THE APPLICATION OF REMOTE SENSING IN OPEN MOORLAND SOIL EROSION STUDIES : A CASE STUDY OF GLAISDALE MOOR, NORTHERN ENGLAND

by

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ABSTRACT

The Application of Remote Sensing in Open Moorland Soil Erosion Studies : a Case Study of Glaisdale Moor, Northern England.

The potential of remote sensing in upland soil erosion studies has been examined on Glaisdale Moor, North Yorkshire Moors. The study considers four different remote sensing sources, viz. sequential air photographs, ground radiometry, Landsat Thematic Mapper (TM) and SPOT simulation. Sequential air photographs have been interpreted in order to elucidate the land use/land cover changes and the drainage development and associated erosion problems in the region. A series of statistical analyses were employed in an effort to establish the relationships between the different spectral variables and the soil/ground variables. Attempts have also been made to evaluate the spectral separability performance of the Ground radiometer, the Landsat TM and the SPOT simulation wave bands. The Landsat TM and the SPOT simulation imagery have been further analysed in order to gather information about the best band and band combinations that would be required to optimize the discrimination of moorland surface types including eroded areas. Digital image processing of the Landsat TM and the SPOT simulation subscene for Glaisdale Moor was performed using the DIAD image processing system.

The land use/land cover classification information derived from the air photographs, the Landsat TM and the SPOT simulation, has been used as an input into a soil loss prediction model (USLE) to predict the soil erosion rate of the study area. Of the various remote sensing systems used, air photographs and TM data proved the most useful in this area.

DECLARATION

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration. Information from other authors which are credited to the authors in question at the appropriate points in the text.

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CHAPTER ONE

Soil erosion and remote sensing

1 Introduction

1.1 Upland management problem

1.2 Remote sensing potential in soil erosion study

1.2.1 Aerial photography

1.2.2 Satellite remote sensing

1.3 The choice of remote sensing data

1.4 The choice of soil/ground variables

1.5 Aims and objectives

1.6 Structure

1. Introduction

The archaeological evidence for Britain (Smith 1975, Bell 1981) suggest that soil erosion has been taking place since the clearance of land for agriculture in the Bronze Age. At present the problem of soil erosion in Britain is viewed as a localized phenomenon (Wilson & Cooke 1980, Morgan 1981) and because of its humid temperate environments soil erosion is generally believed milder. However, instances of severe erosion in Britain have been reported by Douglas (1970), Evans (1971) and Morgan (1973, 1985). Most importantly, there is increasing evidence of soil erosion in upland Britain, particularly in association with sheep grazing (Evans 1977) and recreation (Bayfield 1971, 1973, and Coleman 1977).

Traditionally, the uplands of Britain, such as the Peak district, North Yorkshire Hills are used as a grazing land. A considerable part of these grazing lands are open moorland, consisting of a peaty subsurface. It is estimated that more than one million hectares (10 000 km^2) of the land surface of Britain is peat covered (Taylor 1983) and much of this peat covered area is in the uplands.

These peat covered uplands are facing a severe erosion problem, particularly in the areas such as the Peak district (Anderson & Tallis 1981, Evans 1977, Phillips et al 1981, Shimwell 1981 & Tallis 1973), the North Yorkshire Moors (Imeson 1971), and the Clwyd Range (Baker et al 1979).

At the early and middle of this century, the intensity of peat erosion of upland Britain was reported in a series of ecological investigations, for example : Moss (1904, 1913), Pearsall (1941) and Osvald (1949). In the last few decades, however, a considerable research effort was directed towards the understanding of the morphological features exhibited by eroding peats (Johnson 1957, Bower 1960, Radley 1962), and to examine the possible causes of their erosion (Bower 1962, Radley 1962, Barnes 1963, Johnson & Dunham 1963 and Tallis 1964). In most of the peat erosion research of the last two decades, the problem was approached in three different ways : pollen and stratigraphic studies of peat profiles, to try and deduce the time of onset of peat erosion (Tallis 1965, Bostock 1980); detailed monitoring of rates of peat erosion (Crisp 1966, Imeson 1971, Tallis 1973, 1981) and studies of the hydrological properties of blanket peat and of the action of environmental factors on it (Chapman 1965, Ingram 1967, Crisp & Robson 1979, Burt & Gardiner 1981).

The factors attributed for the peat erosion are considered to be human induced, such as overgrazing and fire caused by poor management. The erosion problems, therefore, are very much related with the managements of the uplands.

1.1 Upland management problem

Although the physical, ecological and economic significance of the uplands, particularly the moorlands are recognised (for example : North York Moors National Park Plan Report 1984-85), their management, specifically, the way the moorlands should be used are not in common agreement. The management of moorlands are thus facing varying levels of conflict. At one level the conflict remains among those who wish to use the uplands for outdoor recreation and others who want to hold it as a nature protection (Simmons 1974, 1976). The uplands, including the moors, are viewed as environmentally fragile in which the impact of outdoor recreation, whether in a small nature reserve or in an extreme wilderness, varies from entire devastation to partial and gradual eradication of flora and fauna and subsequent destabilization of the surface areas depending on the ability of the nature-protection areas to cope with recreationists and relative fragility of the concerned ecosystem (Simmons 1979). At the other level, the conflicts are with those who wish to convert the upland into an agriculture or to forest land and those who want to conserve the moorlands to see with its traditional heather moors. The conservationists argue that the conversion of moorlands into agricultural landscapes reduces its ecological value, destroys archaeological interest and removes most of its recreational potential. Opposingly, the continued existence of moors are, however, viewed as a menace considering its extreme vulnerability to erosion and degradation which results from lack of proper management (North York Moor National Park Report 1984-85).

Because of economic problems, the moorlands were not properly managed in the past. For instance, in the North Yorkshire Moors, over the past 50 years, economic and social changes have resulted in decreased management activity on the one hand and increased recreational activity on the other. Reduced labour forces and increasing costs mean that land owners and flock masters cannot deal with large tracts of vegetation in the traditional ways. Heather is not burnt regularly which gives rise to very old plants with a high fire risk; bracken encroachment with its adverse effects on the economic, scenic and ecological value of the land is increasing by approximately 120 hectares a year (North York Moors National Park Report 1984-85).

The North York Moor National Park Authority have critically appraised the problems of their moors. The interesting facts of these appraisals are as follows:-

1) To maintain the heather moors, a regular burning cycle appropriate to the local conditions is essential.

2) In order to maintain the stability of the moorland ecosystem (Chorley and Kennedy 1971) controlled burning is required, so that the litter/humus layer of the soil does not ignite.

3) Where deep peat has been exposed after uncontrolled fire the area suffered serious surface loss for several years and vegetation recolonisation is extremely slow or non-existent without surface treatment.

4) Large scale field trials have shown that trees can stabilise the badly eroded sites at certain altitudes.

5) Where mineral soils or ashed peat areas have been exposed, there is often a severe surface instability problem. Such sites may act as foci for loss of soils from large areas.

6) Recreational use, particularly on heavily used footpaths, can establish centres of erosion on shallow peat or mineral soil and can cause impaction and dessication on deep peats.

7) In the core moorland areas, which have been badly damaged by fire, there is an urgent need to consider diversion, or temporary

closure of the Lyke Wake Walk if permanent damage to deep blanket peats is to be avoided.

8) 55 per cent of the total moorland area is now overage and a high accidental fire risk.

9) Restoration of large areas of burnt and eroded moorland can only be achieved by large scale exclusion of sheep and other grazing animals, together with a programme of seeding and planting techniques.

In order to give maximum protection to the moorlands and to encourage good management practice, the North York Moor National Park Committee has drawn up a comprehensive policy. One of the most priority sections of this policy is to use its resources to encourage steps to :

1) prevent further erosion and degradation;
2) re-instate badly damaged areas of moorland.

In line with this National Park effort, rapid methods of pinpointing areas undergoing erosion and degradation would be valuable. The problem has two related aspects to consider :

a) the changes in the moors needs to be detected and monitored at regular intervals;

b) to assess the erosion rates involved with the surface cover changes.

There are two possible methods that could be utilized, together or separately, to solve the problems as mentioned above : either regular field surveying and/or remote sensing. The first involves *in situ* field measurements, while the second, gathers data from a distance without coming into physical contact with the objects (Lo 1986). The main aspect in the latter case is that it measures variations in electromagnetic energy that may reveal spectral, spatial and temporal variations in an area (Landgrebe 1976). The logic of remote measurement in change detection is that if there was any change in the landscape, it would be reflected in the electromagnetic energy.

The suitability of either method needs to be carefully considered. The moorland erosions are a nonpoint or area-wide problem in which eroded materials are removed from an extensive source area. In addition, movements of this eroded sediment are intermittent, related to climatic events and is affected by constantly changing landuse/land cover management. *In situ* or field studies can provide detailed data about specific cover changes and associated erosion problems. However, in remote areas such as the upland moors where accessibility is poor, *in situ* or field survey for change detection and erosion assessment is costly and time consuming. Therefore, the alternative method , remote sensing, which involves less field surveying without compromising much with the results would be preferable.

Remote sensing has become an information source for detecting and monitoring land use. With the availability of historical aerial photographs and satellite image data, remote sensing has provided a means to examine the moorlands from season to season, from year to year, or even from decade to decade. Remote sensing can provide planners with information on past moorland conditions and indicate trends that may be monitored in the future. Thus, remote sensing can help alleviate the problem of detecting and monitoring landuse and landcover changes by providing up-to-date coverage of entire watersheds (Morgan et al 1978). In addition, using the landuse/landcover information as an input to an erosion prediction model such as the Universal Soil Loss Equation (USLE), it would be possible to assess the erosion rate involved with the moorland surface cover changes. Thus, remote sensing as a data gathering tool would be the judicious choice for the moorland erosion problem.

1.2 Remote sensing potential in soil erosion

Remote sensing in the form of aerial photographs used to study soil erosion are well documented (Eyre 1971, Malgram & Garn 1975, Parry et al 1969). Two different forms of remote sensing data are now in use in erosion research : aerial photography and satellite remote sensing.

1.2.1 Aerial photography

During the past four decades remote sensing in the form of aerial photography has played an important role in the acquisition of land surface information (Grimbazevsky 1972). Aerial photographs are considered to be a data collecting and an analytical tool (Lo 1976), which provide a base for mapping soil erosion and evaluating soil erosion hazards. Most erosion features are visible in stereoscopic images, and those that are not can be readily inferred from tonal variations (Bergsma 1974). Compared with ground surveys, use of aerial photographs minimizes the time required to produce maps and lowers the cost of surveys (Young 1973). Considering these advantages in aerial photographs, they have been extensively used in mapping the eroded areas (Stallings 1957, Buringh & Vink 1961, Emery 1975 and Jordan 1984) as well as for other qualitative assessment of landuse changes that affects soil erosion (Ishaq and Huff 1974, Ruff 1974 and Williams and Morgan 1976). Recent attention has been directed at quantitatively evaluating soil loss using aerial photographs (Buringh 1961, Jones and Keech 1966, Keech 1972, Atukum 1976, Welch et al 1984, Thomas et al 1986, Aniya 1985a, b). Attempts have also been made to use aerial photographs to measure the USLE factors, C (surface cover and management) in an effort to predict the soil erosion rate in USA (Morgan et al 1978, 1979, Morgan et al 1980, Stephens et at 1982, Fenton 1982, Stephens & Cihlar 1981 and Langran 1983), Multidate/sequential aerial photographs have been used to determine the nature, location and timing of soil management changes and how these changes affect soil erosion on cropland (Stephens et al 1982). This information used in conjunction with detailed topographic maps and the USLE, permit the estimation of past and present rates of erosion and how these rates relate to present landuse (Stephens et al 1982).

Certain limitations are, however, inherent in the use of aerial photography. The effects of erosion may have been masked by vegetative cover at the time of flight. Recent aerial photographs of suitable scale are not always available for the area in which erosion is to be assessed. Correlating the grey tones of black and white photography with the various colours found in soils is sometimes difficult. Variation in film exposure and development can also cause interpretative problems. To overcome the vegetation masking effect on eroded areas, colour infrared photographs have been used with reasonable success (Totterdal and Nebauer 1973, Tueller & Booth 1975, Pihan 1980 and Michelbacher 1978, Morgan et al 1979).

1.2.2 Satellite remote sensing

Apart from the aerial photographic remote sensing, scientists have tested the utility of other forms of remote sensing such as Air borne Multispectral Scanner (MSS) for gathering soil information since the late 1960's, (Kornblau and Cipra 1983). Most of these studies attempt to provide information on the identification and distribution of soil types (Al-Abbas et al 1972, Kristof and Zachary 1974; Matthews et al 1972a, Zachary et al 1972). Because of the prohibitive cost of airborne sensing the research later concentrates on the use of MSS data collected by the Landsat-1 satellite after its launch in 1972. Research by Cipra (1973), Krishnan et al (1980) and Weismiller et al (1977) indicated that Landsat data could provide useful information on the type and distribution of soils. The utility of remote sensing as aids to ground soil surveying have further stimulated interest in the influence of different soil properties on reflectance (Kirschner et al 1978, and Weismiller and Kamisky 1978).

Although the satellite data base research on soil information has not been directed towards the soil erosion problem it has revealed that satellite data can provide useful information for evaluating certain soil properties e.g. soil moisture and organic matter, which are directly related to soil erosion (Mill 1972). Research by Kristof et al (1980) have shown that variations in soil reflectance can be affected by the relative proportion of clay, silt and sand in the soil. Spectral data showed a distinct decrease in reflectance with increasing clay content. On the other hand, reflectance curves for silt and sand contents showed a significant increase of reflected energy when the amount of silt and sand increased. Thus, the soil spectral reflectance properties sensed by satellite could serve as a useful tool for surveying, identifying, differentiating and inventorying soil and some of its important properties which can immensely help in soil erosion study.

Seubert et al (1979) revealed that inspite of differences in soil parent material or, in geographic locations, certain properties characteristic to soil erosion may give similar spectral responses. Research of the laboratory for Applications of Remote Sensing (LARS) indicates that organic matter, clay mineralogy, soil texture, iron and soil moisture content are important factors to be considered in soil reflectance (Stoner et al 1979, Stoner and Baumgardner 1981, and Montgomery 1976). It is suggested that more likely one or a combination of these factors is responsible for the distinct spectral patterns of eroded soils. These revelations of spectral reflectance properties of the eroded soil have been further stimulated by the research result obtained by Krishnan et al (1980), Thompson et al (1983) and Latz et al (1984). They observed that some physical properties, such as soil moisture, organic matter and particle size, significantly affect the spectral reflectance of eroded soil.

Despite these developments in the basic understanding of the soil spectral properties of the remote sensing data in regard to the specific soil erosion attributes, however, it has not yet been tested widely and rigorously for a specific soil erosion research problem such as open moorland erosion.

1.3 The choice of remote sensing data for the present study

Any effective use of remote sensing data closely depends on the relation of pixels to object sizes and the spectral and spatial resolution of the remote sensing data. Eroded bare fields in the moors are often of smaller size. Thus, for proper identification and delineation of the eroded moors, it was apparent that the sensors with higher spatial resolution or small field of view would be useful. Landsat Multispectral Scanner (MSS), therefore, with 79 m spatial resolution would be of less use than the Landsat Thematic Mapper (TM) and SPOT, both of which have higher spatial resolution, 30m and 20m respectively.

Apart from the spatial resolution effect of the sensors, spectral and radiometric resolution is also important to consider in moorland erosion. As the moorland has a very complex vegetation cover and the exposed peat has a wide range of spectral variation depending on the degree and stages of peat formation and accumulation. Therefore, to detect and give proper identification of the peat and vegetation complex, the sensor needs to have narrower wave bands and higher radiometric resolution. Thus, again, the SPOT sensors with higher radiometric resolution and the Landsat Thematic Mapper with its narrow wavebands and high radiometric resolution would probably be more useful than the Landsat MSS data.

Therefore, in the present study Landsat TM and airborne SPOT data have been used as a main remote sensing data source. These remote sensing data were supplemented by ground radiometry and sequential air photographs of 1973, 1978, 1983 and 1985.

1.4 The choice of soil/ground variables

It is recognised that the spectral characteristics of surface/cover types are mainly controlled by energy-matter interactions. The proportion of energy reflected, absorbed and transmitted for each surface/cover type varies depending on the material type and condition (Lillesand and Kiefer 1978). Geologic and geomorphic conditions, soil parameters, climatic variations, vegetation elements and terrain orientation influence the spectral reflectivity of cover types (Smedes 1975 and Curran 1980). Mills (1972) demonstrated that the reliability of remote sensing in soil erosion study depends on how successfully the technique could be utilized to identify some of the environmental soil-ground parameters, that affects soil erosion.

Misclassification of surface types/land cover can be reduced by accounting for the influence of environmental factors on the spectral characteristics of different surface/cover types (Duggin 1983). It means, that *in situ* measurements of the appropriate soil/ground variables will permit more effective use of remote sensing techniques for soil erosion assessment. Therefore, it is essential to determine the appropriate environmental variables that have an effect on the spectral response of surface type sensed by the remote sensors. Opinion about the appropriate environmental variables, however, differs considerably. For example, Bowers & Hanks (1965) recognised that soil moisture, organic matter and particle sizes are the most important contributing factors that influence soil spectral reflectance. While Mills (1972) would include particle size, organic matter, pH, structure and bulk density of the soil.

Adrian et al (1982) observed that soil moisture has a significant influence in both increasing and decreasing patterns of soil reflectance. Bowers and Smith (1982) found a linear relationship between absorbance and percentage of soil moisture. Stoner & Baumgardner (1980) obtained highest correlation with soil moisture at 2.08 to 2.32 μm. Peterson et al (1979) observed that reflectance differs between oven dry state and field capacity. They estimated that such a difference in reflectance is related to the absence of water in these soils. They further noticed that the same relationships existed throughout the visible, near and middle infrared reflective bands. Although it had been demonstrated that moist soil had lower reflectance values than dry soils in the 0.4 to 2.6 μm wavelength region (Hoffer & Johannsen 1969), however, the impact of fluctuation in soil moisture content in varied samples was not clear (Condit 1970, 1972).

Organic matter influences soil colour and thus the soil reflectance characteristics. Apart from that, it does influence a number of soil physical and chemical properties such as water holding capacity, structure, erodibility, cation exchange capacity and thus obviously this influence reflects in the spectral properties. Hoffer and Johannsen (1969) demonstrated that within the 0.4 to 2.5 μm wavelength range an increase in organic matter content was accompanied by a corresponding decrease in soil reflectance values. Kristof (1971) and Baumgardner et al (1970) using digital analysis for processing remotely sensed data, were able to delineate and map five different ranges of organic matter content for mineral soils which contained from 1.5 to 7 per cent organic matter. Stoner and Baumgardner (1979) indicated that the green wavelength region (0.52 to 0.62 μm) showed high correlations with the organic matter content of 481 bench mark soil samples belonging to different taxonomic classes. The organic matter content of these soils varied from amounts lower than 3 per cent to 10 per cent. Earlier studies in the 1960's had also detected certain degrees of influence of organic constituents like humic and fulvic acids on soil reflectance (Obukhov and Oslov 1964).

Although there remains no doubt about the impact of organic matter on soil reflectance characteristics, researchers maintain different opinions with respect to the region of the electromagnetic spectrum most suited for measuring spectral properties of soil organic matter content (Beck et al 1976, Al Abbas et al 1972, Bintin & Changda 1980, Krishnan et al 1980, Kristof et al 1974, Latz et al 1981, Montgomery 1976 and Stoner & Baumgardner 1980).

In respect to the eroded soil study, Pazar et al (1982) noticed that organic matter content together with iron oxide within an eroded soil significantly affects the shape of the overall spectral response.

Soil parent material constitutes an important parameter whose effect on soil reflectance has been recognised in several studies (Stoner & Baumgardner 1980, Matthews et al 1973). Elaborate discussion of soil textural effect on spectral reflectance was made in the previous section of this chapter.

Walsh (1980) recognised a significant influence of vegetation biomass on spectral reflectance. In the present context, identification of the role of percentage of vegetation biomass would be important, as the presence of vegetation masks the effect of other environmental variables.

The effect of slope angle and aspect on spectral reflectance of landscape features are well documented (Walsh 1980, Justice et al 1981, Holben & Justice 1981). Slope angle and slope aspects are the principal terrestrial determinants causing areas to be directly illuminated by the sun or to be in shadow, and hence receive only diffuse sky radiation (Karaska et al 1986). Holben & Justice (1980) observed that a wide range of pixel values can be associated with a single cover because of fluctuations in slope angle and aspect.

After careful consideration of all these environmental parameters, the soil moisture, organic matter content, soil texture, vegetation biomass and slope and aspect are selected as soil/ground parameters, on the belief that these would be most relevant to analyse the spectral variability of the eroded surface types of the study area.

1.5 Aims and objectives

The principal objective of this research is to examine the potential of remote sensing in soil erosion study. As the moorland surface types are very complex and heterogeneous, it is probable that no single soil/ground variable, alone would be able to explain the observed spectral patterns of surface types. Rather, a variety of spatial factors (soil/ground variables) in combination may explain the spectral response variation of surface types. The relative importance of any one or more of these factors may vary within or among the surface types. Thus, a considerable effort will be made to understand which of the soil/ground variables relates most with the spectral variables. Attempt will also be made to evaluate the spatial and spectral characteristics of different sensors considered in the study.

The emphasis will be to what extent the open moorlands surface types are spectrally separable.

The airborne SPOT and Landsat TM imagery will be analysed in order to classify and map the major surface types of the study area. The mapping information thus obtained from the SPOT and TM in conjunction with the aerial photographs will then be used as an input into a soil loss prediction model (USLE) to predict the soil erosion rate of the study area.

Thus, the major objectives of the research are :

1) To evaluate the spectral relationship of the different sensor wave bands with the selected soil/ground variables.

2) To assess the spectral class discrimination performance of all the involved spectral bands.

3) To evaluate the spatial surface type discrimination performance of all the involved spectral bands.

4) To predict the soil erosion rate of the study area.

1.6 Structure

The study first reviews the historical background of heather moors in relation to erosion problems and explains the rationale of selection of the study area followed by a background information. In the third chapter, aerial photographs are interpreted in order to measure the changes in landuse/landcover and to evaluate the drainage development and erosion problems of the study area. This has provided a basis to construct a base map to prepare the ground sampling strategy.

In the fourth chapter, attention is directed to ground-based radiometry to provide a preliminary insight of the spectral characteristics of the major surface types considered. This simulation is followed by airborne SPOT and Landsat TM data analysis in the fifth and sixth chapters respectively. The spectral separability performance of these two sensing platforms are evaluated. The image analysis provided the information about the best band and band combinations that would be required to optimize the discrimination of surface types. It has also provided the information at what extent the moorland surface types could be correctly classified.

Finally, an attempt is made to use the aerial photographs, SPOT and Landsat TM land cover mapping information as an input into the measurement of USLE factor, C, to predict the erosion rate of the study area and this is followed by the summary and concluding remarks drawn from the whole thesis.

CHAPTER TWO

Study Area : Background Information

2.1 Moorland : an introduction

2.2 The heather moors and related erosion problems

2.3 The extent of the moorland erosion problems

2.4 Rational for the selection of the study area

2.5 Physical setting of the Glaisdale Moor

2.1 Moorland : an introduction

The North York Moors cover an area of about 1,432 km² and 36% of this area is open moorland (Figure 2.1). Topographically, the southern part of the Moors are tabular hills. The north and west are central highland, rising well over 424 m. Elevation gradually declines eastwards towards the sea. The slopes of the moorlands are fairly gentle. The soils of the moorland are closely related to local relief and drainage features, to the type and condition of the moorland vegetation, to the present and past exposure of the soil by burning and to any subseqnent erosion by frost, rain and wind. The drainage is equally variable and related to the condition of cover, vegetation, soil, slope and erosion. The average monthly rainfall rates are just over 67 mm.

The vegetation of the Moorland area is dominated by the common heather, (Calluna vulgaris), except at seepage sites and waterlogged areas. The heather is in various stages of development according to the recent history of burning. Where recent burning has been severe, the heather has often failed to regenerate and such areas remain bare or only covered by moss, Bracken (Pteridiumaquilinum) and bilberry (Vaccinium myrtillus) which, together with a wide range of Moorland grasses, although locally common, cover only a small proportion of the Moorland (Sinclair, 1965).

2.2 The heather moors and related erosion problems

Morphologically and functionally, the heather moor is viewed as an ecosystem (Chorley & Kennedy 1971, Park 1980). Its main vegetation,

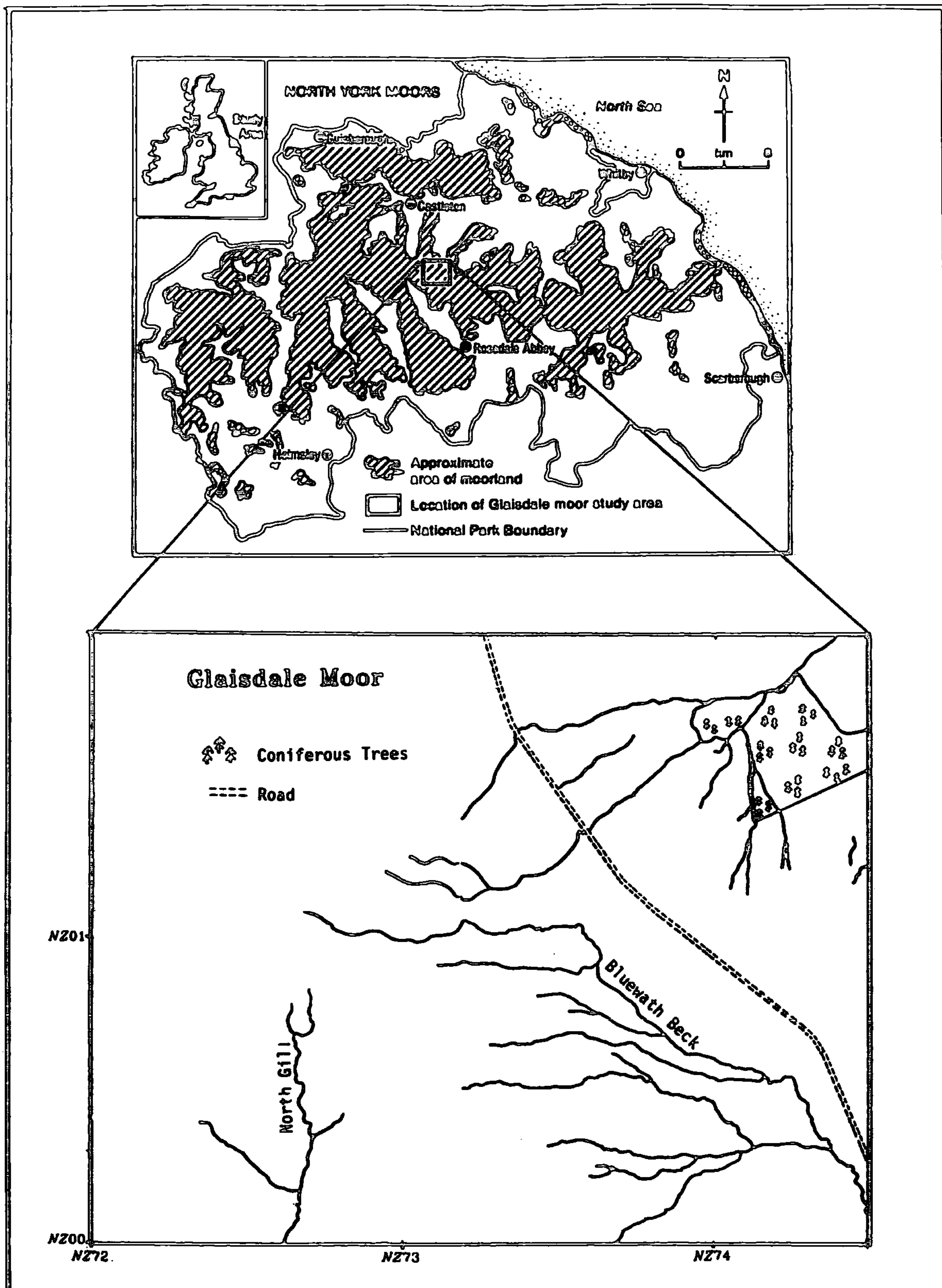


Figure 2.1 Location of Glaisdale Moor

Ling (Calluna vulgaris) and other ericoid shrubs (Gimingham 1972) primarily owes its origin to forest clearance by Bronze Age and Iron Age man (Godwin 1956, Dimbleby 1962, Pennington 1974). The activity of these early cultures coincided with a probable climatic change from the relatively warm, dry sub-Boreal to the cooler and wetter sub-Atlantic, the combined effect being the prevention of tree regeneration which allowed the Ericaceae to dominate. The increased rainfall and cooler temperatures also affected upland soils (Dimbleby 1965). Leaching increased, allowing podsols, now characteristic of the calluna-dominated environment, to develop (Dimbleby 1962), and decompoisition of plant deposits which have since become associated with calluna (McVean & Lockie 1969, Gimingham 1972).

The vegetation history of the North York Moors has been examined in detail by use of both palynological and archaeological evidence (Dimbleby 1952, 1961 & 1962, Simmons 1969, Jones et al 1979, Simmons & Innes 1981) and illustrates the particularly important role of man in the area (Flemming 1971, Atherden 1976a and 1976b, Spratt and Simmons 1976).

The early forest cover, during the Boreal period was a Pinus sylvestris - Corylus association (Jones 1976, 1977, 1978), this changed to mixed deciduous forest in the Atlantic (Jones 1977, Jones et al 1979). During this latter period the influence of man was localised and temporary (Simmons and Cundill 1969), but, following the elm decline marking the boundary between the Atlantic and Sub-Boreal, two major periods of human activity have been distinguished. These were during the Bronze and Iron Ages, the effects being widespread in the Moors (Simmons & Cundill 1974a, b, Jones 1976, 1977, 1978). Initially woodland clearance was gradual, being principally for crop growing (Flemming 1971), but increased as soils deteriorated (Dimbleby 1962) and pastoral activity increased (Jones et al 1979).

The second major period of woodland clearance occurred in the Iron Age and Romano-British period (Atherden 1976, Spratt and Simmons 1976) and resulted in widespread removal of trees and appearance of heather moorland. These conditions prevailed up to the present.

The systematic management of heather moorland by use of fire is only about two centuries old (McVean and Lockie 1969, Miller & Watson 1974). Since 1800 moorland landuse has been primarily concerned with sheep farming and grouse shooting. Land management for either use involves periodic burning of the calluna cover to attempt to satisfy the needs of the animals. Large amounts of research have been carried out on a wide range of aspects, including the interaction of the fire and the physical and chemical environments, the erosion processes and its mechanism. The research result, however, clearly indicates the negative influence of fire on the surface cover which has resulted in widespread erosion and degradation problems in the moors.

The initiation of this erosion has been attributed to a variety of causes. Tallis (1965, 1973 and 1981) and Anderson & Tallis (1981) argue that altitudinal, and climatic factors together with the surface topography of the peat itself are important. Wood (1978) considers a more extensive range of factors, including rainfall erosivity, slope, surface texture and vegetation cover. Detailed studies of Bower (1960, 1961 and 1962) suggest that blanket peat is an inherently unstable system in which erosion is an inevitable outcome.

The weight of environmental circumstances thus points to the probability of a progressive and gradual decline of peat cover in addition to the more dramatic and apparently catastrophic losses which occur due to fire. If important areas of moorland are to be maintained and/or badly eroded zones restored it is essential that a sound scientific understanding of processes and changes is developed. Based on this understanding, the North York Moor (NYM) National Park Authority has concentrated their effort on moorland restoration.

2.3 The extent of the Moorland erosion problem

Since the late seventies and onward, a large amount of research has been directed to the North York Moors, mainly on its post fire ecological problem assessments (Haffey 1978, Bridges 1979, Maltby 1979 and 1980, Fullen 1979, Moorland Research 1977-79), on the extent of changes in the moors (Parry et al 1981) and on the erosion intensity and its controlling variables (Arnett 1978 and 1979, Imeson 1971 and 1974). More recently, the NYM Park Authority (1980-83) carried out a detailed study of erosion in the National Park. This revealed that unstable surfaces and areas of average or poorly managed heather (*Calluna vulgaris*) were the major factors that predisposed the Moors to erosion. The biggest single problem being the potential fire hazard of overage vegetation, since once on fire this vegetation burns slowly and with intense heat, which frequently sets fire to the underlying peat. Once peat has been dried out beyond a certain point it becomes hydrophobic and hence extremely susceptible to erosion. The NYM survey showed that where this had happened revegetation of such areas was extremely slow.

In areal extent, the total degraded area in the deep blanket peats (more than 1 m deep) were estimated at approximately 40.5 km² or 9.5 per cent of the moorland. In thin peat soil (peat less than 20 cm) the degraded area covers about 38.4 km² or 9.5 per cent of the moorland (National Park Report 1980-83). At present, the principal moorland areas under immediate threat of extensive and intense erosion include Danby High, Rosedale, Glaisdale and Wheeldale Moor (Figure 2.1). In total 97.8 km² or 19 per cent of moorland are classified as eroded, eroding or liable to degradation and about 20.3 km² considered to be in imminent danger of being totally degraded (National Park Report 1980-83). Amongst others, Glaisdale Moor is considered to have suffered a serious erosion problem and for the present investigations, it has been selected as the study area.

2.4 Rational for the selection of the study area

Apart from the severe erosion problem of the Glaisdale Moor, there are other factors which have also dictated the choice of this area as a study site. Glaisdale Moor is relatively accessible, it is of manageable size (5 km²) for data collection and site familiarization. Moreover, Glaisdale Moor has a diverse surface types. Most important of all, it has a good aerial photographic data base. The National Park Authority also maintains a small meteorological station on Glaisdale Moor, therefore, the recorded data would be of additional help to understand and predict the erosion intensity of the area.

2.5 Physical setting of the Glaisdale Moor

Glaisdale Moor is located at the centre of the North York Moors (Figure 2.1). It is bordered by Rosedale, Danby High and Wheeldale at the south, west and east respectively. Geologically the rocks are of the Middle Jurassic age. The elevation of the area ranges from 326 m at the east to 402 m at the northwest. Glaisdale Moor however essentially appears as a relatively flat plateau area.

Glaisdale Moor has three major surface types: the vegetated, peat and bare mineral soil areas. A considerable part of the area is covered by very deep peat and drained to the south east by Bluewath Beck and to the south west by the North Gill. In areal extent the Bluewath Beck catchment covers a large part of the exposed peat of the Glaisdale Moor.

Inspite of a serious deep fire during August 1976 and great loss of peat since then, relatively few stone/bare rock surfaces have been exposed. Much of the site is still covered by deep, though bare peat and ashed areas (Figure 2.2). Around the streams of the Bluewath Beck, a considerable area of vegetation, mainly heather and sphagnum mosses has regenerated over the years and the marginal parts have recolonised to some extent. However, vegetation colonisation has been almost non-existant on the bare mineral soil (Figure 2.3).

Carroll and Bendelow (1981) have identified three different soil units in Glaisdale Moor, these are, coarse loamy soils, fine loamy soils and Eriophorum - sphagnum peat. Coarse soils occur at the north-west part of the Glaisdale Moor. The soil texture of this particular unit is either sand loam or sandy silt. The unit has a mixed vegetation including heather, bilberry and bracken.

Fine loamy soils are the second largest unit of the area and cover the north east - northern part. Surface horizons are light brownish

Figure 2.2 The exposed blanket peat of Glaisdale Moor

Figure 2.3 The bare mineral soils of
Glaisdale Moor (White area)

grey or light grey clay loam or clay and sometimes mottled. *Eriophorum*-sphagnum peat is the largest lithological unit in Glaisdale Moor, mainly consisting of raw peat. It occurs on gentle to moderate slopes, or in slight depressions within smoothly undulating ground. The vegetation consists of cross leaved heath and sphagnum. The surface horizon appearance varies, from very dark grey, dark reddish brown to very dark brown semi fibrous peat. The layers mostly consist of *eriophorum*, but *calluna* remains are also common. The more fibrous upper layers are often sphagnum-rich.

In general, the bare peat and the vegetated area contains high moisture and organic matter content. Conversely, the bare mineral soil contains very little moisture and organic content.

The nature of the soil and heather cover of the Glaisdale Moor, clearly reflects the recent history of heather burning, and the intensity of subsequent erosion. Thus, in the next chapter, the extent of surface cover changes in the Glaisdale Moors and its subsequent development of drainage and extent of erosion since 1973 are examined.

CHAPTER THREE

Aerial Photointerpretation of Glaisdale Moor

3.1 Introduction

3.2 Objectives

3.3 Materials and Methods

3.4 Changes in surface cover

3.5 Drainage development

3.6 Mapping drainage density

3.7 Nature and types of erosion

3.8 Conclusion

3.1 Introduction

In order to develop suitable land management strategies the monitoring of changes in landcover/landuse information are of considerable importance to planners (Anderson 1977, and Howarth and Boasson 1983). To monitor the temporal changes in landcover, however, records and inventoring of the landcover at the appropriate time are essential (Crapper and Hynson 1983). Typically, changes in vegetation cover and erosion are identified by interpretation of aerial photographs and by field inspection (Avery 1977, Civco et al 1986, Dymond and Hicks 1986, Hardisky and Klemas 1983, Jones and Keech 1966, Pickup and Nelson 1984, Tomlinson 1984, Vink 1968 and Way 1973). Recently in the U.S., satellite images have also been used to uncover landcover changes (Anderson 1977, Ellefsen and Peruzzi 1976, Gordon 1980, Stow et al 1980, Todd 1977 and Wilson et al 1976). For a successful identification and mapping of land cover changes, it is essential to have a set of sequential aerial photographs (Hardisky and Klemas 1983, Stone 1964).

