Lo, 1986).

In terms of individual categories of change in the Rosedale extract, the post-classification comparison method performed very satisfactorily in detecting areas of moorland regeneration (C3) and neglected/fallow farmland (C5). All the sites checked for the neglected/fallow farmland category of change had been correctly detected under the method. Similarly, 83% of the sites checked for the moorland regeneration category of change had been correctly detected. An accuracy level of 83% is just 2 percentage points lower than the required minimum accuracy of 85%. 75% of the

sites checked for the bracken encroachment (C1) category of change had been correctly detected under the method. The accuracy level for the dead bracken (C2) category of change was 73%.

The approach produced better results for three categories of change in the Wheeldale extract. Of the sites checked for the bracken encroachment (C1) category of change, 88% had been correctly detected. All sites checked for the neglected/fallow farmland (C5) category of change had been correctly detected. Areas of dead bracken had similarly been detected with an accuracy level of 80%. The method was not equally very effective in detecting areas of cleared woodland. Only 57% of the sites checked for this type of change had been correctly detected.

In the Fylingdales extract, the method produced very satisfactory results in the detection of areas of dead bracken, and those on which bracken was encroaching and/or re-developing. All the sites checked for the dead bracken (C2) category of change, and 83% of the sites checked for the bracken encroachment (C1) category of change, had been correctly detected. Of the sites checked for the neglected/fallow farmland (C5) category of change, 75% had been correctly detected. Just as in the Wheeldale extract, here too the method performed less well for the cleared woodland (C6) category of change. Only 67% of the sites checked for this type of change had been correctly detected.

5.6.2 Classification of Residual Images Approach

The areas of change detected under the classification of residual images are presented in Plates 5.1-5.3. The digital classification enabled even very small areas of change to be detected. Thus, areas of change of the size of one or two pixels are equally revealed in Plates 5.1-5.3. This suggests that where information is needed even for small areas of change, then the digital classification of residual images would be a better option.

In terms of overall accuracy, the statistics in Tables 5.5-5.7 show that, in general, the classification of residual images approach performed slightly better than the post-classification comparison approach. This might have been expected as the idea of carrying out integrated methods like the classification of residual images is to increase the accuracy by combining the strengths of the classification and enhancement approaches. The approach gave an overall change detection accuracy of 82% in the Rosedale extract; 84% in the Wheeldale extract and 76% in the Fylingdales extract. The accuracy values achieved in the Rosedale and Wheeldale extracts are respectively 3 and 4 percentage points higher than those obtained under the post-classification comparison approach in the same extracts. In the Fylingdales extract, the accuracy value obtained under the classification of residual images approach is the same as that obtained under the post-classification comparison approach. The values given above translate into an average overall accuracy level of 81%. Once again, this can be considered as a highly satisfactory accuracy level as it is stated that quite often, the detection of change on multi-temporal satellite data using digital methods tends to give accuracy values in the range of 70 to 75% (Lindgren, 1985). However, the 81% accuracy value is still 4 percentage points lower than the stipulated 85% minimum accuracy level required for effective resource analysis operations carried out using remotely sensed data (Jensen, 1986; Lindgren, 1985; Lo, 1986).

The method also gave generally encouraging accuracy values for most of the individual categories of change. In the Rosedale extract, it was very successful in detecting three of the four types of change identified. All the sites checked for the neglected/fallow farmland (C5) category of change had been correctly detected. Similarly, the method gave change detection accuracy levels of 83% for the bracken encroachment (C1) category of change. Moorland regeneration (C3) was also detected with the same level of accuracy. 73% of the sites checked for the dead bracken [post-treatment] (C2) category of change had been correctly detected.

In the Wheeldale extract, the method gave accuracy values of more than 85% for the bracken encroachment (C1) and cleared woodland (C6) categories of change. Areas of dead bracken as well as neglected/fallow farmland plots were detected with an accuracy level of 80%.

In the Fylingdales extract, the method produced encouraging results for the bracken encroachment (C1) and cleared forest (C6) categories of change, just as it did in the Wheeldale extract. It detected bracken encroachment correctly in 86% of the sites checked for that category of change. 83% of the sites checked for the cleared woodland (C6) category of change had also been correctly detected. The accuracy level for the dead bracken (C2) and neglected/fallow farmland categories of change were 75% and 50% respectively.

5.7 IMPLICATIONS OF THE RESULTS FOR RESOURCE MONITORING

The preceding sections have indicated that the post-classification comparison and the integrated change detection approaches were able to give information about the locations of the areas of change, direction/nature of change experienced at each site, and the scale (extent) of the detected areas of change. On the types of change, five out of the six specified categories of change could be detected. These were bracken encroachment and/or re-development (C1), dead bracken [post-treatment] (C2), moorland regeneration (C3), neglected/fallow farmland (C5), and cleared woodland (C6). Rotational burning (C4) type of change could not be detected because on the time t_2 (1991) imagery, the separation of the 1991 burns from burns of the previous two years was not possible owing to the very similar nature of their spectral response patterns.

The overall accuracy levels achieved under both the post-classification comparison and the classification of residual images methods were, however, slightly lower than the stipulated minimum accuracy level required in resource analysis operations

carried out using remotely sensed data. Nevertheless, it might be recalled from Chapter 4, section 4.3.2, where it was stated that an overall classification accuracy value is not a good basis for judging the utility value of data generated from the analysis of remotely sensed imagery. It was further stated that it is the individual class accuracy level that offers a realistic indication of the utility value of the data for that class. In the same manner, the overall change detection accuracy values cannot be regarded as valid bases for making judgement about whether or not the methods can be effectively used in monitoring land cover changes. Whilst, the overall accuracy values were below the required minimum of 85%, there were some individual change categories with accuracy values of 85% or more. It would not be totally correct to make a generalisation that land cover changes cannot be effectively detected through the digital analysis of multi-temporal satellite data just because the overall accuracy values were lower than 85% although some individual change categories had accuracy values of 85% or more.

What it means is that those categories of change that were detected with very high accuracy values can be effectively monitored through the digital analysis of multi-temporal satellite data. One such category of change is bracken encroachment and/or re-development, which was detected with an average accuracy value of 86% under the classification of residual images approach. The method also produced statistics that indicated that bracken encroachment was taking place at an annual rate of 1%. As stated earlier (section 5.4.3.3.1), the National Park authorities (NYMNP, 1986) and other researchers (Barber, 1986; Weaver, 1986) also put the bracken annual encroachment rate at 1%. This indicates that the method did not only give correct information on the location of areas where bracken encroachment was taking place, but it also gave realistic estimation of the encroachment rate. Information requirements on the location of areas where bracken is spreading into, and the rate at which the encroachment is taking place, can therefore be satisfied through the digital analysis of multi-temporal satellite data, particularly through the classification of residual images approach.

Both the post-classification comparison and the classification of residual images approaches gave an average accuracy level of 83% for the moorland regeneration (C3) category of change. This accuracy level is just 2 percentage points lower than the required minimum of 85% and could as well be considered satisfactory. This implies that the methods can also be effectively used in monitoring moorland regeneration.

Similarly, the classification of residual images approach proved very effective in detecting cleared woodland areas. It gave an average accuracy of 85% for that category of change.

The accuracy values for dead bracken [post-treatment] (C2) and neglected/fallow farmland (C5) categories of change lacked consistency. For instance, in the Fylingdales extract, the dead bracken [post-treatment] (C2) category of change had an accuracy level of 100% under the post-classification comparison method, but in the Rosedale extract, the value was as low as 73%. The classification of residual images approach equally did not give consistently encouraging results for this category of change. Similarly, the neglected/fallow farmland (C5) category of change had an accuracy value of 100% in Rosedale extract under both methods, only to drop to an accuracy value of 50% in the Fylingdales extract under the classification of residual images approach. Because of these inconsistencies, it cannot be confidently concluded that these two categories of change can be effectively monitored through the digital analysis of multi-temporal satellite data. It is those inconsistencies that brought down the overall accuracy values.

In the final analysis, it can therefore be said that important land cover changes like bracken encroachment, moorland regeneration, and the clearance of woodland can be effectively monitored through the digital analysis of multi-temporal Landsat TM data. More work, however, is required to assess whether or not dead bracken [post-treatment] (C2) and neglected/fallow farmland (C5) categories of change can be

effectively detected using multi-temporal Landsat TM data. The results obtained in this project were not consistent enough to allow a conclusion to be made about the two categories of change.

The ideal resource monitoring programme is one which is able to provide timely and accurate data at relatively low costs. Ground-based surveillance would certainly provide accurate information about land cover changes. However, the information would not be obtained in a timely and cost-effective manner. Similarly, it is practically difficult to carry out ground-surveillance over very large areas. On the other hand, the use of multi-temporal satellite data is a cost-effective method that provides timely information, and the results of the present project have indicated that it can provide generally encouraging results in the detection of important land cover changes like bracken encroachment, moorland regeneration and the clearance of woodland. Since satellite data cover very large areas, then it would also be possible to use multi-temporal images to monitor land cover changes over large areas like a whole district in a province. Data from satellites like NOAA cover even more extensive areas. But the 1.1Km spatial resolution of NOAA's sensor, the AVHRR, is too coarse to allow relatively small scale changes like those studied in this project to be effectively detected. However, studies like those carried out in Africa (Hielkema *et al*, 1986; Justice and Hiernaux, 1986; Justice *et al*, 1986; Tucker *et al*, 1986) have shown that AVHRR data can be useful in monitoring large scale changes at national to major regional levels.

The encouraging results obtained for the cleared woodland (C6) category of change suggests that multi-temporal satellite data could be used to monitor forest areas. Normally, when plantations are developed to the maturity stage, it is relatively difficult to access the interior sections owing to the dense undergrowth. It therefore becomes difficult to obtain comprehensive information about conditions of all forest sections using ground surveillance methods. The results obtained in this research project suggest that remotely sensed data could offer a remedy to the problem of

monitoring the less accessible forest zones. Similarly, the work undertaken by Singh (1986) indicated that in tropical forest areas, where the problem of accessibility is even worse, the use of remotely sensed data might be the only practically viable option for monitoring the valuable forest resources.

".....the 'executive summary' .....is usually the only part read by senior personnel.....who do not have the time or .... interest to study the details of the report."

D. Dent and A. Young (1981) **p 219**

"In the conclusion the researcher offers his decision or judgement about the problem.,.....In so far as the evidence is adequate and the reasoning logical, these conclusions are based upon a solid base."

B. Mitchell (1979) **p 33**

"A distinction should be kept between conclusions and recommendations."

D. Dent and A. Young (1981) **p 219**

CHAPTER 6
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter provides a summary of the work undertaken in this project. It also presents conclusions drawn from the findings, and some recommendations for further research.

6.1 SUMMARY

Moorlands constitute the largest and probably the most important semi-natural terrestrial environment in Britain. Over the years, land owners seeking higher economic returns from their land have converted significant amounts of moorland areas into seeded pasture and coniferous plantations. The demand for recreational use of the relatively quiet and spacious moorland areas has grown and this has increased the risk of damage to the vegetation and soils through the trampling and erosion of footpaths, as well as through the proliferation of roads, car parks and service facilities. Factors related to changes in traditional moorland management practices have also given rise to rapid spread of bracken resulting in loss of moorland vegetation.

In England and Wales, most of the large stretches of moorland have been designated national parks in order to offer them some form of protection. The largest tract of moorland in England and Wales is enclosed within the boundaries of the North York Moors National Park. This area is therefore very suitable for studying the nature of moorland environment and the pressures to which it is being subjected.

As a resource management institution, the North York Moors National Park Committee is required to formulate policies relating to the rational use and/or conservation of moorland and related natural resources in the park. It is also required to help in the implementation of those policies. To be able to formulate sound

resource management policies, the Committee requires information about the resources available, their spatial distribution and condition. This information helps in identifying and analysing resource problems, as well as in choosing the best strategy to be followed in trying to solve these problems.

The conventional way of acquiring resource information is by carrying out ground-based surveys. But these are becoming increasingly costly especially where large areas are involved. There are also problems related to the ways in which the survey data are normally presented and stored. All these have led to a re-evaluation of the strategies for acquiring data about land resources, and satellite remote sensing is now being considered as a potential alternative source of land resource data.

Satellite data are spatially comprehensive. Each scene of satellite data covers large areas including those that would not be easily accessible to ground-based surveyors. The data are acquired repetitively and are readily amenable to quick computer processing and safe storage on disks and magnetic tapes from which they can be easily retrieved at will for revision or collation with other types of spatial data in digital format. More importantly from an economic point of view, information per unit area of land is cheaply obtained through the analysis of satellite data than through the execution of ground-based surveys.

Because of the advantages stated above, resource management institutions, including the North York Moors National Park Committee, increasingly consider satellite data as a solution to the problems faced in acquiring resource information. It is expected that satellite data would be used in monitoring management trends and moorland changes. However, this proposed operational use of remotely sensed data needs to be preceded by research to assess the suitability of the data for mapping and monitoring moorland and related land cover. The present project is one among several other works carried out by researchers in the North York Moors to evaluate the suitability of remotely sensed data for inventorying moorland and related land cover, and for

detecting their temporal changes. The specific objectives of the present work are to discover how much of the different land cover types in the North York Moors can be visually and/or spectrally discriminated on Landsat TM imagery; to assess the effectiveness of image classification techniques in extracting and presenting information about land cover from sets of Landsat TM multispectral data; and to assess the effectiveness of digital change detection techniques in identifying areas that had undergone change, and in determining the scale and the nature/direction of the changes on a set of multi-temporal Landsat TM data.

The main data used in this work consisted of two sets of digital Landsat 5 TM bands covering the south-eastern quarter of TM scene 203/22. One set was for data acquired on May 31st, 1985 and the second was for data acquired on August 20th, 1991. The analysis was carried out on TM bands 3(red), 4 (near-infrared), and 5 (mid-infrared) of these two data sets. There were also non-image data sets that were acquired and analysed in order to obtain supplementary information to help in making the analysis of satellite data very effective. Among these were ground data on vegetation communities collected in a series of field visits. These provided "ground truth" relating to the types, structure and spatial pattern of vegetation communities that exist in the area of study. Other types of data acquired and used in this work were *in situ* spectral data collected using a Macaulay two-band ground radiometer; panchromatic and colour aerial photographs; North York Moors National Park conservation maps; Phase 1 Habitat Maps; Ordnance Survey Tourist Maps; unpublished North York Moors National Park bracken control scheme map; and forestry management maps obtained from the Forestry Commission Offices in Pickering.

Data analysis began with the ancillary data in order to obtain background information which is essential in the interpretation of image data. The aerial photographs were qualitatively interpreted using image characteristics of tone, texture, shadow, pattern, association, shape and position/site. The identified land cover types were classified into categories following the classification scheme used by Hunting Technical

Services Limited in the *Monitoring Landscape Change Project* which was carried out in the 1980s.

The analysis of maps mainly involved the identification, enumeration, classification and recording of features and/or land cover types in each square of the map grid. From this type of analysis, it was possible to determine very common cover types in the area (i.e those that occurred in many squares on the maps), as well as occasional land cover types (i.e those that occurred in very few squares on the maps). Because the maps have topographical information in the form of contours, it was equally possible to relate the distribution pattern of a given land cover type to topographical conditions.

The ground data on vegetation communities collected from different sites, were comprehensively compared to discover the communities' differences and/or similarities in terms of such characteristics as floristic composition, stratification, stage of development and vigour, sociability and cover-abundance. The discovered similarities and/or differences enabled the categorisation of the communities into community/habitat types. The categorisation was carried out following the classification schemes used by Hunting Technical Surveys in the *Monitoring Landscape Change Project* , and by Silsoe College in the *Monitoring Landscape Change in National Parks Project* which was carried out in early 1990s.

The spectral data acquired in the field using a ground radiometer were used in making non-destructive measurement of amounts of green vegetation structures in different communities. This involved calculating normalized difference vegetation indices for the various communities. Thriving bracken fronds and young heather shoots recorded the highest vegetation index values suggesting that there were greater amounts of green vegetation structures in these two types of canopies than in the others. The spectral reflectance values were also plotted in a two dimensional feature space with near-infrared values on the x axis and red values on the y axis. This step was

undertaken to see if the different land cover types could be discriminated using the radiometer data.

The 1991 imagery was geometrically rectified to the British National Grid by registering it to the 1985 imagery which had already been geometrically corrected by the supplier. Ground control points (GCPs) were identified on the 1985 and 1991 image extracts. The root mean square (RMS) error statistic was computed to assess how correctly the GCPs had been located on the 1985 and 1991 image extracts. Only those GCPs with RMS error values of 1 or less were considered for use in the registration process. Those with RMS error values of more than 1 were edited out. The image processor then regressed the x, y co-ordinate values of the GCPs on the 1985 imagery against corresponding values on the 1991 imagery to obtain transformation coefficients. The coefficients were used in transformation polynomial equations to work out the co-ordinates of a new geometrically correct grid for each extract. The process was completed by assigning DN values to the cells in the newly created grids. The nearest neighbour resampling method was employed in determining the DN values to be assigned to each cell.

An analytical land cover classification scheme (see Table 3.6) was adopted specifically for use in this project. It presents a structure of land cover units which provides a framework for the analysis and generalisation of information. The objectives of the present study and the spatial resolution of the Landsat TM data were the main determinants of the size of the smallest land cover units that were included in the scheme. The scheme that was formulated was essentially an adaptation of the classification scheme used in the *Monitoring Landscape Change in National Parks Project* carried out by Silsoe College.

Two colour composite displays were prepared for each extract. One comprised the three 1985 data bands and the other comprised the three 1991 bands. Once loaded, these were contrast stretched and analysed visually using principles of aerial photo

interpretation. In addition, 60 pixels were randomly selected for each land cover category in each extract. The DN values for those pixels were recorded. The range and mean of the pixel values for each land cover type were determined, and standard deviations were also calculated. These steps were undertaken on the extracts of the 1985 imagery, and repeated on those of the 1991 imagery. The obtained mean values and standard deviations were used in the calculation of the normalized difference index of spectral separability which is a measure of the spectral distinctiveness of land cover categories.

The mean pixel values of each land cover on the spring 1985 data extracts were compared with corresponding values on the summer 1991 data extracts to discover the seasonal differences in their spectral reflectance values.

The spring 1985 and summer 1991 data were also independently classified using three supervised classification strategies. These were minimum distance, maximum likelihood and parallelepiped classification strategies. All steps followed in the classification process were carried out on the extracts of the 1985 imagery and were later repeated on the extracts of the 1991 imagery. The classification process itself began with the selection of training areas on the colour composite displays. The image processor then worked out statistics from the training pixels. The data for the training classes were evaluated to ascertain the degree to which they (the training classes) could be regarded as the true representatives of their respective parent classes. Less representative training classes were revised, and the classifiers were run using the evaluated training data. They were run one at a time, and each study extract underwent six classifications. These were: minimum distance, maximum likelihood, and parallelepiped classifications for the 1985 data bands; and minimum distance, maximum likelihood, and parallelepiped classifications for the 1991 data bands. The image outputs of the classifications had a "salt-and-pepper" appearance. They were therefore filtered to suppress the pixels responsible. On R-CHIPS, the outputs of minimum distance and maximum likelihood classifications are grey scale images

which show less contrast between classes. In this project therefore, distinct colours were interactively assigned to the classes in order to make each class visually distinctive. This operation converted the grey scale image outputs of the two classifications into colour images.

Classification accuracy assessment was carried out by comparing the classified images with 1:10 000 reference maps. This comparison was undertaken for selected sample areas. The 1Km x 1Km grid squares on the 1:10 000 maps were the sampling units and in each extract, five 1Km x 1Km squares were randomly selected to constitute a 5.6% sample. The selected squares were manually registered to the corresponding areas on the images. They were also stratified into cells that corresponded with the pixels on the images so that it was possible to compare a pixel on the classified images with a corresponding cell on the reference maps. Through this type of comparison, correctly and incorrectly classified pixels could be identified. The numbers of correctly and incorrectly classified pixels were used in the calculation of some measures of classification accuracy and error. The accuracy measures calculated were class accuracy level (%), and overall accuracy level (%). For error, the measures calculated were level of omission error in a class (%); level of commission error in a class (%); overall error of omission (%); and overall error of commission (%). The confidence limits of the accuracy levels achieved were computed at 99% confidence level.

The second major part of the project involved assessing whether types of land cover changes that affect resource management policies in the North York Moors could be effectively detected through the digital analysis of a multi-temporal set of satellite data comprising 1985 and 1991 Landsat TM data. Three groups of change detection techniques were employed in this part of the project. These were multispectral classification approaches, image enhancement approaches, and "hybrid" approaches integrating the principles of the other two types of approach.

Post-classification comparison was one of the two multispectral classification approaches used in this work. In this project, this approach involved the comparison of the maximum likelihood classifications of the 1985 and 1991 imagery. Hard copies for these classifications were photographically generated and copied to transparencies using a colour photocopier. For each extract, the transparencies for the 1985 and 1991 classifications were overlaid and analysed to detect changes. Detected areas of change were then delineated on a fresh transparency spread over the overlay set.

The second multispectral classification technique employed in the analysis of change is the spectral-temporal (direct multi-date) classification. Because R-CHIPS cannot display colour composites comprising more than three bands, this technique was followed using principal components. In each extract, the first three principal components were displayed as colour composites. It was expected that changed areas would appear in unique colours on such displays and would consequently be classified.