Various approaches have been proposed and used to identify changes in land cover/landuse from remote sensing. Both digital and photographic methods have been used for mapping landcover changes (Crapper and Hynson 1983). In digital techniques, the common means of identifying landcover changes are ratioing or differencing of images (Angelici et al 1977, Stauffer and McKinney 1977 and Weismiller et al 1977) or classification and comparison of images from two dates (Ellefsen and Peruzzi 1976, Rubec and Thie 1978). In general , however, the accuracy of the results has been disappointing (Howarth and Boasson 1983). While in some applications, photographic imagery proved to be more appropriate. For example, Laut et al (1977) used photographic imagery in conjunction with existing maps to identify pattern boundaries and Jones (1976) used photographic imagery to classify areas of uniform landcover. More recently, Williams and Goodman (1980) used photographic imagery to produce a terrain type map of a Navajo Indian reservation in U.S.

Crapper and Hynson (1983) suggested the simplest means of mapping land cover changes is to compare two aerial photographs and map those areas in which change has occurred. This technique however gives better results when the photographs are of large scale and of similar scale. Fortunately, for Glaisdale Moor, there are large scale aerial photographs for four different periods (1973, 1978, 1983, 1985) available for use.

In Peak District, Anderson and Tallis (1981) using aerial photographs, successfully mapped the land cover changes and areal extent of erosion features. More recently, in Northern Ireland, Tomlinson (1984) used aerial photographs in mapping the moor land cover changes. Thus, against this background, aerial photographs have been used in this analysis to obtain precise information on the extent of landcover changes of Glaisdale Moor.

Singh (1986), has identified three aspects of using aerial photographic data in relation to the assessment and mapping the landcover changes. The first is that of detecting changes in landcover; the second lies in the identification of the nature of the change and the third involves mapping the areal extent of the changes.

3.2 Objectives

The precise objectives of the aerial photointerpretation are as follows:

1) To identify and map the surface cover changes in the study area;

2) To identify and map the changes in drainage conditions of the study area;

3) To explain the nature and types of erosion which have occurred in the study area.

3.3 Materials and Methods

3.3.1 Aerial photographs

Four sets of black and white photographs of Glaisdale Moor for the period of 1973, 1978, 1983 and 1985 were used in the visual interpretation. All of these photographs were taken at spring to summer. The photographs of 1973, 1978 and 1985 were provided by the North York Moors National Park Authority and the 1983 photographs were obtained from the Natural Environment Research Council (NERC). The scale of the photographs were 1:10,000.

3.3.2 Photointerpretation criteria

The criteria chosen for the present photointerpretation followed the guidelines given by Stephens (1983) and Stone (1964). The most characteristic features considered in the interpretation were predominantly pattern, tone and texture.

Pattern refers to the spatial arrangement of objects. The representation of certain spatial arrangements is characteristic of many features, both natural and cultural, and gives a pattern that the photointerpreter uses in recognizing them.

Tone refers to the relative brightness of features on aerial photographs. On black-and-white photographs brightness changes occur as grey tones, from black to white.

Texture is the spatial frequency of tonal changes on the photographic image. Texture is produced by an aggregation of individual features and is a product of their size, pattern, shadow and tone.

Frank (1984) observed that differences in vegetation amount are evident by grey tone or colour variations that represent the brightness of red and near-infrared reflectance. Differential reflectance is viewed as a pattern of grey tones or colours caused by mosaics of vegetation and bare ground. Visual combinations of tonal and textural characteristics of the photographs can be useful in interpretating the changes in vegetation cover or spatial patterns associated with erosion features, such as rills and gullies (Frank 1984).

3.3.3 Identification of mapping units on the basis of tone

On the basis of visual photointerpretation, six distinct photographic tones were identified on the Glaisdale Moor air photographs. The tones identified on the photos were delineated on overlays on the photographs and numbered accordingly. The mapped overlays were then field verified and necessary corrections of the mapping units were made. In the field, it was clear that the tonal variations were mainly associated with the density of vegetation. A generalised estimate of the vegetation density of the different mapping units was obtained by using a 1m x 1m grid in the field. The surface area of each mapping unit was measured using a planimeter on the field corrected overlays. Table 3.1 shows the aerial extent of the mapping units/surface types of the Glaisdale Moor.

3.3.4 Mapping the drainage density

1) Choice of grid-mesh approach

The drainage density was calculated and mapped on a grid square basis rather than for drainage basin areas. The logic for adopting such a grid-mesh mapping system was as follows: A drainage basin approach would not be suitable particularly for Glaisdale Moor, as it would give only a general indication of the drainage condition and would fail to expose the range of drainage densities according to the ground conditions. The grid-mesh approach would allow a more representative and complete scenario of Glaisdale Moor drainage development. Furthermore, the grid-mesh would also help to assess the drainage density variation over the years in a more quantitative manner. More specifically, the drainage density variation among the surface categories could reliably be established, and the grid-mesh approach would

Tonal Characteristic	Surface type	1973	1978	1983	1985
White	Bare soil	0.51	5.74	6.12	13.5
		(0.61)	(1.76)	(1.89)	(4.18)
Light and dark grey	Exposed peat	-	221.53	203.79	195.0
			(68.25)	(63.2)	(60.4)
Light to dark grey, rough texture	Vegetation (0-<10 per cent cover)	121.87	27.96	68.49	12.7
		(38.1)	(8.6)	(21.23)	(3.9)
Light grey, smooth	Vegetation (10-<40 per cent cover)	43.70	64.81	39.0	98.4
		(13.6)	(19.9)	(21.0)	(30.5)
Moderately dark	Vegetation (40-80 per cent cover)	75.22	4.43	5.16	2.86
		(23.5)	(1.4)	(1.6)	(0.88)
Dark	Complete Vegetation cover, Over 80 per cent	78.55	-	-	0.24
		(24.5)			(0.07)

Table 3.1 - Areal extent of six surface types, Glaisdale Moor, North York Moors. Interpretation is from aerial photographs. Figures are in hectares, and in brackets percentages.

also permit easy identification and delimitation of the area prone to severe drainage and erosion problems. This has important implications for land management and conservation.

In choosing the grid size it was desirable to adopt as fine a mesh as possible to represent the spatial variability in the environment. However, attention was drawn to the issue as reported by Walsh (1985) that the excessively smaller grid square size may be too small to be representative of the local environment and, moreover, it may introduce excessive errors or noise in the data. A grid square mesh of $100m^2$ based on the Ordnance survey grid system was finally selected as the basic unit, in the belief that this will make best use of the information available without being too detailed to cause the problems discussed by Walsh (1985).

2) The grid maps

The grid maps were produced using a program to generate a segment file for rectangular arrays (Shennan and Donoghue, personal communication) as input to the GIMMS mapping package Waugh & McCalden, 1983). Map production was a three stage process:
First, a segment file was generated using the program. The topology of this file was then checked using a simple plotting routine. Second, a GIMMS command file was written to build polygons : each polygon corresponding to an individual map unit. Finally, a GIMMS command file was written to generate a grid map for drainage density data.

The FORTRAN programs and GIMMS command files used for map production are listed in appendix 1 and 2.

3) The calculation of drainage density

The total length of stream channels in each grid square was measured using a chartometer and then converted to drainage density by division by the grid square area. Drainage density maps of Glaisdale Moor were produced using these values.

3.3.5 Identification of erosion features

In order to identify the erosion features of Glaisdale Moor, the classification followed by Lueder (1959), Sharp (1960) and Poole (1969) was applied in the present study. The erosional forms identified on the 1985 aerial photographs of Glaisdale Moor include sheet wash, rill wash and gullying.

1) Sheet wash as defined in this study includes all slope wash where no significant channelization by natural overland flow has occurred. The main criteria developed for such feature recognition and identification were:
   - i) Bare soil exposures depicting sheet wash registered from white to light grey.
   - ii) There was frequently a sharp tonal contrast between the areas affected by sheet wash and those adjacent areas which showed no affect at all.

2) Rill wash mainly a channelized form of erosion. Rill wash is reflected in several patterns depending on conditions of slope and on the stage of rill development (Figure 3.1).

Occasionally it was difficult to determine from photointerpretation precisely when the rill wash ends and the gullying begins.

The criteria developed and used in the study include:

i) Rills, most often form parallel to sub-parallel channels and sometimes anastomosing pattern.

ii) Rill channels are narrow and extremely shallow.

iii) A minimum of sheet wash was associated with rill wash and it was largely confined to areas between channels.

3) Gullying defined in the present analysis includes those deeply incised channels which have exposed or completely removed the overlying peat.

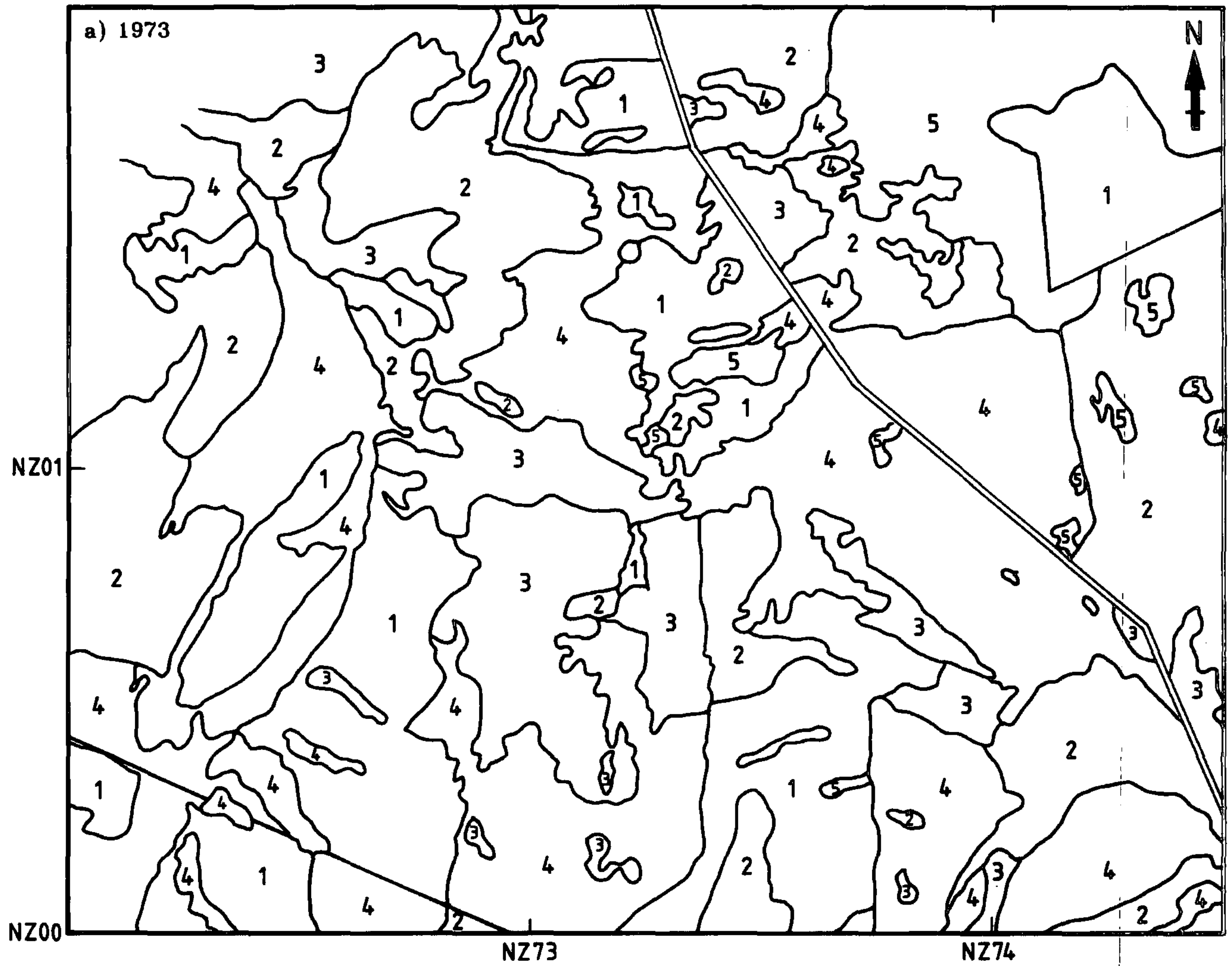
The criteria developed and used to recognize and identify gully forms include:

i) Gullied channels are deep and wide in comparison to rilled channels.

ii) Tributary channels are numerous.

iii) Channels are generally intermittant, but seepage may occur in some channels, where this occurs the moistened sections of the channel register a dark grey tone in contrast to the target background.

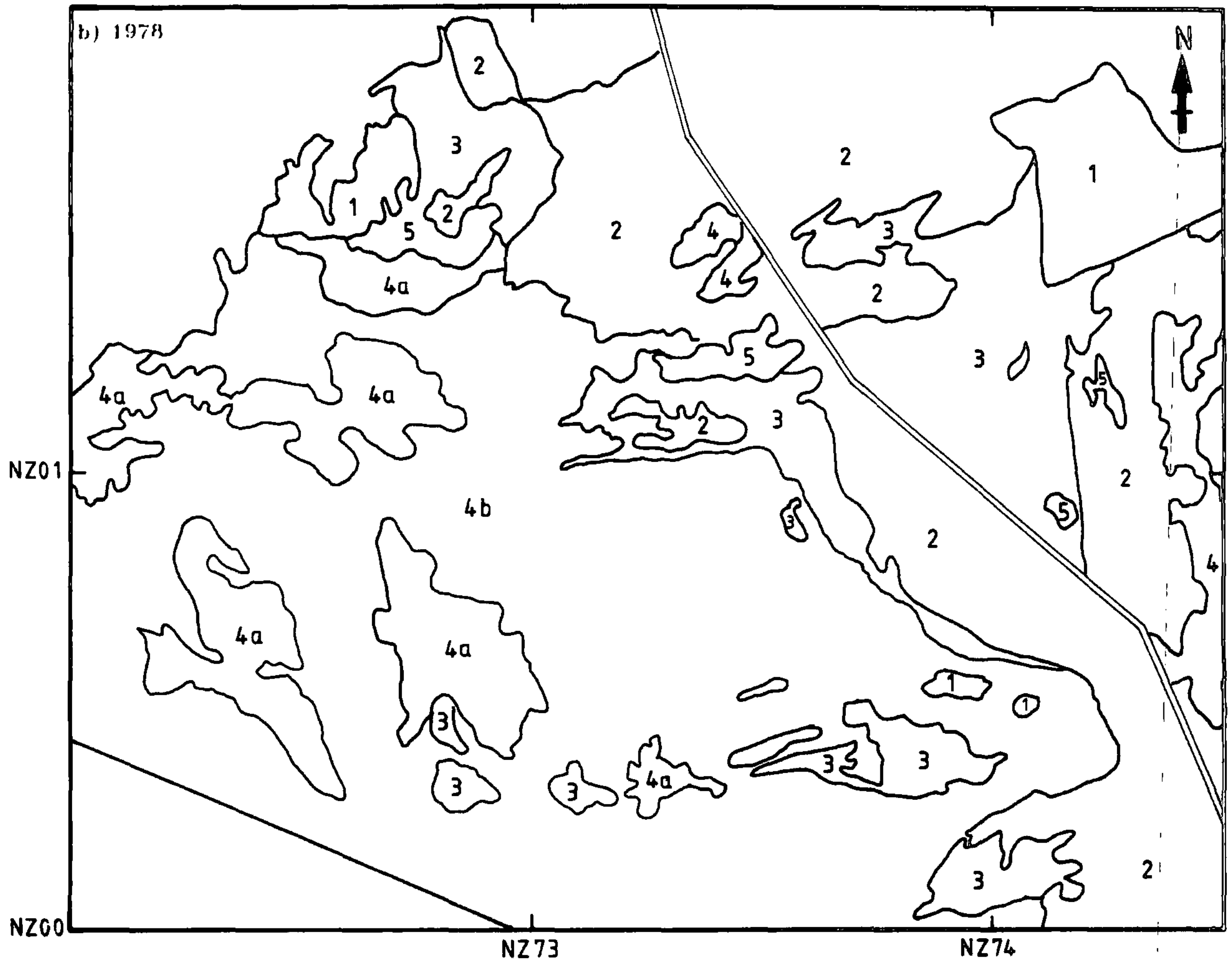
Figure 3.1 Rilling patterns of Glaisdale Moor



Key : 1 Vegetation, more than 80 % cover 3 Vegetation, 10–40 % cover 5 Bare soil

2 Vegetation, 40–80 % cover 4 Vegetation, less than 10 % cover

Figure 3.2a Land cover changes on Glaisdale Moor–1973



Key : 1 Vegetation, 40–80 % cover

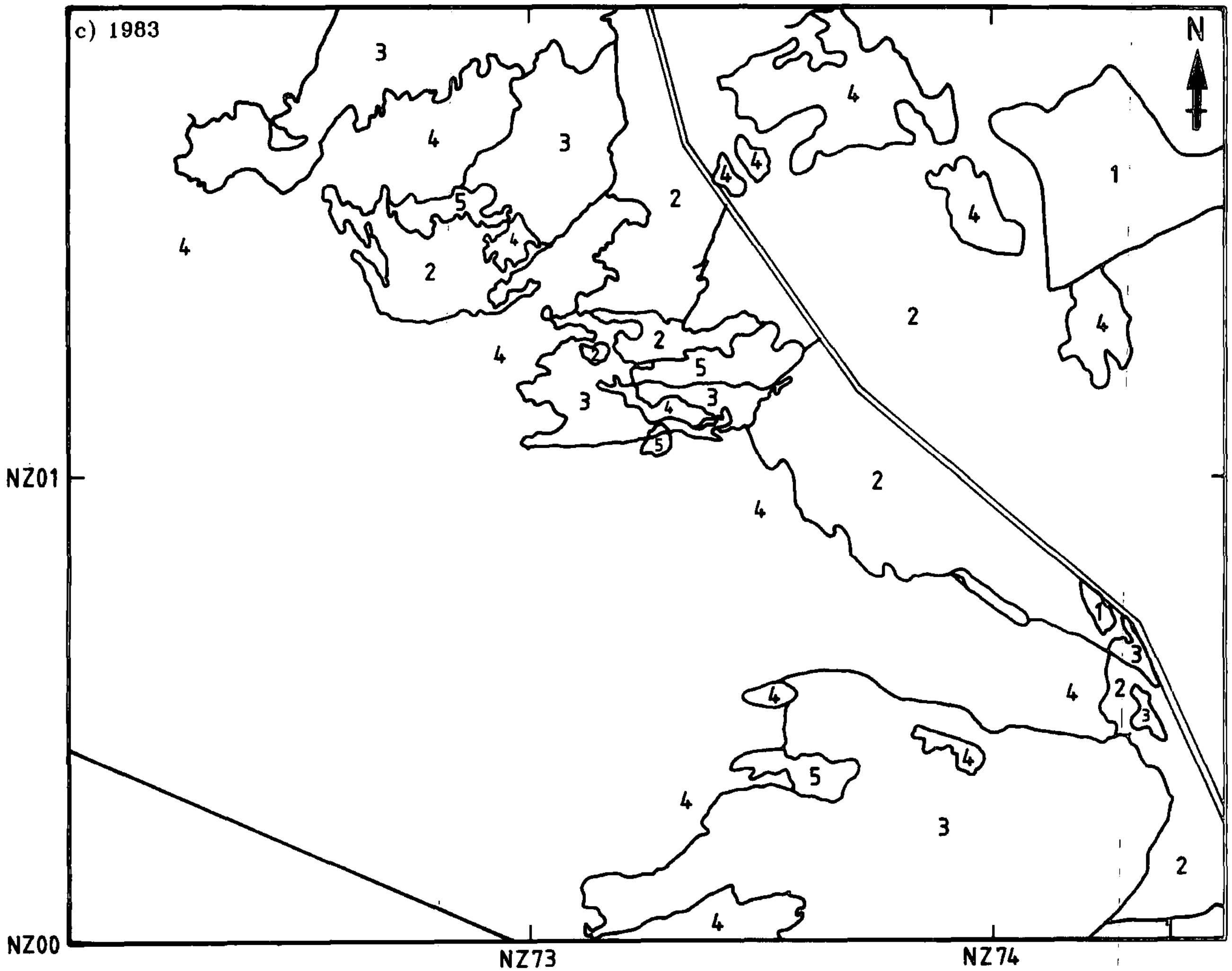
2 Vegetation, 10–40 % cover

3 Vegetation, less than 10 % cover

4 Exposed peat a) Dry
b) Wet

5 Bare soil

Figure 3.2b Land cover changes on Glaisdale Moor – 1978



Key : 1 Vegetation, 40–80 % cover

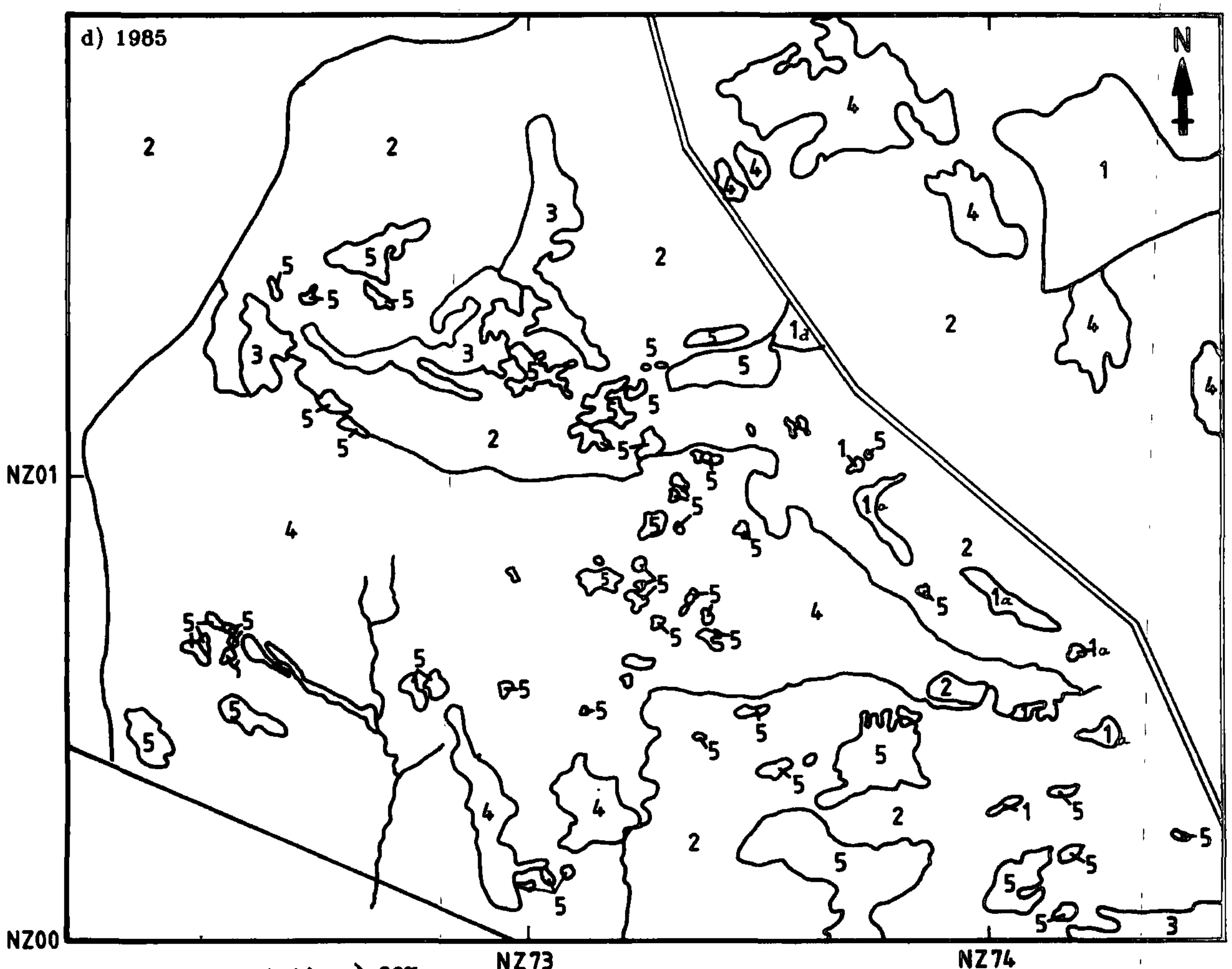
3 Vegetation, less than 10 % cover

2 Vegetation, 10–40 % cover

4 Exposed peat

5 Bare soil

Figure 3.2c Land cover changes on Glaisdale Moor – 1983



Key : 1a Vegetation, ≫ 80% cover
1b Vegetation, 40–80 % cover
2 Vegetation, 10–40 % cover
3 Vegetation, less than 10 % cover
4 Exposed peat
5 Bare soil

Figure 3.2d Land cover changes on Glaisdale Moor – 1985

iv) Considerable rill wash was usually associated with gully development.

v) The channels of gullies register in grey tones from moderately dark to light especially where the channels have water flow.

3.4 Changes in surface cover

The sequential air photographs of Glaisdale Moor reflect six different types of tonal characteristics (Table 3.1). These characteristic tonal types are mainly associated with the density of surface vegetation (Figure 3.2a). The highest density of vegetation (over 80 per cent) appeared as dark, while bare soil with no vegetation appeared as white.

Table 3.1 shows the areal extent of each of the six cover types for the four years of data measured from aerial photographs. The effect of 1976 fire is clearly reflected in the surface cover changes of the study area.

The dark tones appeared very smooth and associated with the completely vegetated area (over 80 per cent vegetation). This type of tonal category was observed on a larger extent only in the 1973 photographs. Because of the 1976 fire, no such tonal category appeared in either the 1978 or 1983 photographs. By 1985 however four small areas of this type had reappeared (Figures 3.2b, c and d).

Moderately dark tone was relatively less smooth than the dark tone. This type of tonal category has seriously suffered from fire and the density of vegetation ranges from 40-80 per cent. The areal extent of this category has reduced from approximately 23.5 per cent in 1973 to 1.4 per cent in 1978, 1.6 per cent in 1983 and 0.96 per cent in 1985.

Moderately light tones have 10-40 per cent vegetation cover. The tonal degradation of this category was mainly due to its poor vegetation cover. In terms of areal extent, the category appears to have improved considerably from 13.6 per cent in 1973 to 30.5 per cent at 1985, in part due to regeneration of vegetation.

Light tones are characteristic features of very sparse, widely scattered vegetation, with a range of 0 to 10 per cent vegetation. Exposed surfaces within the category have resulted in an uneven textural composition. In areal extent, the category seems to have fluctuated most since 1973.

Light to deep grey tones reflect the exposed deep blanket peat area. The tonal intensity within category varies because of:

1) differential local relief;
2) varying levels of peat formation;
3) density of micro channels; and
4) varying levels of ground moisture.

Within the exposed peat category field checking further revealed that there are three different types of peat formation, a) charred peat with columnar structure, b) ashed hollows and residual charred peat, and c) hagged peat, reliable identification of these types was not however possible from the air photographs.

The exposed peat of the study area was mainly attributed to the 1976 fire. The areal coverage of this category reached its peak at 1978 (being 68.25 per cent), thereafter, due either to gradual regeneration of vegetation or erosion, the category decreases to about 60 per cent of the area in 1985.

White tones are associated with the bare soil and exposed mineral soil. The subsurface soils are mainly coarse to fine loamy and some parts have very thin peat cover. The category completely lacked any vegetation cover. Bare soil area of the Glaisdale Moor has significantly increased since the 1976 fire, rising from only 0.61 per cent in 1973, to 4.18 per cent in 1985.

The overall tonal sequences in all the air photographs of the study area however, did not clearly develop a systematic pattern of tones. The probable reasons are as follows:

1) Within the dark tone there was significant irregularity which has resulted in the break of tonal texture and smoothness.
2) Apart from the dark and white tones, tonal variations were very inconsistent and irregularly merged at varying levels between the other categories.

It appears clear from Table 3.1 that since 1978 changes in surface cover of Glaisdale Moor was unprecedent in scale, especially in the bare peat. Although some parts of Glaisdale Moor have recovered after recolonization, however, the regeneration process was rather slow. Most significantly, no part of the Glaisdale Moor has yet established a complete vegetation cover since 1978.

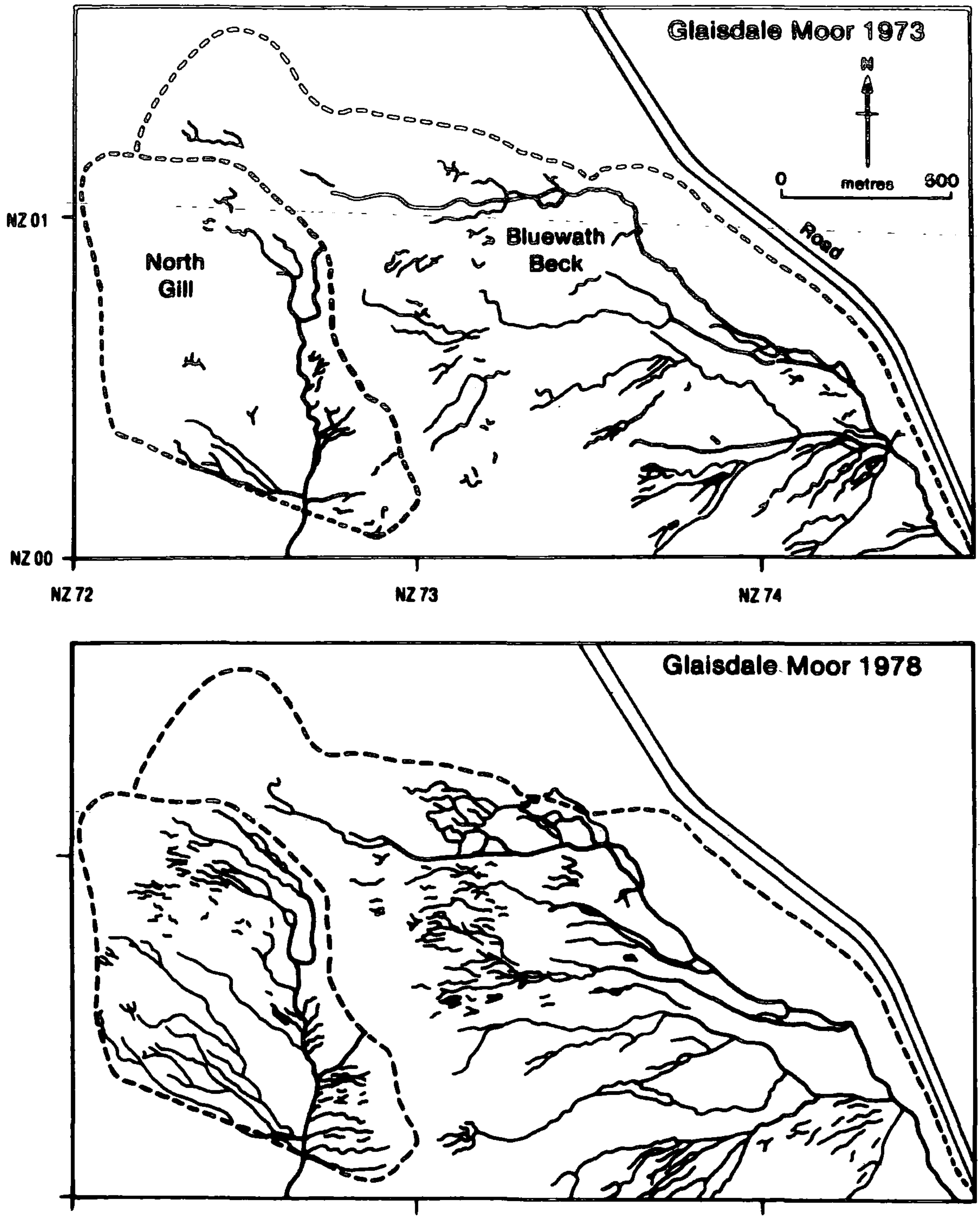
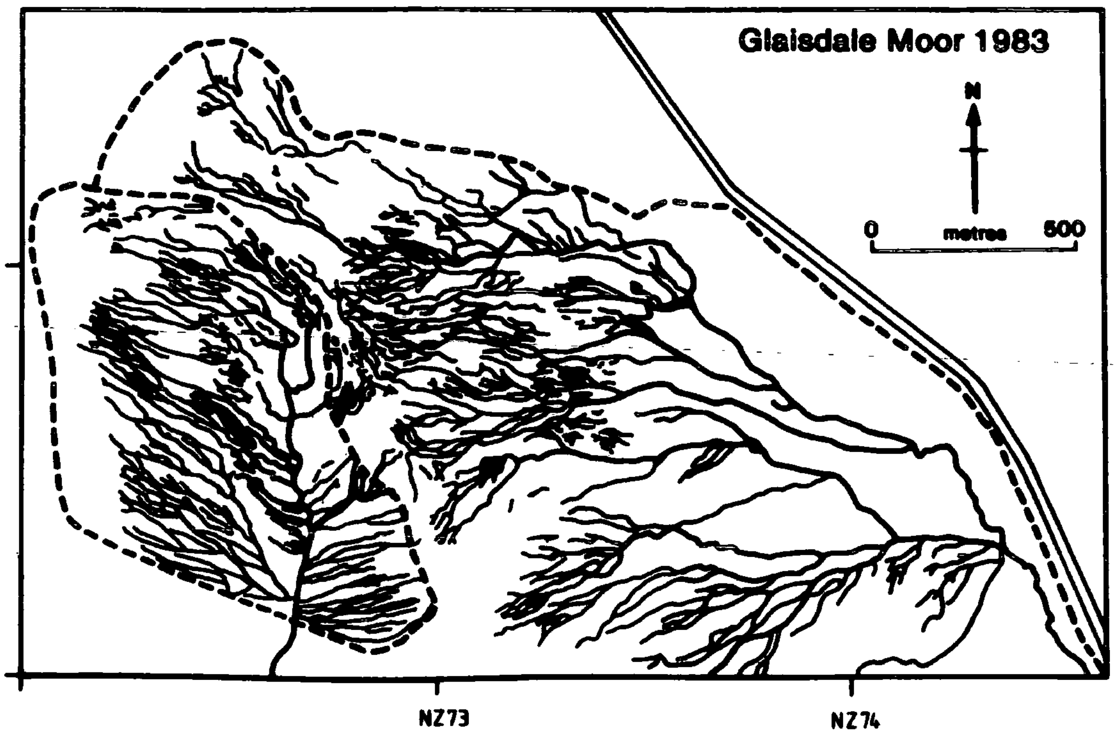


Figure 3.3a Drainage patterns of Glaisdale Moor. 1973–1978.



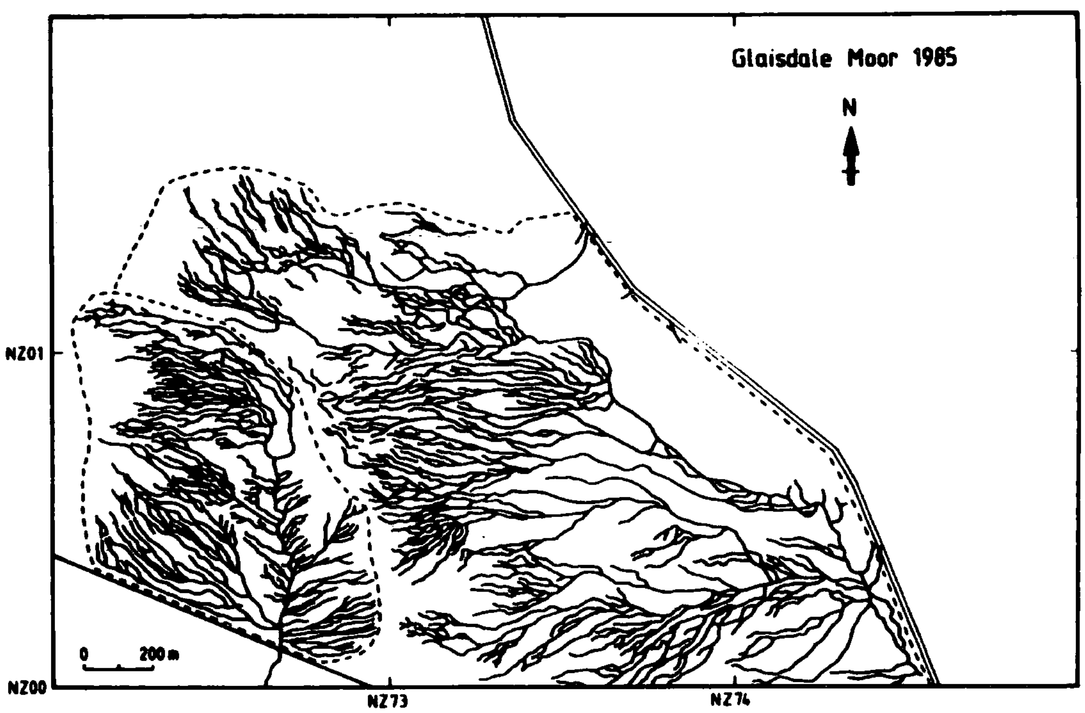


Figure 3.3b Drainage patterns of Glaisdale Moor. 1983-1985.

3.5 Drainage development

The 1973 aerial photographs of Glaisdale Moor indicate two distinct smaller watersheds, one at the mid eastern section called the Bluewath Beck and another, at the south-western section, called the North Gill (Figure 3.3a). All the channels as appeared in Figure 3.3a are mainly rills associated with few gullies and essentially of ephemeral nature.