Image differencing, image ratioing and principal component analysis were the three image enhancement change detection techniques employed in this work. Under image differencing, TM3, TM4, and TM5 of the 1985 data were respectively subtracted from TM3, TM4 and TM5 of the 1991 data in each extract. The value 127 was employed as a constant for rescaling the difference/residual values into the positive range of 0 to 255. The process generated grey scale images. These were density-sliced to highlight the areas that had undergone significant change. Positive change was represented by the slice range 192 - 255 and negative change was represented by slice range 0 - 64. These slice ranges were empirically determined as the most effective in presenting areas of positive and negative change.

Under image ratioing, TM3, TM4 and TM5 of the 1991 were divided by TM3, TM4 and TM5 of the 1985 data. The resulting ratios were multiplied by a constant value of 127 to rescale them into the conventional range of 0 to 255. The ratio images, which

were also grey scale in nature, were density-sliced using the 0 - 64 slice to present areas of negative change, and the 192 - 255 slice to present areas of positive change.

Change was also investigated using principal components analysis. The three 1985 and the other three 1991 data bands were together subjected to principal component transformation which generated six grey scale PC files representing the total variance in the six original bands. These files were displayed one at a time and were visually analysed to see if areas of change could be detected on each display.

The "hybrid" approaches involved analysing changes on colour composite displays comprising three residual image files; then on colour composite displays comprising three ratio image files; and on similar displays comprising three high-order PC files. Areas that had undergone change were expected to appear in unique colours on such displays. Where these were identified, some were selected to constitute training areas. Classification was then carried out using the training data from those training sites.

The image outputs of the three integrated approaches were flick-displayed to examine similarities and/or differences in the location of the detected areas of change. It was discovered that the three approaches gave basically the same results in terms of the location of the areas of change, but they differed in terms of the number of pixels detected under each category of change. The method that had detected more changed pixels was therefore selected to stand in lieu of all integrated approaches in the assessment of change detection accuracy. In this case it was the classification of residual images approach.

The accuracy with which the classification of residual images and post-classification comparison approaches had detected the changes was assessed. The areas of change, as detected by these two methods, were checked on the ground and on unpublished official bracken control and forestry management reference maps to discover whether the detected changes were genuine.

6.2 CONCLUSIONS

In this part, the main findings of the work are described and the conclusions drawn from the findings are presented. The section is divided into two. The first sub-section presents the general findings and conclusions, while the second part focuses on what have been discovered to be major problems of the techniques employed in this research project. Ways for overcoming these problems have to be investigated in order to improve the quality and/or quantity of information that can be derived from the analysis of remotely sensed data.

6.2.1 General Findings and Conclusions

6.2.1.1 *Visual Identification and Discrimination of Land Cover Types*

It was discovered that all land cover categories included in the analytical classification scheme used in this work could be identified and discriminated by the visual analysis of contrast stretched colour composite displays using elements of aerial photo interpretation. Colour proved to be the single most important criterion for identifying and distinguishing different land cover types. However, there were some land cover types that could not be easily distinguished on the basis of colour alone. For instance, on the spring 1985 imagery, there was little difference in colour between spring (largely dead) bracken and bare fields; deciduous woodland and stands of old heather; and deciduous woodland and unimproved grass. On the summer 1991 imagery, there was great confusion in colour between summer (live thriving) bracken and green crops/pasture. The photo interpretation elements of site and association (context) helped in distinguishing land cover types where their differences in colour were subtle. Just like in aerial photo interpretation, background information relating to the types and spatial distribution of land cover in the area of study proved essential.

The conclusion drawn from this part of the work is that moorland and related land cover types can be effectively identified and distinguished on analogue forms of Landsat TM imagery following principles of aerial photo interpretation.

6.2.1.2 *Spectral Discrimination of Land Cover Types*

A two dimensional feature space plot of *in situ* red band and near-infrared spectral data showed that a number of land cover types were spectrally distinct. These were live bracken, dead bracken, bare peat, wet heath and acid grass. The only case of spectral confusion was between *Calluna vulgaris* and *Vaccinium myrtillus*. Normalized difference indices of spectral separability calculated using DN values from the Landsat TM data bands also showed that about 64-73% of the pairs of land cover categories in each extract were spectrally separable in the TM3 (red) bands; and about 72-80% in TM4 (near-infrared); and about 69-75% in TM5 (mid-infrared) bands. Thus, in both spring and summer imagery, more pairs of land cover categories were spectrally separable in the infrared bands, particularly in TM4 (near-infrared). However, the indices also showed that some pairs of land cover categories were spectrally separable in the visible red band (TM3) but not in the infrared bands. These included young heather and established heather; as well as bare fields and broadleaved woodland.

Comparing the same bands on the spring and summer imagery, it was discovered that more land cover categories were spectrally separable in the spring 1985 data bands than in the summer 1991 data bands. However, there were other land cover types that were more spectrally separable in the summer data bands than in the spring bands. These included broadleaved woodland and bare fields; as well as bare fields and bracken.

A number of conclusions can be drawn from these findings. One is that, in general , moorland and related land cover types have different spectral response patterns so that

it is possible to distinguish them on the basis of their reflectance values recorded on remotely sensed data. The second conclusion is that although more land cover types are spectrally separable in the near-infrared band, no band can be regarded as the optimum in terms of providing land cover information since there were some land cover types that were not separable in the near-infrared band but were separable in the other bands. Therefore, a corollary conclusion is that much more land cover information would be obtained when more than one data band are analysed together (i.e multispectral analysis) than through the analysis of near-infrared band on its own. The other conclusion is that although more land cover types are spectrally separable in the spring data bands than in the summer data bands, all the same spring cannot be regarded as the optimum season for acquiring remotely sensed data for the purpose of studying moorland and related land cover types since the results showed that there were other categories that were not spectrally separable in the spring data bands but were separable in the summer data bands. The corollary conclusion is that the quality and quantity of information obtained from remotely sensed data would increase if data acquired during different seasons are to be analysed together.

6.2.1.3 *Seasonal Variations in Land Cover Reflectance*

The study discovered that most of the land cover categories had different reflectance levels in the spring and in the summer data bands. These differences largely result from seasonal growth changes in the plant communities. The conclusion drawn from this finding is that it would be possible to study or to monitor phenological changes in moorland and related land cover using remotely sensed data acquired during the different seasons in a year.

6.1.2.4 *Extraction of Land Cover Information Through Image Classification*

The three classifiers employed in the classification of the spring 1985 and summer 1991 images performed quite differently. On the whole, the maximum likelihood

classification strategy performed more satisfactorily than the minimum distance and parallelepiped strategies. It gave high and fairly consistent class and overall accuracy levels in the classification of both the spring and summer data bands. It also left negligible numbers of unclassified pixels indicating its efficacy in extracting information from all parts of the image data. By contrast, minimum distance and parallelepiped classifiers gave relatively low overall classification accuracy levels. Although they gave some high individual accuracy levels, they were not consistent and many categories were very unsatisfactorily classified by these two techniques. They also left substantial amounts of unclassified pixels.

Although the maximum likelihood classifier produced encouraging results on both the spring 1985 and summer 1991 data, it was discovered that some individual classes were much more correctly classified on the 1991 imagery than on the 1985 imagery, and *vice versa* for others. Bracken, fire damaged moorland, and wet heath were generally much more correctly classified on the spring 1985 imagery than on the summer 1991 imagery. By contrast, dry heather moorland was generally much more correctly classified on the summer imagery than on the spring imagery.

One of the conclusions drawn from the image classification operations is that the maximum likelihood classifier, because of its strong conceptual basis, is able to extract information from almost all parts of image data with satisfactory levels of accuracy. Therefore, the corollary conclusion is that the classification of remotely sensed data using maximum likelihood decision rule can provide a sound data base for use in making decisions related to the rational use and/or conservation of moorland and related land cover. The other conclusion is that, since some land cover types were more correctly classified on the summer imagery than on the spring imagery, and *vice versa* for others, then the results of the classification of an image acquired on any single date cannot be used to compile a complete and highly reliable land cover map of the area. It would require classification of image data acquired

during different seasons in order to obtain highly reliable information on all significant land cover types in the area.

The study also arrived at a conclusion that the outputs of minimum distance and parallelepiped classifications cannot be regarded as very reliable thematic data bases on their own because the accuracy levels obtained under the two approaches were, in most cases, lower then the 85% required minimum. However, it was also indicated that it is possible to supplement them with information obtained from ground checks undertaken in those sections that are misclassified or unclassified on the imagery in order to generate highly reliable thematic data bases. It was equally explained that the resource maps that can be produced by integrating classification and ground survey data would be even more reliable than those produced exclusively from ground surveys (see section 4.5.3, chapter 4 for details). This leads to the conclusion that the most reliable land cover data would be obtained where conventional resource surveys and remote sensing techniques are regarded as complementary approaches and not as competing substitutes.

6.2.1.5 *Detection of Land Cover Changes*

The post-classification comparison approach yielded information on the location of areas that had experienced change as well as the nature/direction of the change that had taken place at each site. The change maps produced under this method (see Figure 5.2-5.4) also gave rough estimates of the extent of the areas that had undergone a particular type of change. Five out of the six categories of change could be detected and these were bracken encroachment and/or re-development (C1); dead bracken [post-treatment] (C2); moorland regeneration (C3); neglected/fallow farmland (C5); and cleared woodland (C6). Rotational burning (C4) type of change could not be detected because on the time t_2 (1991) imagery freshly-burnt areas could not be distinguished from those burnt within the previous two years.

Direct multi-date classification failed to give results. Although some zones that had been identified as areas of change under the post-classification comparison approach appeared in unique colours on the colour composite displays comprising PC1, PC2 and PC3, it still proved difficult to extract adequate pure training pixels so that classifying the supposedly changed pixels into change categories C1 to C6 failed.

Enhancement procedures like image differencing, image ratioing, and principal component analysis simply highlighted areas that had experienced gain and/or loss in digital values between the two image dates. They gave no additional clues to allow those areas to be categorised into C1 to C6 classes of change.

The integrated ("hybrid") approaches provided information on location of areas that had undergone change, nature of the changes, as well as number of pixels involved in each category of change. Just like the post-classification comparison approach, these methods also detected five categories of change. These were bracken encroachment (C1), dead bracken [post-treatment] (C2), moorland regeneration (C3), neglected/fallow farmland (C5), and cleared woodland (C6). The image outputs of the three "hybrid" methods showed that all of them had performed almost similarly in detecting the areas of change. However, the extent of the areas of change were differently detected. Of the three methods, the classification of residual images approach detected more pixels of change. Since the project aimed at detecting as much change as possible, then the results of the classification of residual images were considered to be good representatives of all the integrated methods.

An assessment of change detection accuracy showed that the post-classification comparison approach gave an average overall accuracy level of 78%, whereas the best of the integrated methods, the classification of residual images approach, produced an average overall accuracy level of 81%. These accuracy values were considered to be very encouraging because it is stated that the detection of change on multi-temporal satellite data using digital methods quite often tend to give accuracy

levels in the range of 70 to 75% (Lindgren, 1985). However, the 78% and 81% accuracy values are still lower than 85% which is regarded as the minimum accuracy level required in resource evaluation and monitoring operations carried out using remotely sensed data (Jensen, 1986; Lindgren, 1985; Lo, 1986; Robinove, 1981). Whereas overall accuracy values were lower than 85%, the methods gave accuracy values of around or over 85% for some of the categories of change. Bracken encroachment (C1) category of change was detected with an accuracy value of 86% under the classification of residual images approach. It could also be calculated from the statistics obtained under the method, that bracken encroachment was taking place at an annual rate of 1%. The National Park Committee (NYMNP, 1986) and other researchers (Barber, 1986; Weaver, 1986) also put the annual rate of bracken encroachment at 1%. Both the post-classification comparison and the classification of residual images approaches detected moorland regeneration with an average accuracy value of 83% which is just 2 percentage points lower than the required minimum accuracy level of 85%. This was therefore considered as a satisfactory accuracy level in this project. Similarly, the classification of residual images approach gave a satisfactory accuracy value of 85% for the cleared forest (C6) category of change.

A number of conclusions were drawn from the change detection part of the project. One is that it is possible to obtain reasonably reliable information about the location, nature and magnitude of change by overlaying and comparing the results of well-classified multi-temporal satellite data. A second conclusion is that the spectral-temporal (direct-multi date) classification approach may not be a very effective method for detecting land cover changes especially when lower-order PCs are used in lieu of the original multi-band data, as was the case in this project. As for the enhancement approaches (image differencing, image ratioing and principal component analysis) the conclusion arrived at is that these methods would be quite effective in analysing change caused by two conflicting processes like vegetation clearance and regeneration; land development and abandonment; decrease or increase in water levels; and rural-to-urban and urban-to-rural land use changes, to mention a

few. They are not so effective where land cover changes are caused by many unrelated factors. It was also concluded that the integrated methods, particularly the classification of residual images, can give more reliable information on the location, nature and extent of change particularly for the bracken encroachment, moorland regeneration and cleared woodland categories of change.

A more general conclusion is that the digital analysis of change on multi-temporal satellite data can be effective in detecting important land cover changes like bracken encroachment, moorland regeneration and the clearance of woodland. A corollary general conclusion is that finer resolution satellite data like Landsat TM and SPOT offer practically viable options for monitoring land resources. The fact that satellite data cover large areas means that changes can be monitored over extensive areas which may be difficult to accomplish with ground-based surveillance techniques. The relatively short intervals between consecutive acquisitions of satellite data (16 days for Landsat TM, 26 days for SPOT in a normal viewing mode and $2^1/_2$ days on average in off-nadir viewing mode) mean that they are more suitable for providing timely information about changes caused by episodic events like uncontrolled fires and floods. The use of remotely sensed data is also relatively more cost-effective than ground-based surveillance techniques. The encouraging results obtained in detecting forest clearing (C6) type of change equally suggest that the use of remotely sensed data can provide a solution to forestry monitoring problems which result from the fact that sections deep in the middle of well-established large forest areas are normally less accessible to ground surveyors. In tropical rain forest areas, where the problem of accessibility is even worse, then the use of remotely sensed data might be the only practically viable option for monitoring the forest resources. All these advantages combine to make remotely sensed data good tools for monitoring land cover changes although it may not be possible when using such data to pin-point the areas of change and estimate their extent with the precision of a ground surveyor.

6.2.2 Problems of the Techniques

The project discovered that there are some major problems with the classification and change detection techniques. In terms of classification, one of the problems shared by all three classifiers is the failure to do well in the gradual zones of transition between different land cover types. The minimum distance and parallelepiped classifiers either misclassified or failed to classify the pixels in the transitional zones. Most of the pixels misclassified by the maximum likelihood classifier also occurred in similar zones. Pixels for those transitional zones portray information of two or more land cover types. Since a classifier can only assign each pixel to one and only one land cover class, then such mixed pixels tend to be either misclassified or left unclassified. This means that even a robust classifier like the maximum likelihood technique can seldom extract correct land cover information in the transitional zones.

Another problem that was discovered is that the 30m x 30m resolution of the Landsat TM data is still too coarse to allow for the effective classification of narrow, linear features and/or small and isolated features. Such type of features include acid flushes (wet peat grass moor); upland grass moor on the moorland edge; hedge rows and broadleaved woodland plots on farms, along streams and along the sides of roads. Most of these are less than 30m wide, which means they cannot register a signal filling the whole of a 30m x 30m pixel. Because of this, they are mostly represented by mixed pixels which even the maximum likelihood strategy fails to classify properly.

A problem specific to the parallelepiped/box classification algorithm used in this project is that it is able to classify land cover into a maximum of only 8 classes. Given the complexity in land cover structure in areas like the North York Moors, it means that the approach can only be effective when working with less meaningful tiny extracts. Otherwise, land cover categories have to be combined to form broad classes

which do not provide adequate information about the real structure of land cover on the ground.

The minimum distance and parallelepiped classification strategies have a common major conceptual and practical problem, and this relates to the fact that they do not consider the correlation of pixel values in the different data bands. The satellite sensor detects a continuous signal from the ground. This is then sampled a number of times (4 times for Landsat MSS, and 7 times for Landsat TM) to give the 4 MSS bands or the 7 TM bands. Since these bands are generated from a continuous signal, then there are always some degrees of correlation among them (Thomas *et al*, 1987). For a classifier to be effective in assigning pixels to their respective land cover categories, it should consider the correlation of the values of a pixel in the different bands. Failure to do so results in misclassification of many pixels. Since the minimum distance and parallelepiped classifiers do not consider the correlation, then they would not be expected to be as effective as the maximum likelihood classifier which uses correlation data in the classification process.

There are also well-recognised problems with the digital change detection techniques. One relates to the usual failure to achieve perfect (i.e zero RMS error) registration of multi-temporal satellite data. This means that it is almost impossible to avoid recording small spurious changes even in a well-executed change detection project (Lindgren, 1985; Singh, 1986). Another problem is that the digital methods of change detection, just like the conventional classification strategies, use nothing more than the spectral information recorded on the multi-temporal satellite data. The assumption is that the ground features are perfectly represented by the brightness intensity (DN) values recorded on the satellite data so that when the DN value of a specific pixel in an image of time t_2 is different from its value in an image of time t_1, then it is automatically taken to imply that land cover change has taken place. In reality, however, there is no one-to-one relationship between ground objects and the brightness intensity (DN) values recorded on remotely sensed imagery (Wang and

Newkirk, 1987). The DN values are rarely the records of pure reflectances of ground objects because of the effect of atmospheric conditions, and "noise" which is introduced in the process of data scanning, recording and transmission (Wang and Newkirk, 1987). In this way, even if maximum care is taken in carrying out digital analysis of multi-temporal satellite data to detect change, it is almost impossible to avoid recording bogus changes and at the same time failing to detect some genuine changes.

The specific change detection approaches also have their own specific problems. The success of the post-classification comparison approach, for instance, depends on a high degree of accuracy in the independent classification of the original multi-temporal images. As stated earlier, it is difficult to obtain very high classification accuracy levels in areas of complex land cover structure and/or complex topography. This means that the post-classification comparison approach will always have limited success in detecting land cover changes in such areas.

Direct multi-date classification has practical problems especially when working with image processing systems that are unable to display more than three bands at a time. Carrying out a principal component transformation of the original multi-band data and then using the first three PCs as representatives of the original bands may not completely solve the problem in this case because the work on principal component analysis proper (see chapter 5, section 5.4.3.2.3) has shown that it is the higher-, and not the lower-order PCs that contain much information about change. However, the lower-, and not the higher-order PCs are the rightful representatives of the original multi-band data, and therefore using the higher order PCs in the spectral-temporal classification would be defying the very concept of "direct" multi-date classification.

The main problem with the enhancement approaches (image differencing, image ratioing and principal component analysis) is their failure to give information on the nature/direction of land cover changes. These approaches simply highlight areas that

had experienced gain or loss in radiance between the two image dates. Where there are only two types of change caused by two conflicting processes like forest clearing and regeneration, then it is possible to imply that the areas of negative change represent forest clearing and those of positive change represent regeneration. But when there are more processes causing gain or loss in radiance, then the information about the different types of land cover conversions cannot be obtained from the image outputs of these methods.

Integrating classificatory and enhancement procedures into "hybrid" approaches is not without its own problems. Quite often, errors may be introduced in the course of integrating the two types of approach. For instance, the pixels of change may not be quite distinct so that it might be difficult to select pure training pixels for the different categories of change. The use of less pure training areas may result in the classifier being less able to assign changed pixels to their correct classes of change. There are also the normal limitations of conventional classifiers. All these may make integrated methods (classification of residual images, classification of ratio images, classification of higher-order PCs) unable to perform well in some respects. In the present work, for instance, the average accuracy levels for the dead bracken [post-treatment] (C2) and neglected/fallow farmland (C5) categories of change were respectively 84% and 85% under the post-classification comparison approach, and 76% and 77% respectively under the best of the integrated approaches, the classification of residual images approach. These results show that the integrated methods performed less well than the post-classification comparison approach for the two specific categories of change.

6.3 RECOMMENDATIONS FOR FURTHER RESEARCH

Some hypotheses have been generated from the findings of the present project relating to how the quality and/or quantity of information obtained from the analysis of remotely sensed data can be improved. It is therefore suggested that further work

should be carried out to investigate these hypotheses. The recommended research projects are briefly explained below.

6.3.1 *The Integrated Use of Multi-band Data Acquired During Different Seasons*

It has been discovered in the present project that each of the bands used had some advantages to offer which the others did not. It is believed that if all the 7 TM bands had been assessed in the same way, we would come to the same conclusion. This implies that in order to obtain maximum information from the remotely sensed data, all the 7 TM data bands should be incorporated into the analysis. It was also discovered in the project that some land cover types could be discriminated and classified much more correctly on the spring imagery than on the summer imagery, and *vice versa* for others. Thus, neither the spring nor the summer imagery could provide adequate information about all types of land cover in the area. If the summer and spring images were to be integrated and analysed together, it would probably be possible to obtain much more information as each set of imagery would in part, compensate for the shortcomings in the other. The addition of an autumn image would probably give even better results.

The hypotheses stated in the preceding paragraph prompted the recommendation that an investigation should be carried out to prove whether more information for land cover inventorying purposes would actually be obtained from visual analysis and digital classification of combined multi-band data acquired in summer, autumn and spring. In view of the practical problems of analysing 21 data bands (i.e 7 TM bands x 3 seasons of acquisition) at a time, it is therefore suggested that the multi-band data can be subjected to principal component transformation and a few low-order PCs can then be used in the analysis in lieu of the original data bands.