The drainage pattern of Glaisdale Moor was significantly changed after the 1976 fire which was reflected in the 1978 aerial photographs (Figure 3.3a). Two watersheds : Bluewath Beck and North Gill were far clearer on the 1978 photographs. The Bluewath Beck and the North Gill watersheds appear to have laterally extended and numerous micro-channels have emerged. The impact of sparse vegetation cover on the Glaisdale Moor drainage system was evidently clear.

In 1983 and 1985 the drainage network of Glaisdale Moor has further intensified, although the drainage intensity difference between two periods was less apparent. Over the years, the Bluewath Beck and the North Gill have developed an extensive drainage network, covering most of the Glaisdale Moor (Figure 3.3b). Intense incision, lateral erosion and most importantly surface rilling are the reasons for the phenomenal drainage development.

3.6 Drainage density

The interpretation of Glaisdale Moor air photographs has revealed the nature of the problem in terms of the changing surface cover and the drainage. In this section, attention is focussed on the micro-level temporal and spatial drainage density variation of the Glaisdale Moor. The drainage density maps are produced from the drainage maps, (Figure 3.3a and b) and these are shown in Figure 3.4. Detailed discussion about the drainage density mapping was given in section 3.3 of this chapter.

The drainage density maps, Figure 3.4 indicate a wide range of temporal and spatial variation in drainage density. A pair-wise t-test was employed to examine if the drainage density variations from 1973 to 1985 are significant. The results of the pair-wise t-test show a significant difference exists between the different years considered except between the 1983 and 1985 (Table 3.2). The lower significance level of the drainage density between 1983 and 1985, was perhaps due to limited extension of drainage since 1983 because of gradual recolonization of vegetation. The t-statistic for the 1973 and 1978 pair was also relatively low, which needs some careful examination. Before the August 1976 fire on Glaisdale Moor, the area was less disturbed. But the hydrological balance was immediately affected after the fire, thus the established ecosystem of the basin was lost (Imeson 1981). There was very little interception and transmission of rainfall energy available because of lack of surface vegetation, therefore, more surface runoff was generated. Eventually, the higher runoff has developed a new drainage network. In the present context, two years difference between 1976 and 1978 was not sufficient to make a significant alteration to an established drainage system, and perhaps that was the main reason for the lower t-statistic between these two years.

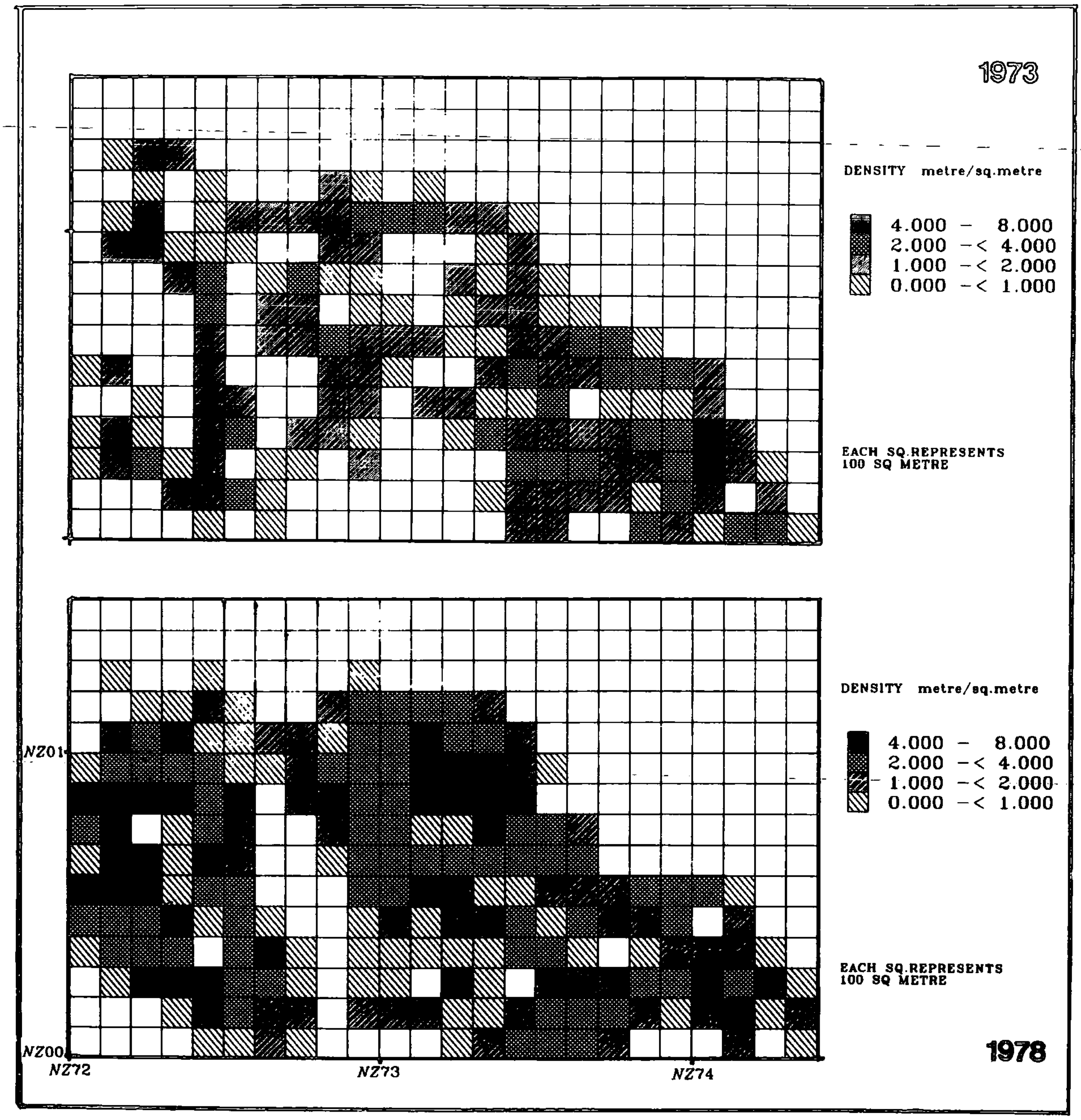


Figure 3.4a Drainage density of Glaisdale Moor

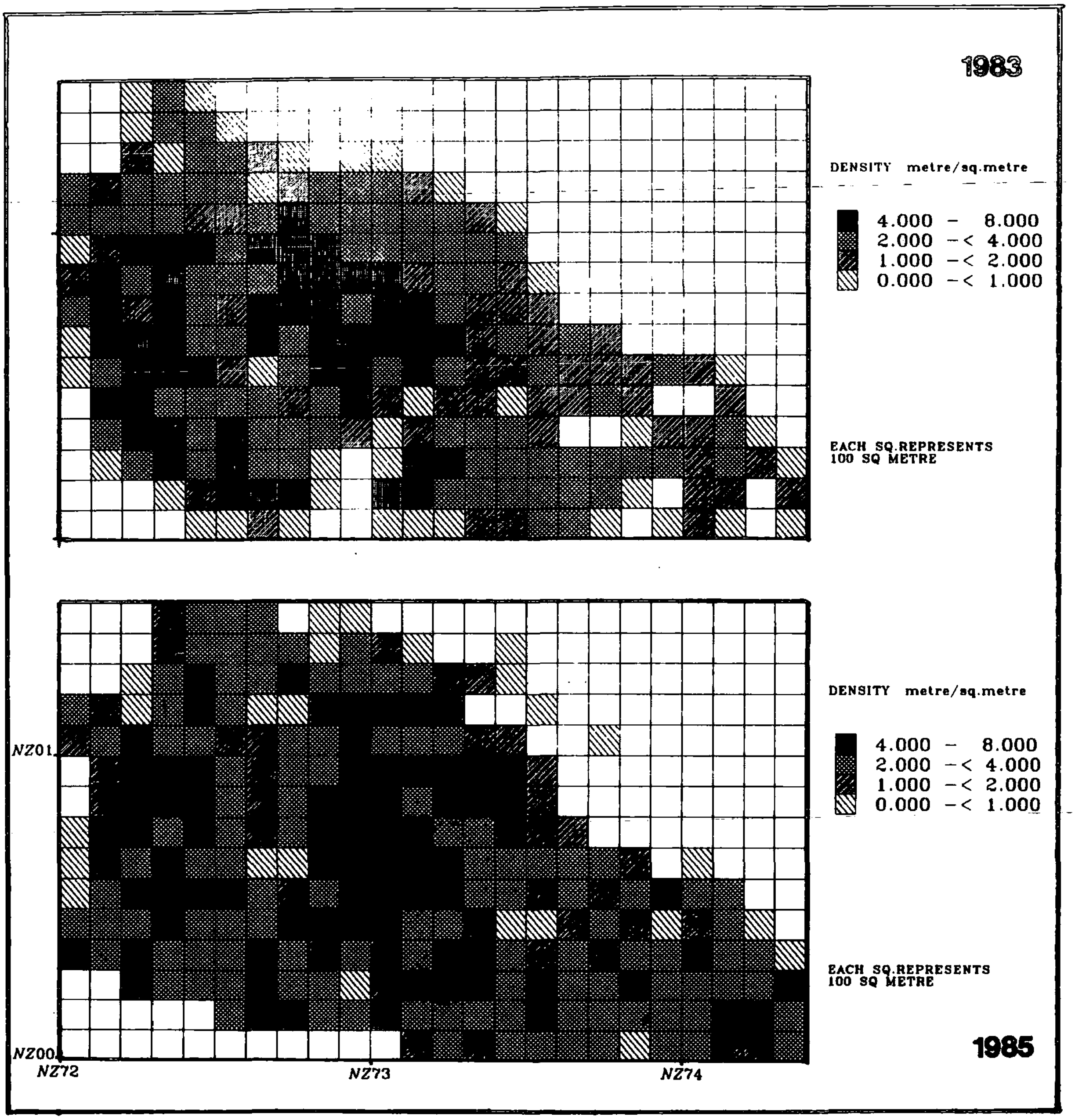


Figure 3.4b Drainage density of Glaisdale Moor

Table 3.2 Pairwise 't' tests of changes in drainage density 1973-1985

Variable	Mean	Mean difference	Standard deviation	t statistic	Significant at α =
1. Dd73	1.288	-0.338	1.303	-3.174	0.001
2. Dd78	1.626	-- N = 149 --			
1. Dd73	1.288	-1.507	1.795	-10.248	0.0001
3. Dd83	2.795	-- N = 149 --			
1. Dd73	1.288	-1.723	1.955	-10.759	0.0001
4. Dd85	3.012	-- N = 149 --			
2. Dd78	1.590	-1.237	1.890	-8.254	0.0001
3. Dd83	2.828	-- N = 159 --			
2. Dd78	1.590	-1.493	1.895	-9.935	0.0001
4. Dd85	3.084	-- N = 159 --			
3. Dd83	2.828	-0.255	2.032	-1.588	0.15
4. Dd85	3.084	-- N = 159 --			

Dd73 Drainage density 1973

Dd78 Drainage density 1978

Dd83 Drainage density 1983

Dd85 Drainage density 1985

Apart from the temporal variation in drainage density of the Glaisdale Moor, there was a wide range of localized density variation within the basin. The localized drainage density variation was also reported earlier by Imeson (1971) in the N.York Moors and by Tallis (1981) in the Pennines. The possible reason for this localized drainage density variation may be primarily due to the variations in subsurface lithology, and the variations in intensity of surface vegetation cover (Morgan 1986 and Rose 1971). The mean drainage density variation among the major types : vegetation (2.42 m/m^2) bare peat (3.44 m/m^2) and base soil (2.78 m/m^2) was tested by analysis of variance. The null hypothesis was that there was no significant variation in drainage density among the surface types of Glaisdale Moor. The 1985 drainage density data were used for the ANOVA. The result indicates a high F-value and the level of significance was very high = 0.0001 (Table 3.3). Therefore, statistically the drainage variation among the surface types appears to be valid.

The higher drainage density of the peat can be attributed mainly to its higher intensity of infiltration and quick through flow. The higher infiltration and through flow rate accelerates the elevation and solution and intensity of the development and extension of seepage faces (Imeson 1981). In addition, due to the exposed condition of the peat, it dries very quickly and cracks along the margins. When rain falls, the cracked margins emerge as a microrill and with further lateral extension along the cracks, the microrill develop as bigger rill and eventually a new drainage network develops.

The lower drainage density in the vegetated surface was attributed to its controlled infiltration and through flow rate (Imeson 1981).

Table 3.3 The results of the analysis of variance testing the significance of the temporal variation in drainage density

Source	Degree of freedom	Sum of squares	Mean squares	F Statistic	Significant at α =
Between	2	58.871	29.436	12.221	0.001
Within	253	609.38	2.408		
Total	255	668.25			

This means the surface vegetation has played a key role in controlling the drainage density rate of Glaisdale Moor. This proposition was examined by Pearson's product moment correlation between the drainage density and the percentage of vegetation. The result indicates a negative correlation r = -.388, significant at = 0.01 level, which means decreasing cover has a significant positive effect on the drainage density rate.

3.7 Nature and types of erosion

The major erosional forms identified on the 1985 aerial photographs of Glaisdale Moor include : sheet wash, rill wash and occasional gullying (Figure 3.5).

Sheet wash in Glaisdale Moor was very much confined to the bare mineral soil and occasionally to some extent at the down slope of very thin peat areas. Because of the poor infiltration and throughflow capacity of the bare mineral soil, precipitation cannot pass through quickly, thereby it rushes down slope as a sheet wash without any concentration.

Rill wash represents the early stage of gully formation. This form of erosion features are very extensive in the peat areas (Figure 3.1).

Gullying was not an extensive feature of the Glaisdale Moor. Two major gullies identified in the 1985 aerial photographs of the Glaisdale Moor were in fact the two main channels : the Bluewath Beck and the North Gill.

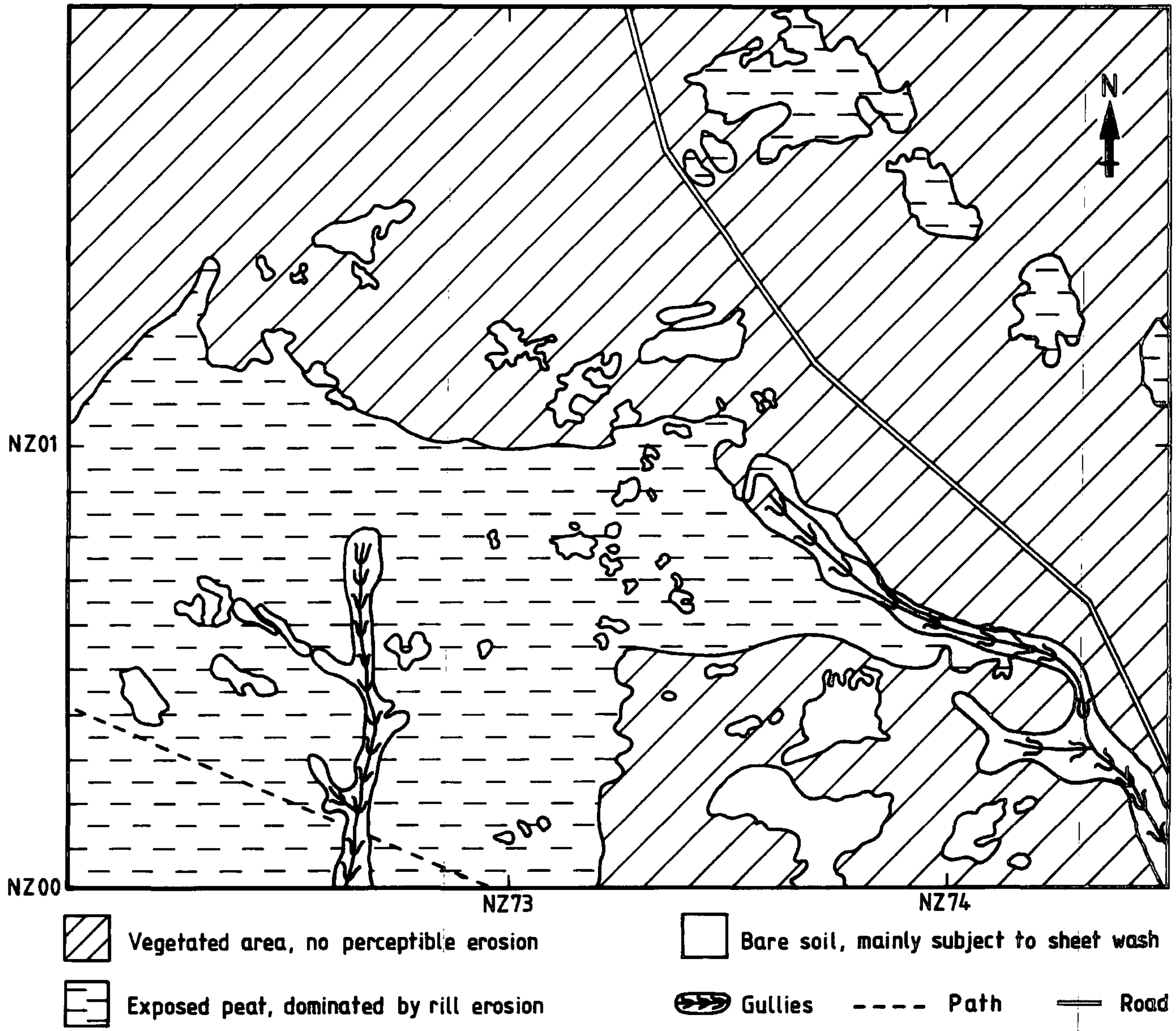


Figure 3.5 Erosion features of Glaisdale Moor

Because of extensive rilling, the overall intensity of erosion appears to be much higher at the blanket peat than either the bare soil or the vegetated area.

3.8 Conclusion

The objective of photointerpretation was to identify and map the following : the surface cover changes, the drainage and the erosion types occurring on the Glaisdale Moor. Based on the above photointerpretation, the following observations can be made:

1) The surface cover of Glaisdale Moor has experienced a drastic change between 1973 and 1985. The worst affected part of the Moor was the blanket peat, as the whole area became totally exposed after the fire. Over the years, the area of bare soil has increased at the expense of the thinner peat area.
2) The overall drainage density of Glaisdale Moor has increased at a phenomenal rate from 1.28 m/m^2 at 1973 to 3.08 m/m^2 at 1985. Because of extensive rilling the deep blanket peat has the highest mean drainage density of 3.44 m/m^2, while the vegetated area has the lowest rate of 2.42 m/m^2 and the bare soil has the intermediate rate of 2.78 m/m^2.
3) The nature and types of erosion in the Glaisdale Moor are mainly controlled by the pedological and topographic diversity. Extensive rilling in the peat was the most important erosion feature of Glaisdale Moor.

Having established the areal extent of the surface cover changes which have occurred in Glaisdale Moor since 1973 and the drainage development with its related erosion extent, attention is drawn to the next chapter about the relationships between spectral reflectance and soil-ground variables which are related to erosion.

CHAPTER FOUR

Spectral Characteristics of Glaisdale Moor Surface Types and their discrimination potential

4.1 Introduction

4.2 Objectives

4.3 Methodology

4.4 Relationships between ground variables and surface reflectance

4.5 Grouping and spectral discrimination of surface cover types

4.6 Conclusion

4.1 Introduction

Remotely-sensed data are used routinely in the Earth Sciences for the discrimination of surface characteristics. Soil scientists have used remote sensing data (particularly Landsat MSS data) for the mapping of different soil classes (Cipra 1973, Ezra et.al. 1984, Kirschner et.al. 1978, Weismiller et.al. 1977) and for the identification of soil types and soil properties (Al Abbas et.al. 1972, Kristof and Zachary 1974, Kristof et.al. 1974, Matthews et.al. 1973, Zachary et.al. 1972). Discrimination in most of these cases was achieved using the spectral differences of ground surface parameters including soil physical and chemical properties, vegetation and terrain parameters (Huete et.al. 1984, Crouse et.al. 1983, Townshend 1984, Siegal and Goetz 1977). The maximum overall discrimination accuracy in some cases with MSS data has been reported as 58 per cent (Thompson et.al. 1981), 56 per cent (Hancock 1982) and 50 per cent (Siegal and Abrams 1976). Huete et.al. (1984) found difficulty in discriminating bare soil from low vegetation densities.

4.2 Objectives

The objective of the study reported here is the examination of the spectral reflectance properties of soil and vegetation in Glaisdale Moor with the aim of discriminating the surface cover types. The study first examines the relationships between ground physical parameters and ground radiometer measurements, and the second part of the analysis investigates which wave band best discriminates surface types.

4.3 Methodology

The estimation of an environmental variable at a point and later extrapolation over a wider area needs reliable and representative ground data (Curran and Williamson 1985). The Glaisdale Moor study area was divided into three pedological groups:- coarse loamy, fine loamy and Eriophorum sphagnum peat, based on the Soil Survey of England and Wales map (Carroll and Bendelow 1981)

After initial stratification of the area into the three pedological groups, each stratum was then further subdivided into five substrata on the basis of tonal characteristics on the aerial photography (Table 4.1). A stratified random sampling scheme was then used to identify 70 field sites at which a number of soil characteristics were measured in May 1985 (see Appendix 1 and 2). The soil characteristics measured include soil texture, moisture, organic matter, biomass and slope. The list of soil variables is shown in Table 4.2. Laboratory methods used for soil texture, moisture and organic matter analysis were taken from Avery and Bascomb (1974) and Black et.al. (1965). The hydrometer method was followed for textural analysis, and the loss on ignition method to determine the organic matter content. Vegetation biomass was measured using the harvest method (Pearson and Miller 1972, Tucker and Maxwell 1976). The surface vegetation of 1m square was harvested and weighed. After drying the vegetation the sample was weighed again and this value was taken as the vegetation biomass.

At each of the 70 field sites the reflectance of the surface was also measured. The instrument used was a Milton Multiband Radiometer (Milton 1980) equipped with four wavebands comparable to those of the LANDSAT Multispectral Scanner, viz. 0.5-0.6, 0.6-0.7, 0.7-0.8 and 0.8-1.1µm. At each site the surface radiance and the radiance of a Kodak grey card were measured three times. The radiometer sensor head was positioned 2m above the surface and measurements were taken between 11.00 and 14.00 hours BST during the period 12-15 May 1985. From these data bi-directional reflectance (BDR) of the ground surface in each waveband was calculated by

$$BDR = \frac{Rs}{Rg} \times 100 \text{ (per cent)}$$

where Rs is the radiance from the ground surface and Rg is the radiance of the Kodak grey card.

Before any parametric statistical analysis was performed the frequency distributions of all the variables were analysed. The summary statistics of all the variables are shown in tables 4.1 and 4.2. On inspection some of the variables had high skewness and were transformed. Logarithmic transformations (base e) were applied to the soil moisture, surface silt and clay and subsurface clay and slope variables. Square root transformations were applied to the four spectral reflectance variables. Further references in this paper to the variables refer to the relevant transformed variables, but for simplicity the original names are employed.

Table 4.1 Summary statistics of the ground variables

Variable		N	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis	Transformation
Percent moisture		70	0.120	29.900	5.926	6.036	1.715	3.690	$\log_e$
Per cent organic matter		70	2.290	91.610	36.145	28.692	0.261	-1.312	-
Biomass gm/m^2		40	209.69	2245.9	1476.6	502.93	-0.409	-0.294	-
Per cent sand	Surface	60	48.630	91.950	76.149	10.525	-0.548	-0.024	-
Per cent silt	Surface	60	4.03	40.280	14.385	6.188	1.074	3.429	$\log_e$
Per cent clay	Surface	60	2.02	37.350	10.902	8.085	1.852	3.165	$\log_e$
Per cent sand	Subsurface	60	35.150	93.490	72.291	16.007	-0.853	-0.339	-
Per cent silt	Subsurface	60	0.010	37.250	12.850	8.124	1.030	0.781	-
Per cent clay	Subsurface	60	2.01	39.150	14.805	10.610	0.958	-0.343	$\log_e$
Slope		70	10.30	51.340	25.052	9.275	0.971	0.980	$\log_e$

Table 4.2 Summary statistics of the surface reflectance variables

Variable	N	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis	Transfor-mation
Channel 1 (0.5-6 µm)	70	2.97	82.54	27.107	19.790	0.723	-0.393	Square root
Channel 2 (0.6-0.6 µm)	70	2.77	98.65	35.081	23.173	0.387	-0.737	Square root
Channel 3 (0.7-0.8 µm)	70	9.68	176.18	47.396	36.607	1.779	3.106	Square root
Channel 4 (0.8-1.1 µm)	70	15.82	212.83	65.528	35.497	1.698	4.075	Square root

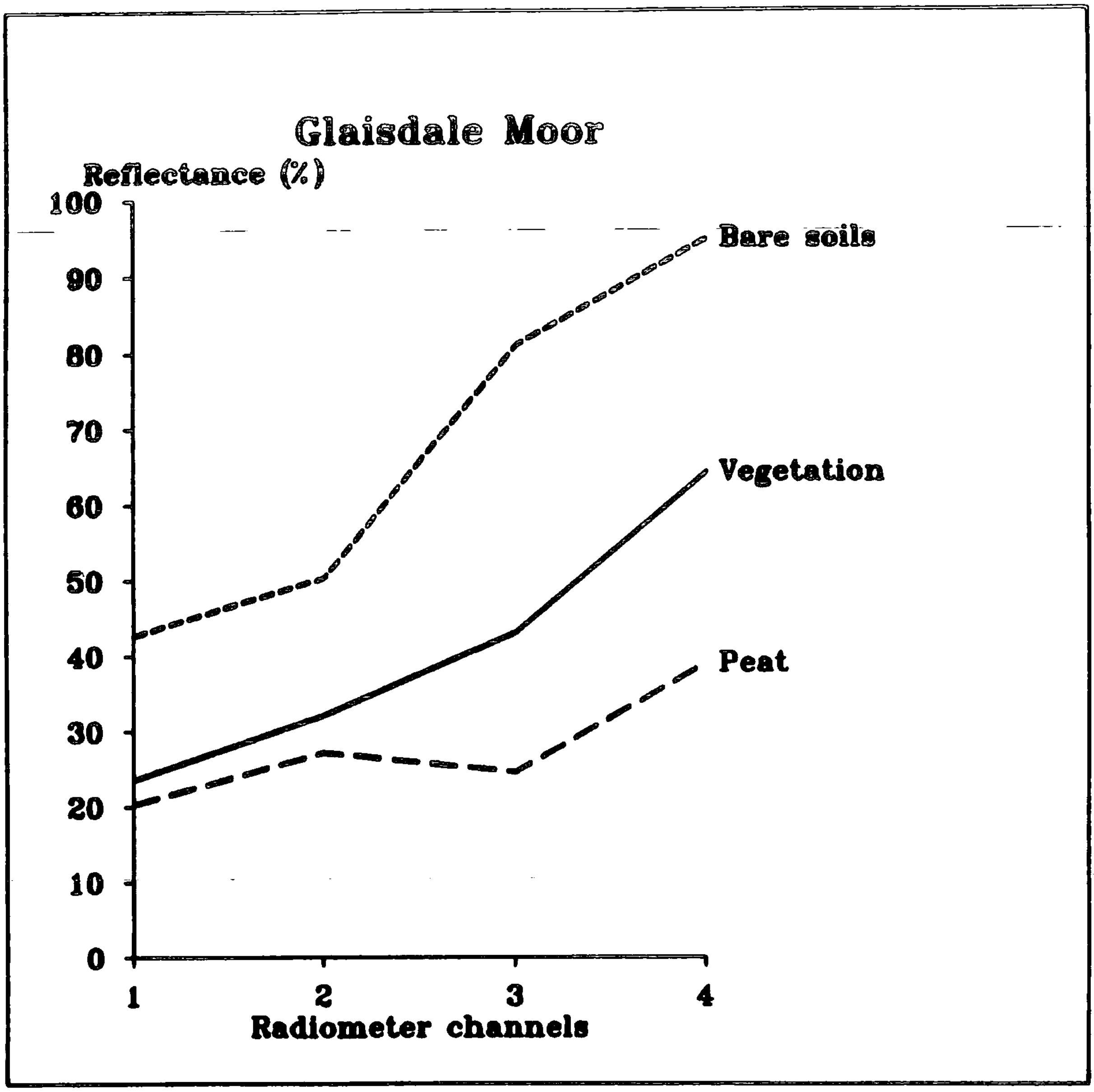


Figure 4.1 Spectral reflectance of three surface types in Glaisdale Moor: peat, vegetation and bare soil. The four radiometer channels are compatible with the Landsat MSS, viz. 0.5–0.6, 0.6–0.7, 0.7–0.8 and 0.8–1.1 μm respectively.

Table 4.3 Pearson's product-moment correlation coefficients among the soil and spectral variables

	Moisture per cent	Organic matter per cent	Biomass gm/m^2	Surface			Sub surface			Slope
				Sand per cent	Silt per cent	Clay per cent	Sand per cent	Silt per cent	Clay per cent	
Channel 1(0.5-0.6μm)	-0,150	-0.331**	-0.315*	-0.322*	-0.212	0.386**	0.138	-0.432**	0.113	-0.181
Channel 2(0.6-0.7μm)	-0.057	-0.142	-0.482**	-0.425**	-0.128	0.542**	-0.019	-0.253	0.222	-0.161
Channel 3(0.7-0.8μm)	-0.311**	-0.361**	-0.590**	-0.175	-0.124	0.246*	0.206	-0.357*	-0.005	0.107
Channel 4(0.8-1.1μm)	-0.327**	-0.436**	-0.594**	-0.240	0.049	0.335**	0.155	-0.210	0.028	0.238*
Cases	70	70	40	60	60	60	60	60	60	70

* Significant at $\alpha = 0.05$ ** Significant at $\alpha = 0.01$

4.4 Relationships between ground variables and surface reflectance

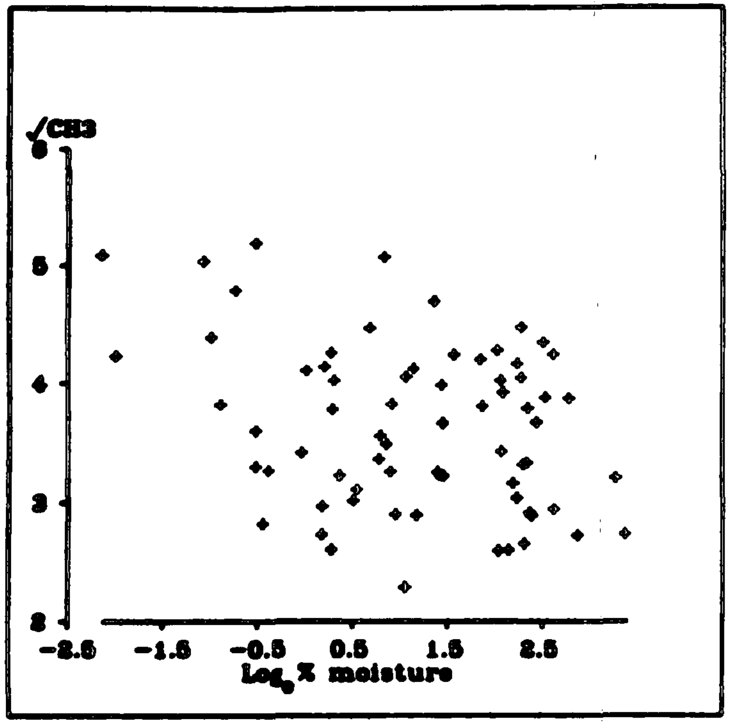
4.4.1 Spectral reflectance

It is important to note that the spectral reflectance values for the vegetation substratum were merged into one to represent the vegetation category. Thus there are three groups in this analysis : vegetation, peat and bare soils.

The average spectral reflectance curves for these three main groups are shown in figure 4.1. The peat category shows the lowest reflectance in all wavebands because of its high soil moisture and high organic matter contents. The vegetation category has high reflectances comparable to those of peat at visible wavelengths, but has a higher near-infrared reflectance. The vegetation curve is not simply a function of chlorophyll absorption because the heather vegetation is not so biologically active in May. Rather, the increasing reflectance with longer wavelengths is related to the higher near-infrared reflectance of the components of the heather canopy such as leaves, stems and twigs. The bare soil category has the highest reflectance in all wavebands because of its lower organic matter content and lower soil moisture.

4.4.2 Bi-variate relationships

Pearson's product-moment correlation coefficients were calculated for all the combinations of ground variables and spectral variables. The results are shown in Table 4.3. Scatter plots of the soil variables with each of the reflectance variables were created and showed that most of the soil variables had negative relationships with i)



ii)

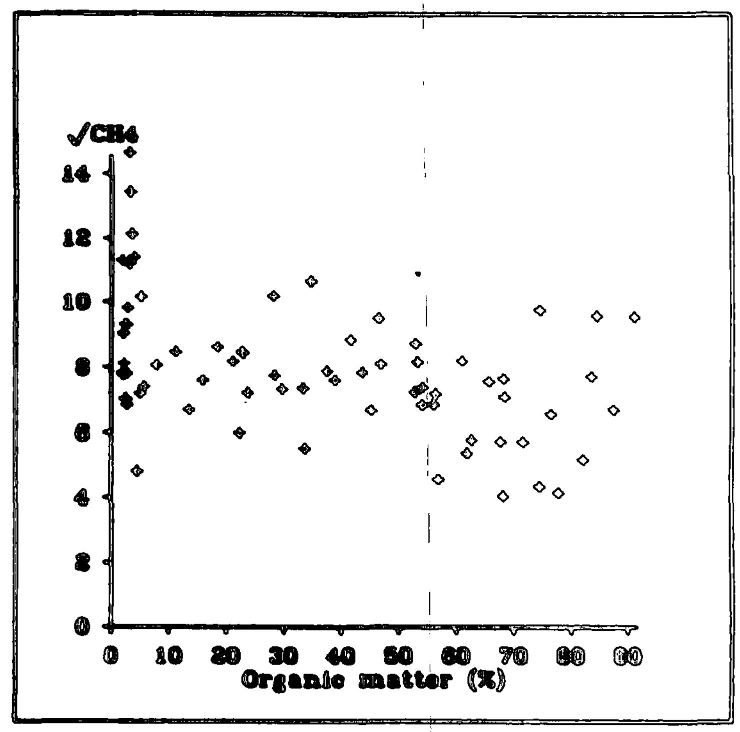


Figure 4.2 a Scatter plots of selected spectral and ground variable combinations. i) Soil moisture and red waveband (CH3) and ii) soil organic matter and near infrared waveband (CH4).