6.3.2 *The Use of Probability Surface Mapping Technique*

Probability surface mapping is a variant of trend surface mapping, a method of spatial analysis whose importance in geographical research was thoroughly discussed by Chorley and Haggett as early as 1965 (Chorley and Haggett, 1965). In essence, trend surface analysis is a technique used to examine the change of phenomena over space. The analysis aims at discriminating regional trends from localised patterns. This discrimination is accomplished by specifying and fitting an appropriate trend surface model (Wrigley, 1977a; 1977b; Unwin, 1975). The normal trend surface model is actually a linear regression model in which the explanatory variables are the geographical (x, y) co-ordinates of each site or locality in the spatial series (Wrigley, 1977a; 1977b). The technique has been used to examine spatial trends in phenomena as diverse as erosion surfaces, glacial cirques, soil pH, rainfall and levels of atmospheric pollution (Unwin, 1975).

The trend surface mapping method works only with variables measured at either ratio or interval scale, and not with those measured at either nominal or ordinal scale. The probability surface mapping approach was therefore developed as a variant of the trend surface mapping method applicable to data measured at the nominal or ordinal scale (Wrigley, 1977a; 1977b). Under this approach, the degree to which a spatial point conforms to a specified nominal or ordinal surface trend is measured as a probability on the normal 0 to 1 range. Where the spatial point does not have any characteristic of the given surface trend, then its probability of fitting in that trend is zero. Where it has all the characteristics of the trend, then its probability of fitting in that trend is 1. These probabilities are determined using some mathematical models conventionally known as probability surface models. When the probabilities have been computed for all x, y (geographical) points, then it is possible to categorise all points with similar or nearly similar probability values into zones/regions. This results in the partitioning of the spatial surface into equiprobability zones with respect to the nominal or ordinal spatial trend (Wrigley, 1977a).

The probability zones that the technique produces are reminiscent of the vegetation clines that vegetation ordination techniques generate. The clines reflect the continuous nature of the distribution of plant species over space. If remotely sensed data were to be analysed through either the surface probability mapping technique or ordination approaches, then it would be possible to model the continuous nature of vegetation distribution over space. This would be more helpful when analysing remotely sensed data for semi-natural environments such as moorlands where definable communities form the end points of continua, and where the gradual zones of transition between different land cover types are therefore represented by mixed pixels which tend to be misclassified or left unclassified by even a robust classifier like maximum likelihood. Ordination programmes for use with remotely sensed data are not yet readily available on the market. On the other hand, the probability surface mapping technique uses parameters derived from maximum likelihood or linear discriminant classification approaches to model the surface trends (Wrigley, 1977a, 1977b). Probability surface mapping can therefore be considered as an extension of conventional classification operations. If the analysis of remotely sensed data is carried out on an image processor that has spatial modelling functions, then probability surface mapping can be accomplished by inputting the probability parameters derived from maximum likelihood or discriminant classification into the appropriate trend surface model and then running the whole modelling programme to generate a land cover probability surface map.

Research work is needed to prove the hypothesis that it might be possible to model the continuous nature of moorland vegetation communities using the probability surface mapping technique. Pioneering work in probability surface mapping of moorland areas using remotely sensed data has already been undertaken by Wood and Foody (1989) and Foody and Trodd (1990, 1993). But this has covered only a small area in Surrey, and it is therefore necessary to assess the effectiveness of the technique in mapping larger areas. Wood and Foody (1989), and Foody and Trodd (1990, 1993) have also simply highlighted the advantages offered by the probability

surface mapping technique without presenting its limitations and problems. It is therefore equally essential to make a thorough investigation of the limitations and problems of the method before recommending it to ordinary users of remotely sensed data.

6.3.3 *The Use of GIS-supported, Knowledge-based Classification Approaches*

The present study has shown that even a sophisticated classifier like the maximum likelihood could not provide 100% accurate data. It is actually argued that despite the advances in digital remote sensing and image classification, skilled aerial photo interpreters achieve a very high level of accuracy in target identification that is not yet readily achievable in the digital analysis of image data (Trotter, 1991). The skilled aerial photo interpreter achieves higher accuracy level in target identification because his analysis is based on background information about topography, climate, soils, road network and other physical and cultural features. These sets of ancillary information are synthesised by the human brain into sets of rules for recognising and describing features on the aerial photographs.

Better classification results would probably be achieved if algorithms for analysing satellite data had an element or function that simulates the brain of an expert aerial-photo interpreter in that they would be able to synthesise ancillary information into rules for recognising and describing features on the satellite imagery (Goodenough *et al* , 1987; Srinivasan and Richards, 1990; Trotter, 1991). Algorithms developed to work in the way just stated above are known as knowledge-based or "expert" systems (Burrough, 1986). Most of the "expert"/knowledge-based image classification approaches developed have been GIS-supported because the integration of multi-source spatial data is best achieved through Geographical Information Systems (GIS). An example of a GIS-supported, knowledge based classification approach is outlined in Figure 6.1. In that approach, image classifiers are used to generate spectral and/or textural class "maps". The class data are then "interrogated" using some image

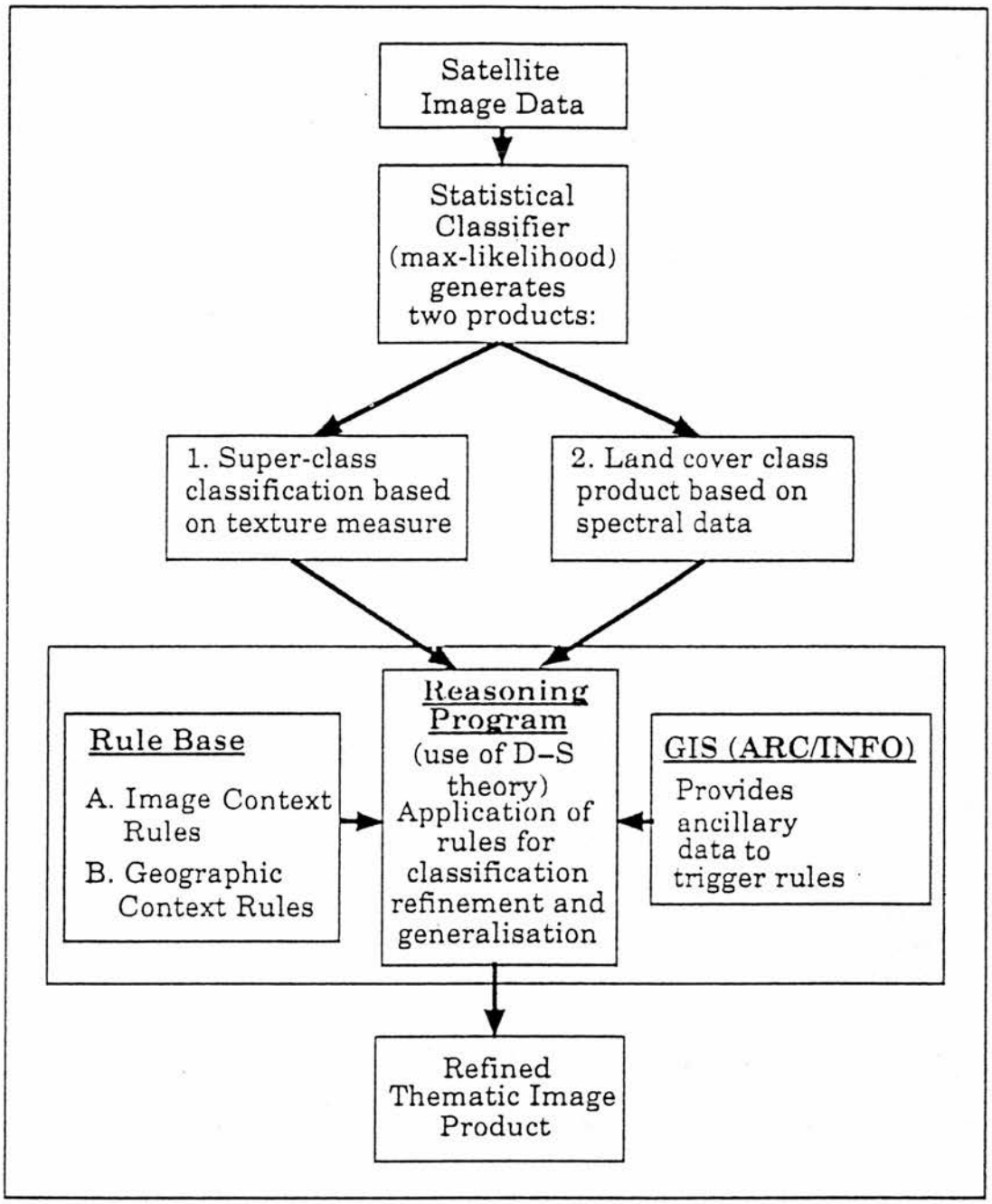


FIGURE 6.1 AN EXAMPLE OF A GIS-SUPPORTED KNOWLEDGE-BASED SYSTEM USED BY KONTOES *et al* , (1993)

context and geographical context rules generated from the ancillary data in the GIS. The "interrogation" is based on Dempster-Shafer (D-S) theory of evidence in which each identified class is given a value of confidence, which is a measure of the degree to which the class can be considered to be pure. These values are computed based on the combined evidence derived from the multi-source ancillary data in the GIS (Kontoes *et al*, 1993). Those classes that are identified with low degrees of confidence can then be re-classified. Refined thematic image outputs can be generated from the system once the analyst has been satisfied with the achieved degrees of confidence for all the classes.

It is recommended for further work that attempts should be made to acquire knowledge-based programmes and use them in analysing remotely sensed data on systems that are linked with GIS. The results that would be generated from such GIS-supported, knowledge-based classification techniques should then be compared with those generated from conventional classification algorithms in order to discover whether the former methods would actually improve the quality and/or quantity of information that can be obtained from the remotely sensed data.