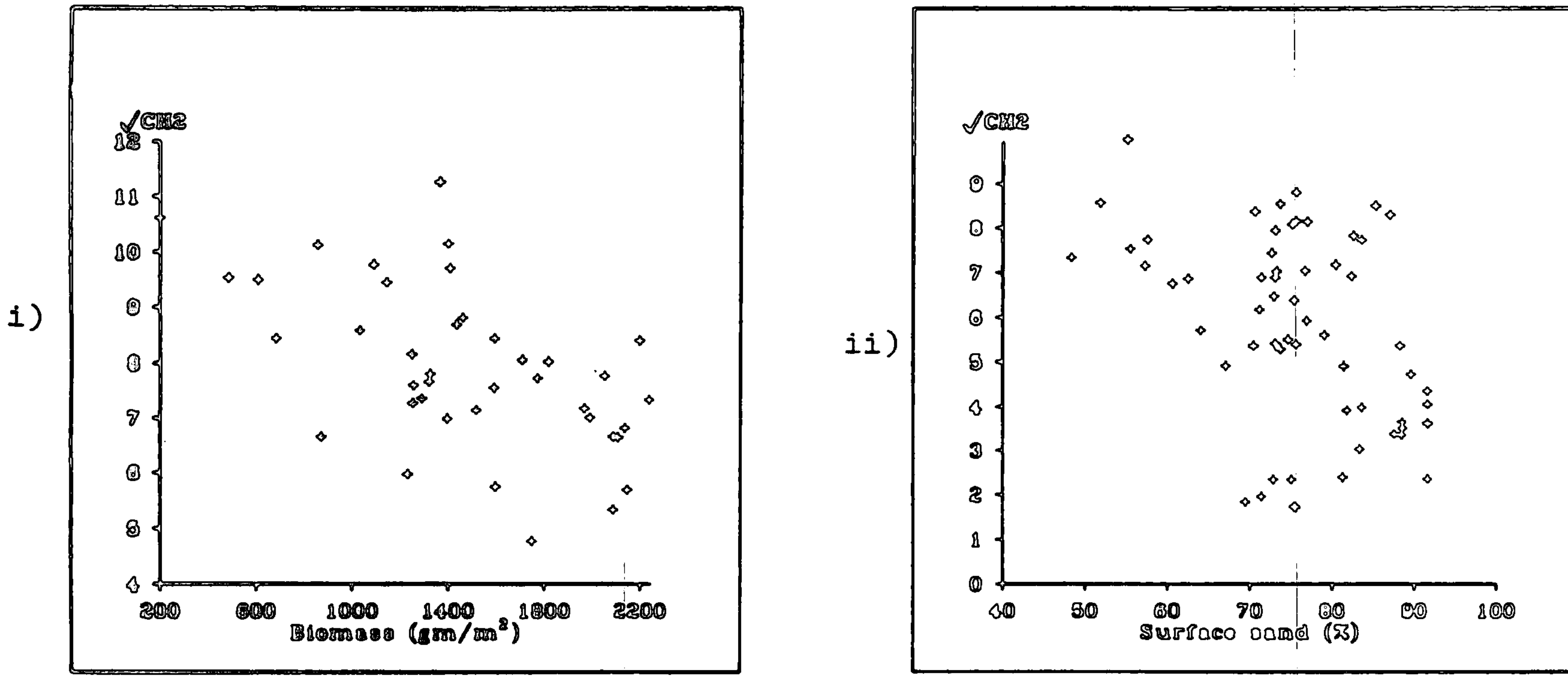
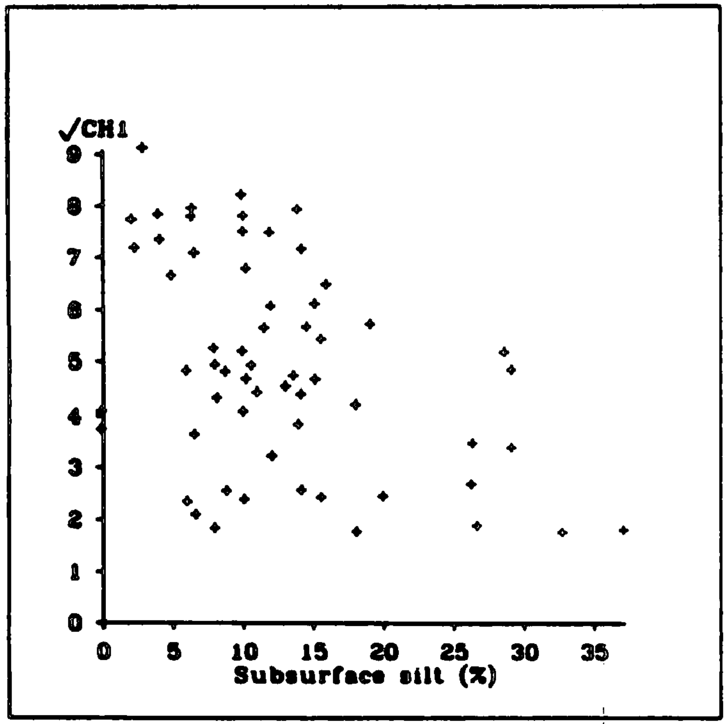


Figure 4.2 b Scatter plots of selected spectral and ground variable combinations . i) Vegetation biomass and green wave band (CH2) ; and ii) surface sand and green wave band (CH2).

i)



ii)

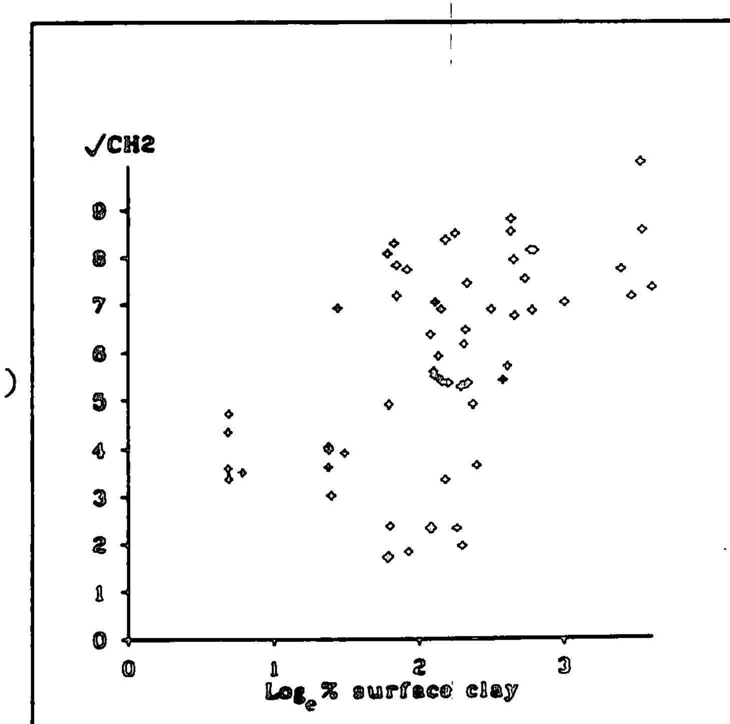


Figure 4.2 c Scatter plots of selected spectral and ground variable combinations. i) Subsurface silt and blue wave band(CH1). and ii) surface clay and blue wave band (CH1)

reflectance. Moisture, organic matter, biomass, sand and subsurface silt all had negative relationships with reflectance, while subsurface clay had a positive relationship.

Figure 4.2 shows scatter plots of six of the relationships. Figure 4.2a(i) shows that as moisture content increases then near-infrared reflectance decreases because of the higher reflectance of dry soils (Curran 1985). Jensen (1985) observed that the presence of soil moisture not only reduces the surface reflectance in visible wavelengths but also in near infrared wavelengths. The negative relationship of reflectance and organic matter (Figure 4.2a(ii)) has been observed also by Page (1974) and by Hoffer (1978). The negative relationship between organic matter and reflectance is attributed to the darkness of soil organic matter. Therefore its presence decreases the reflectance from the soil. For naturally occuring materials the exact relationship may be influenced by the presence of other factors, such as soil moisture. The decrease in reflectance with increasing biomass (Figure 4.2b(i)) is attributable to energy absorption by water in the vegetation canopy, and the increased diffuse scattering and surface roughness with increasing biomass.

The negative relationships of surface sand and subsurface silt with visible reflectance (Figures 4.2b(ii) and 4.2c(i)) supports similar findings by Hoffer 1978 who suggests that the larger particle sizes of sandy soils means greater scattering and so lower reflectance. The positive relationship between reflectance and surface clay content (Figure 4.2c(ii)) supports this mechanism as scattering will reduce with a smoother surface composed of finer particles. However, it should be remembered that the figures for sand, silt and clay are percentage figures and that an increase in one of these variables will cause a commensurate decrease in one or both of the other two.

The results of the correlation calculations shown in table 4.3 indicate that visible reflectance is not strongly correlated with any of the ground parameters, with the possible exception of surface clay where r = -0.542. In all other cases r is less than 0.5. While the correlations increase slightly in the near-infrared channels the values are still relatively low, although in several cases statistically significant. One conclusion from the correlations given in table 4.3 and the scatter plots in figure 4.2 is that no single ground variable can be said to have a dominant affect on the spectral reflectance. It may be that the spectral reflectance variables as a group are related to the ground parameters as a group. This proposal is examined in the next section.

4.4.3 Canonical correlation

Canonical correlation allows the examination of the relationship between an independent group of variables and a dependent group of variables. In this study the ground parameters are taken as the independent group (group 1) and the spectral variables as the dependent group (group II). Details of canonical correlation are given in Kendall (1972), Morrison (1967) and Johnston (1980) and see also Chapter 5 (Section 5.4.3).

The canonical correlation results are shown in Table 4.4. The largest canonical correlation coefficient is 0.765 which means that 58.5 per cent of the variance in the spectral variables can be explained by the variance in the ground variables. This is a relatively poor performance which may be attributable partly to the exclusion of the biomass variable from the analysis because it was not available for peat and bare soil.

The relationship between the two groups of variables was also examined by multiple regression analysis. The dependence of each spectral variable on the independent ground variables was not high, with the coefficients of determination ranging from 0.396 to 0.564.

From these analyses it is clear that there is a great deal of spectral variation still to be accounted for. This is explored further by using the stratification of the data into the separate vegetation, peat and bare soil groups.

Table 4.4 Canonical correlation of ground and spectral variables

		Correlation		
Group 1	Group II	1	11	111
Soil moisture	Channel 1			
Organic matter	Channel 2	0.765	0.717	0.560
Sand	Channel 3			
Silt - Surface	Channel 4			
Clay				
Sand				
Silt - Subsurface				
Clay				
Slope				

Number of cases = 60.

4.5 Grouping

The assumption behind the grouping is that the groups are meaningful. If the groups have a high variance then the result would not form a reasonable basis for further analysis (Whitelock et.al. 1982). Therefore the quality of the grouping needs to be tested first, and this was done using one way analysis of variance (ANOVA). The null hypothesis for this ANOVA was that the spectral reflectances of individual cases were not distinctly different between groups. Table 4.5 shows an ANOVA which used the spectral reflectance data as the dependent variables and the strata as the treatment. Channels 1, 3 and 4 have F ratios which are significant at P = 0.1. These results positively support the contention that the grouping is meaningful, and so the groups were used in the analysis discussed below.

Table 4.5 Analysis of variance of spectral variables to test the stratification discussed in the text

	Channel 1	Channel 2	Channel 3	Channel 4
Between-group sum of squares	35.258	24.523	7.2662	71.044
Between-group mean square	17.629	12.261	3.6331	203.07
Within-group sum of squares	220.06	276.63	23.447	35.522
Within-group mean square	3.3342	4.1914	0.355	3.077
F ratio	5.2863**	2.9253*	10.227**	11.545**

* Significant = 0.1. ** Significant = 0.05.

Table 4.6 Multiple correlation between the spectral variables and the ground variables for three groups

	N	Multiple R	R^2	F	Significance
		Vegetation			
Channel 1	40	0.721	0.519	3.136	0.007
Channel 2	40	0.762	0.762	4.009	0.001
Channel 3	40	0.772	0.596	4.286	0.001
Channel 4	40	0.806	0.651	5.407	0.001
Independent variables included: moisture, organic matter, biomass, surface sand, silt and clay, subsurface sand, silt and clay, slope.					
		Peat			
Channel 1	15	0.847	0.717	9.313	0.002
Channel 2	15	0.811	0.658	7.073	0.006
Channel 3	15	0.823	0.677	7.710	0.004
Channel 4	15	0.904	0.818	16.58	0.001
Independent variables included: moisture, organic matter, slope					
		Bare soil			
Channel 1	15	0.959	0.921	6.518	0.026
Channel 2	15	0.958	0.919	6.346	0.027
Channel 3	15	0.994	0.989	52.85	0.001
Channel 4	15	0.984	0.969	17.702	0.002
Independent variables included: moisture, organic matter, surface sand, silt and clay, subsurface sand, silt and clay.					
		Bare soil			
Channel 1	15	0.935	0.875	9.370	0.002
Channel 2	15	0.941	0.885	10.345	0.002
Channel 3	15	0.987	0.975	53.069	0.001
Channel 4	15	0.955	0.913	14.121	0.001
Independent variables included: surface sand, silt and clay and subsurface sand, silt and clay.					

Having grouped the data, the next stage in the analysis was the use of multiple regression analysis to examine for each group the relationships between each spectral variable and the set of independent grouped variables. The results are shown in Table 4.6 and it can be seen that quite high values of R^2 are obtained, even with a small sample number. The lowest R^2 values are found in the vegetation group, with higher values of R^2 at longer wavelengths. Peat has higher R^2 values, and the bare soil category has values near or above 0.9, that is 90 per cent of the variance in the spectral response is explained by the variance in the ground variables. Two analyses are given for bare soil: the first includes the organic matter, moisture and slope variables, the second does not. In all cases the removal of these three variables reduces the R^2 values, although by relatively small amounts.

4.5.1 Spectral discrimination of surface cover types

Having established the relationship between the ground properties and the spectral variables, an attempt was made to explore the discriminating power of the ground radiometer data for the three surface types in the study area: vegetation, peat and bare soils. Stepwise linear discriminant function analysis (Nie et.al. 1970) was employed. The aim of discriminant function analysis is to find a set of functions of selected variates (wave bands) allowing classification of spectral observations into one of a designated number of populations (Abrams and Brown 1984). A stepwise discriminant analysis is a sequence of analyses which moves from one stage to the next by adding or deleting classification variables from the linear discriminant functions. The selection of variables at each step is controlled to maximize the ratio of the between-group dispersion to the within-group dispersion. Further discussion on the use of stepwise discriminant analysis is given in Chapter 5 and 6 (section 5).

The results produced from the stepwise discriminant analysis are presented in table 4.7. The order of inclusion of the wave bands in this stepwise analysis was channels 4, 1, 3, 2. The upper part of table 4.7 shows that the first discriminant function is positively weighted on the near-infrared channels and negatively weighted on the visible channel: the reverse is true with the second discriminant function. The largest coefficient in function 1 is for channel 4, and the largest in function 2 is for channel 1.

Table 4.7 Discriminant analysis of the radiometer data: standardized canonical discriminant function coefficients

	Function 1	Function 2
Channel 1	-0.13743	1.32065
Channel 3	0.45673	-0.46396
Channel 4	0.70719	-0.31977

Classification results

Actual group membership	Predicted group membership: Vegetation	Peat	Bare soil
Vegetation	20	8	12
Peat	2	13	0
Bare soil	3	2	10

Grouped cases correctly classified = 61.4 per cent.

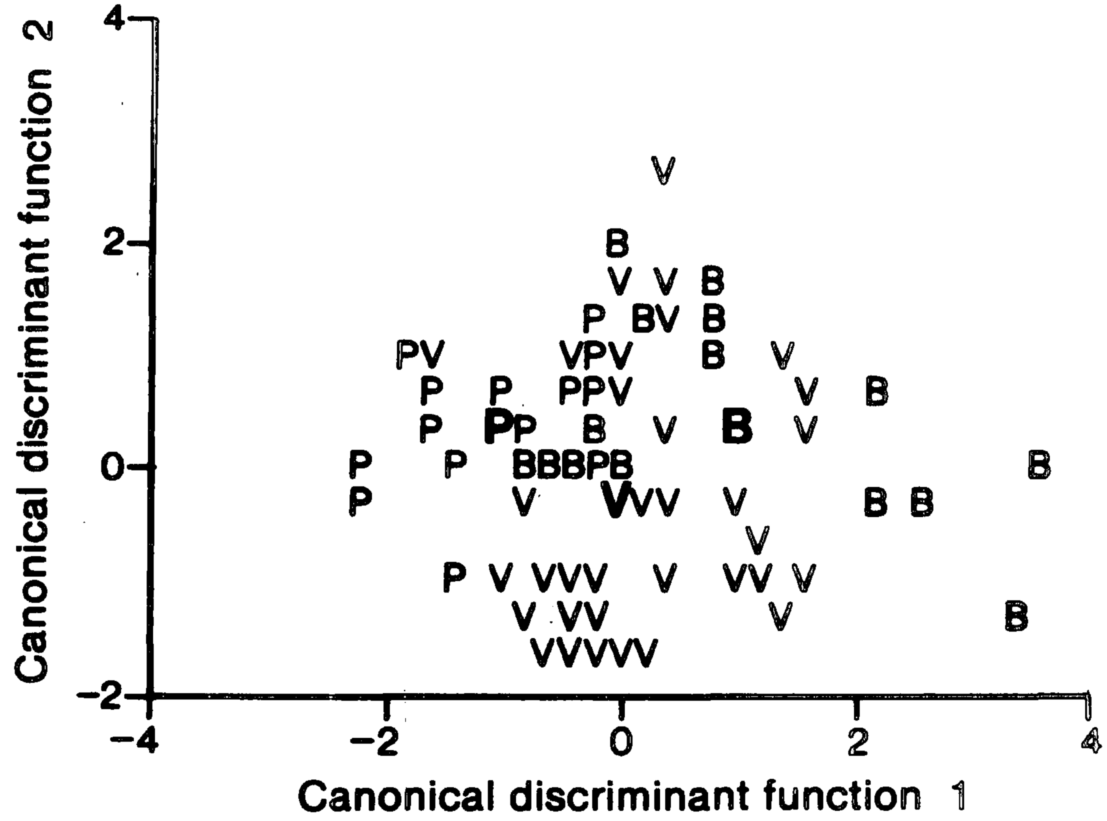


Figure 4.3 Scatter plot of three surface types shown on two discriminant function axes. P = peat, V= vegetation B = bare soil. The means of each group are shown by bold letters.

The scatter plot of the three groups on the two discriminant function axes is shown in figure 4.3. The group centroids are spaced relatively closely and indicate spectral similarity in the different groups. The classification results in the lower part of table 4.7 indicate that 61.4 per cent of grouped cases are correctly classified by the two discriminant functions. The vegetation and bare soil group have been seriously misclassified while the peat group has fewer misclassifications because of its distinctly lower reflectance. The poor performance of the vegetation and bare soil groups may be caused by the heterogeneity of surface conditions found at the surface, particularly for the vegetation category.

Although the discriminant analysis did not give clear results it does indicate that the best band for overall discrimination in the study area is channel 4, followed by channels 1 and 3. However, any conclusive remarks about the discriminating power of the ground radiometer data cannot be made without reservation.

4.6 Conclusion

The severe erosion in Glaisdale Moor has provided a focus for the study of the relationships between spectral reflectance and ground variables which are related to erosion. There is no clear, simple relationship between individual wave bands and single ground variables, but grouping and stratification have shown that aggregate effects can be determined. A number of factors are important in the area when assessing the results, and these are listed below.

1) The vegetation category has a high degree of internal variation as it ranged from <10 per cent to complete

cover and encompasses varying stages of vegetation maturity. Low density vegetation includes area of exposed soil and dead ground litter.

2) The spatial resolution of the ground radiometer is c. 1m. This scale is larger than the scale of spatial variation of the surface categories so that the spectral reflectance measurements will encompass surface type variation within each radiometer field of view.

3) The peat category encompasses a range of peat types including burned and eroded peat of varying moisture content and peat with exposed surface minerals.

The relationships between spectral response and ground variables are neither simple nor direct, but the analysis discussed here has shown the shape of some of these relationships.

The spectral characteristics of the Glaisdale Moor surface types are further examined with the air borne SPOT data in Chapter 5.

CHAPTER FIVE

Evaluation of SPOT simulation imagery potential for surface type discrimination

5.1 Introduction

5.2 Objectives

5.3 The SPOT simulated data

5.4 Spectral relationships with the ground data

5.5 Spectral separability

5.6 Image processing and results

5.7 Conclusion

5.1 Introduction

The SPOT spacecraft is an operational and commercial system. It carries two identical sensors, called HRV (Haute Resolution Visible), made of static solid state arrays of detectors (CCD). They operate in two modes, either in the panchromatic mode or multispectrally in three spectral bands between 0.49 and 0.91μm. Among the innovative features of SPOT are the relatively high ground resolution of the imagery it will produce (20m in the multispectral mode, 10m in the panchromatic mode) and the ability of its sensors to point up to 27° east and west of the local vertical axis. This latter feature offers possibilities for increasing the number of opportunities to obtain views of a given area. It also permits stereoscopic observations by combining views taken at different angles from the vertical and therefore opens up the possibility of third dimension (altitude) determination, which is an important requirement for cartographic applications (Brachet 1986). The principal characteristics of SPOT are summaried in Appendix 3.

As a prelude to the launch of the SPOT system, considerable research was undertaken using airborne sensors to simulate the SPOT data set. The objectives of the SPOT simulation programmes were to provide information on the potential applications of the SPOT satellite data.

The SPOT simulation programme was carried out in several parts of the world including Bangladesh, West Africa, United States and Europe. Preliminary results of these SPOT Simulation confrimed that in such field as topographic and thematic mapping, forest inventory, crop production statistics, urban planning, engineering and geology, the

SPOT images may very well replace high altitude aerial photography (Brachet 1986). For example, in Bangladesh, the SPOT simulation result appears to be very encouraging in the inventory of the resources and mapping of mangrove vegetation and coastal areas (Blasco et al 1982 and Favard and Chaudhury 1982). In Mali, West Africa, scientists using colour composites of simulated SPOT imagery were able to discriminate lithofacies and the structural features (Simmon et al 1981). The SPOT simulation imagery also proved to be useful for forecasting rice production in West Africa (Berg 1981), in the investigation of tropical coastal areas (Verger et al 1981) and in the detection and inventory of large ecological and pastoral resources in semi-arid and Sahel region (Wispelaere et al 1981). In most of these cases simulated SPOT imagery would appear to offer almost the same capabilities as medium scale (1:25,000 to 1:60,000) colour infrared (CIR) aerial photography.

There have also been extensive efforts in the United States to evaluate the potential of SPOT simulation, particularly its resolving power in comparison with Landsat MSS, TM and/or CIR for a variety of aspects. For instance, Colwell and Poulton (1984), Dolan et al 1984 and Milazzo and Deangelis (1984) compared the interpretability of urban, suburban and fringe covers. SPOT simulation was also used for assessing the potential utility for discriminating multiple crop types and agronomic conditions (Degloria 1984 and Merritt 1984); for the identification of cover types in forest as well as in agricultural lands (Buchheim et al 1984 and Sailer et al 1984). The spectral and spatial resolution of the simulated SPOT data appears to be a valuable aid in a high level of classification accuracy for range land as well as for agricultural cover types (Maslanik et al 1984, Roebig et al 1984 and Toll and Kennard 1984), for delineation of Wetland vegetation and hydrodynamic processes (Ackleson et al 1984 and Parks et al 1984) and for water quality assessment (Edwards et al 1984). There has also been examination of the simulated SPOT and Landsat TM for information content analysis (Buis 1984 and Price 1984), for geological mapping and interpretation (Bailey and Dwyer 1984, Borengasser and Taranik 1984, Chavez and Berlin 1984 and Connors et al 1984).

SPOT simulation investigations carried out in Europe, particularly in France, are also very wide ranging. For example, the Central French Agency for Agricultural Statistics have been examining the possibility of incorporating SPOT remote sensing data in to its system of agricultural statistics (Saint et al 1981). Combeau and Noel (1981) and Revillion (1981) evaluated the ground resolution characteristics of the SPOT simulated imagery for the landuse mapping of a highly heterogenous, complex small scale agricultural plots of Porto-Vecclico in Southern Corsica and very large scale plots of the Paris Basin. The increased high ground resolution offered by simulated SPOT imagery over the Landsat MSS was also examined for urban land use mapping (Ballutch et al 1981), for the detection and mapping of dying Oaks of Troncais forest (Riom and Torres 1981), for the detection of forest stands of the Landes Forest of S.W. France (Greyon et al 1981) and for the investigation of coastal studies, primarily the intertidal zone of the Loire estuary in France (Belbeoch and Loubersac 1981).

A similar SPOT simulation programme was carried out in the U.K. The objective of the programme in the U.K. was to examine the potential of SPOT data especially its higher resolution effect on aspects of the environment, which included the contemporary coastal and hydrological processes, the distribution of geological resources, and land use. The most recent work in the UK on SPOT simulated data potential was centred around agriculture (Betts et al 1986, Harris & Weaver 1985, Hume et al 1986, Wright and Birnie 1986, Essery and Wilcock 1986), water resources and environmental applications (Budd 1985, Chidley and Drayton 1986, Davis and Chaston 1986) and urban planning (Buchan and Hubbard 1986). In most of these above mentioned studies it was concluded that the SPOT simulated data showed a considerable improvement in image interpretation because of improvement in spatial resolution.

5.2 Objective

In the context of the present study, the primary objective is to evaluate the spatial and spectral characteristics of the simulated SPOT data for the discrimination of surface types : bare peats, bare soil and vegetation in the Glaisdale Moor test site. The specific spatial and spectral related objectives are as follows:

(a) To use a series of statistical techniques to evaluate the spectral relationship of the SPOT simulation data with the ground data.

(b) To assess discrimination performance of the three multispectral SPOT bands.

The availability of airborne simulation data covering the SPOT bands, not only at a nominal spatial resolution of approximately 20m, but also at a nominal resolution of approximately 10m, provided an opportunity to examine the effect of changes in spatial resolution on the discrimination of land cover types found over Glaisdale Moor. In addition to the two specific objectives mentioned above, Chapter also considers a third:

(c) The effect of spatial resolution on cover type discrimination using multispectral data at the SPOT wavelengths.

5.2.1 The SPOT simulation data

The image data described here was part of a simulation programme mentioned in the previous section. The simulation was carried out over the North York Moors in the spring/summer of 1984 by Huntings Geophysical Surveys Ltd. using a Daedalus DS-1268 scanner mounted in an aircraft flown at an altitude of 7000 m (14 May 1984) and 3500 m (7 July, 1984) (Figure 5.1). The Daedalus 1268 scanner was configured to simulate the satellite-data. The scanner's precise spectral ranges are : band 1, 0.5-0.59 μm (green); band 2, 0.61-0.68 m (red) and band 3, 0.79-0.89 μm (near-infrared). Because of altitudinal difference of the scanner on the two dates, the nominal spatial resolution of the May data was 20m and the July data was 10m.

5.3 Approaches

The study first concentrates on the analysis of pixel values extracted from a subscene of the simulated SPOT data sets for May and July 1984 covering Glaisdale Moor. In particular the aim was to determine the relationships between certain ground variables and spectral radiance in the simulated SPOT bands as measured by the airborne scanner.

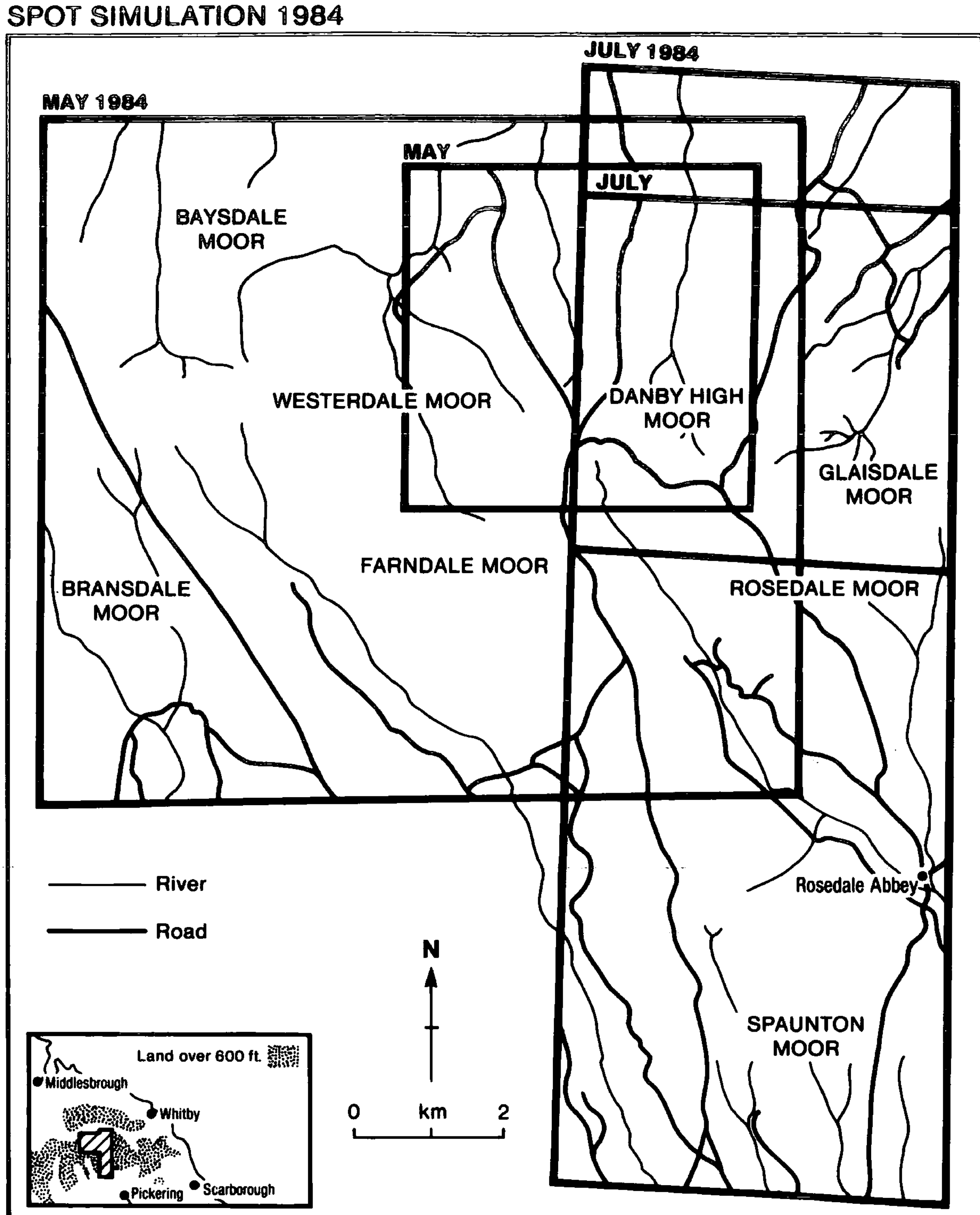


Figure 5.1 Location of the SPOT simulation coverage on North York Moors

Subscenes of the two different images were displayed on a DIAD interactive display device. The location of pixels coincident with ground sample points was determined through a quantitative cross correlation of land cover patterns in the imagery and 1 : 10,000 black and white aerial photograph on which latter were located. DN values for each selected pixel were output onto a terminal and noted down. An underlying assumption was that the extracted pixel values were representative of a particular land cover unit. In addition it was assumed that the ground parameters measured on a single ground sampling point were representative of the same parameter over the area on the ground covered by the pixel. There was however a problem in relating the pixel data of May and July 1984 with the ground variables measured in May 1985, specifically with the dynamic variables such as the soil moisture content and vegetation biomass. Bonn (1976) referred that the collection of ground data synchronous with imaging is most desirable when the observed properties are dynamic. Justice and Townshend (1981) recognised that although such timing is ideal for interpretation of imagery, practical constraints often hinder its accomplishment, such as the present case, where imagery was acquired one year before the ground sampling was done. However, as the soil moisture sample was collected during the same season, it is assumed that the level of moisture content in the soil would be reasonably similar. Likewise, the biomass content during May 1984 and 1985 were not expected to be considerably different partly as changes in cover types were expected to be minimal.

To analyse the spectral relationships with the ground data, bivariate and multivariate relationships of the extracted spectral point data and their corresponding ground data were examined. It was anticipated that the spectral and ground spectral relationships of these temporal data would provide information on the relative suitability of the May and the July data in terms of spectral separability performance of the SPOT spectral bands.

The spectral data were further examined by discriminant function analysis to select the best band and band combination that would give the highest spectral class discrimination performance of the three multispectral SPOT bands. This was followed by an analysis of a number of image processing techniques including image enhancement, contrast stretching, ratioing and maximum likelihood classification. The results were then compared with the air photographs.

5.4 <u>Spectral relationships with the ground data</u>

5.4.1 Descriptive measures

The descriptive measures of the SPOT May and July data show (Table 5.1) a considerable difference in their mean values, and ranges of the July data vs the May data, in part due to differences in spatial resolution of the two data sets; possible differences in ground conditions; together with the likely variations in atmospheric conditions of two dates, and the lack of calibration of the imagery. Table 5.2 shows two aspects:

(a) The mean DN values for the SPOT band 1 and band 2 are very similar.

(b) The characteristic surface type variation : vegetation, bare peat and bare soil has been reflected in their respective mean spectral

Table 5.1 Descriptive measures of simulated SPOT May and July data

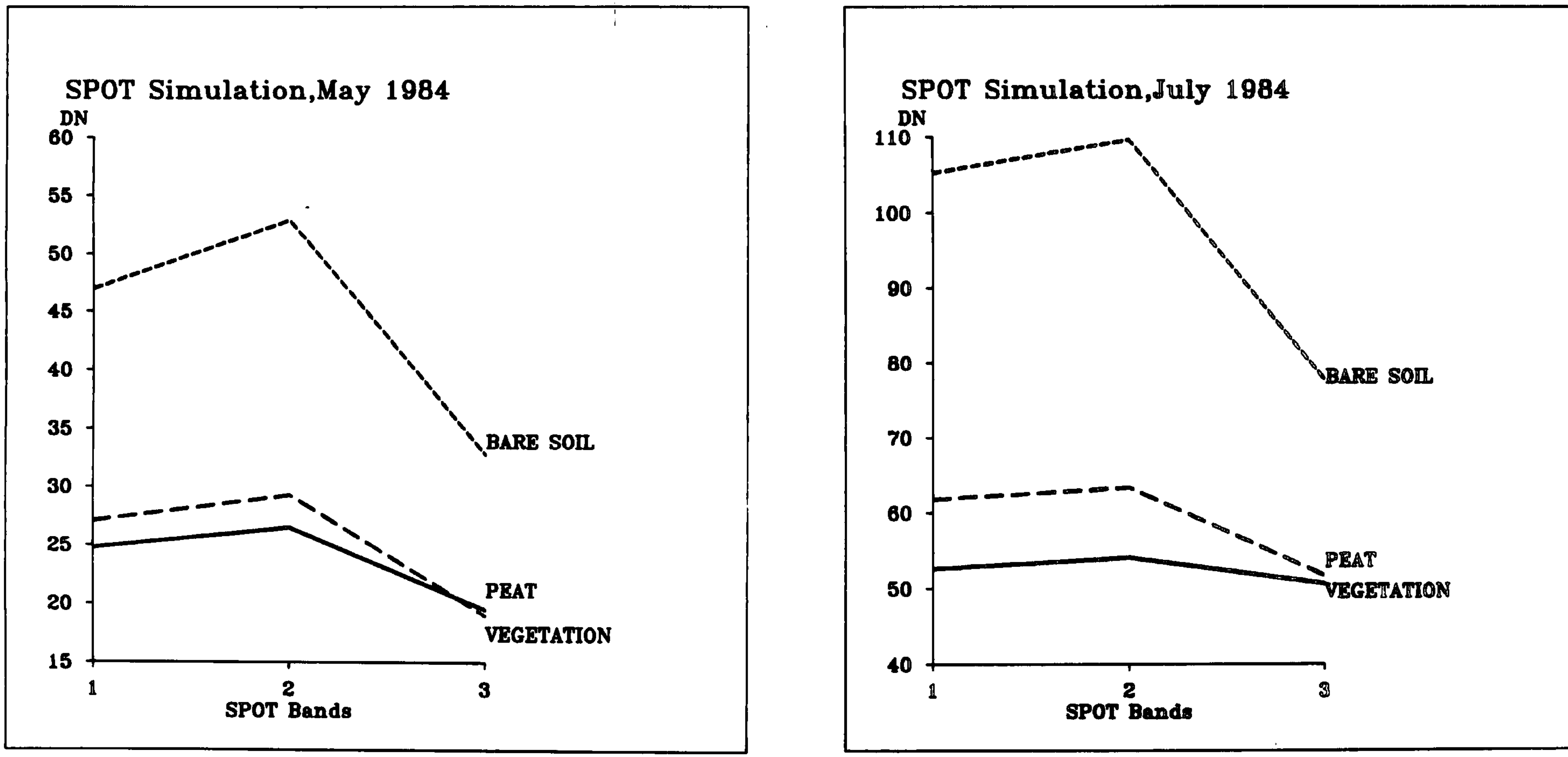
a. May

Variable	Category	N	Min.	Max.	Mean	STD Dev.	Skewness	Kurtosis
SPOT 1	Vegetation	40	23.0	27.0	24.87	1.48	.122	-1.506
SPOT 2	"	40	24.0	29.0	26.55	2.06	-.161	-1.510
SPOT 3	"	40	16.0	22.0	19.57	1.29	-.238	.350
SPOT 1	Peat	40	24.0	30.00	27.15	1.76	-.288	-1.369
SPOT 2	"	40	27.0	33.00	29.35	1.91	-.177	-1.544
SPOT 3	"	40	16.0	25.00	19.07	2.24	.497	- .354
SPOT 1	Bare soil	40	32.0	84.0	47.07	13.68	1.07	.046
SPOT 2	"	40	33.0	96.0	52.97	16.84	.97	- .270
SPOT 3	"	40	20.0	52.0	32.87	9.22	.68	- .819
b. July								
SPOT 1	Vegetation	40	50.0	59.0	52.72	1.99	1.30	1.874
SPOT 2	"	40	50.0	62.0	54.22	2.31	1.32	2.497
SPOT 3	"	40	41.0	59.0	50.75	4.94	-.276	- .699
SPOT 1	Peat	40	55.0	77.0	61.92	3.51	2.18	7.462
SPOT 2	"	40	55.0	76.0	63.50	3.30	1.18	4.514
SPOT 3	"	40	41.0	61.0	51.80	5.25	-.10	- .849
SPOT 1	Bare soil	40	69.0	183.0	105.35	30.86	.769	- .449
SPOT 2	"	40	70.0	194.0	109.75	34.42	.730	- .604
SPOT 3	"	40	44.0	127.0	77.75	24.15	.354	- .979

DN values. For example, the bare soil has the highest mean DN value and it was followed by the bare peat and the vegetation. The mean spectral curve of the three spectral classes drawn for the vegetation, bare peat and bare soil using the raw DN data as shown in Figure 5.2. Figure 5.2 reflects that in both the May and July data, band 3 (near infrared) has the lowest mean DN values, while band 2 (red) has the highest DN values. The DN curves for both May and July data, thus appeared to be different from curves plotted from the in situ spectral data (Figure 4.1, Chapter 4). The lower DN values at the near infrared band were unexpected.

The mean DN curves (Figure 5.2), therefore should be treated cautiously, because it is not unlikely that the system parameters in the SPOT imagery may have influenced the spectral response characteristics of ground targets. Munday (1985) and others have indicated that the spectral response characteristics of ground targets are markedly influenced by the Landsat MSS system parameters. It is important to stress that none of the May and July SPOT simulation imagery have been calibrated. Therefore, it is essential to mention that in using the DN values alone, incorrect conclusions may be drawn about the spectral character of a given surface.