6.3.4 *The Use of GIS-supported, Knowledge-based Change Detection Approaches*

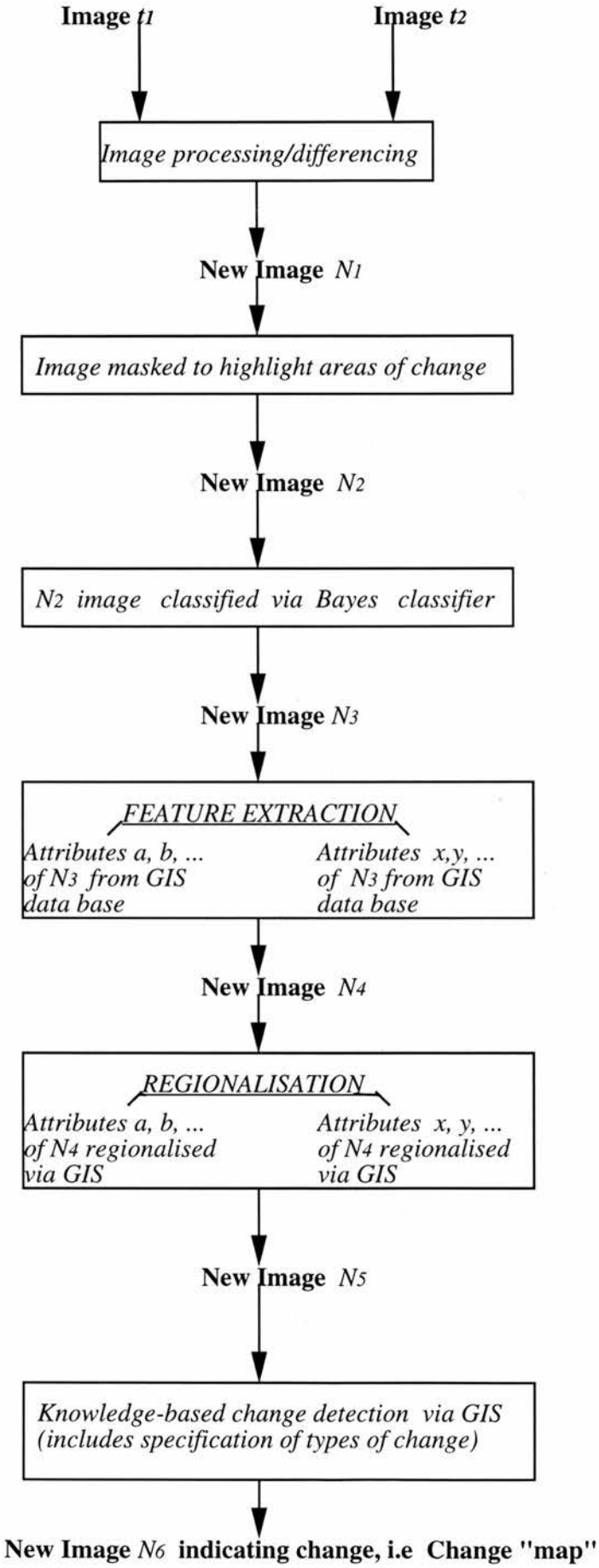
It has been stated earlier (chapter 5, section 5.7) that the results on the detection of neglected/fallow farmland and dead bracken lacked consistency, so that it could not be concluded with much certainty that the methods can equally be effectively used in monitoring those two types of land cover change. At the same time, although the methods proved reasonably effective in detecting types of changes like bracken encroachment, moorland regeneration and the clearance of woodland, it is stated that, on the whole, digital change detection methods at their present level of development cannot be as effective as the manual analysis of multi-temporal aerial photographs carried out by expert aerial photo interpreters (Jensen, 1986; Lindgren, 1985). This means that improvements in the digital change detection techniques are needed in

order to make them capable of giving higher and more consistent accuracy levels for all categories of change.

As stated under section 6.2.2, a major factor that limits the performance of digital change detection techniques is that they work on the basis of spectral information on its own, although in reality, the spectral (DN) values recorded on the remotely sensed imagery are rarely the precise "fingerprints" of ground objects since the pure radiation reflected by ground features is quite often tampered with by energy scattered from the atmosphere and "noise" which is introduced during the processes of data scanning, recording and transmission (Wang and Newkirk, 1987). A proper way to improve the performance of these methods is to reduce the reliance on spectral information *per se* by incorporating more non-spectral information into the actual change detection process. This would require algorithms that are able to synthesise information from ancillary (non-image) data sets to generate some rules for identifying land cover changes. Since such algorithms would, to a certain extent, have to work like the brain of an expert manual analyst, they would therefore have to be knowledge-based/"expert" change detection algorithms. They would also have to be GIS-supported since the synthesis of data from different sources is best achieved through Geographical Information System (GIS).

There have already been attempts to design and work with GIS-supported, knowledge-based systems for change detection. An example is one designed and described by Wang and Newkirk (1987), Newkirk and Wang, (1990) and is summarised in Figure 6.2. The technique basically involves the use of "expert" rules stored in a GIS to "interrogate" the results of a classification of residual images approach. It therefore begins with the normal differencing of images of times t_1 and t_2. The areas of change on the residual images are then highlighted through image masking techniques. The masked residual images are then classified using a supervised classifier, in this case Newkirk and Wang (1987), Wang and Newkirk (1990) used a modified maximum likelihood decision rule called Bayes classifier.

FIGURE 6.2 SIMPLIFIED DIAGRAMMATIC REPRESENTATION OF A GIS-SUPPORTED KNOWLEDGE BASED CHANGE DETECTION PROCESS. (Simplified from Newkirk & Wang,1990; Wang & Newkirk, 1987)



The ancillary information in the GIS are then accessed to discover attributes of the classified, but yet unconfirmed areas of change. The attributes include size; land cover at times t_1 and t_2; land form; soil capability; and other characteristics as might be available on the ancillary data. This step is known as feature extraction in Figure 6.2. Pixels with similar sets of attributes are aggregated into regions. Once these common regions of change have been identified, a set of "expert" change detection rules in the GIS are accessed to make inference about the types of change represented by the various groups of pixels with similar attributes. This final change identification operation generates a change map with different colours indicating different types of change (Wang and Newkirk, 1987; Newkirk and Wang, 1990).

It is being recommended that further work in the analysis of land cover changes using multi-temporal satellite data should look into the possibilities of acquiring and using these GIS-supported, knowledge-based change detection algorithms in order to assess their full potentials and limitations *vis-a-vis* the conventional digital change detection approaches used in this thesis.

"It is quite easy to distinguish a piece of academic work from a journalistic report. One of their differences is that the former will normally have a section where references are listed; the latter won't have such a section under normal circumstances."

Late Justice Mlia [former professor of Earth Science & Geography, University of Malawi] *Personal Communication*

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"The research process is essentially one of collecting and analysing information related to some specified objectives. The more information one collects and analyses, the better. Of course not all of this information would be presented in the main body of the report or dissertation. Some, but still not all, would be presented in the appendix."

John Soulsby *Personal Communication*

APPENDIX I

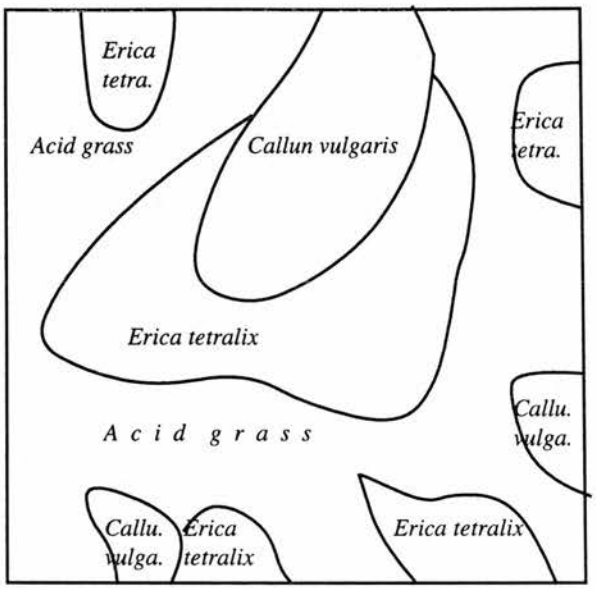
SPECIES' FREQUENCY OF OCCURRENCE OUT OF 100 STEP-POINTS OF OBSERVATION IN 9 SAMPLE 30m x 30m AREAS

LOCATION OF SITE	SPECIES OBSERVED	FREQUENCY (%)
NZ 709053	Dead *Pteridium* stems	53
	Litter of dead *Pteridium*	21
	Live *Pteridium aquilinum*	17
	Epibolium latifolium	02
	Orobanche pallidiflora	02
	Arnoseris minima	02
	Nettles	01
	Cirsium spp	01
	Agrostis tenuis	01
NZ 710053	*Vaccinium myrtillus*	53
	Live *Pteridium aquilinum*	14
	Agrostis tenuis	08
	Dead *Pteridium* stems	07
	Erica cinerea	06
	Empetrum nigrum	04
	Nardus stricta	04
	Calluna vulgaris	02
	Potentilla erecta	02
NZ 772029	*Calluna vulgaris*	50
	Erica cinerea	24
	Vaccinium myrtillus	15
	Empetrum nigrum	10

	Erica tetralix	01
NZ 772030	Charred *Calluna* stems	56
	Calluna brash	31
	Vaccinium myrtillus	07
	Young *Calluna* shoots	03
	Empetrum nigrum	02
	China Pickers Moss	02
NZ 765028	Young *Calluna vulgaris*	56
	Calluna brash	12
	Bare peat	14
	Polytrichum spp	10
	Empetrum nigrum	06
	Sphagnum spp	01
	Cladonia spp	01
SE 743995	Live *Polytrichum spp*	38
	Dead *Polytrichum spp*	37
	Grazed *Calluna vulgaris*	07
	Ungrazed *Calluna vulgaris*	07
	Empetrum nigrum	05
	Juncus squarrosus	02
	Seedlings of *Calluna*	02
	Agrostis tenuis	01
	Bare peat	01
SE 799992	Mature *Pteridium aquili.*	35
	Vaccinium myrtillus	16

	Dead *Pteridium aquili.*	13
	Agrostis tenuis	10
	Stressed *Pteridium*	06
	Young *Pteridium*	06
	Galium saxatile	04
	Rumex acetosella	03
	Empetrum nigrum	03
	Polytrichum spp	02
	Lotus corniculatis/tenuis	01
	Calluna vulgaris	01
NZ 765013	*Agrostis-Festuca-Galium*	46
	Polytrichum spp	25
	Juncus effesus	21
	Cirsium spp	03
	Eriophorum vaginatum	03
	Calluna vulgaris	01
NZ 758013	*Calluna vulgaris*	66
	Eriophorum vaginatum	13
	Bare peat	11
	Cladonia spp	11
	Polytrichum spp	01