Before attempting any further measures on the spectral data, it was essential to normalise both the May and July data (Table 5.1). Different transformations were used to reduce the skewness of the May and July data. The natural log transformation was relatively successful in reducing the skewness (Table 5.2).



a) b)

Figure 5.2 Mean spectral signature for three surface types in Glaisdale Moor: vegetation , peat and bare soil.

a. Raw data

Variable		N	Min.	Max.	Mean	STD Dev.	Skewness	Kurtosis
SPOT 1	May	70	23.00	47.00	28.25	5.66	1.44	1.21
SPOT 2	"	70	24.00	51.00	30.38	6.33	1.32	1.03
SPOT 3	"	70	16.00	31.00	20.87	3.07	1.33	1.66
SPOT 1	July	70	50.00	183.00	65.31	25.63	2.79	7.85
SPOT 2	"	70	50.00	194.00	67.40	27.77	2.87	8.11
SPOT 3	"	70	41.00	127.00	56.28	16.54	2.73	7.57
b. Transformed data								
SPOT 1	May	70	3.13	3.85	3.32	0.181	1.16	0.372
SPOT 2	"	70	3.17	3.93	3.39	0.189	0.97	0.171
SPOT 3	"	70	2.77	3.43	3.03	0.137	0.95	0.723
SPOT 1	July	70	3.91	5.21	4.13	0.286	2.07	3.84
SPOT 2	"	70	3.91	5.26	4.15	0.295	2.16	4.18
SPOT 3	"	70	3.71	4.84	4.00	0.228	2.01	4.24

Table 5.2 Raw and transformed spectral variables, SPOT simulation May and July 1984

The variables used in the analyses includes: soil moisture, organic matter, surface sand, silt and clay, subsurface sand, silt and clay and vegetation biomass.

5.4.2 Bivariate relationships

The bivariate relationships between the spectral variables and the ground data were examined by scatter plots to visualize the distribution pattern on the spectral image plane. The spectral variables plotted against some of the ground variables are presented in Figures 5.3 and 5.4.

In Figure 5.3, the scatterplot of soil moisture and May SPOT simulated band 2 (red) indicates a negative trend, i.e. with increasing soil moisture radiance value appears to decrease. Jensen (1983) also observed similar spectral response between the visible wavelengths and the soil moisture. The surface spectral reflectance continues to fall until the soil is saturated; at which point further additions of moisture have no effect on reflectance.

The scatter plot of soil organic matter and May SPOT simulated band 1 (green) in Figure 5.3 reflects a negative relation. A similar negative relationship was also evident in the scatterplot of organic matter versus DN values for July SPOT simulated band 2 (red) in Figure 5.4. Such a relationship supports the widely held view that as soil organic matter is dark, its presence will decrease the reflectance. Increasing organic matter up to 5% results in a rapid non-linear decline in reflectance (Appendix 4). Both scatterplots as mentioned above show a similar trend when compared with the Page's diagram.

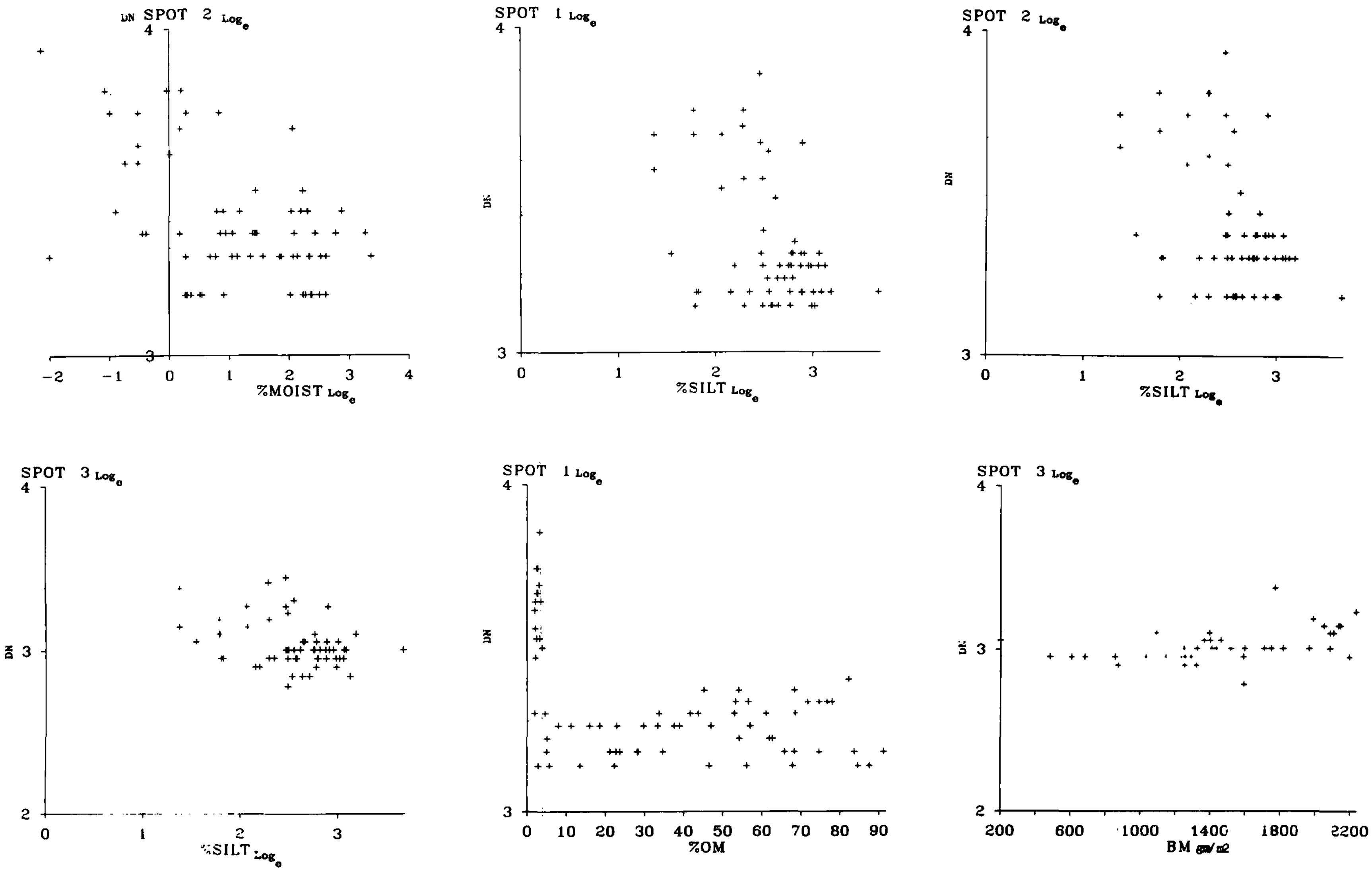


Figure 5.3 Scatter plots of selected simulated SPOT May spectral and ground variable combinations.

In respect of particle size, the scatter plots of silt content and the May SPOT simulation bands 1, 2 and 3 (Figure 5.3) indicate a negative trend. Similar negative trends are also evident in case of sand and July SPOT simulation band 1 and 3 (Figure 5.4). This negative trend in the present case might be attributed to the influence of coarser particle size, such as sand and silt, in reducing overall reflectivity. Bowers and Hanks (1965); Shockley et al (1962); Obukhov and Orlov (1965); and Orlov (1966) concluded from their studies that larger particle sizes reduce overall reflectivity. Because of the fact that the smaller particle sizes smoothens the surface thereby reflecting more of the incident radiation. Similar reason can be attributed to the positive trend in scatter plots of clay and July SPOT simulation bands 2 and 3 (Figure 5.4). However, this behaviour contradicts that observed by Myers and Allen (1968). According to them under natural conditions clay particles flocculates to form large aggregates which often exceed the size of sand particles, due to which clay-rich soils may exhibit lower reflectances. They further argue that the natural state is further complicated by the presence of moisture in the upper layers of the soil; when higher moisture contents are combined with the larger aggregate sizes found in clay soils an overall decrease in reflectance is to be expected. The differences between the results presented here and those of Myers and Allen (1968) may be indicative of a complex interaction between ground variables and reflectance in Glaisdale Moor study area. Examination of simple bivariate relationships may be misleading, and further work is warrented in studying the combined interactions of ground variables as they related to spectral radiance rather than treating them in isolation.

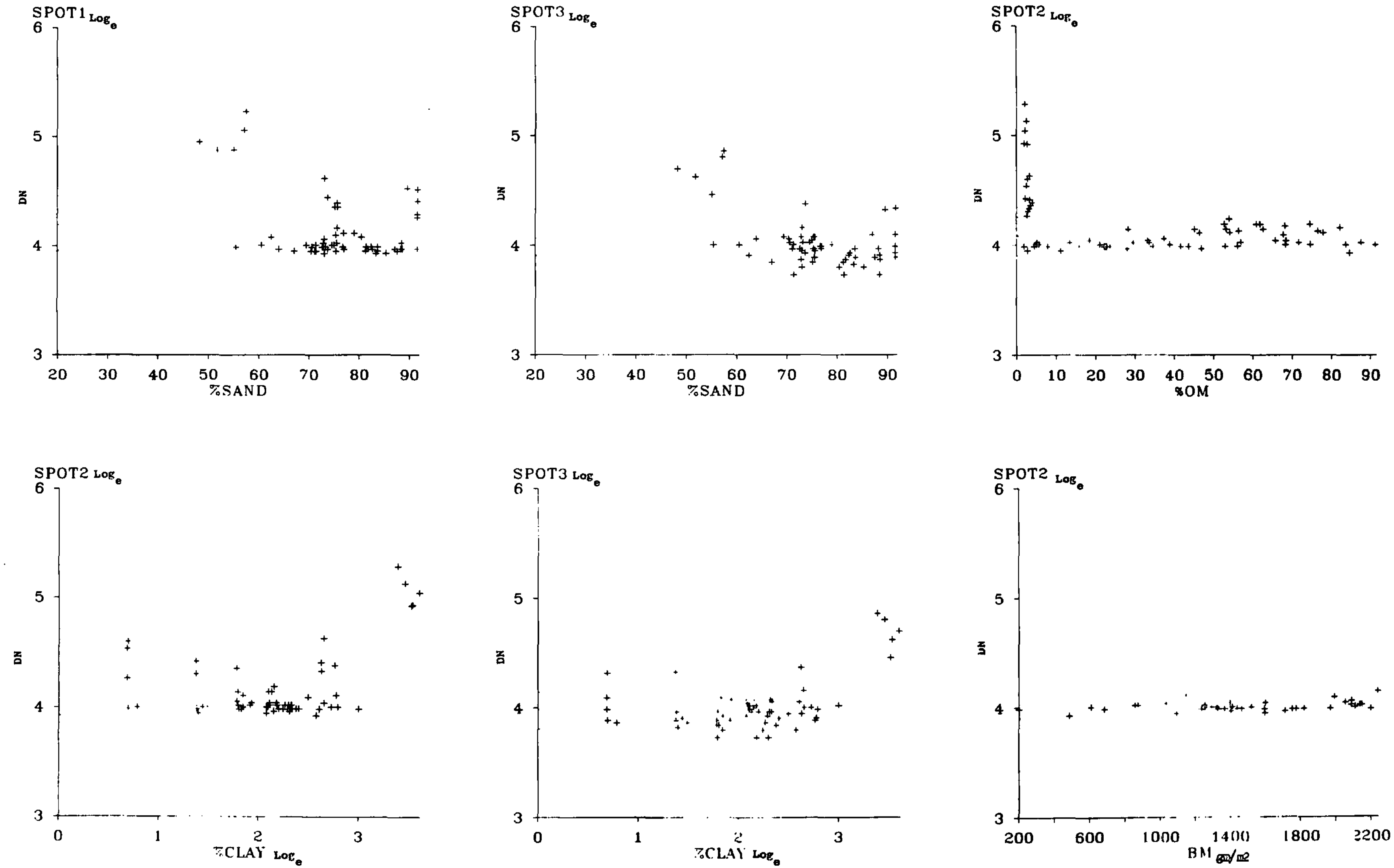


Figure 5.4 Scatter plots of selected simulated SPOT July spectral and ground variable combinations.

In addition particle size was determined for the upper 10cms of the soil. Mean variations in particle size within that profile may not be representative of the particle size distribution within the surface few mm where energy-matter inactions takes place.

The scatter plot of vegetation biomass versus SPOT simulation band 3 (0.79 - 0.89μm). (May), (Figure 5.3) shows a slightly positive trend with increasing biomass intensity. This accords with what one might be expected for this particular band. However, the scatter remains unchanges in case of July SPOT simulation band 2 with the vegetation biomass (Figure 5.4). The slightly positive trend in the May scatter of vegetation biomass may be due to a substrate influence on spectral radiance of vegetation. During May, the vegetation density remains low, with regrowth just beginning. Parts of the substrate are exposed and would therefore have a significant influence on the spectral radiance. The relatively flatter trend of the July scatter (Figure 5.4) may possibly attribute to the fact that unlike the near infrared (band 3), red (band 2) is less sensitive to vegetation biomass, i.e. small change in biomass IR radiance relative to red. Such a relationship was shown in a graph (Appendix 5), where it was apparent that in a green leaf, lower spectral reflectance is to be expected from red band. For further analysis of the spectral relationships with the ground variables it is essential to know the strength of the relation between the spectral and the ground variables.

Pearson's product moment correlation coefficients between SPOT bands 1, 2, and 3 and the ground variables were calculated and the results are presented in Table 5.3. The correlation results were

Table 5.3 Pearson's product moment correlation coefficient between the ground variables and the spectral variables

Ground Variable	N	MAY SPOT1	MAY SPOT2	MAY SPOT3	JULY SPOT1	JULY SPOT2	JULY SPOT3
Moisture %	70	-.501**	-.503**	-.529**	-.373**	-.353**	-.244*
Organic Matter %	70	-.487**	-.450**	-.413**	-.426**	-.426**	-.377**
Sand % (Surface)	60	-.107	-.102	-.146	-.436**	-.439**	-.535**
Silt % (Surface)	60	-.412**	-.411**	-.334**	-.265	-.264	-.136
Clay % (Surface)	60	.077	.104	.253	.420**	.412**	.484**
Sand % (Subsurface)	60	-.026	-.037	-.042	-.228	-.233	-.353**
Silt % (Subsurface)	60	-.095	-.084	-.107	-.1160	-.118	-.026
Clay % (Subsurface)	60	.047	.057	.057	.295*	.301*	.411**
Biomass gm/m^2	40	.514**	.541**	.450**	.433**	.446**	.064

** Significant at .01

* Significant at .05

indicative that only the moisture and organic matter variables are well correlated with the spectral variables (significant at α= .01 level). The overall correlation was rather poor.

In case of soil moisture, the correlation result must be treated with considerable caution. If we assume that moisture conditions in May 1985 were exactly the same as May 1984 when the images were acquired, then the relationship may be valid. However, if conditons have changed between acquisition of images and ground samples then these correlations may not represent the true nature of the relationship. They may be totally fortuitious.

The negative relationships between organic matter and the simulated SPOT band 1, 2 and 3 (Table 5.3) in both May and July suggests a reduction in spectral radiance in the 0.50 - 0.89µm wavelength range with the increasing organic matter. Thus, it seems inappropriate to fit a linear least squares when the relationship is non-linear; higher correlations might be expected when fitting a non-linear polynomial.

The positive relations between the spectral data and the percentage clay supports the similar findings with field radiometry mentioned in Chapter Four. As Hoffer (1978) mentions the larger particle sizes show a lower reflectance value because of a greater scattering effect, while the finer particles such as clay reduce the scattering effect because of its smoother surface. The negative relationships of all the SPOT bands 1, 2 and 3 with sand and silt agree with similar observations by Page (1974) and Hoffer (1978).

In regard to the subsurface soil texture, the relationships as shown in Table 5.3 should be treated carefully. The reason explained by the fact that the incoming solar radiation is either scattered from the earth's surface or absorbed and re-emitted in the thermal portion of the spectrum (Goetz et al 1985). The process of scattering and absorption takes place in the upper few millimetres of the surface. Therefore, it is likely that the subsurface sample would have little effect on the radiance. For the same reason as just mentioned, if there was any significant correlation, as in the case of sand and clay with the July SPOT band 3 (Table 5.3) the relationship might be fortuitious.

The relationships between the biomass and the simulated SPOT wave bands indicates a slightly unexpected trend. Near infrared radiation might be expected to increase with increasing biomass (eg: Curran 1985). Despite the low reflectance expected in visible wave bands and higher reflectance expected in near-infrared band from a green leaf, in the present case the reason mentioned before that during May as there is very low vegetation growth, therefore, radiance remains higher in the visible part of the wavelenghts. On the other hand, because of substrate influence there would be some absorption effect in the near infrared wave band (Curran 1985). In the present case this latter effect can be attributed to the lower relationship of the infrared band and the biomass.

The spectral relationships between the July SPOT simulated bands and the biomass indicates an unexpected trend. This unexpected relationship in part may be because of ground data acquisition versus airborne data acquisition differences in temporal terms.

Although the level of correlation between the spectral data and the ground data was relatively lower in the July data in comparison with the May data, the number of correlated variables was much higher in the July data. The lower correlation in the July data was possibly due in part to the differences in spatial resolution between the May (20m) and July (10m) imagery. With lower resolution (20m), because of integration within the field of view, internal variations within the covertype remain suppressed in comparison with higher resolution (10m).

The dominance of soil moisture (%) in the correlation with all the SPOT bands 1, 2 and 3 (r = -0.50, -0.50 and -0.53 respectively) of the May data was apparent. While in the July data, the soil moisture (%) showed a lower correlation with all the bands (r = -0.37, -0.35 and -0.24). The organic matter, however, correlates with all the bands nearly equally in both the May and July, although slightly higher in the May data. The variation in the correlation of the May and the July data can possibly be explained by the dynamic nature of the moisture content (Wright and Birnie 1986). The soil moisture content does vary quite rapidly in time, whereas the organic matter content and soil texture being inherent soil properties and do not vary rapidly. The higher soil moisture content in the field during May may have masked the influence of other ground properties especially the particle size, and thereby the correlation figure was significantly lower with the particle size. Conversely, the lower moisture content in the field during July had significantly reduced the moisture effect on the DN values and thereby, the number of correlated ground variables were higher.

The poor correlation of both the May and July data as shown in Table 5.3 implies that no single ground variable can be said to have a dominant effect on the DN values. Possibly, the spectral class variation in terms of DN values can be better explained by the ground variables together and this is examined in the next section.

5.4.3 Canonical correlation

Canonical correlation was defined in the previous chapter (section 4.4.3) as the technique to evaluate the relationships between a set of dependent variables and a second set of independent variables. From the correlation matrix orthogonal canonical vectors are extracted, so as to maximise the correlations between the components of the variables of the independent variables set and those of the components of dependent variables set. In other words, canonical vector I is located so that the correlation between the scores on the independent variables set for that vector and the scores on the dependent variables set is as high as possible, and each subsequent vector is similarly located among the residual correlations.

In the present context, the objective is to verify what extent the canonical correlations can explain the spectral variation in the wavelength region covered by the simulated SPOT by the ground variables considered. The ground variables were considered as an independent variable (Group 1) and the spectral bands as dependent variable (Group 2). The program used was the MIDAS package available in Durham University.

The result of the canonical correlation is shown in Table 5.4, the highest canonical correlation for the SPOT May data being 0.768 and the corresponding figure for the SPOT July data was 0.825. The canonical correlation result can explain, therefore, only 58% and 68% of the spectral variation respectively with the available ground variables. This may be due to variations arising from the contrasting spatial resolutions between the two dates, but equally it may be that the ground conditions in July 1985 were more similar to those at the time of ground sampling in May of the previous year. However, the canonical correlation result must be treated with care given that some of the ground variables considered are dynamic.

5.4.4 Multiple correlation

The canonical correlation just mentioned above (Section 5.3) indicated the degree of achievable accountability in the spectral variation. However, it was essential at this stage to establish the relationships of individual bands with the ground data in a group. It was most likely that the response of the joint effects of the ground data would vary in different spectral bands. In order to examine the influence of all the measured ground variables on spectral radiance in each band, multiple regression was employed. Like the canonical correlation, the spectral variables were regarded as the dependent variable and the ground data as the independent variables.

The results of the multiple regression analysis are reported in the Table 5.5. It appears that the variation in bands 1 (green) and band 2 (red) accounted for by variations in the ground variables are similar.

Table 5.4 Canonical correlation of ground and spectral variables

Dependent variable (Group II)	N	I	II	III	Significance
May					
SPOT 1	60	0.768	0.538	0.222	0.0001
SPOT 2					
SPOT 3					
July					
SPOT 1	60	0.825	0.592	0.296	0.0001
SPOT 2					
SPOT 3					

Independent variables (group I) included: soil moisture (%), Organic matter (%), surface sand (%), silt (%), clay (%) and subsurface sand (%), silt (%) and clay (%).

Table 5.5 Multiple correlation between the single channel spectral variables and the ground variables

Dependent variable	N	Multiple R	R^2	F	Significance
May					
SPOT 1	60	0.733	0.537	7.40	.001
SPOT 2	60	0.722	0.520	6.93	.001
SPOT 3	60	0.748	0.560	8.11	.001
July					
SPOT 1	60	0.802	0.644	11.55	.001
SPOT 2	60	0.803	0.644	11.56	.001
SPOT 3	60	0.798	0.636	11.17	.001

Independent variables included: soil moisture (%), organic matter (%), surface sand (%), silt (%) and clay (%) and Subsurface sand (%), silt (%) and clay (%).

The low correlations implies that other ground variables that were not either measured (such as surface roughness) or considered here (such as biomass) might be significant in explaining further the spectral variations of the individual simulated SPOT bands.

Correlation coefficients for the July data set are slightly better when compared with those for May data set. However, such a comparison between correlation coefficients should be treated with caution bearing in mind that the remote sensing data were gathered at different times, and that they were not calibrated to some common reference.

It was clear from all the bivariate and multivariate analyses that none of measured ground variables had any dominant influence on the spectral radiance in the simulated SPOT bands. However, other variables that were not examined (e.g. biomass, surface roughness) may be significant in explaining spectral variance. Further work is required to elaborate on this.

5.5 Spectral separability

In order to evaluate the separability of the different surface cover types found in the study area, as a function of their spectral characteristics in the simulated SPOT bands, the data were analysed using stepwise linear discriminant analysis. The technique provides an objective means to assess the spectral class discrimination performance of the three multispectral SPOT bands.

The mathematical objective of this technique is to weight and linearly combine a set of discriminating variables (the spectral bands in the present case) in a way that a set of a priori established groups are forced to be as statistically distinct as possible (Klecka 1975). The linear transformations on the original variates are defined as discriminant functions, and are constructed to provide an optimum statistical separation between specified groups relative to the scatter within these groups. The assumptions used in discriminant analysis are that the selected groups or classes have similar variance-covariance matrices, and that the variables are normally distributed (Mather 1976).

A stepwise discriminant procedure was performed on spectral data for the three Glaisdale Moor surface cover types; vegetation, peat and bare soils. This particular approach selects variables for inclusion in the discriminant function on the basis of their discriminating power. At each step, the spectral variable that contributes significantly to the separation of all the groups was entered, with that having the greatest discriminating power being entered first. As variables are selected for inclusion, some previously selected may lose their discriminating power. This occurs because the information they contain about group differences is now available in some combination of the other included variables. Such variables thereby become redundant, and are removed. A variable which has been removed at one step may re-enter at a later step if it then satisfies the selection criterion being utilized (Klecka 1975).

The selection criterion used in this case was the Mahalonobis D^2 statistic, which is a measure of overall similarity, between two of the closest groups based upon all the variables (Mather 1976). If D^2 is high then the two groups are similar, and conversely, if it is low, they are well separted.

For discriminant analysis, the SPSS package (Nie et.al. 1970) was used. The data used in the analysis was the May and the July SPOT data and the number of samples for each class was 40.

In Table 5.6, results from the discriminant analysis illustrate that the first discriminant function for May data set accounted for 88.8 per cent of the variance in the original spectral variables - the 3 SPOT bands. The second discriminant function (Table 5.6) of May data accounted for 11.1 per cent of the variance in the brightness value of all the SPOT bands for the three surface types. Therefore, it suggests that only two functions are adequate enough to account for 100 per cent of the spectral variation in all three of the simulated SPOT bands. However, only moderate success in the classification was achieved of the different cover types because the group mean score (mean discriminant function score) was nearly similar for the May data. The group mean score on each discriminant function provides a means for determining the separability of groups along individual functions. For example, differences between the group mean scores of each cover type along the first discriminant function derived from the May data were small. This is indicative of problems in separating the three cover types using data for three spectral variables measured in May. In particular, the group mean scores for the vegetation and bare peat in the two discriminant functions were very narrow, suggesting that separating these two groups would be more problematic. This was evidenced by an overall classification accuracy of 74.1 per cent (Table 5.6).

Like the May data, "a reduction of the dimensionality of the data" (Swain 1978) was achieved with the July data. Two functions accounted for 100 per cent of the spectral variations (first function, 98.2 per

Table 5.6 Discriminant analysis results for SPOT simulation with vegetation, bare peat and bare soil

Function	Percent of Variance	Group Mean Score		
		Vegetation	Bare Peat	Bare Soil
May				
1	88.83	-0.959	-0.865	1.825
2	11.17	0.551	-0.570	0.019
July				
1	98.02	-1.448	-0.599	2.048
2	1.98	0.217	-0.286	0.069

Percentage of correct classification

Actual	Predicted		
	Vegetation	Bare Peat	Bare Soil
May			
Vegetation	70.0	30.0	0.0
Peat	20.0	80.0	0.0
Bare soil	12.5	15	72.5
	Overall classification accuracy 74.17		
July			
Vegetation	87.5	12.5	0.0
Peat	30.0	67.5	2.5
Bare soil	5.0	15.0	80.0
	Overall classification accuracy 78.33		

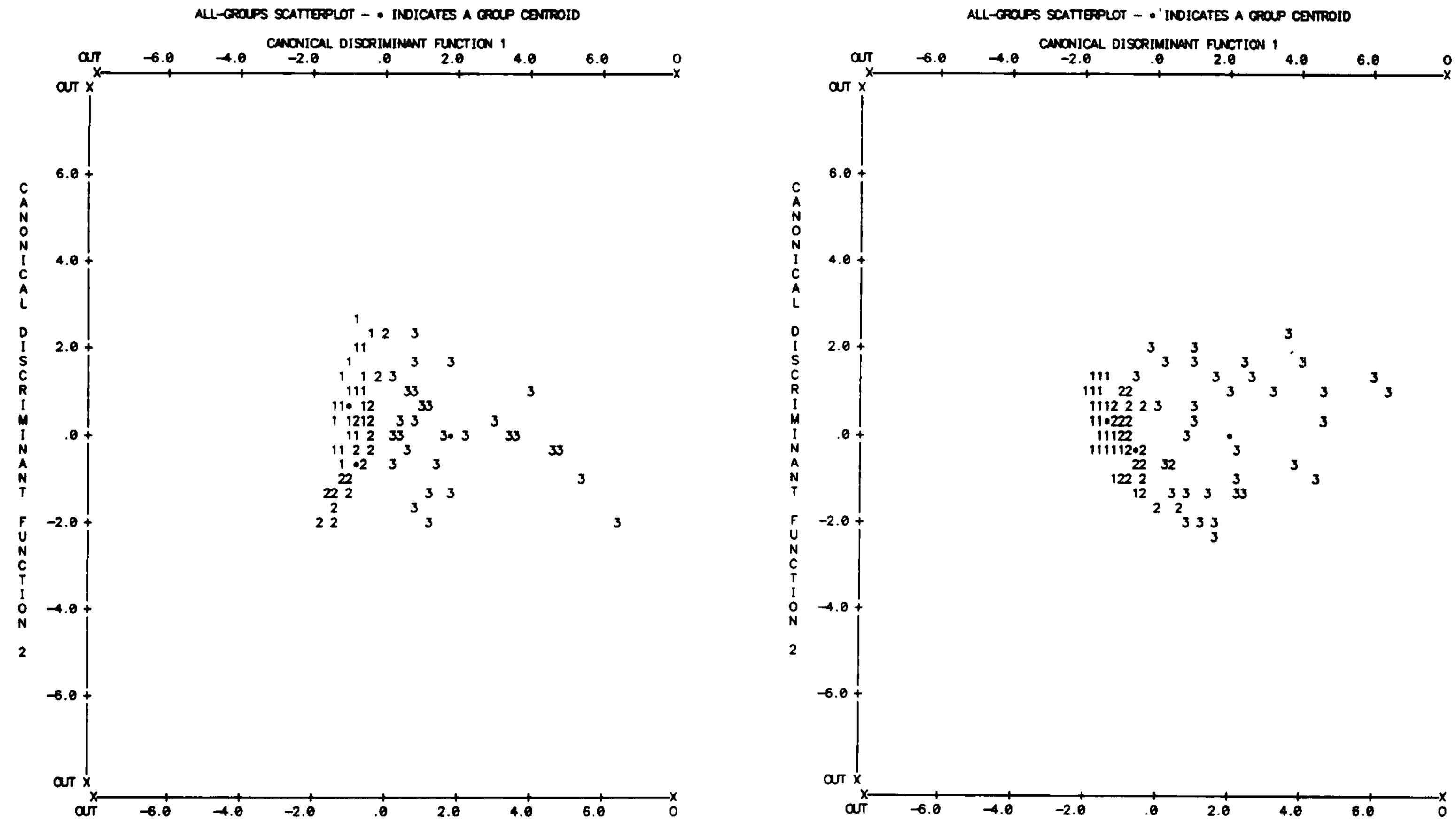
cent and second function, 1.98) in all the simulated SPOT bands. The second function of the July data however suggests that this would not contribute to any great extent to the discrimination between the groups. The group mean score was slightly improved for the July data, especially between the vegetation and bare peat with function 1 and this has resulted in the overall classification accuracy, at 78.3 per cent. The reason for differences in classification accuracy of the May and the July data may be because of their contrasting spatial resolution.

Townshend (1980) identified that changes in classification accuracy with spatial resolution arise from two conflicting trends. Firstly, the variance of spectral response will decline with coarsening resolution which will usually help improve classification accuracy. The degree of spectral heterogeneity within a cover class controls the strength of improvements. Secondly, with coarsening resolution boundary pixels will increase and this will tend to lower classification accuracies. These increasing and declining trends in classification accuracy are themselves largely a function of the spatial properties of the terrain which is being observed.

In the present case, it may be that 20m spatial resolution of May simulated SPOT data has exceeded the inherent spatial variability of the terrain, resulting in an increase in the number of boundary pixels. As boundary pixels record a mixed response from the two cover types, spectral separability may be reduced and classification accuracy would tend to decline. Conversely, with the 10m spatial resolution of July simulated SPOT data the number of boundary pixels might have decreased i.e. the pixels lie within the dimensions of the inherent variability of the cover types. The number of mixed pixels would correspondly decrease and classification accuracy might be expected to increase. This represents one possible interpretation of differences in the classification accuracy between the two dates. Additional work is required to accurately resolve the causal mechanisms for these differences. The distribution of the spectral classes in the discriminant function feature space (Figure 5.5) has reflected the group mean score which shows that the vegetation was highly misclassified with the peat in the May data in comparison with the July data.

The probable reason for the misclassification of vegetation with the peat in the May data was the high bare peat to vegetation cover ratio. The high bare peat to vegetation cover ratio slightly improves during July as the regenerated vegetation begins to appear on the surface and thereby reduces the spectral similarity in the vegetation and the bare peat. The high vegetation cover ratio effect on the spectral class discrimination using simulated SPOT data was also reported by Sailer et.al. (1984) in the USA.

Table 5.7 lists the sequence in which the SPOT bands (both May and July) were selected by the discriminant function. The Wilks-Lambda values were calculated. Wilks's lambda is a multivariate measure of group differences over several variables (the discriminating variables). The lambda is an 'inverse measure' of the discriminating power in the original variables which have not yet been removed by inclusion in the discriminant function. Values of lambda which are near zero denote high discrimination (i.e: the group centriods are greatly separated and very distinct relative to the amount of



a) b)

Figure 5.5 Scatter plots of three surface types shown on two discriminant function axes. 1 = vegetation , 2 = peat and 3 = bare soil. a) May data and b) July data . Note that in both a) and b) the group mean score for the vegetation and peat in both functions is very narrow.

Table 5.7 Summary table for stepwise discriminant analysis for SPOT simulation

Step	Variable entered	Wilk's Lambda	ΔWilk's Lambda
May			
1	SPOT 2	0.403	
2	SPOT 3	0.337	0.066
3	SPOT 1	0.303	0.034
July			
1	SPOT 1	0.374	
2	SPOT 3	0.314	0.06
3	SPOT 2	0.292	0.02

dispersion within groups). As lambda increases towards its maximum value of 1.0, it is reporting progressively less discrimination. When lambda equals 1.0, the group centriods are identical (no group differences) (Klecka 1980).

The Wilks's lambda has indicated the discriminating power provided by each variable in the discriminant function. The SPOT band 2 (May) and band 1 (July) were identified as having the greatest discriminating power for the surface types examined. The second band selected by the discriminant analysis was band 3 in both the May and July data. The selection SPOT band 2 in the May data and band 1 in the July data may in part due to the vegetation versus substrate effect, which is higher in May.

Improvements in the overall classification accuracy of Glaisdale Moor surface types could be achieved using two possible solutions. The first would be to increase the sample size for each surface types; such as peat, vegetation and bare soils. This could yield a more accurate characterisation of the cover types in spectral terms, thereby increasing classification accuracy. The second would be to examine the radiance in wavelength bands different to the simulated SPOT system in order to determine if greater discrimination is possible. The effects of the later solution are examined to a limited extent in Chapter 6.

5.6 Image processing and results

In the previous section, results from the discriminant analysis indicated that the July data set was more suitable for the overall higher level of discrimination among the major surface categories, such as the vegetation and the bare soil. It was therefore decided that for subsequent image analysis only the July data would be used.

The image processing system used in the analysis is a DIAD system installed on a PDP 11/44 computer. The imagery was analysed to examine whether each of the major cover types could be delimited consistently from the others.

5.6.1 Image classification

A 512 x 512 pixel sub-scene was extracted from the main image. The subscene was first examined in each of the SPOT bands, then in false colour composites. Band ratios and a maximum likelihood classification were also generated from these data.

The single band imagery shows a large scale variation within and among the covertypes appearing as wide variation in grey tones. Similar levels of variation between cover types were apparent as the blue to red gradations in FCC's (false colour composites) of the three SPOT simulation bands (Figure 5.6).

Analysis of the FCC's (Figure 5.6) shows that exposed blanket peat (pale blue and black) could be recognised relatively easily. The calluna covered areas appeared bright and because of high infrared sensitivity. The senescent sphagnum could be compared with some bare mineral soils. In the FCC's wet peat appeared as black, while the dry peat was difficult to separate from the bare soil especially where the bare soil has still a thin veneer of peat mixed with the bare mineral soils. The large gullies within the blanket peat were identified as they appeared black probably because of the water they contained.

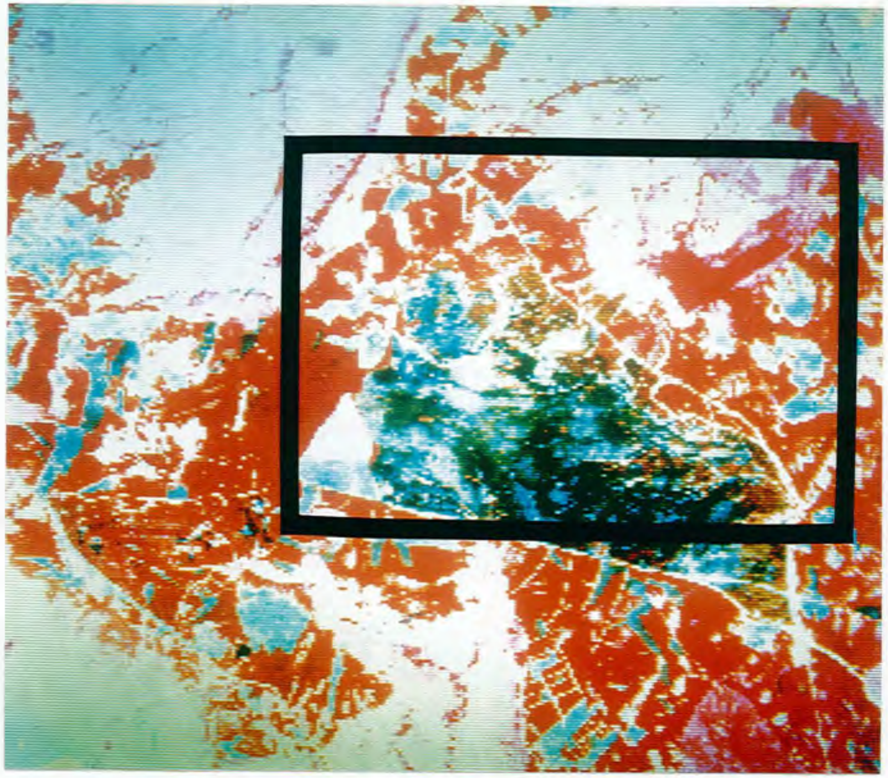


Figure 5.6 False colour composites of the SPOT Simulation July Imagery for Glaisdale Moor. Red = Vegetation, mainly Calluna vulgaris, Yellow = Sphagnum moss, Pale Blue = Bare peat, Black = Bare Peat (wet), White = Bare soils, Green = Mixed vegetation.

Band Nos. 1 (Green), 2 (Red) and 3 (Near Infrared)

Study Area

In the FCC's considerable difficulty was encountered when trying to separate bare soil from agriculture as well as with the dry peat. Although, the bare soil with washed out peat was very easily identified. The problem of working with FCC's as a means for separating cover types arises in the interpretation of the different colours and textures. The interpretations are subjective, and therefore prone to error. Effective interpretation requires a priore knowledge of the area.