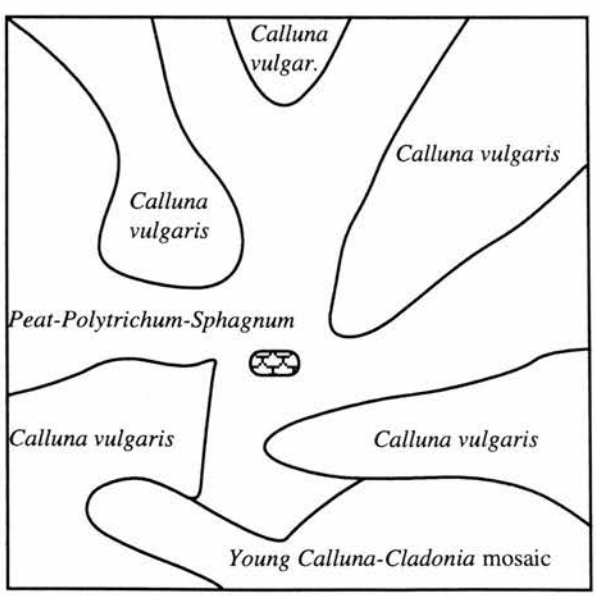
APPENDIX II: 10 SAMPLE 1m x 1m QUADRATS



QUADRAT 1

Site: SE 735969

Wet heath area

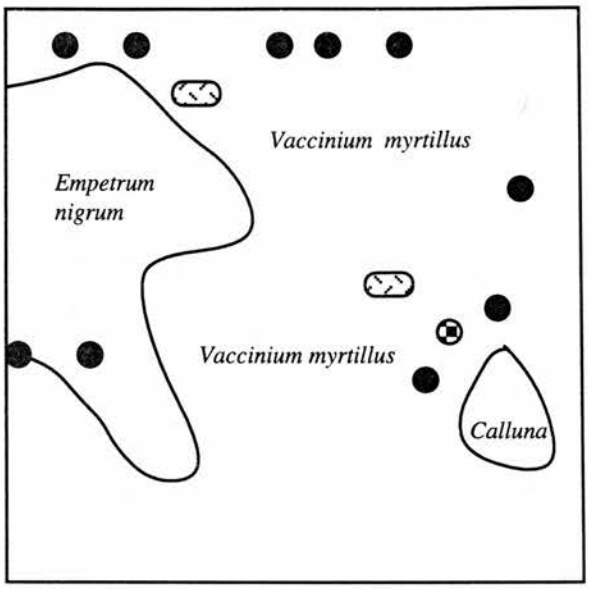


QUADRAT 2

Site: SE 743995

regenerating moorland

Cladonia



QUADRAT 3

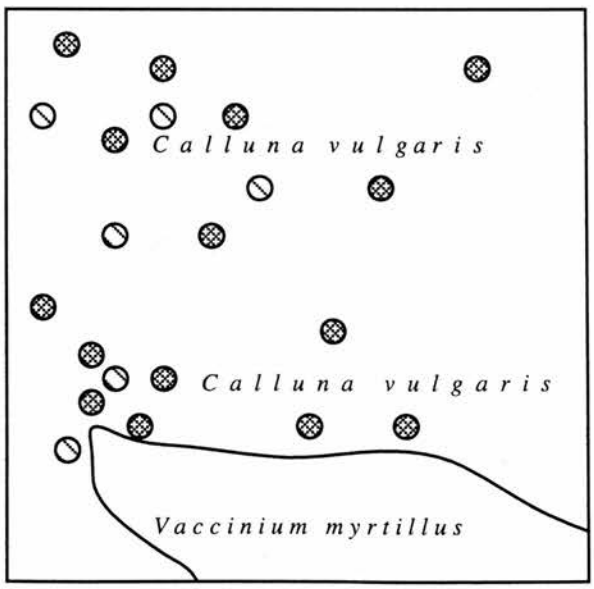
Site: NZ 710053

Dry heath area

Tufts of *Agrostis tenuis*

Tufts of *Nardus stricta*

Fronds of *Pteridium aquil*



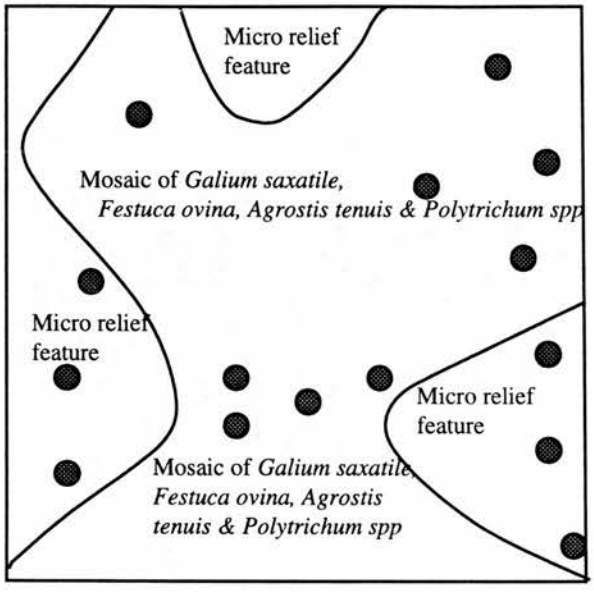
QUADRAT 4

Site : NZ 772029

Dry heath area

Empetrum nigrum

Erica cinerea

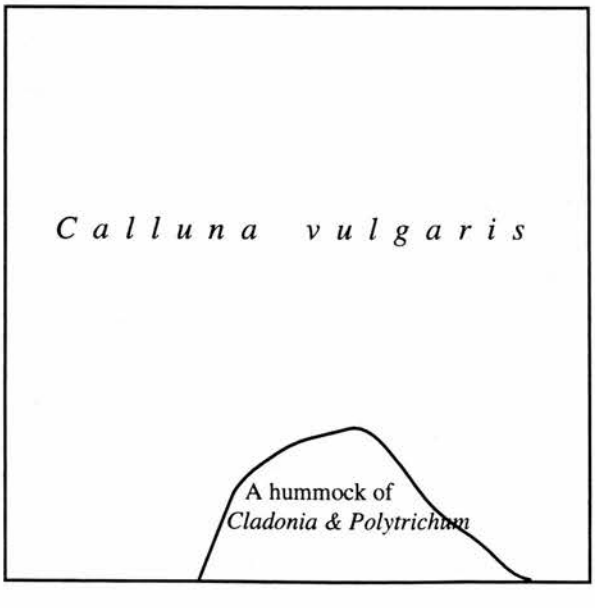


QUADRAT 5

Site:NZ 765013

Abandoned pastureland

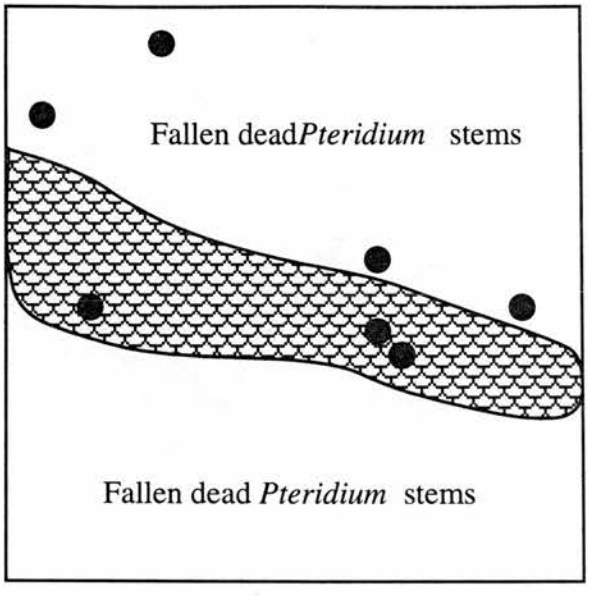
● *Juncus effusus*



QUADRAT 6

Site: NZ 758013

Dry bog area



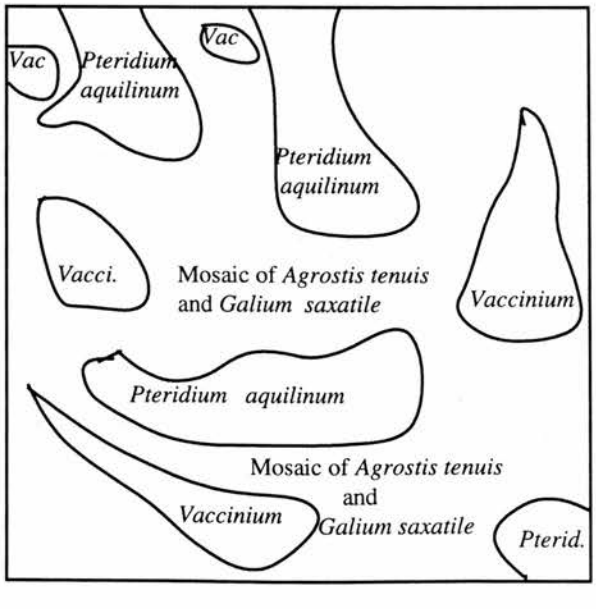
QUADRAT 7

Site: NZ 709053

Treated bracken

Litter and humus of dead *Pteridium aquilinum*

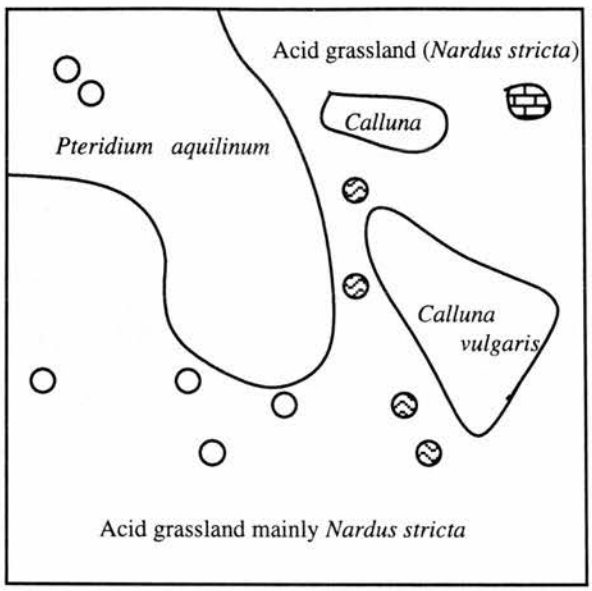
Live *Pteridium*



QUADRAT 8

Site: SE 799992

Mixed vegetation along a stream



QUADRAT 9

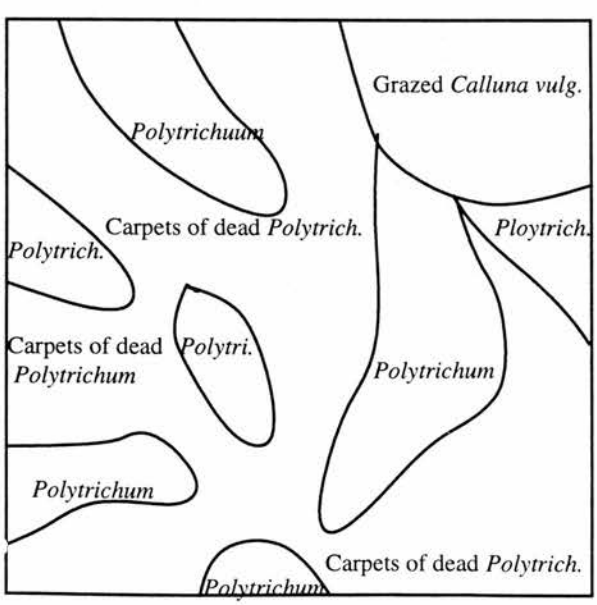
Site: SE 728937

Wet heath-grassland-bracken transition

Clover

Erica tetralix

Heath bedstraw



QUADTRAT 10

Site: SE 742997

Fire damaged moorland

APPENDIX III

Tables presenting summary of pixel values
on summer 1985 and spring 1991 data bands.