The effectiveness of band ratios particularly infrared/red as an aid in the image classification and therefore the discrimination of different cover types was previously suggested by Pearson and Millar (1972) and this was later supported by similar observations by Chalmers and Harris (1981) with Landsat MSS data. Ratios are used to "subtract out" or "divide out" the undesirable effects of the atmosphere or variable scene illumination (Swain 1975). Such an image usually suppress detail common to the two images (Sabins 1978, Condit and Chavez 1979, Townshend 1981) and enhance differences between the two images. Thus, band ratioing was attempted here to determine its utility for enhancing spectral differences between cover types. For the discrimination by band ratioing it was essential to chose effective band combinations. Figure 5.7 indicates the relationships between bands. Band 3 was relatively poorly correlated with both bands 1 and 2 (Figure 5.7). The high correlation between band 1 and 2 (r = 0.998) was apparent in the Figure 5.7, as was the lower correlation between bands 2 and 3 (r = 0.846). A band 3/2 or IR/red ratio was chosen to assess the spatial cover discrimination performance. Curran (1983)

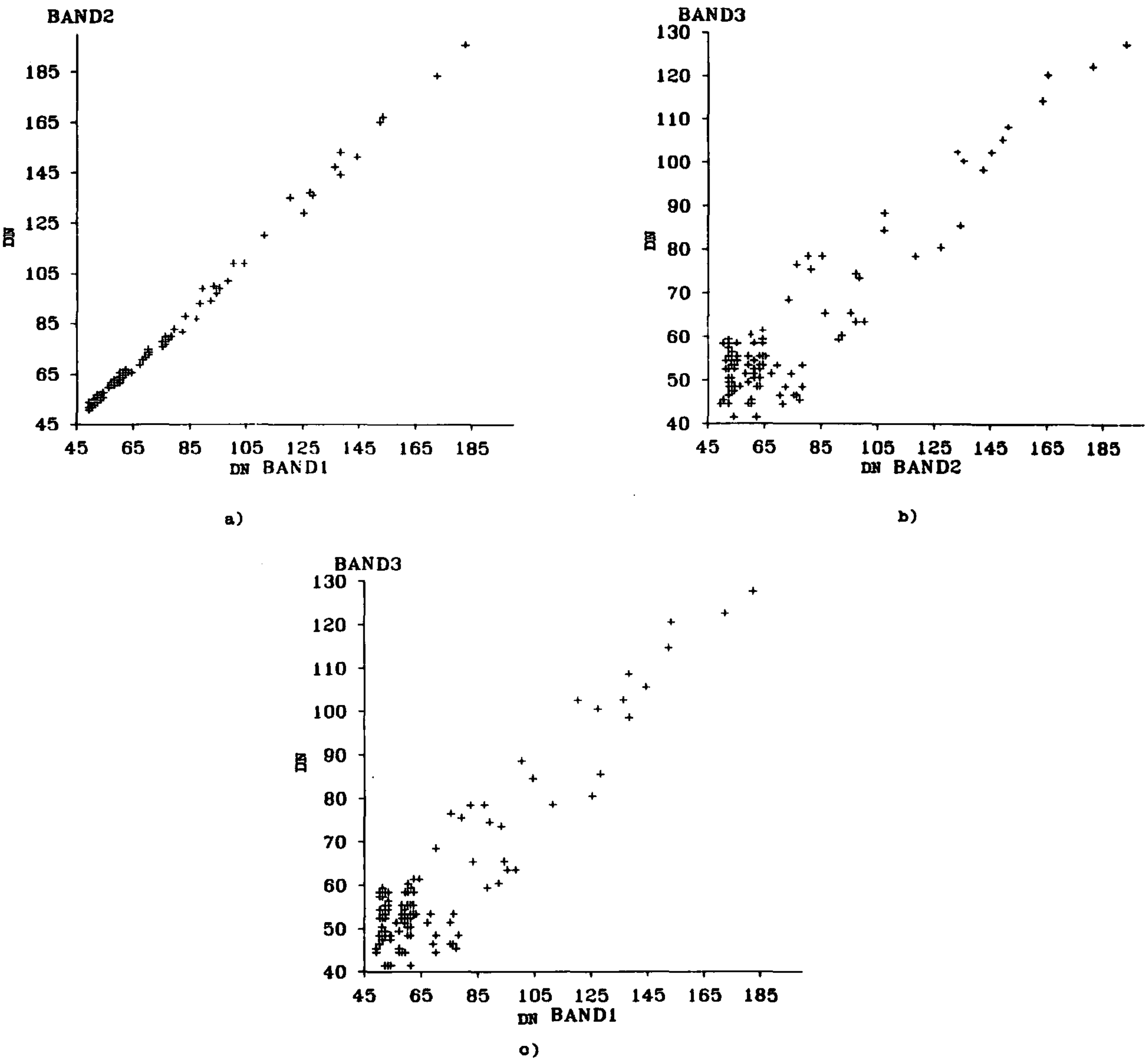


Figure 5.7 Scatter plots of all test pixels for three SPOT simulation bands.

differences between vegetation versus non-vegetation. The variations displayed in this ratio were enhanced further using density slicing to produce a colour representation of the extent and variations occuring between and within cover types (Figure 5.8). The band ratioing was moderately successful in delimiting the blanket exposed peat (purple) from the bare soil (black) and vegetation (white, green and light blue).

FCC's provided a guide to the spatial distribution of the main cover type, as did the ratio. However, as mentioned previously, the interpretation of these data was subjective, and therefore, prone to error. A more objective approach to the delineation of the main cover types would be through the automated classification of the imagery. One approach is through the use of a supervised maximum likelihood classification.

The maximum likelihood classifier uses a probabilistic discriminant function in order to assign data (i.e: pixels in the image) to pre-defined groups according to statistical parameters estimated from the covariance matrix of each training set. From a knowledge of the prior probability of allocation to each class a conditional probability is calculated for each pixel according to its spectral values and this is compared to the class conditional probability density functions for each class. Because each pixel value possesses a non zero probability it will always be allocated to the class at which the estimated conditional probability density function is maximised.

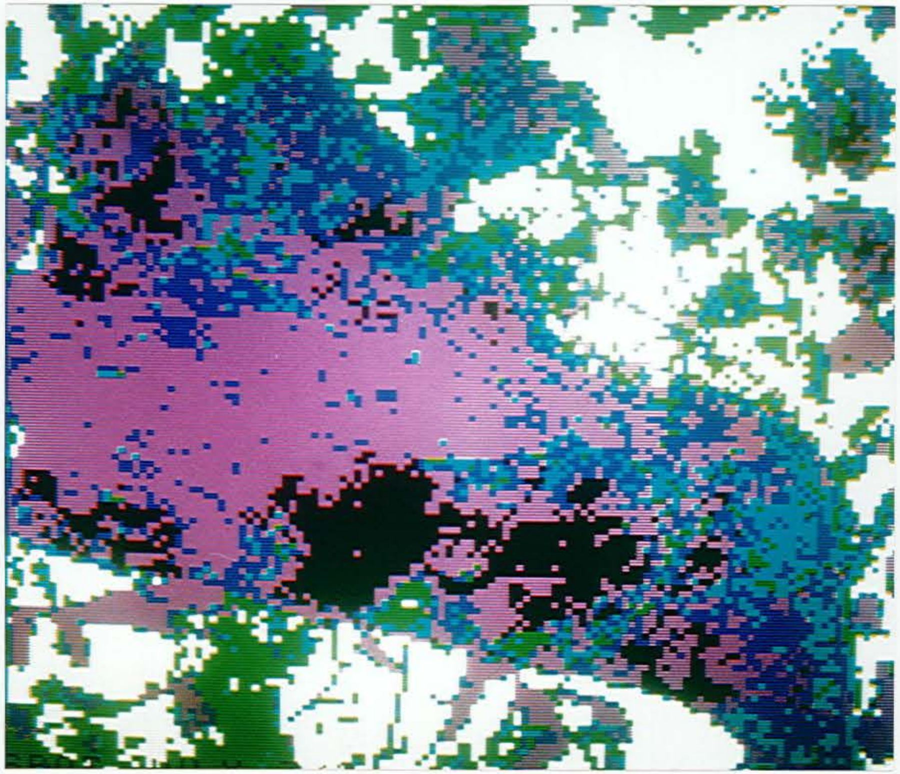


Figure 5.8 A band-3/band-2 ratio image of Glaisdale Moor. Approximate area of the image is 2.5 km x 2.5 km. Purple = Peat, Black = Bare soil and others = Vegetation.

This method is a parametric technique, it assumes a multivariate normality of training set data as covariance matrices are used to estimate the magnitude and direction of the probability density functions for each class. Probability density functions are estimates and so they will not perform as well as if we know their true values. Because the maximum likelihood decision rules are optimised for training set parameters extrapolation to ther image data will not be optimal even when such data are random samples drawn from the distribution.

The results of maximum likelihood classification are presented in Figure 5.9. Ignoring the classification external to the Glaisdale Moor study area, a subjective assessment of the results from this classification indicated that broad categories : vegetation, peat and bare soils are separable with a considerable success. In the classification map, exposed peat appears as green, vegetation as red and bare soils as blue. Although to a greater extent the exposed peat has been classified, however, some smaller patchy vegetation and dry, dessicated sphagnum moss are misclassified as peat. Similarly, smaller bare soil units are also misclassified as peat, especially where subsurface soils are recently exposed. Scenescent Sphagnum moss, with partially decomposed appears to be an important source of error in classification between vegetation and peat. Quantitative measures of correct and incorrect classification were not possible in this instance, and therefore the objective comparison between results obtained from this approach and the others mentioned previously could not be determined.

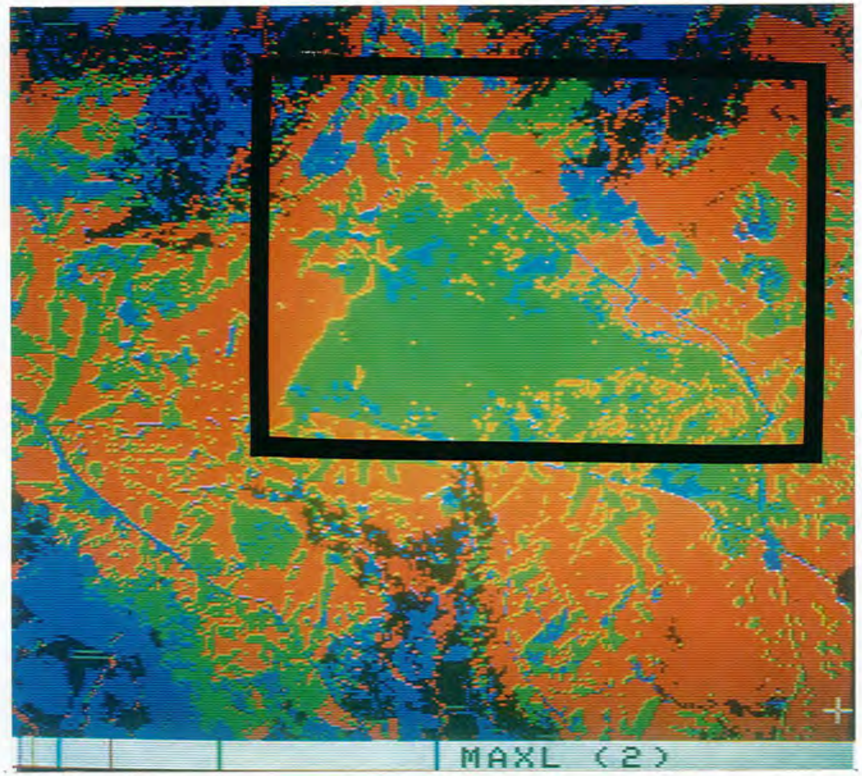


Figure 5.9 A computer classification of the SPOT simulation July data, produced using a supervised maximum likelihood technique. Green = Peat, Blue = Bare soils, and Red = Vegetation.

Study Area

5.7. Conclusion

The objectives of the chapter were to assess the spectral characteristics, assess the spectral class discrimination performance and evaluate the surface type discrimination performance of the SPOT wave bands. The following observations and suggestions are made.

(a) Both bivariate and multivariate analyses suggested that no single ground variable can be said to have dominance over others in terms of accountable spectral variation. The ground variables in a group can better explain the spectral variation, the highest being 58% for the May and 68% for the July data. Such a difference in accountable spectral variation may have arose in part from the contrasting spatial resolutions between the two dates, and in part as a result of the ground conditions in July 1985 being more similar to those at the time of ground sampling in May of the previous year.

However, such a comparison of accountable spectral variation should be treated with caution as, the images were not calibrated to some common reference and some of the ground variables considered (e.g; soil moisture) are dynamic phenomena.

(b) The discriminant analysis suggested an overall classification accuracy of 74.1% for the May and 78.3% for the July data respectively. The difference in classification accuracy between these two dates can be attributed to their contrasting spatial resolution, being 20m for May and 10m for July data. With 20m spatial resolution of May simulated SPOT data, number of boundary pixels are expected to be higher; conversely such a boundary pixel problem might be decreased with 10m spatial resolution July data, thereby classification accuracy is higher.

(c) The result of the imagery analyses implied that the increased spatial resolution was sufficient enough to expose the details even in a small area with intricate variations, such as Glaisdale Moor. However, it was equally the fact that due to the minute detail in spectral variation it was difficult to map clearly the eroded surface. The enhanced imagery allowed only to distinguish the broad surface types more easily.

Interpretation of the False Colour Composite indicates that exposed peat could be recognised with ease, although some confusion remains to separate dry peat from bare soil, especially where the bare soil has a thin veneer of peat mixed with the bare mineral soils. Considerable difficulty was also encountered when trying to separate bare soil from agriculture land cover types. A band ratio 3/2 (infrared/red) was useful in delimiting the blanket exposed peat from the bare soil and vegetation.

An interpretation of the maximum likelihood classification result suggests that broad categories : vegetation, peat and bare soils could be effectively separated although some misclassification might occur in some cases between smaller patchy vegetation and dry dessicated sphagnum moss with peat. The FCC's, ratio image and maximum likelihood classification map provided a guide to the spatial distribution of the main cover types, however, the interpretation and comparisons should be viewed as subjective.

Having demonstrated the spectral class discrimination and the spatial classification ability of airborne SPOT data for Glaisdale Moor, the analyses were repeated for the Landsat Thematic Mapper data to see if there could be any further improvements in the classification ability of the surface types.

CHAPTER SIX

The discrimination of surface types using Landsat Thematic Mapper data

6.1 Introduction

6.2 Objectives and approaches

6.3 Landsat Thematic Mapper data

6.4 Spectral relationships with the ground data

6.5 Classification of surface types with spectral variables

6.6 Thematic Mapper data processing

6.7 Evaluation of Thematic Mapper data processing results

6.8 Conclusion

6.1 Introduction

With the launch of Landsats 4 and 5 in 1982 and 1984, respectively, a new generation of Landsat Thematic Mapper data have been introduced to the user's community. Although the geographic area covered by both the Landsat MSS and TM sensors is virtually identical, the TM has greatly improved spatial, spectral and radiometric resolutions (Lathrop and Lillesand 1986). These sensor refinements are expected to enhance the usefulness of TM data relative to MSS data (Irons and Kennard 1986). Detailed descriptions of the TM are provided in Engel and Weinstein (1983), Barker (1983), Beyer (1983), Anuta et al (1984), Malila et al (1984) and NASA (1984).

Thus, Landsat Thematic Mapper (TM) data with its favourable high spatial resolution may offer possibilities for the assessment and mapping of open moorland erosion and degradation. Landsat TM data have already been utilized in a wide range of environments for the observation of physical surface features as well as for the classification of land use and land cover.

While broad classification, delineation and mapping of some environmental aspects, such as wet land with MSS was more successful (Carter 1978, Ernst and Hoffer 1979, Caster and Richardson 1981, Bartlett and Klemas 1982) however, these had some difficulty in classification of other aspects. For example, Landsat MSS was less successful in the classification of forested regions (Beaubin 1979, Harris et al 1978, Bryant et al 1980, Latty and Hoffer 1981, Markham and Townshend 1981) and problem were also encountered in delineation of urban and suburban land covers (Carters and Jackson 1976, Jensen and

Toll 1982). These limitation are generally attributed to the poor spatial resolution of the MSS (Haack et al 1987).

Prior to launching the TM, scientists examined airborne TM data (simulated to match TM characteristics) in order to determine what improvements in land use and land cover identification can be expected from the new data (Dottavio and Dottavio 1984). The simulated TM data have been analysed by Latty and Hoffer (1980) over a forested region in South Carolina; Teillet et al (1981) in British Columbia, Canada; more recently Nelson et al 1984 in Maine and by Hack (1983) and Toll (1984) for urban land cover delineations. Most of these studies concluded that TM data would be more useful than MSS for discriminating land use and land cover types.

The critical aspect of the TM data based land surface type classification lies in the classification accuracy which in general is a function of the smaller number of boundary pixels and the spatial resolution (30 m) of the image data (Ioka and Koda, 1986). Extensive effort was made by Williams et al (1984), Toll (1984, 1985) & Irons et al (1985) to explain the effects of the Landsat TM improvements on classification accuracy. Their studies revealed the fact that while the improved spectral and radiometric characteristics have increased the classification accuracy, the improved spatial resolution on the other hand substantially decreased the classification accuracy for some applications. Thus, it appears that the relationship between the spatial resolution and classification accuracy are closely integrated. Townshend and Justice (1981) and Markham and Townshend (1981) explained the high spatial resolution effect on classification accuracy. They believed that since the increase in spatial resolution generally results in an increase in the variance of pixel values in the feature space, the classification accuracy as a result tends to decrease. Conversely, the lowering in spatial resolution reduces the number of mixed or boundary pixels, and hence higher accuracy may be achieved (Thomson et al 1975, Pitts and Badharar 1980, & Jackson et al 1983). Iron et al 1985 concluded with the idea that the ultimate effect of increasing spatial resolution depended on the spectral and field dimension attributes of the land cover categories.

Considering the previous classification accuracy with the ground radiometer data (61.4 per cent) and with 20m (May) and 10m (July) spatial resolution airborne SPOT data (78.33 per cent) as reported in Chapters 4 and 5 respectively it was anticipated that TM data with 30 m spatial resolution would further improve the overall classification accuracy. Thus, in the present research, attempts will be made to assess the improvement of Landsat TM data in spectral discrimination of the moorland surface types.

6.2 Objectives and approaches

The research aim of this chapter is to evaluate the spatial and spectral characteristics of the Landsat TM data. The emphasis will be on the spectral discrimination of vegetation, bare peat and bare soil in the Glaisdale Moor study area. The specific spatial and spectral related objectives are as follows:

1) To evaluate the spectral relationship of the Landsat TM bands, with the selected ground variables. The aim of this evaluation is to determine the impact of ground variables on the spectral

response of surface types sensed by the Thematic mapper. The spectral response in all the TM bands (except the Thermal band 6) were statistically tested against 10 related ground variables to determine the degree to which all ten variables and each individual ground variable influence the spectral response of the surface types. The implication of such an identification of statistically significant environmental variables which explain TM spectral response is that it will improve the effectiveness of cover type mapping by detailing which environmental variables are vital as in situ measures for correlation to remotely sensed information.

2) To assess the spectral class discrimination performance of the Landsat TM bands.

3) To evaluate the spatial cover discrimination performance of the Landsat TM bands.

The study first examines the test pixels extracted from the subscene of Landsat TM image using a series of statistical techniques ranging from simple descriptive measures to multivariate discriminant analysis. This was followed by the various image classification techniques including image enhancement, contrast stretching, ratioing and supervised classification.

6.3 Thematic Mapper data

The Thematic Mapper (TM) operates in seven spectral bands, six of which were selected primarily for vegetation monitoring, the seventh for its ability to discriminate between rock types. To improve the radiometric accuracy of the data the range of values has increased from 0-64 to 0-256. A further advantage of the TM is its high spatial resolution, being 30m x 30m in all but band 6 which made it possible to classify areas as small as 2-4 hectares. More detailed characteristics of the TM are given in Table 6.1.

Calibrated TM data used in this analysis were collected by Landsat-4 on 23 April 1984. The thermal infrared data, which have 120-m spatial resolution were not used here and therefore, band 6 was dropped from the subsequent analysis. A 512 x 512 subscene covering the Glaisdale Moor was used in this analysis. Using a cursor on the screen 40 pixel values of each TM bands were taken randomly for each of three surface types : vegetation, peat and bare soil. The pixel values (DN, brightness value) were then used in the subsequent analysis to relate to the ground data and later in the spectral discrimination.

6.4 Spectral relationships with the ground data

6.4.1 General characteristics of the spectral data

The descriptive measures of the raw spectral data (Table 6.2) show that TM bands 2, 3 and 4 have lower ranges compared with bands 1, 5 and 7. The close mean values in the visible bands (20.4 for band 2 and 22.9 for band 3) and near infrared band (30.4 for band 4) probably suggest that these bands will provide near similar spectral response in the test site. TM bands 1, 5 and 7 data have a wider spectral range (72.4 for band 1, 69.1 for band 5 and 104.2 for band 7), which perhaps indicates the suitability of these bands for better separability of surface types in the test site.

Table 6.1 Thematic Mapper spectral characteristics

Band	Spectral range (μm)	Radiometric Sensitivity (NEΔP)*	Principal application
TM1	0.45 - 0.52	0.8%	Coastal water mapping soil/vegetation differentiation
TM2	0.52 - 0.60	0.5%	Green reflectance by healthy vegetation
TM3	0.63 - 0.69	0.5%	Chlorophyll absorption for plant species differentiation
TM4	0.76 - 0.90	0.5%	Biomass surveys
TM5	1.55 - 1.75	1.0%	Snow/cloud differentiation
TM6	10.4 - 12.5	0.5k** NETD	Thermal mapping
TM7	2.08 - 2.35	2.4%	Hydrothermal mapping

Ground IFOV 30 M (Band 1-5 ,7)

120 M (Band 6)

Data Rate 85 MB/ S

Quantization levels 256

* NEΔP : Noise equivalent change in surface reflectance

** NETD : Noise equivalent temperature diff.
(Source : Salomonson et al 1980)

Table 6.2 Descriptive statistics of the Landsat TM data of Glaisdale Moor

a. Raw data

Variable	N	Minimum	Maximum	Mean	STD Dev.	Skewness	Kurtosis
TM1	70	16.000	247.00	72.429	76.178	1.517	.698
TM2	70	16.000	39.000	20.400	6.1300	1.893	2.415
TM3	70	16.000	53.000	22.929	7.2738	1.697	3.028
TM4	70	16.000	55.000	30.400	9.8502	.583	-.187
TM5	70	13.000	247.00	69.143	67.959	1.634	1.407
TM7	70	23.000	255.00	104.23	66.145	1.271	.368
b. Transformed data							
TM1	70	1.2040	2.3930	1.6747	.38280	.642	-.553
TM2	70	1.2040	1.5910	1.2945	.10788	1.562	1.366
TM3	70	1.2040	1.7240	1.3427	.11862	1.052	.471
TM4	70	1.2040	1.7400	1.4605	.14056	.015	-.992
TM5	70	1.1140	2.3930	1.6796	.35858	.563	-.526
TM7	70	1.3620	2.4070	1.9435	.25188	.243	-.195

The spectral response of the TM bands 2, 3 and 4 are generally controlled by vegetation, particularly the presence of chlorophyll and the physical structure of the leaves. Thus, quite expectedly the lower spectral range of bands 2, 3 and 4 can be attributed to the surface condition of the study area, particularly its bare peat and bare soil. Similarly, the higher spectral range of TM bands 1, 5 and 7 are perhaps mainly associated with the high moisture bearing peat of the test site.

In previous studies, Salomonson et al (1980) and Townshend (1984) mentioned that the TM band selection was intended to take advantage of distinctive characteristics of the spectral response of vegetation. This was reflected in the spectral data range (Table 6.3) of the present study which shows that water absorption TM bands 5 and 7 are most highly correlated (r = 0 0.890 and 0.898) with band 1. The other most notable high correlation is with TM band 2 (r = 0.862) with band 3. The high correlation between the band 2 and 3, and 5 and 7 possibly indicate that one of the bands from each group will be redundant. These results suggest that the possible spectral band combination : one each from the visible, the near-infrared and middle infrared (band 5 or band 7) would be likely to perform as the best discriminant combination. Similar band combinations were also reported by Townshend et al (1983).

6.4.2 Correlation between ground and spectral data

Pearson's product moment correlation between the ground data and the TM data was employed. The same ground data referred to in the correlation with the ground radiometer data were applied here (Chapter

Table 6.3 Pearson's product moment correlation of extracted pixels of Glaisdale Moor, for the six Thematic Mapper bands

VARIABLE						
TM1	1.0000					
TM2	.7220**	1.0000				
TM3	.7999**	.8624**	1.0000			
TM4	.6478**	.7263**	.7954**	1.0000		
TM5	.8909**	.7489**	.7867**	.7265**	1.0000	
TM7	.8980**	.6898**	.7273**	.5679*	.9037**	1.0000
	TM1	TM2	TM3	TM4	TM5	TM7

** Significant at 99% level

4). The problems of relating data from different dates were recognised here, and the limitations arising from this problem were discussed in Chapter 5 (Section).

The raw TM data was transformed into natural log (Table 6.2) before it could be used in the correlation. The correlation result, presented in Table 6.4 indicates that only soil moisture and organic matter and to some extent the surface silt content are moderately correlated with the TM bands. Considering the dynamic nature of soil moisture, as discussed before in Chapter 5, section 5.4.2, the correlation must be treated with care. The negative relationships between organic matter and Landsat TM bands, also confirms the similar result obtained with simulated SPOT bands reported in the Chapter 5, section 5.4.2. The relationships between the biomass and the Landsat TM bands are very poor. The TM bands 2, 3 and 4, which are in spectral form similar to the SPOT simulated band passes appear to be poorly correlated with the biomass. This may be explained by low levels of biomass in April. Influence of soil substrate on reflectance remains more significant at low levels of biomass.

The relationships between surface soil texture and Landsat TM bands also appears to be poorly correlated. Only surface silts appears significantly correlated with spectral radiance.

Non significant relationships of the Landsat TM bands spectral advance with subsurface woil texture may be attributed to the same reason as mentioned in the previous Chapter 5, section 5.4.2, namely that the process of scattering and absorption takes place only in the top few millimetres of the surface. Therefore, these would have little effect of the subsurface on spectral radiance.

Table 6.4 Pearsons product moment correlation between the ground variables and TM data

Variable	Moisture %	Organic matter %	Slope	Biomass gm/m^{v}	Surface sand %	Surface silt %	Surface clay %	Sub-surface sand %	Sub-surface silt %	Sub-surface clay %
TM1	-.4181**	-.4743**	-.2091	.3225*	-.1160	-.4564**	.1549	-.0720	-.1100	.0713
TM2	-.3707**	-.4671**	.0965	.1295	-.0936	-.2482	.0544	-.0017	-.0230	-.0566
TM3	-.4742**	-.5269**	-.0504	1822	-.0047	-.4746**	.0382	.0701	-.1353	-.1096
TM4	-.4623**	-.6024**	.0719	.1910	-.2154	-.2588	.1625	-.2390	.293	.2721
TM5	-.3645**	-.3245**	-.0989	.2618	-.2013	-.4369**	.2077	-.1238	-.0299	.0760
TM7	-.3190**	-.2370*	-.1378	.3869*	-.1680	-.3781**	.1625	-.0909	-.088	.0376

Number of cases : TM1 - TM7		=	70
Moisture		=	70
Organic matter		=	70
Slope		=	70
Sand	Surface	=	60
Silt	Surface	=	60
Clay	Surface	=	60
Sand	Subsurface	=	60
Silt	Subsurface	=	60
Clay	Subsurface	=	60

** Significant at α = .01
 * Significant at α = .05

The importance of soil moisture, organic matter content and surface silt in determining the range of spectral response in TM bands is clear. However, it is also apparent that none of the ground variables have any clear domination over others in controlling the spectral response. The highest explainable spectral variation (TM band 4) would be achieved by organic matter (r^2 = 36 per cent). A similar poor correlation result was also observed with the ground radiometric data. These poor correlations may relate to the problems of trying to compare data from different dates as discussed before in Chapter 5, section 5.4.2. Thus, in the next section canonical correlation was employed in various TM spectral band combination and ground data in different groups, in order to increase the accountable spectral variation.

6.4.3 Canonical relationship

Canonical correlation was calculated using the TM spectral bands as dependent variable and the ground data as independent variables. The results, given in Table 6.5, clearly show the significant improvement in the correlation result. The first and highest achievable canonical correlation being r = 0.806 (significant at 99.9 per cent level) was a significant improvement in terms of accountable spectral variation. The correlation with fewer band combinations and small number of ground variables, however, significantly lowers the canonical correlation result. For instance, the correlation result (Table 6.5b) between TM band 2, 3 and 4 (similar to SPOT) and the soil moisture, soil organic matter and slope was only r = .665. Similarly, with the same ground variables, the TM band 1, 5 and 7 (Table 6.5c) has the correlation result of only 0.572.

Table 6.5 Canonical correlation of ground and spectral variables (TM bands)

Group I		Group II	Correlation I	Correlation II	Correlation III
a)					
Soil moisture		TM1			
Organic matter		TM2	0.806	0.627	0.466
		TM3			
Sand	Surface	TM4			
Silt	Surface	TM5			
Clay	Surface	TM7			
Sand	Subsurface				
Silt	Subsurface				
Clay	Subsurface				
Slope					
Number of cases = 60					
b)					
Soil moisture		TM2			
Organic matter		TM3	0.665	0.28	0.03
Slope		TM4			
Number of cases = 70					
c)					
Soil moisture		TM1			
Organic matter		TM5	0.573	0.20	0.12
Slope		TM7			
Number of cases = 70					

6.4.4 Multiple correlation

The canonical correlation result has indicated the maximum extent of explainable spectral variation with the selected ground data. However, it is appropriate at this stage to establish the relationship of individual bands with the ground data in a group. This objective assessment would indicate which of the bands best relate with a specified set of ground data. To achieve this, the multiple regression technique was employed. Like the canonical correlation, the spectral variables were regarded as the independent variables. The result (Table 6.6) indicates poor accountability by all the ground variables (highest being 52 per cent for the TM band 1, 5 in set a). The TM spectral accountable variation in all the bands further drop as the inclusion of the number of ground variables reduces (highest being 40 per cent for the TM band 4 in set b, and 45 per cent for the TM band 5 in set c). These poor multiple correlations possibly may be due to the integration of data from three spectrally distinct surface types, such as vegetation, bare peat and bare soil.

6.5 Classification of surface types with spectral variables

One of the most fundamental issues in using remote sensing data is how good are the spectral bands in measuring ground attributes. If there is more than one, two or a combination of spectral bands suitable for a particular surface type mapping, then the initial question is which band or band combinations are appropriate. An answer to this question needs to develop a classifier that will select the best bands (Labovitz 1986). The selected best band or optimal band combinations, thus, can be of great help in determining the levels of classification

Table 6.6 Multiple correlations between the TM spectral bands and the ground data

Dependent variable	N	Multiple R	R^2	F	Significance
a) TM1	60	0.724	0.525	6.14	0.001
TM2	60	0.607	0.369	3.25	0.003
TM3	60	0.711	0.505	5.68	0.001
TM4	60	0.716	0.513	5.85	0.001
TM5	60	0.724	0.524	6.12	0.001
TM7	60	0.648	0.421	4.04	0.001
Independent variables included ; moisture, organic matter, surface sand, silt and clay, subsurface sand, silt and clay and slope					
b) TM1	70	0.537	0.288	8.929	0.001
TM2	70	0.505	0.255	7.538	0.001
TM3	70	0.569	0.323	10.535	0.001
TM4	70	0.634	0.402	14.816	0.001
TM5	70	0.401	0.161	4.224	0.008
TM7	70	0.354	0.125	3.154	0.030
Independent variables included : moisture, organic matter and slope					
c) TM1	60	0.603	0.364	5.06	0.001
TM2	60	0.433	0.188	2.04	0.07
TM3	60	0.578	0.334	4.44	0.001
TM4	60	0.498	0.248	2.92	0.01
TM5	60	0.675	0.456	7.42	0.001
TM7	60	0.598	0.358	4.93	0.001
Independent variables included : surface sand, silt and clay and subsurface sand, silt and clay					

performance that could be obtained using only a subset of spectral bands from the TM data. If this were possible, data quantity and processing costs could be considerably reduced.

The optimal subset of bands are conventionally chosen by adopting some form of empirical strategy. The most popular type of empirical strategy is the stepwise strategy. Therefore, in the present analysis a stepwise discriminant analysis was performed using the available TM data set.

In general, the purpose of the stepwise procedure is to separate the three known surface types (i.e. vegetation, bare peat and bare soil) by their spectral characteristics. However, more specifically, the purpose of this analysis can be threefold :

1) To find out the correlation between spectral variables (TM data set) and the linear discriminant function;

2) To determine the overall classification accuracy;

3) To determine the sequence in which the TM bands were selected by the discriminant function.

Spectral separation of surface types was achieved in the statistical analysis by deriving linear combinations (discriminant functions) of the TM bands that provided the greatest discrimination among classes. In a stepwise procedure, individual bands would be selected and placed into the linear function in order of the band's decreasing discriminating power. In other words, at each step in the procedure, the band that maximized the separation between classes, while minimizing the multiple correlation among the bands selected in the previous step, was included in the derivation of the linear discriminant function.

6.5.1 Correlations between the spectral variables and linear discriminant functions

The correlation between each variable and the linear discriminant function score for each sample was computed to examine the discriminating variables, here the spectral variables and the discriminant functions. Results of this analysis are presented in Table 6.7. To facilitate interpretation, the matrix was ordered. Variables are grouped according to the function with which they are most highly correlated. Within each such group, variables were sorted in descending order by the absolute value of the correlation coefficient.

Table 6.7 illustrates that the first discriminant function was only moderately correlated with the TM band 5 and band 1. This moderate correlation in the first function indicates that although the spectral response in TM-band 5 and band 1 differs considerably between the surface types, this function would probably be important to distinguish between surfaces. The second function, however, was clearly better correlated with TM band 4 and moderate with band 7. This correlation suggests that surface types in the present study site can possible be best distinguished by TM band 4 together with band 7.

Table 6.7 Correlations between spectral variables (discriminating variables) and linear discriminant functions

Spectral variable	Function		Significance at α=
	1	2	
TM5	0.609	-0.041	0.001
TM1	0.599	-0.314	0.001
TM3	0.530	0.197	0.001
TM2	0.395	0.0587	0.001
TM4	0.403	0.701	0.001
TM7	0.539	-0.608	0.001

6.5.2 Classification accuracy and the group mean score

Results of the discriminant classifier are presented in Table 6.8 which indicates a 95 per cent overall classification accuracy for the three surface types. The discriminant function accounted for most of the variance in the DN value of all the bands for the three surface types. Perfect classification was achieved for the peat and bare soil, which had distinctly different mean discriminant function scores for the two classes (i.e. -2.78 for peat and 5.30 for bare soil). Classification for the vegetation was not as accurate. There was some confusion between the vegetation and bare peat surfaces, such that 15 per cent of the vegetation samples were assigned to the bare peat surface. Bare soil was sufficiently different from either vegetation or bare peat so that no confusion existed. The mean discriminant function scores for vegetation and peat on the first and second discriminant function were nearly identical (-2.52 and -2.78; 1.29 and -1.25 respectively). Thus, the discriminant result clearly shows that the bare soil can be successfully separated from both peat and vegetation while there will be some misclassification between vegetation and bare peat.

When the TM discriminant analysis results are compared with those obtained using the ground radiometric data (similar to Landsat MSS wave bands) and the simulated SPOT multispectral May and July data, it appears that TM wavebands are more successful in separating the Glaisdale Moor surface types. With 1m ground resolution, the ground radiometric data shows a classification performance of only 61%, while with the 10m ground resolution of the July simulated SPOT data, classification accuracy improves up to 78%. This decreases by 4% however with the 20m ground resolution May simulated SPOT data. The

Table 6.8 Discriminant analysis results for Landsat TM with vegetation, bare peat and bare soil

Function	Percentage of variance	Group Mean Score		
		Vegetation	Peat	Bare soil
1	92.87	-2.52	-2.78	5.30
2	7.13	1.29	-1.25	-0.04

	Percentage Correct Classification		
	Predicted		
Actual	Vegetation	Peat	Bare soil
Vegetation	85.0	15.0	0.0
Peat		100.0	0.0
Bare Soil			100.0
	Overall classification accuracy		95.0

highest classification accuracy (being 95%) was achieved using the 30m ground resolution of the TM data.

The higher classification accuracy achieved with the TM data may be due to that the TM data has higher spectral resolution (narrow band width) and an extended spectral coverage. For example, in the ground radiometric data (similar to Landsat MSS band passes), band widths are broad (0.11 - 0.3µm) and spectral coverage is limited (0.5 - 1.1µm) and there is no wave bands in the short wave infrared (1.1 - 2.5µm) region. In the simulated SPOT data there are only three spectral bands and band widths are 0.5 - 0.89µm. However, the SPOT data set is lacking in coverage of the blue band in the visible region and no band in the short wave region (e.g. TM band 5 and 7). TM band 1 (blue) provides information for soil/vegetation differentation. TM band 5 and 7 are more sensitive to soil moisture, and hence may be more effective for separation of high moisture bearing peat from vegetation and bare soils. Thus, high classification accuracy in TM data may be due to its improved spectral separability of the cover types arising from the improved spectral resolution and coverage. It may also be that the sampling process in selecting pixels from each cover type avoided many boundary pixels. The real determining factors for the increase in overall classification accuracy compared with the SPOT data sets remain undetermined.

6.5.3 Selection of optimal set of bands

Table 6.9 lists the sequence in which the TM bands were selected by the discriminant function. The Wilks-Lambda test is a measure of the discriminating power provided by each variable in the discriminant function.

Table 6.9 Sequence of Landsat TM band selection

Step	Variable entered	Wilk's Lambda	Δ Wilk's Lambda	F value
1	TM4 (0.76-0.90 m)	0.2568	-	169.265
2	TM7 (2.08-2.35 m)	0.0675	0.1893	165.120
3	TM5 (1.55-1.75 m)	0.0544	0.0131	125.947
4	TM2 (0.52-0.60 m)	0.0438	0.0106	107.634
5	TM3 (0.63-0.69 m)	0.0349	0.0089	98.354
6	TM1 (0.45-0.52 m)	0.0307	0.0042	87.809

In the discriminant function analysis, the TM band 4 was identified as having the greatest discriminatory power for the surface types examined. The second, third and fourth spectral bands selected by the discriminant analysis are TM6, TM5 and TM2, respectively. This result agrees with the earlier studies of Hoffer et al (1975), Dottavio & Williams (1982), Nelson et al (1984), Thompson et al (1984) and Townshend (1984) which showed that optimum separation of surface cover types is achieved by classifying multispectral data having at least one band from each of the major regions of the electro-magnetic spectrum (visible, near infrared, and middle infrared).

However, considering Cover and Van Campenhout's (1977) "all-possible-subset" strategy to select a non biased optimal subset, discriminant analysis was extended. The forward stepping discriminant analyses were used to determine the effects of additional spectral bands such as the best single, the best two bands, best three, four, five and six bands on classification accuracy. The classification accuracy of these analyses are shown in Table 6.10, which illustrates that TM bands 7, 4 pair may provide significant discriminant information for the peat and bare soil. However, clearly the best band combinations appear to be the TM band 1, 5, 7 and/or TM band 4, 5 7 for a successful discrimination of the three Glaisdale Moor surface types. This new result revealed some interesting facts which are analysed in Figure 6.1. It highlights 1) the amount of discriminatory information added by the individual bands as a function of bands previously entered, and 2) it also illustrates the effects of limited sample size. The second point refers to the fact that the classification accuracy reaches its peak with a specific set of band combination (band 4, 7, 5) and then with the new addition of band do not change the classification

Table 6.10 Test pixel classification using single TM bands and band combinations to discriminate 3 surface types in Glaisdale Moor. Table accuracies are in per cent

TM Bands	Vegetation	Peat	Bare Soil	Overall
1	75.0	85.0	82.5	80.8
2	42.5	82.5	70.0	65.0
3	60.0	90.0	95.0	81.6
4	52.5	97.5	82.5	77.5
5	52.5	52.5	100.0	68.3
7	80.0	97.5	82.5	86.6
4,7	82.5	100.0	100.0	94.2
4,7,5	90.0	100.0	100.0	96.6
4,7,5,2	85.0	100.0	100.0	95.0
4,7,5,2,3	85.0	100.0	100.0	95.0
4,7,5,2,3,1	85.0	100.0	100.0	95.0
2,3,4	67.5	97.5	95.0	86.6
1,5,7	95.0	100.0	100.0	98.3

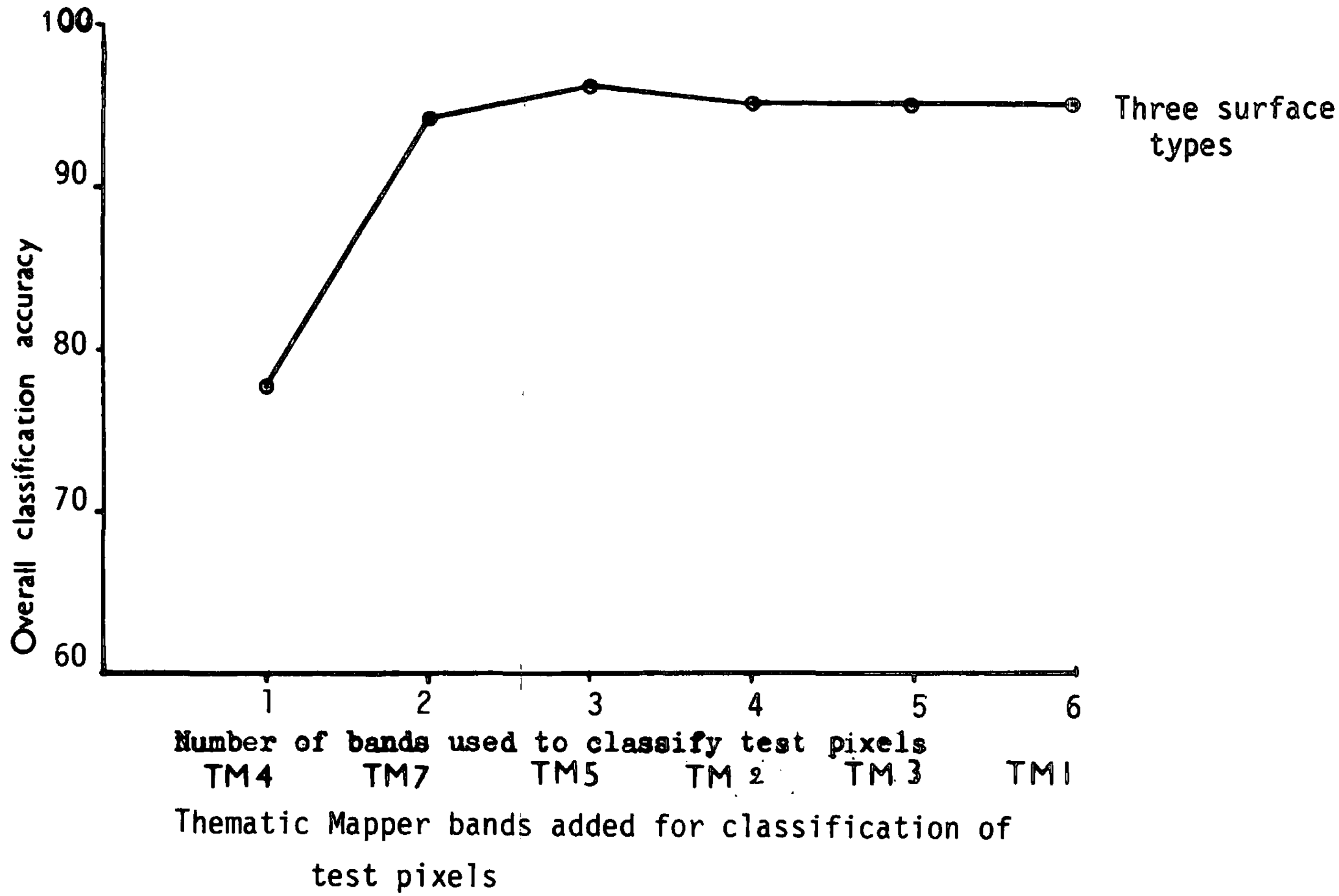


Figure 6.1 Test pixel classification accuracies (in percent) as a function of bands used.

accuracy. Similar results were also reported by William & Nelson (1986) and Nelson et al (1984) in forest classification using ATM data in USA. Swain and Davis (1978) suggests that lack of change in accuracy with the new band addition may be a function of a fixed amount of data (the test samples) and increasing dimensionality. Further, with a fixed test sample size classification accuracy will peak and slowly diminish as more and more dimensions (bands) are added.

6.6 Thematic Mapper data processing

The result of the discriminant function analysis discussed in the previous section provided an estimate of the performance that may be expected for Glaisdale Moor using TM data. Thus, in the present section, the TM imagery would be analysed with similar objectives as for the SPOT data : whether each of three surface types could be delimited consistently from the others and how much detailed information could be discerned.

6.6.1 Image classification

A 512 x 512 pixel subscene was extracted from the main Landsat TM image. The subscene was first examined in each of the TM bands, then in the false colour composites, ratios and supervised classification. The image processing was done in a DIAD system run on PDP 11/44 computer in the University of Durham Geography department.

6.6.2 The analysis of subscene frequency distribution histograms

Subscene contains a very wide range of surface types including agriculture field, open moorland with a wide range and type of semi-natural vegetation including heather, bracken, mosses, woodland, settlement, bare peat and bare soil. Thus, one would expect a wide range of digital values. According to the graph bands 1, 2 and 3 show limited dispersion while band 4, 5 and 7 reveals a wider dispersion which may possibly be attributed to the different sensitivity of the bands with scene content. The dispersion thus suggests that most informative bands of this area would be 4, 5 and 7.

6.6.3 Supervised classification

In the previous Chapter 5, section 5.6.1, it was mentioned that the supervised approach utilizes visual interpretation or relevant ground data as _a priori_ knowledge or design data sets, and therefore, it can usually extract a realistic information (Ioka and Koda 1986).

Similar to the statistical discriminant analysis supervised classification utilizes training samples which were extracted from known populations, and each unknown individual pixel is discriminated according to the statistical distance on similarity between the pixel and known sample clusters. Such a classification approach have also been used in Central Wales using Airborne Thematic Mapper imagery (McMorrow & Hume 1986).

Considering the range of spectral information available in the individual TM wave bands (Figure 6.2) and overall spectral clarity of the FCC's of bands 3, 4 and 5, a combination of TM band 2, 3, 4 and 5 was selected to use in the maximum likelihood classification. Selected statistics of the training data sets are provided in Table 6.11.

Table 6.11 Selected statistics of the training data sets for Glaisdale Moor. TM bands used: 2,3,4,5.

	Covariance Matrix				Means			
Class - Peat								
	TM2	TM3	TM4	TM5	TM2	TM3	TM4	TM5
TM2	0.509				24.72	24.60	26.55	46.44
TM3	0.354	1.121						
TM4	0.479	0.946	4.97					
TM5	1.220	2.421	0.039	23.977				
Class - Bare Soil								
TM2	22.240				35.40	40.80	48.50	93.40
TM3	31.280	46.160						
TM4	32.500	46.700	48.650					
TM5	62.640	99.280	96.500	362.439				
Class - Vegetation								
TM2	0.693							
TM3	0.427	1.048			22.76	21.39	32.89	39.73
TM4	0.219	0.316	1.06					
TM5	1.406	1.933	1.328	9.756				

6.7 Evaluation of TM data processing results

6.7.1 Interpretation of TM bands in context to the Glaisdale Moor

The single band images show (Figure 6.2) an interesting range of spectral and spatial variation within the major surface types. Based on the visual interpretation following obervations can be made:

Band 1

The blue band was most useful for identifying the bare mineral soil. The nearby woodland and *calluna* appeared similar. The bare peat could not be perfectly separable from the *sphagnum* moss. The bare agriculture field was confused as bare soil.

Band 2

This band contains almost identical information to band 1. The bare peat was recognizable. The bare mineral soil appeared very bright, however, bare soil mixed with organic peat was not separable.

Band 3

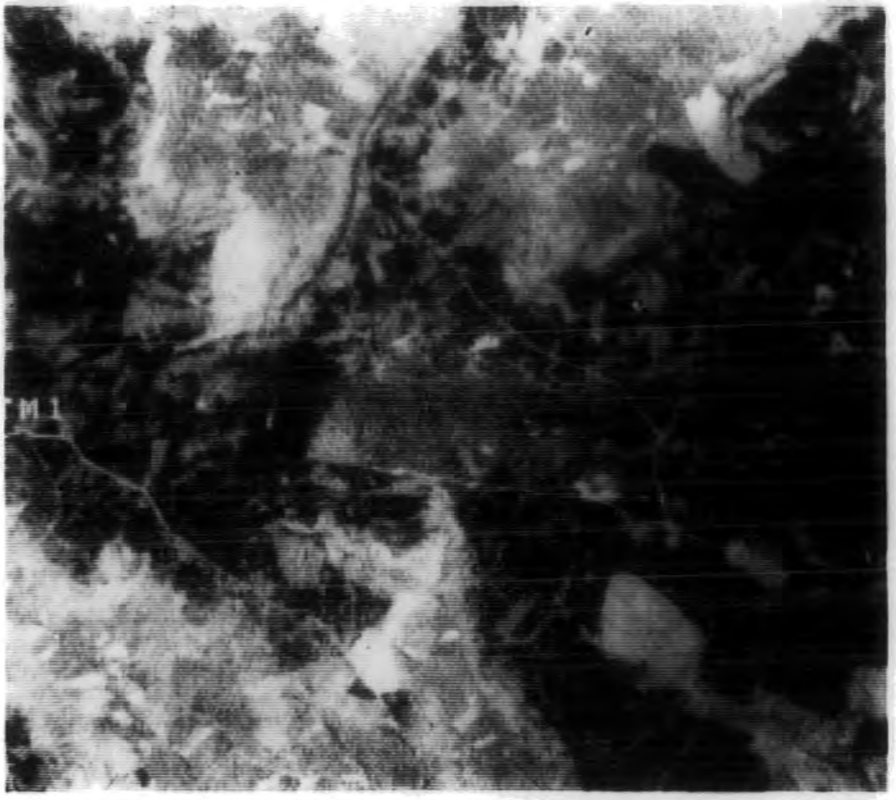
The utility of the red band for differentiating bare peat and *sphagnum* moss was limited. In terms of spatial clarity the blue band was more useful than the red. The bare mineral soil was brighter and separable from the agricultural field.

Band 4

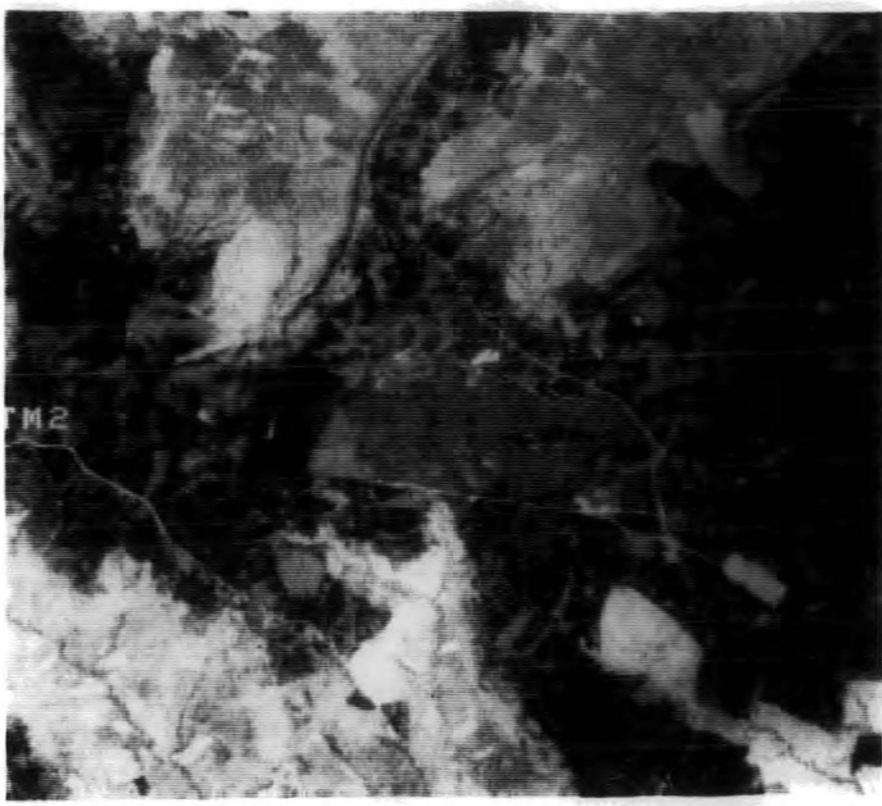
The near infrared response was not useful for any clear separation of surface types. The bare mineral soil was the same as the bare agricultural field.

Band 5 and 7

The two middle infrared bands provided significant discriminant information for the three surface types considered in this study. Both of the bands contain enough unique spectral information concerning grey

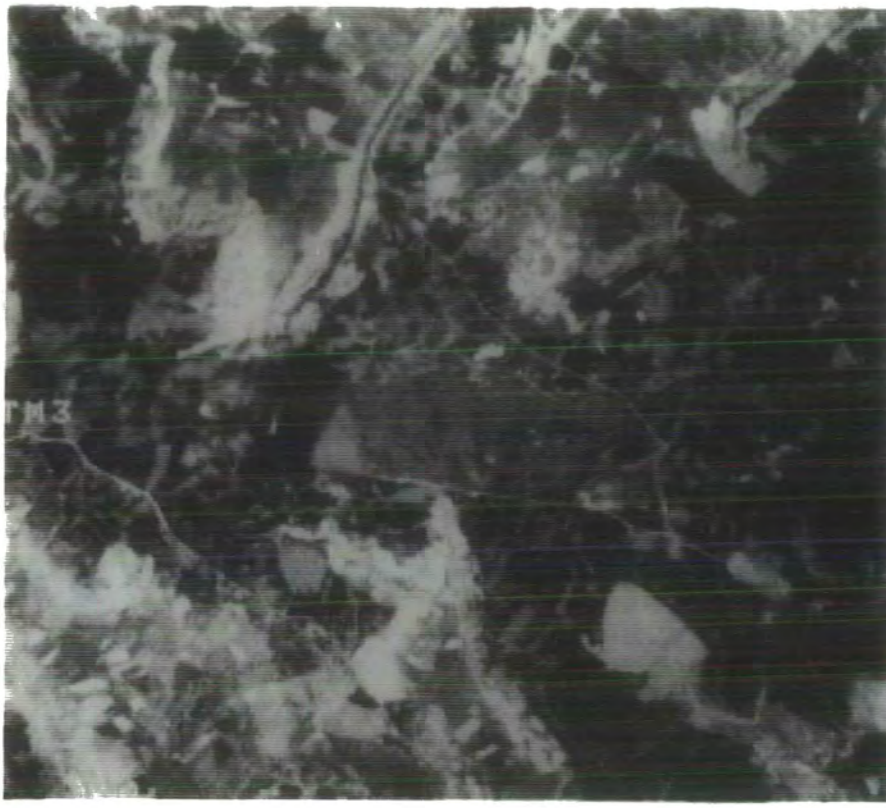


TM Band 1

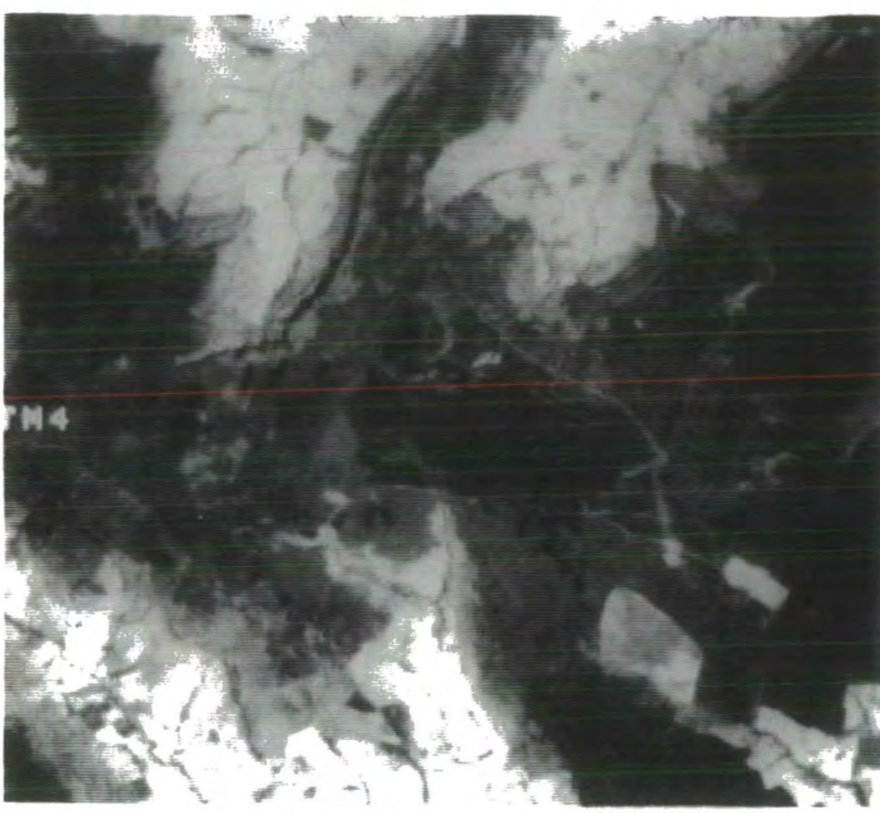


TM Band 2

Figure 6.2a Landsat Thematic Mapper bands 1 and 2 of the Glaisdale Moor.

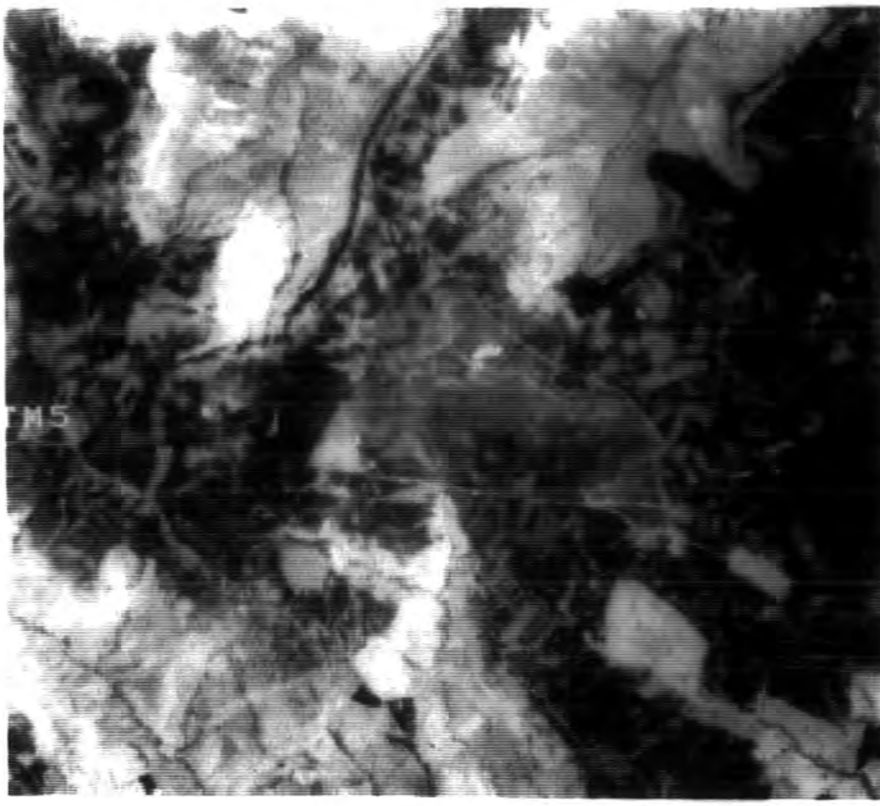


TM Band 3

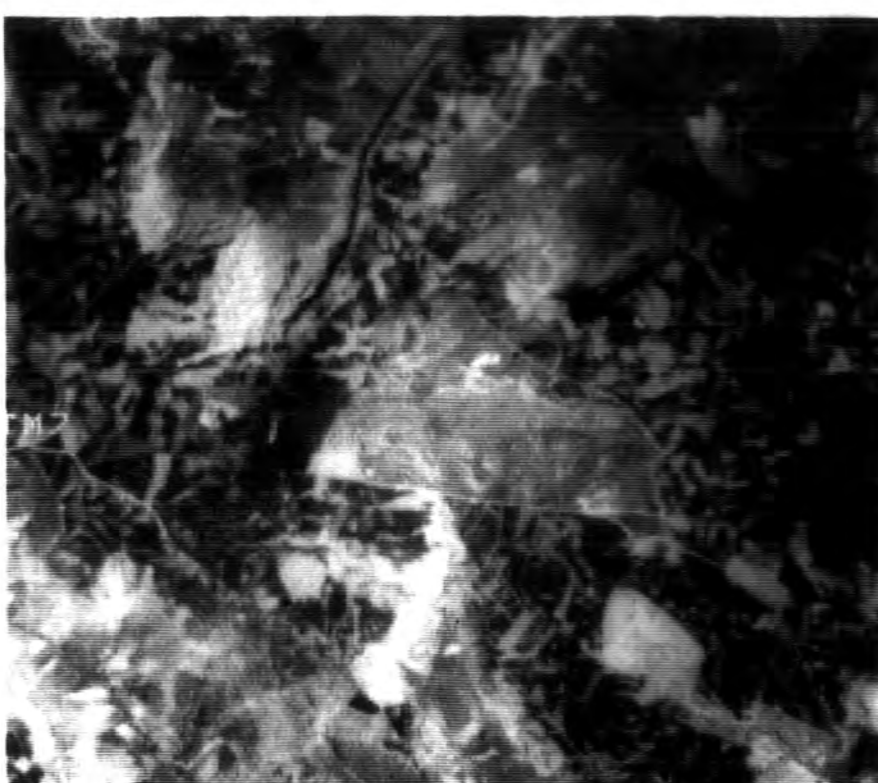


TM Band 4

Figure 6.2b Landsat Thematic Mapper bands 3 and 4 of the Glaisdale Moor.



TM Band 5



TM Band 7

Figure 6.2c Landsat Thematic Mapper bands 5 and 7 of the Glaisdale Moor.

tones to discriminate the vegetation from woodland, sphagnum from calluna vulgaris. The bare mineral soil was clearly separable from the bare peat and vegetation. However, the second middle infrared band was more useful for differentiating all surface types. It also appears that for the Glaisdale Moor surface types, the two middle infrared bands did not contain redundant information.

6.7.2 False colour composites

Like the individual TM wave bands, visual interpretation of the false colour composites also revealed a wide range of information on the Glaisdale Moor. The observed information regarding the suitability of the FCC's (Figure 6.3) are explained in Table 6.12.

Apparently it seems, that, different band combinations would be necessary to separate successfully the spectrally three contrasting surface as considered in this case. For the bare soil discrimination, TM bands 2, 3, and 4 would be the best and for the bare peat and vegetation dicrimination either of the TM band combination 1, 5, 7 and 3, 5, 7 would be suitable.

6.7.3 Maximum likelihood classification result

The result of the maximum likelihood classification of the Glaisdale Moor was not fully successful (Figure 6.4) as there was a considerable misclassification of vegetation with peat. The classification was successful in clearly delimiting the bare peat boundary. The bare soil areas more than 30 metre in size was clearly separable, however, it was occasionally misclassified with bare

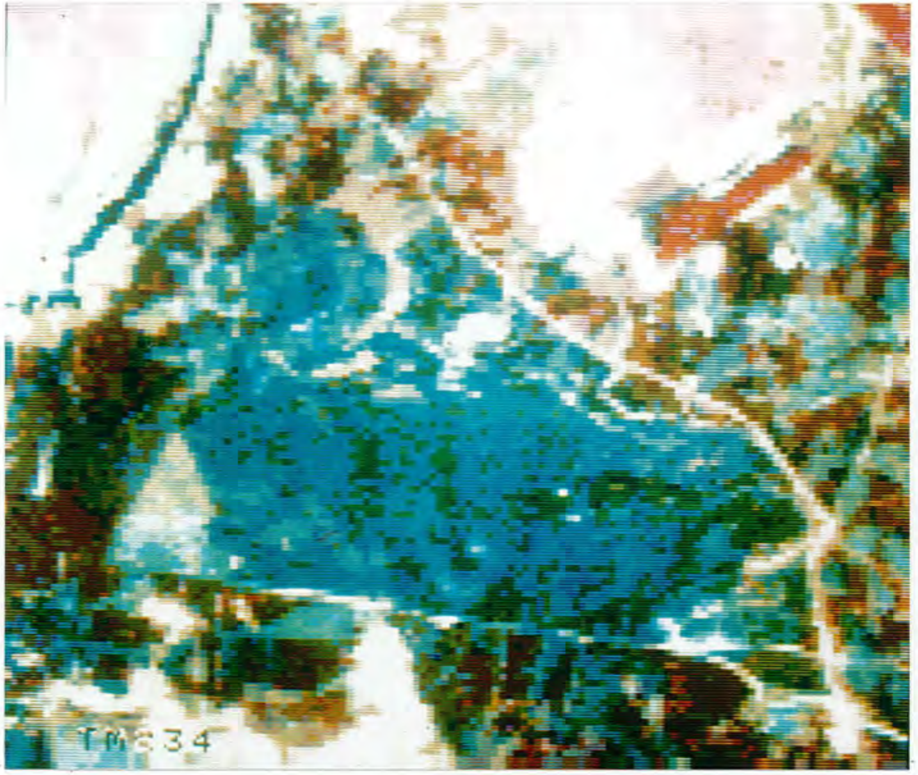


Figure 6.3a False colour composite of the Landsat Thematic Mapper bands 2, 3 and 4 for Glaisdale Moor.
Red and Green = Vegetation, Blue = Peat, White = Bare Soils.

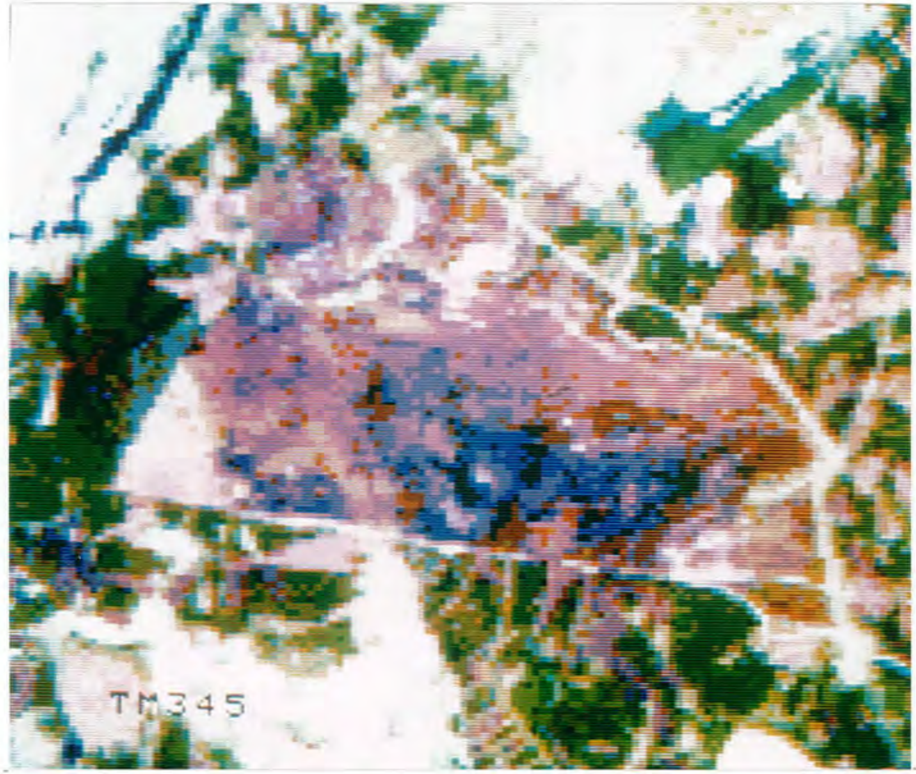


Figure 6.3b False colour composite of the Landsat Thematic Mapper bands 3, 4 and 5 for Glaisdale Moor.
Green = Vegetation, Purple and Blue = Peat, White = Bare Soils.

Figure 6.3c False colour composite of the Landsat Thematic Mapper bands 1, 5 and 7 for Glaisdale Moor.
Deep Green = Vegetation, Light Yellow and Purple = Peat, White = Bare Soils.

Figure 6.3d False colour composite of the Landsat Thematic Mapper bands 3, 5 and 7 for Glaisdale Moor.
Deep Green = Vegetation, Light Yellow and Purple = Peat,
White = Bare Soils.

Table 6.12 Results of visual interpretation of the different Landsat TM band combinations for Glaisdale Moor

Band Combination	Remark
TM band 2, 3, 4	Bare mineral soil appeared very bright and was clearly separable from agriculture. The smaller units of bare soil within the peat category was not separable. Vegetation was separable from the woodland. Unambiguous discrimination between vegetation and peat was difficult.
TM band 1, 5, 7	This was one of the best band combinations to separate the bare peat and vegetation. The spectral information was unique for the spectral classes and within class spectral variation was sufficient enough to warrant ranges of variation. The bare mineral soil was not clear.
TM band 3, 5, 7	This band combination was also found extremely useful to separate the bare peat and vegetation, however, bare mineral soil was not readily identifiable.
TM band 3, 4, 5	Considering the overall separability of the surface types, this was proved to be a useful combination as far as bare peat and vegetation was concerned. The stagnant watermass within the bare peat was clearly visible. The bare mineral soil seems not so clear, as appeared in the TM band combination 2, 3 and 4.

Figure 6.4 A computer classification of the Landsat Thematic Mapper bands 2, 3, 4 and 5 produced using a supervised maximum likelihood technique.

agriculture fields. The most important source of error in misclassification of vegetation was the bare peat. The misclassifications are mainly associated with the spectral and field dimension attributes of the smaller vegetation units. The subsurface of these smaller vegetation units are mainly composed of organic peat, quite often with a varied range of empty space within the cover, which has not only increased the spectral variability with the vegetation category but also the spectral similarity with the peat. Similar difficulty of moorland vegetation classification was reported by other authors e.g. Morton (1986) and Weaver (1984). Despite the limitations of the maximum likelihood classification result in the separation of vegetation, it appears that with the inclusion of more categories of cover types in the training data sets, the classification result could further be improved.

6.8 Conclusion

The objectives of the chapter were to evaluate the spectral relationships with the ground data, assess the spectral class discrimination performance and evaluate the spatial cover discrimination performance of the TM wave bands. On the basis of different analyses performed the following observations can be made:

1) Both bivariate and multivariate analyses suggested that like the ground radiometer and SPOT bands, TM bands were better correlated with the ground data in a group (being 65 per cent). The ground variables : soil moisture, soil organic matter and surface silt were better correlated with most of the TM bands.

2) The discriminant analyses suggested that useful waveband combinations include at least one band from the visible, near infrared and middle infrared spectral regions.

3) The near infrared band (TM4) proved to be the most useful for discriminating the surface types. The forward stepping selection process ranked the two middle infrared (TM5 and 7) bands second and third respectively in overall utility for assessing all surface types.

4) The blue band (TM1) in combination with band 5 and 7 proved to be the most useful classifier, particularly for the peat and bare soil.

5) The result of the TM imagery analyses implied that TM spectral and spatial resolution was sufficient enough to uncover the detail spectral class variation of Glaisdale Moor. Because of spectral and spatial diversity of the surface types in the study area, different TM band combinations would be essential for unambiguous delimitation of the broad surface categories. The bare soil would be best discriminated by the TM bands 2, 3 and 4, while the bare peat and vegetation would be best separated by the TM bands 1, 5 and 7 and/or 3, 5 and 7. The maximum likelihood classification was most useful in separating the bare peat and moderate for the bare soil and least effective for the vegetation.

6) Three of the four most useful bands for discriminating Glaisdale Moor surface types (bands 1, 5 and 7) are not available in the SPOT sensor and ground radiometer (similar to Landsat MSS). Therefore, significant improvements may be expected in the ability to spectrally differentiate the open moorland surface types using TM data.

So far, the research has been directed at examining the potential of remote sensing data for the spectral discrimination and classifications of the surface types on Glaisdale Moor. At the next stage attempts were made to utilize available information in the form of aerial photographs, airborne SPOT and Landsat Thematic Mapper data as an input to a soil erosion prediction model.

CHAPTER SEVEN

Prediction of Soil Loss on Glaisdale Moor

7. Introduction

7.1 Development of erosion prediction models

7.2 Selection of soil loss model

7.3 Study methods

7.4 Results and discussion

7.5 Conclusion

7. Introduction

The purpose of this chapter is to examine the potential of remote sensing and collateral information to predict soil loss from the Glaisdale Moor.

Whilst aerial photographs or remotely sensed imagery provide immediate evidence of areas undergoing active erosion, they do not provide any information as to either the cause or the rate of erosion (see Chapter 1). As both the cause and rate of erosion are determined essentially by the interaction of the same factors (eg Morgan, 1986). An understanding of these would enable not only the actual rate of erosion to be predicted but also identification of areas of potential erosion hazard. With such information available appropriate prevention measures could be taken.

The factors which influence erosion include climate, soil, topography and vegetation cover (Foster and Meyer, 1977). The influence of individual erosion factors varies in time and space and therefore, the severity of erosion also differs considerably (Morgan, 1986). Morgan (1986) further emphasizes that the relative importance of the factors controlling spatial variations in erosion is dependent upon scale - macro to micro. In passing from the macro- to the micro-scale, gradual changes occur in the dominant variable. In the case of soil erosion, climate is supposed to dominate at the macro-level, while at the smaller scales, climate remains uniform and soil and vegetation become important.

In recent decades, soil conservationists have attempted to estimate soil loss from individual fields or slopes. In order to rationalize the choice of erosion estimation and various control methods, numerous equations have been formulated linking soil loss at field scale to causal and conditional erosion factors (Roose, 1977).