LAND COVER	RANGE OF PIXEL VALUES			MEAN OF PIXEL VALUES			STANDARD DEVIATION		
	TM3	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
Bracken (B1)	39-50	54-75	105-133	43	66	116	3.4	5.3	7.4
Fire damaged moor. (D1)	17-22	21-32	31-51	18	25	40	3.0	3.2	6.4
Young heather (D2)	24-31	33-55	75-100	27	41	87	2.1	5.8	6.9
Established heather (D3)	15-19	31-45	42-59	18	37	48	0.9	3.2	0.4
Broadleaved woodland (F1	18-25	66-99	55-82	21	73	62	1.4	11.1	7.7
Coniferous woodland (F2)	16-20	36-71	30-47	16	47	36	0.9	9.2	5.0
Grass moorland (G1)	21-29	75-108	68-101	22	80	74	2.3	8.2	10.6
Fallow/semi-imp. ps (G2a)	20-27	102-128	78-98	24	100	90	1.7	2.1	5.6
Crops/imp. pasture (G2b)	17-20	96-154	52-87	18	133	69	1.0	11.4	9.2
Bare fields (P1)	31-54	42-78	33-51	42	57	88	3.0	3.2	6.4

TABLE AIII.1 SUMMARY OF PIXEL VALUES ON 1985 DATA BANDS: ROSEDALE EXTRACT

LAND COVER	RANGE OF PIXEL VALUES			MEAN OF PIXEL VALUES			STANDARD DEVIATION		
	TM3	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
Bracken (B1)	21-24	97-117	55-70	22	102	63	1.0	6.0	7.6
Fire damaged moor. (D1)	24-28	51-69	57-71	26	59	62	1.6	5.0	5.4
Young heather (D2)	23-30	37-59	45-81	27	48	69	1.5	5.0	5.0
Established heather (D3)	21-25	56-79	42-53	24	66	46	1.8	4.3	5.1
Broadleaved woodland (F1	20-24	54-84	33-56	21	57	36	0.9	7.0	8.4
Coniferous woodland (F2)	20-25	48-72	29-50	21	55	31	1.4	5.4	6.0
Grass moor (G1)	22-27	67-88	53-83	24	80	74	1.4	6.7	7.8
Fallow/semi-imp. ps (G2a)	25-29	73-92	66-99	27	83	82	1.2	4.8	6.3
Crops/Imp. pasture (G2b)	21-26	97-116	66-99	42	101	71	1.5	6.7	4.9
Bare fields (P1)	34-41	51-90	60-90	36	66	88	2.8	7.6	6.3

TABLE AIII.2 SUMMARY OF PIXEL VALUES ON 1991 DATA BANDS : ROSEDALE EXTRACT

LAND COVER	RANGE OF PIXEL VALUES			MEAN OF PIXEL VALUES			STANDARD DEVIATION		
	TM3	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
Bracken (B1)	39-49	56-82	93-119	43	65	114	2.7	5.7	8.7
Fire damaged moor. (D1)	23-33	27-37	41-59	28	33	57	1.3	1.6	2.6
Young heather (D2)	26-33	34-44	74-99	29	38	88	1.7	2.1	5.3
Established heather (D3)	16-19	31-44	41-58	17	37	47	1.1	2.9	4.6
Broadleaved woodland (F1	17-22	62-87	49-69	19	64	55	1.5	6.2	4.9
Coniferous woodland (F2)	15-19	40-60	22-35	16	40	30	1.1	5.5	5.3
Grass moor (G1)	23-27	61-98	69-79	25	88	72	2.2	3.8	5.4
Fallow/semi-imp. ps (G2a)	27-30	93-105	82-100	28	96	92	2.7	2.7	4.6
Crops/Imp. pasture (G2b)	17-33	109-142	61-100	20	132	76	2.9	11.4	8.5
Bare peat (P1)	35-49	41-60	66-99	43	50	83	3.8	4.5	7.1
Wet heath (W1)	23-35	26-43	54-78	28	36	66	3.1	7.8	3.1

TABLE AIII.3 SUMMARY OF PIXEL VALUES ON 1985 DATA BANDS: WHEELDALE EXTRACT

LAND COVER	RANGE OF PIXEL VALUES			MEAN OF PIXEL VALUES			STANDARD DEVIATION		
	TM3	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
Bracken (B1)	21-25	95-125	53-73	22	100	61	0.8	6.4	4.7
Fire damaged moor. (D1)	27-35	49-59	50-76	34	46	64	2.0	4.7	6.3
Young heather (D2)	23-30	41-57	60-81	27	51	67	1.5	5.7	6.5
Established heather (D3)	21-24	56-76	38-55	22	63	43	0.9	4.0	4.3
Broadleaved woodland (F1	20-23	59-82	30-50	21	60	38	1.0	6.1	6.3
Coniferous woodland (F2)	19-28	39-64	19-41	21	59	36	2.7	6.9	4.2
Grass moor (G1)	23-30	78-103	69-92	26	89	78	1.7	4.9	6.8
Fallow/semi-imp. ps (G2a)	32-49	58-91	78-116	35	76	89	4.4	7.5	9.0
Crops/Imp. pasture	21-25	91-101	69-81	24	93	71	1.0	7.5	4.0
Bare fields	21-25	41-59	56-78	23	56	75	4.7	8.2	9.6
Wet heath	28-35	44-56	36-55	33	47	49	2.4	4.6	5.9

TABLE AIII.4 SUMMARY OF PIXEL VALUES ON 1991 DATA BANDS : WHEELDALE EXTRACT

LAND COVER	RANGE OF PIXEL VALUES			MEAN OF PIXEL VALUES			STANDARD DEVIATION		
	TM3	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
Bracken (B1)	36-50	49-72	99-121	41	62	104	3.0	4.4	8.7
Young heather (D2)	27-32	35-50	77-97	28	41	85	2.5	4.6	8.1
Established heather (D3)	16-21	27-41	40-53	18	33	45	2.0	3.9	5.0
Broadleaved woodland (F1	17-25	58-87	35-77	19	66	57	1.7	7.3	7.3
Coniferous woodland (F2)	14-19	39-73	25-45	18	42	33	2.6	8.7	5.0
Grass moor (G1)	22-29	60-95	57-99	27	79	84	5.1	9.1	7.9
Fallow/semi-imp. ps (G2a)	25-31	80-105	74-95	28	90	89	2.4	6.1	6.6
Crops/Imp. pasture (G2b)	16-18	109-114	48-74	17	113	71	1.3	1.5	9.3
Bare peat (P1)	36-60	41-69	60-95	40	56	85	7.4	8.0	7.4
Wet heath (W1)	20-29	35-53	45-72	24	42	64	2.6	5.7	7.4

TABLE AIII.5 SUMMARY OF PIXEL VALUES ON 1985 DATA : FYLINGDALES EXTRACT

LAND COVER	RANGE OF PIXEL VALUES			MEAN OF PIXEL VALUES			STANDARD DEVIATION		
	TM3	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**	**TM3**	**TM4**	**TM5**
Bracken (B1)	21-25	95-124	51-66	23	100	59	1.1	6.2	4.8
Young heather (D2)	25-30	40-60	59-86	27	47	47	1.1	5.6	6.6
Established heather (D3)	21-25	55-74	37-58	23	64	43	1.2	5.4	4.3
Broadleaved woodland (F1	20-22	59-77	36-60	21	69	45	0.8	6.7	5.3
Coniferous woodland (F2)	18-22	38-65	19-33	19	52	25	1.4	6.6	3.1
Grass moor (G1)	21-28	60-91	50-80	27	81	79	1.1	6.0	6.7
Fallow/semi-imp. ps (G2a)	21-25	73-97	68-93	23	85	79	1.8	5.0	6.2
Crops/Imp. pasture (G2b)	20-26	98-121	67-78	22	105	69	1.7	7.5	5.9
Bare peat (P1)	26-41	44-68	37-76	35	57	56	3.3	7.0	6.9
Wet heath (W1)	20-23	41-59	36-52	22	49	43	0.9	4.0	3.5

TABLE AIII.6 SUMMARY OF PIXEL VALUES ON 1991 DATA BANDS: FYLINGDALES EXTRACT

APPENDIX IV : GROUND PHOTOGRAPHS

(All photographs were taken by Dr. John Soulsby)

TOP PHOTO: DANBY HIGH MOOR AROUND NZ 704030

Dry heather moorland

Calluna vulgaris (purple on the photo) is the dominant shrubby heath species on the central watershed zone and on the ridges. One of its associate species, *Vaccinium myrtillus* (yellowish-green on the photo) is common on steeper slopes over rocky valley edges or sandstone like here on Danby High Moor. The burnt patches on the left side of the photo provide evidence of moorland management through rotational burning.

BOTTOM PHOTO: ESKLETS SLACK AROUND NZ 661023

Wet heath

Wet heath communities occur in areas of saturated peat, seeping springlines or flushes, and in enclosed mires like here in Esklets Slack. They are normally rich in species . The wet heath community in the photo has *Calluna vulgaris* (purple); *Erica tetralix* (also purple, not clearly distinguished from *Calluna*); *Juncus effusus; Eriophorum angustifolium* (white flowers on the photo); *Sphagnum spp*; and acid grass species. Note *Vaccinium myrtillus* on the rocky sides of the valley.

TOP PHOTO: EGTON GRANGE AROUND NZ 782035

Acidic grassland and neglected farmland

Stretches of acidic grassland like the one in the photo occur on the moorland fringe marking the transition from shrubby heath uphill (note the shrubbs in purple) and the agricultural land down in the valleys. The agricultural land on the photo has been neglected and bracken (in green on the background) has encroached.

BOTTOM PHOTO: WESTERDALE MOOR AROUND NZ 658022

The Bracken Problem

Bracken (*Pteridium aquilinum*) occurs naturally on the steeper, well-drained slopes of upland heath areas, but factors related to changes in traditional moorland management practices have led it to spread into areas of open moorland and agricultural land. This is a problem because bracken is an ecologically disastrous species; it is toxic to stock and grouse; and has little economic and amenity value. On the photo, bracken has taken much of the *Vaccinium* moorland on Wheeldale Moor. The area was sprayed with chemicals to clear it (note the darkish patches of dead bracken litter, and the greyish patches of dead bracken stems), but it has re-encroached as evidenced by the thriving green fronds on the photo. A number of follow-up treatments are necessary in order to succeed in clearing it out completely, and this makes the whole operation costly.

TOP PHOTO: GLAISDALE AROUND NZ 740034

Agricultural land in valleys

The valleys/dales between the heather-clad ridges are basically agricultural land. Skilfully managed enclosed fields like those on the photo present a dramatic contrast to the surrounding semi-natural moorland environment. Surely, they add another dimension to the peculiarity of the landscape in the North York Moors National Park.

BOTTOM PHOTO: ESKLETS , WHEELDALE MOOR NZ 570019

Plots and/or stretches of woodland

There are also areas of broadleaved and coniferous woodland in the national park. Broadleaved woodland is mainly restricted to coastal inlets, hill sides, dale heads, and along wet river sides like this area on the photo. Small plots of broadleaved woodland are also found on estates (see photo above) where they are managed for economic and amenity purposes. More areas of heath and bog bave been reclaimed and planted with species of coniferous trees by private land owners and the Forestry Commission. Coniferous woodlots like the one to the right on the photo, are common features on privately owned land. However, much of the plantations owned by the Forestry Commission are in large blocks and they create less striking monotonous landscapes over large areas such as Cropton, Dalby and Wykeham.