The prediction of soil loss has improved over many years as the understanding of the erosion processes has increased. Most of the early soil loss estimates were considered to be primarily qualitative in nature. Initially, equations were developed to describe soil loss using a single independent variable, while taking other contributing factors as constants in a local situation (Mitchell and Bubenzer, 1980). Later, more quantitative multiple factor equations were developed such as Musgrave's equation (1947), Hudson's equation (1961), Wischmeier and Smith's (1965) Universal Soil Loss Equation, Elwells equation (1977) and Morgan (1980), as more data became available and researchers were better able to describe contributing factors. A simple subdivision of predictive models can be made into those that use the drainage basin as the basic unit (e.g. Kirkby, 1969 and Walling, 1974), and those that use smaller areas within drainage basins (e.g. Morgan et al 1984, Wischmeier and Smith, 1978).

For the present study, with detailed information available for 100 m grid squares, attention was focused on the 'small area' models. Before discussing this further however, it is appropriate to review in some detail the development of the various small area prediction models.

7.1 Development of erosion prediction models

The history of scientific study of erosion can be traced back to the late nineteenth century (Hudson 1971). Although the results of the early work were qualitative in nature, a basic understanding of the factors affecting erosion was developed, dating from the experimental work initiated by U.S. Forest Service in 1915 (Ayres 1936). The importance of raindrop impact in the erosion process was first appreciated by Law (1940) and later by Ellison (1947). Scientists began to develop empirical equations as data were accumulated. Zingg in 1940 proposed a relationship of soil loss to a power. The relationship of rainfall characteristics to the amount of soil eroded was proposed by Musgrave (1947). The equation proposed by Musgrave was:

$$E = (0.00527)\ IRS^{1.35}\ L^{0.35}\ P_{30}^{\ 1.75}$$

where : E = the soil loss, mm per year,

I = the inherent erodibility of a soil at 10 per cent slope and 22 m slope length, mm per year,

R = a vegetal cover factor,

S = degree of slope, per cent,

L = degree of slope, per cent,

P_{30} = the maximum 30 minute rainfall, mm.

The Musgrave equation was used for estimating gross erosion from watersheds. Lloyd and Eley (1952) provided a graphical solution of the Musgrave equation for use in the North Eastern United States.

Both Smith (1941) and Browning et al (1947) developed factor relationships which later provided a basis for the development of the Universal Soil Loss Equation (USLE). Van Doren and Baztelli (1956) evaluated the applicability of these factors as they affected soil loss in Illinois.

In a consolidated effort in 1954, a re-evaluation of the various factors affecting soil loss was undertaken (Smith and Wischmeier 1957, Wischmeier and Smith 1958, and Wischmeier et al 1958) which resulted in the development of the Universal Soil Loss Equation (USLE) by Wischmeier and Smith in 1965. This equation was later refined as more data was received from runoff plots, rainfall simulation, and field experience (Wischmeier & Smith 1978).

The USLE model was also applied outside the U.S.A. For example, Hudson (1961) proposed an erosion equation for subtropical Africa which was:

$$E = TSLPMR$$

where E is erosion and the remaining factors are functions of soil type, slope gradient and length, agronomic or agricultural practice, mechanical protection, and rainfall respectively. Another important soil loss equation for the Southern Africa was developed by Elwell (1977):

$$Z = K\ C\ X$$

where :

Z = predicted mean annual soil loss,

K = mean annual soil loss, from a standard field plot 30m x 10m at a 4.5 per cent slope for a soil of known erodibility under bare fallow,

C = the ratio of soil lost from a cropped plot to that lost from the standard plot, and

X = the ratio of soil lost from a plot of length L and slope S to that lost from the standard plot.

All the above models have been derived for the prediction of soil loss from agricultural land. Therefore, without valid modification their application to the non-agricultural land such as the Glaisdale Moor would be questionable.

7.2 Selection of Soil Loss Model

Field observations at various times of the year suggested that water was the principal agent of erosion on Glaisdale Moor, with rill and interrill processes being particularly important. Therefore selection of a soil loss model for Glaisdale Moor had to be one that accounted for soil loss from rill and interrill erosion. The Universal Soil Loss Equation (USLE) developed by Wischmeier & Smith (1978) can be applied to estimate soil loss caused by these processes. Furthermore, the USLE model can also be applied to non-agricultural areas.

After an extensive literature search for previous work on the use of erosion models in upland areas of the U.K. or indeed from uplands in a similar environment elsewhere, only one report, that of Baket et al (1979) from Moel Famau in Clywd was found. In this, an essentially field based report, they compared the effectiveness of three predictive models; USLE, Fournier and Kirkby and found that the USLE model gave the best estimate for soil loss. Thus, despite the difficulty likely to be encountered in assessing the various USLE parameters (see below) it was decided to try to apply the USLE model to Glaisdale Moor.

The USLE incorporates a series of coefficients/indices (figure 7.1), which cover the erosivity of rainfall (R), the erodibility of the soil (K), the length and angle of slope (LS), the extent of plant cover or crop management (C) and a conservation factor (P). The full equation is:-

$$A = R.K.L.S.C.P.$$

in which A = annual soil loss in tons/acre.

In recent years remote sensing data have been used to derive a number of coefficients of the USLE. In particular the crop management factor has been successfully derived using remote sensing data for a variety of environments in the USA, e.g. Berger and Jansen (1980), Degane et al (1979), Morgan et al (1978, 1979, 1980), Morgan & Nalepa (1982), Paterson and McAdams (1980), Singer et al (1986), Spanner (1982), Stephens and Cihlar (1981) and Stephens et al (1982).

Thus given its demonstrated applicability in non-agricultural areas and its flexibility in allowing coefficient derivation from remotely sensed data, the USLE was selected as the most appropriate model to use in the estimation of soil loss by water erosion from Glaisdale Moor.

7.3 Study methods

7.3.1 Mapping the parameters for the calculation of the USLE

A grid square approach was adopted to calculate as well as measure the USLE parameters. The advantage of using grid square measurements

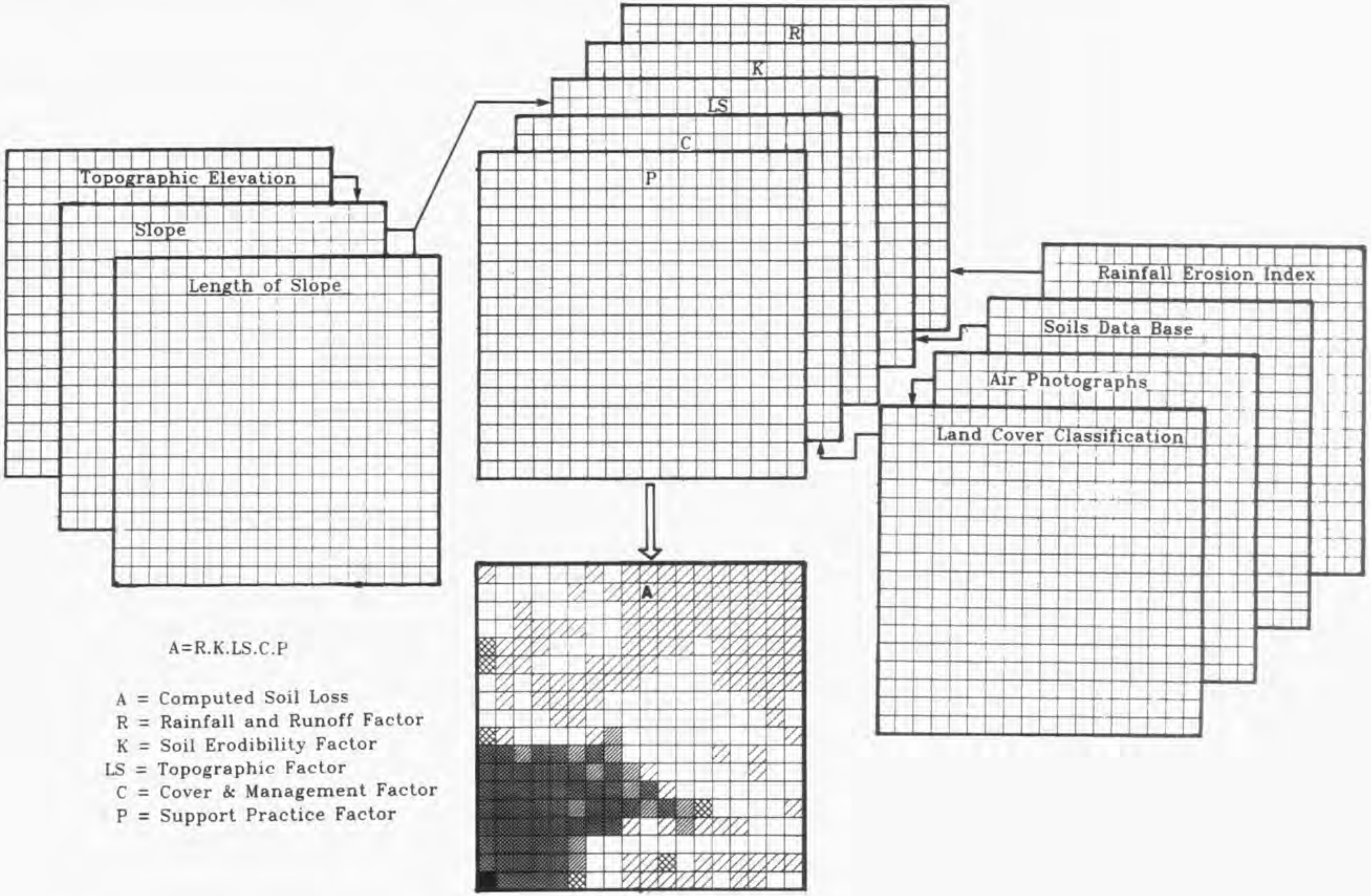


Figure 7.1 Conceptual Scheme of a USLE Data Base

has been discussed previously in chapter 3, section 3.3.4, in which a grid system was used for mapping the drainage density. The choice of a grid square mapping unit also fitted well with the measurement requirements of the USLE parameters, since the USLE model is only applicable to a small area, an essential requirement if a detailed erosion map is to be produced for the Moor.

The grid represents the uniformly subdivided study area on the ground. The values in the USLE equation were calculated square by square to produce a two-dimensional image file for each input and output variable. Because the input data sources are geographically referenced automatically, all subsequent data files, including the USLE A-factor derived from them, can be spatially overlaid and compared square by square. Thus, it is not simply an overall estimate of soil erosion from the Moor which is computed, as totals for each individual square can be recognised and compared, a fact which has important considerations for land management practices and erosion control.

Further, the R, K and LS factors in the USLE are controlled by natural processes and usually remain constant for a relatively small area (or grid square). In contrast, the land use management factors (C and P), can vary appreciably for year to year. Once a USLE data base is established, periodic re-evaluation of erosion within a watershed can be performed on a grid square-by-square basis by photointerpretation of land use changes.

The grid mesh spacing chosen for the determination of the USLE parameter was the same $100m^2$ grid as was used in the assessment of drainage density (chapter 3, section 3.3.4). This gave a total number of 460 squares for the area of the Moor.

7.3.2 Identification of vegetation classes from photointerpretation

An interpretation key of the vegetation of study area was prepared based on the 1985 air photographs and subsequent field verification. Three main vegetation categories were identified on the basis of tonal types on air photographs (Table 7.1); these were vegetated areas, exposed peat and bare mineral soil.

The major tonal types were identified and delineated on transparent overlays of the air photographs. The delineated tonal types were then field varified to correct the tonal boundaries and to estimate the vegetation cover intensity associated with the individual tonal categories. In the field a 1m x 1m grid square was used to estimate the percentage of vegetation for all the major tonal types. Thus, a corrected land cover map was prepared, which was later used to derive C factor values for the 460 grid squares.

Unlike the aerial photographs, it was difficult to produce a reliable land cover map for a small area like Glaisdale Moor purely based on Landsat TM and simulated SPOT imagery for two reasons. Firstly, because of excessively detailed ground spectral variation, the composite false colour maps produced by both systems were extremely complex. Although the maximum likelihood classifications (in case of TM) and ratio image (in case of SPOT) was helpful to some extent in identification of the major cover types boundaries remained blurred. Secondly, because of the time lag (one year) from image acquisition to interpretation, neither of these imageries could be field verified after image classification. Thus, the interpretation key had to be based on experience gained in a later field visit of the study area.

Table 7.1

Interpretive key used in assessing the vegetation cover from the 1985 air photographs of Glaisdale Moor

Tonal Type	Mapping Unit	Characteristics
1. Dark	Vegetated area	>80% cover, mainly calluna
2. Moderately dark	Vegetated area	40-80% cover, mixed mainly Sphagnum & Calluna
3. Light grey, smooth	Vegetated area	10-40% cover, mixed
4. Light & dark grey	Exposed peat	<10% Vegetation
5. White	Bare mineral soil	<10% Vegetation

The interpretation key for the Landsat TM and simulated SPOT was created by starting with the reliably known areas such as the complete vegetation cover (more than 80 per cent vegetation) which appeared as deep green in TM and deep red in SPOT, the bare soil area (without vegetation) which appeared as white in TM and SPOT, and the exposed peat, which appeared as purple and blue in TM and light blue and black in SPOT. From field experience, keys for the complex areas such as mixed vegetation, which appeared as green-purple-yellow in TM and light red-green-yellow, was established. This category was supposed to have a range of 40-80 per cent cover density and thus the remaining areas were assumed to comprise the remaining category of 10-40 per cent cover density.

Using this interpretation key, the false colour composite imageries together with the maximum likelihood classification map of the Landsat Thematic Mapper (Figure 6.3 and 6.4) was used to produce the surface vegetation cover of the study area (Figure 7.4). This in turn was used to estimate the percentage of vegetation cover for the same 460 squares of the survey grid used in the air photograph interpretation. The operation was repeated for the SPOT data (Figure 5.8 and 5.9), from which a further surface vegetation cover map was produced (Figure 7.4). A third estimate of the percentage of vegetation type for the same 460 grid squares was derived from this map.

7.3.3 Measurement of USLE parameters

The usual calculation for the determination of the erosivity index R, involves either the assessment of the EI_{30} index, or the EI>25 index. The former is a compound index derived from the summation of the kinetic energy (KE) and the maximum 30 minute rainfall for each storm event, whilst the latter involves the summation of the KE received in time increment for each storm when rainfall intensity exceeds 25 mm h^{-1}. Bolline (1985) however, considers that the EI_{30} index is inappropriate for the west European context, because rainfall is of low intensity and any intense rainfalls are of very short duration (ie <30 mins.). Morgan (1977) on the other hand believes that Hudson's KE>25 index is too limiting in temperate latitude since few storms reach an intensity of 25 mm h^{-1}, he suggest instead, that a lower threshold such as KE>10 includes all storms over 10 mm h^{-1} intensity are considered.

A further complication arose in this study since the only rainfall records available for Glaisdale Moor were daily totals recorded for a two year period by an automatic weather station operated by the NYM Parks authority. Thus an erosivity index had to be derived from the very limited data, (see Table 7.2). A first approach to this problem was made by using the method of Richardson _et al_ (1983), to calculate the EI_{30} index from total daily rainfall records (see Appendix 3). The derived erosivity index R, for Glaisdale Moor using Richardson _et al_ (1983) was 187.8, which, in comparison with figures obtained from elsewhere in western Europe (eg 25 for north Wales (Baker _et al_, 1979) and 22.8 - 62.0 from Belgium (Bolline _et al_, 1978)), seemed rather high. A not unexpected problem, given the concensus that the EI_{30} index is of questionable validity in such an environment (Bolline, 1985). Thus an alternative index was sought, lack of the necessary continuous rainfall records prevented the direct calculation of the KE>10 index, Morgan (1980) however, has produced a small scale map of

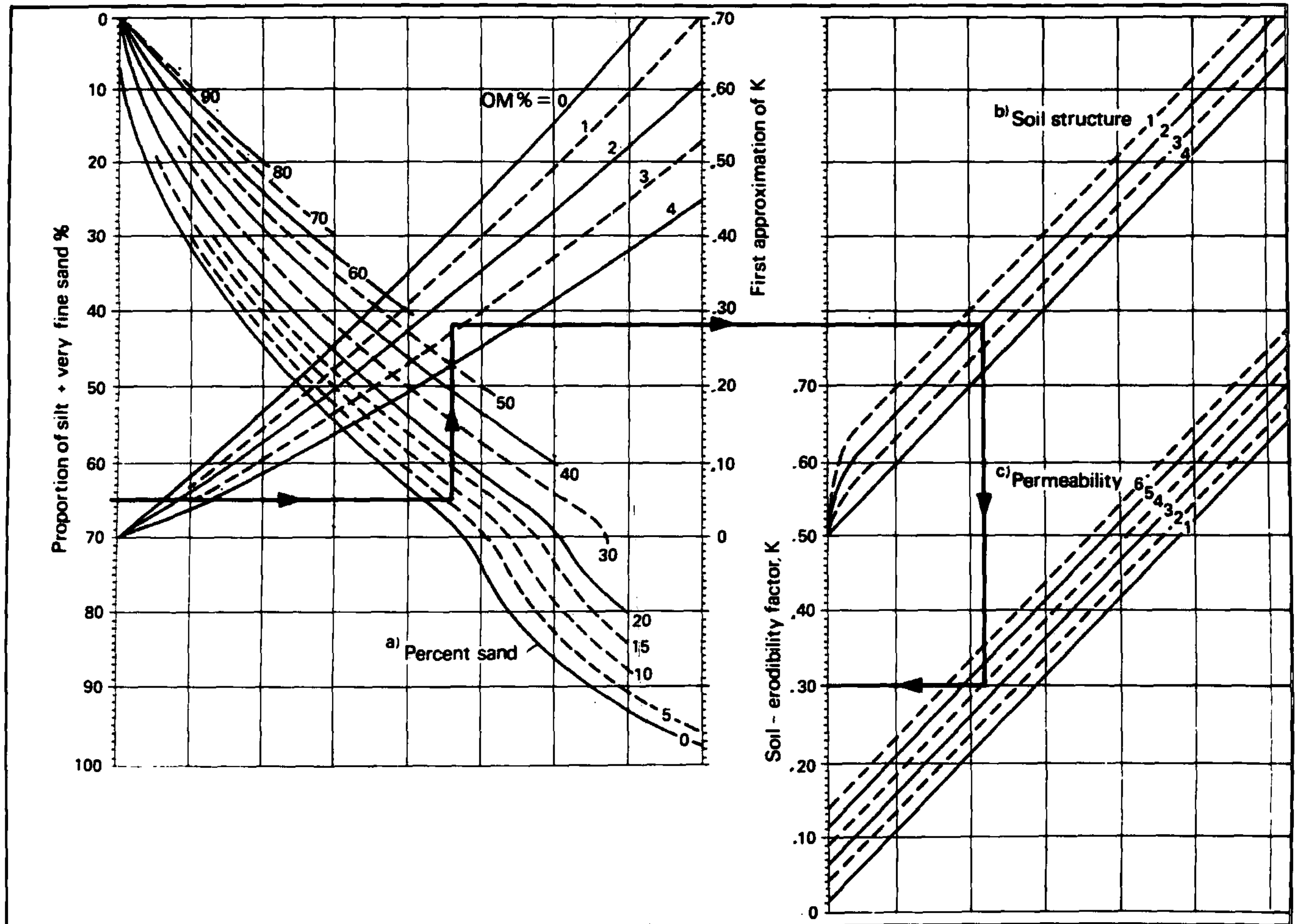
Table 7.2 The range of rainfall intensities recorded over a two year period at Glaisdale Moor

Rainfall Intensity (mm 24 hr^{-1})	Number of storm events	Percentage of storm events
0.1 - <1.0	39	15.0
1.0 - <10.0	160	61.54
10.0 - <20.0	41	15.76
20.0 - <30.0	11	4.23
30.0 - <40.0	5	1.92
40.0>	4	1.54
Total	260	100.0

annual erosivity for the Great Britain using the KE>10 index. The approximate position of Glaisdale Moor was located as accurately as possible on the map and was found to coincide with an area having a KE>10 index of >1300 Jm^{-1}. In his written account of the procedures used in determining the KE>10 index, Morgan reported that only a few locations had a KE>10 of >1400 Jm^{-1}, as this did not include the North York Moors, the value of 1300 Jm^{-1} was used for the KE>10 index for Glaisdale Moor. This gave an erosivity index of 57.3, considerably lower than the 187.8 obtained using the formula of Richardson et al (1983). With the KE>10 index being considered more suitable for the west European context, the erosivity index of 57.3 was used in the determination of A. Given the small area of the Moor the same index was applied to each grid square.

In order to determine the soil erodibility factor K, available soil information previously mentioned in the Chapter 4 (section 3 and Table 4.1) were used. Using the Wischmeier and Smith (1978) erodibility nomograph (Figure 7.2), values of K were derived for the bare soil category.

For both the vegetated and exposed peat soils the erodibility nomograph is far from satisfactory, since both have higher organic matter contents than the 4% allowed for in the graph. Considerable thought was given to this problem, and as mentioned in the previous section 7.2, only one study was found in which the USLE model had been applied to areas of peat or peaty soils. The Moel Famau study of Baker et al (1979), suggested that a figure of k = 1 might be appropriate (they justified this by reference to Schwab et al 1966). The problems involved in assessing a suitable K value for peat soils hinge one the



Notes:

a. Sand taken as particles with diameter 0.1 to 2.0mm

b. Key to structural classes

1 Very fine granular
2 Fine granular
3 Medium or coarse granular
4 Blocky, platy or massive

c. Key to permeability classes

1 Rapid
2 Moderate to rapid
3 Moderate
4 Slow to moderate
5 Slow
6 Very slow

Source: *Wischmeier et al. (1971).*

Figure 7.2 Nomograph for estimation of soil erodibility (K) excessive variability in the properties of peat, with organic matter contents up to 90% or more. When dried out, peat loses cohesion becomes very friable and hydrophobic and hence will not rewet. In addition, degrees of humification of peat varies depending on the horizons (Soil Survey Field Handbook 1974). For example, Peat horizon, of, composed mainly of fibrous peat; Om, composed mainly of semi-fibrous peat; Oh, thorganic fraction is mainly amorphous; and Ohh, matter occuring as black (when dry) and rewets very slowly after drying. Thus, the bulk density of peat on Glaisdale Moor will vary both with moisture content and degree of humification, these factors will also influence the erodibility of the peat and peaty soil. For example, two samples collected from Glaisdale Moor - give bulk densities of 0.09 g/cm³ for dry burnt peat and 0.13 g/cm³ for moist humified peat, whilst Maltby (1980), quoted 0.2 g/cm³ for moist, humified peat. The burnt pear with its hydrophobic low bulk density, non cohesive particles was considered to be extremely erodible and in all probability much more so than any mineral soil. On this assumption a decision had to be made on the K value to be allocated to the bare peat material. The maximum value that could be given to the K factor was 1 (Wischmeier and Smith 1978). The highest K value found in the literature was 0.61 for marls in Tunisia (Armstrong et al 1980). Because of the extreme susceptibility of burnt peat to erosion, it was finally decided to allocate the maximum value of 1 for the K factor. The vegetated peat on the other hand is massive and strongly bound by soil water and highly organic and hence it is suggested, of very low erodibility, these soils were therefore allocated a K value of 0.01. The actual value of K used in each grid square was derived assessing the proportional value appropriate to the areal extent of each vegetation type within the square (see 7.3.2).

Slope length (L) and gradient (S) were derived for each grid square from a 1:10 000 scale topographic map with a 5 m contour interval. Slope length was measured directly from the map, whilst the slope gradient was calculated using the following formula:

$$\tan \theta = \frac{\text{vertical height}}{\text{horizontal distance}} \quad \text{(estimated from contours)}$$

The results were then transformed to percentage slope using Wischmeier and Smith's (1978) slope-effect chart (see Appendix 9) to coincide with the USLE LS factor, (see figure 7.3). Values for LS ranged from 0.22 - 14.0 with a mean of 1.27.

The cover and management factor (C) of the USLE is the ratio of soil loss from land covered under specific vegetation to the corresponding loss from a clean-tilled, continuous fallow. Glaisdale Moor is mainly a mixture of pasture and moorland; the characteristics of which are similar to those described by Wischmeier and Smith (1978) for pasture, range and idle land. Applying the Wischmeier and Smith criteria to Glaisdale Moor the following C factor values were obtained:

	C value
Bare soil and peat $\leq$9% cover	1.00
10-39% vegetation cover	0.45
40-79% vegetation cover	0.11
$\geq$80% vegetation cover	0.01

The appropriate C value was determined for each grid square by using a transparent overlay in which each grid square was subdivided into 100

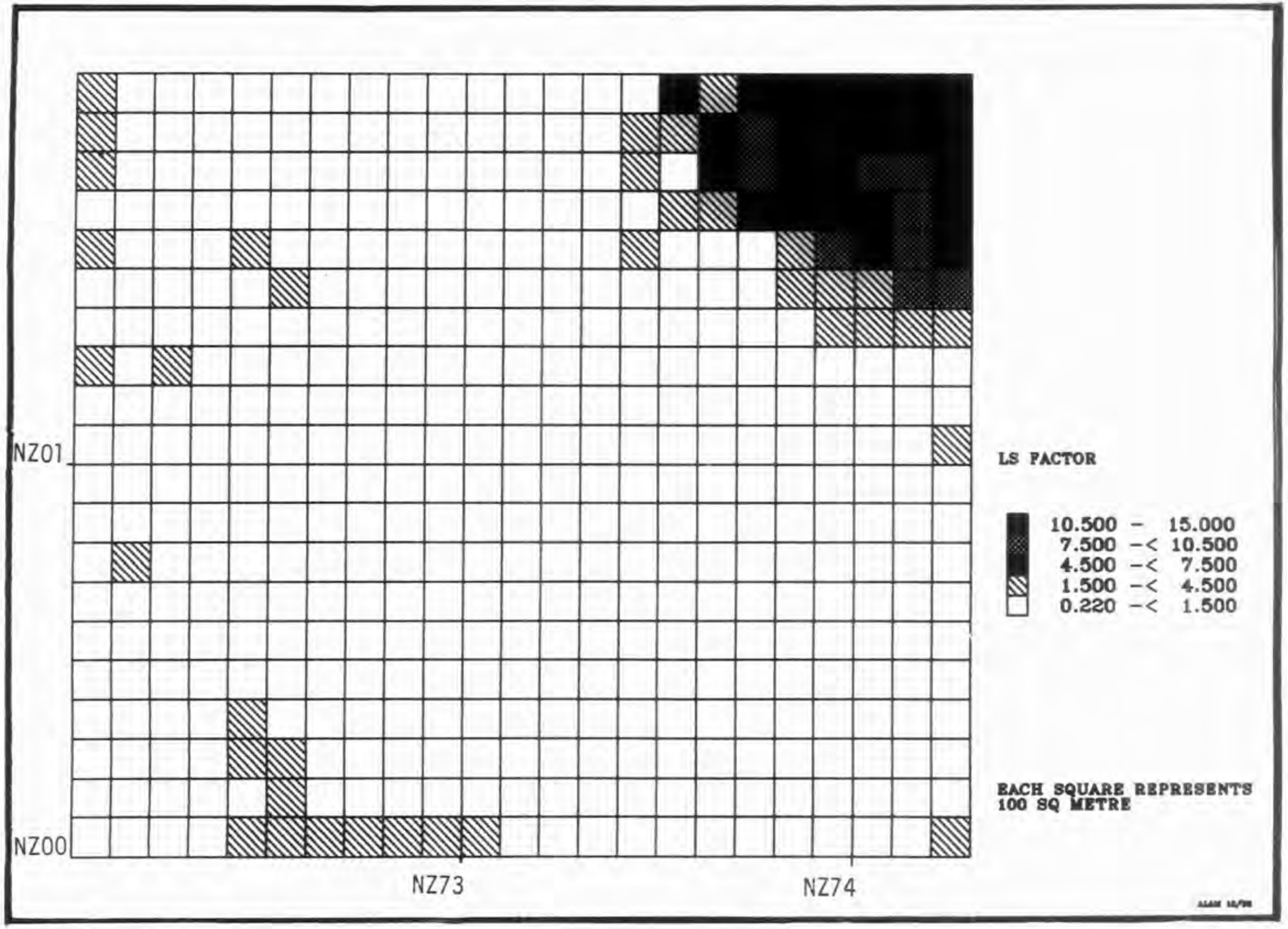


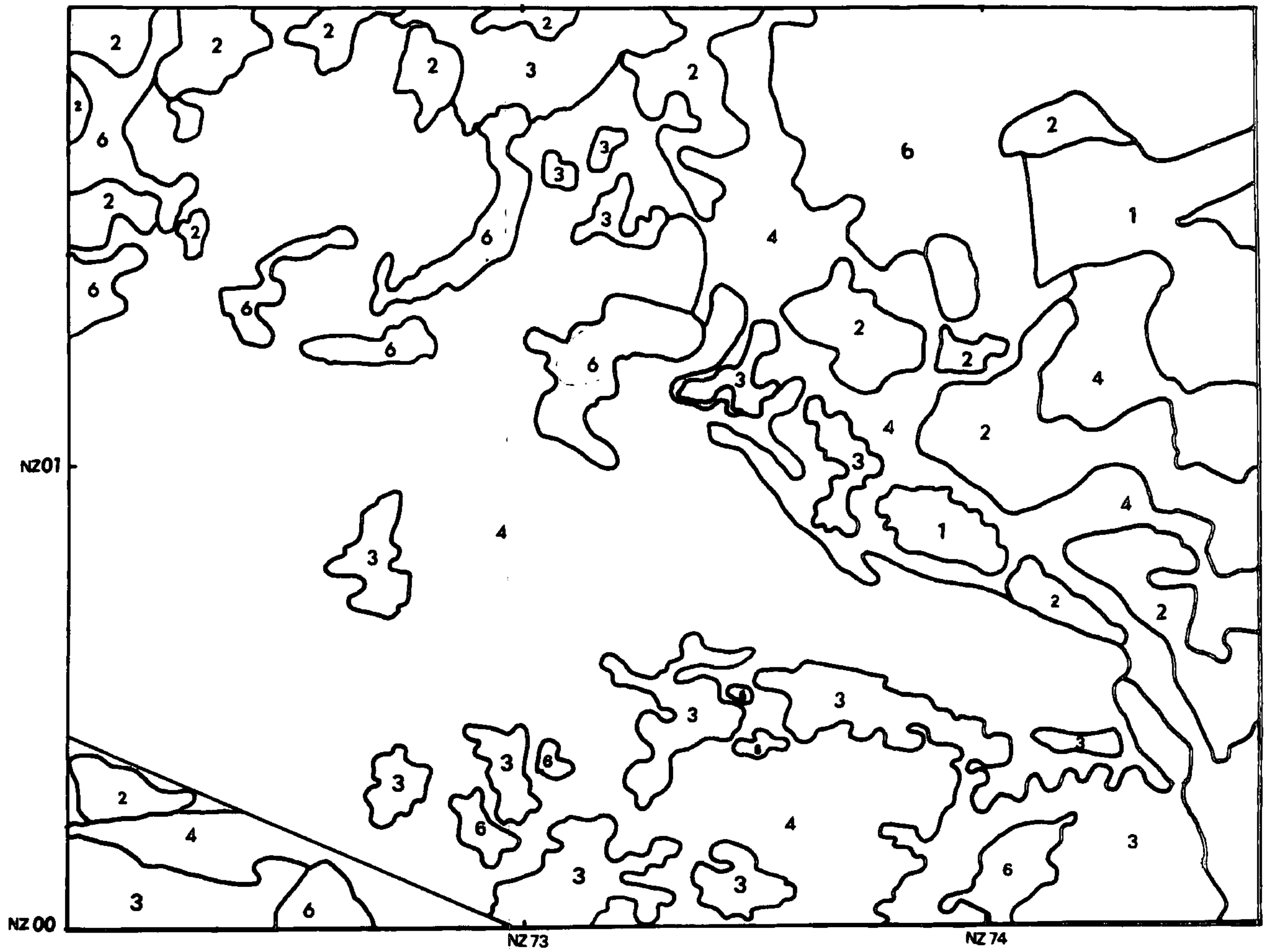
Figure 7.3 Topographic factor, LS, of Glaisdale Moor

cells. This overlay was placed over all the surface vegetation cover maps (aerial photo, Landsat TM and simulated SPOT based) and the percentage vegetation cover and its appropriate C value was determined for each of the cells. From this a weighted mean C value was obtained for each grid square. Since no complete grid square coincided with either an entire area of bare peat or bare soil, the maximum C factor for any square was 0.45, rather than the theoretical maximum of 1 for each category. Figure 7.5 shows the resultant map of the C values for the Moor.

For the conservation management factor (P) consideration was given to the problem of relating the values derived from agricultural produces to uncultivated moorland. It was finally decided that since no conservation measures are taken then a factor value of 1 should be used. A similar assumption was made by Baker et al (1979) in their study at Moel Famau.

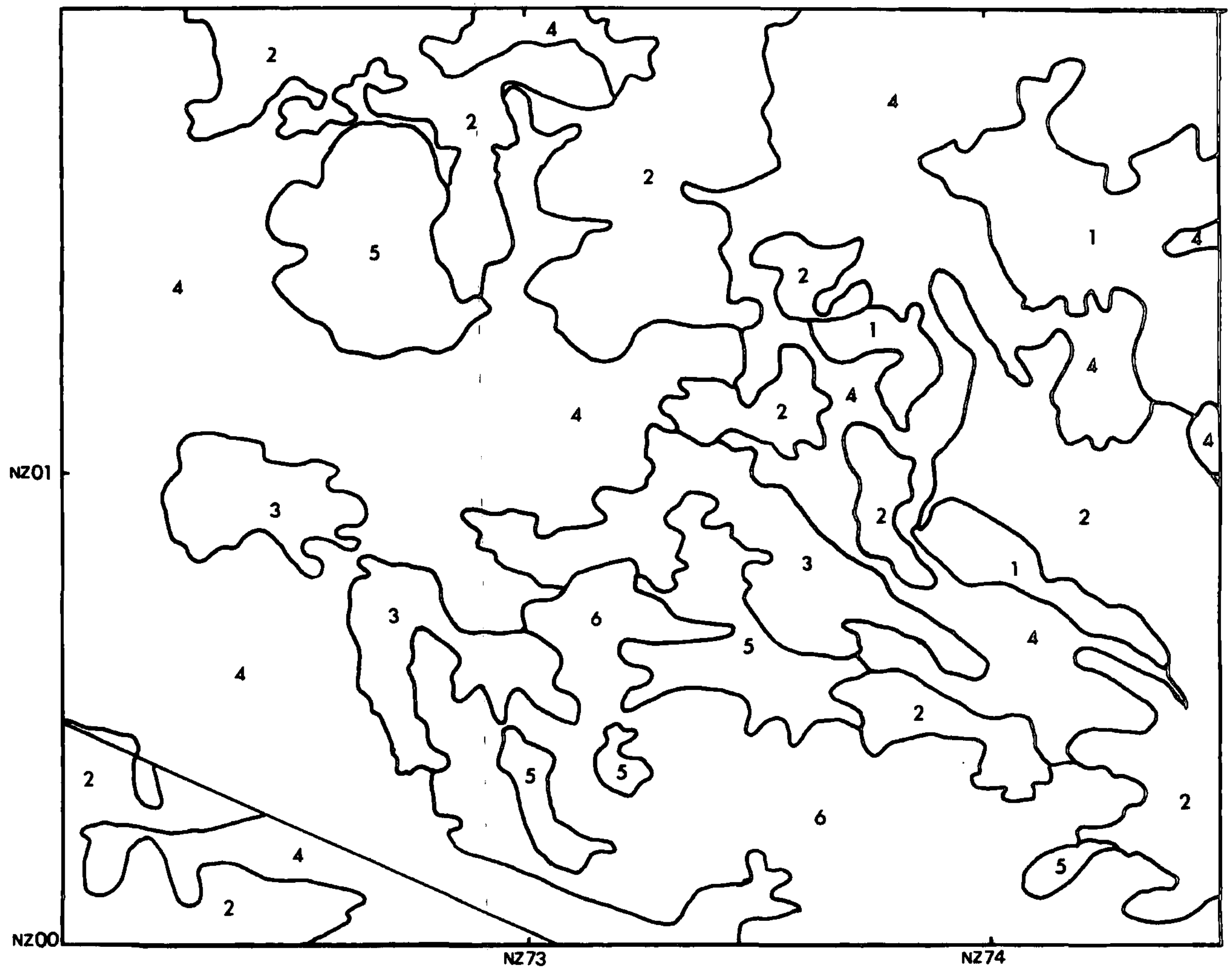
Using the indices listed above, a number of estimates of erosion were obtained by applying the USLE to different spatial units within the Moor.

For all estimates of soil loss, a constant value of R = 57.3 and P = 1 were used. Depending on the scale at which the USLE was applied, the values of the remaining factors, K, C and LS were changes. At the most detailed level, soil loss was estimated for each of the 460 grid squares using the appropriate values of K, C, and LS determined separately for each square, (see Figure 7.6 and Table 7.3). At a smaller scale, an estimate of soil loss was calculated for each of the



Key: 1 Vegetation, more than 80% cover
2 Vegetation, 40-80% cover
3 Vegetation, 10-<40% cover
4 Dry exposed peat with <10% vegetation cover
5 Wet exposed peat with <10% vegetation cover
6 Bare soil with <10% vegetation cover

Figure 7.4a Land cover map of Glaisdale Moor based on Landsat Thematic Mapper image, April 1984.



Key: 1 Vegetation, more than 80% cover
2 Vegetation, 40-80% cover
3 Vegetation, 10-<40% cover
4 Dry exposed peat with <10% vegetation cover
5 Wet exposed peat with <10% vegetation cover
6 Bare soil with <10% vegetation cover

Figure 7.4b Land cover map of Glaisdale Moor based on SPOT simulation image, July 1984.

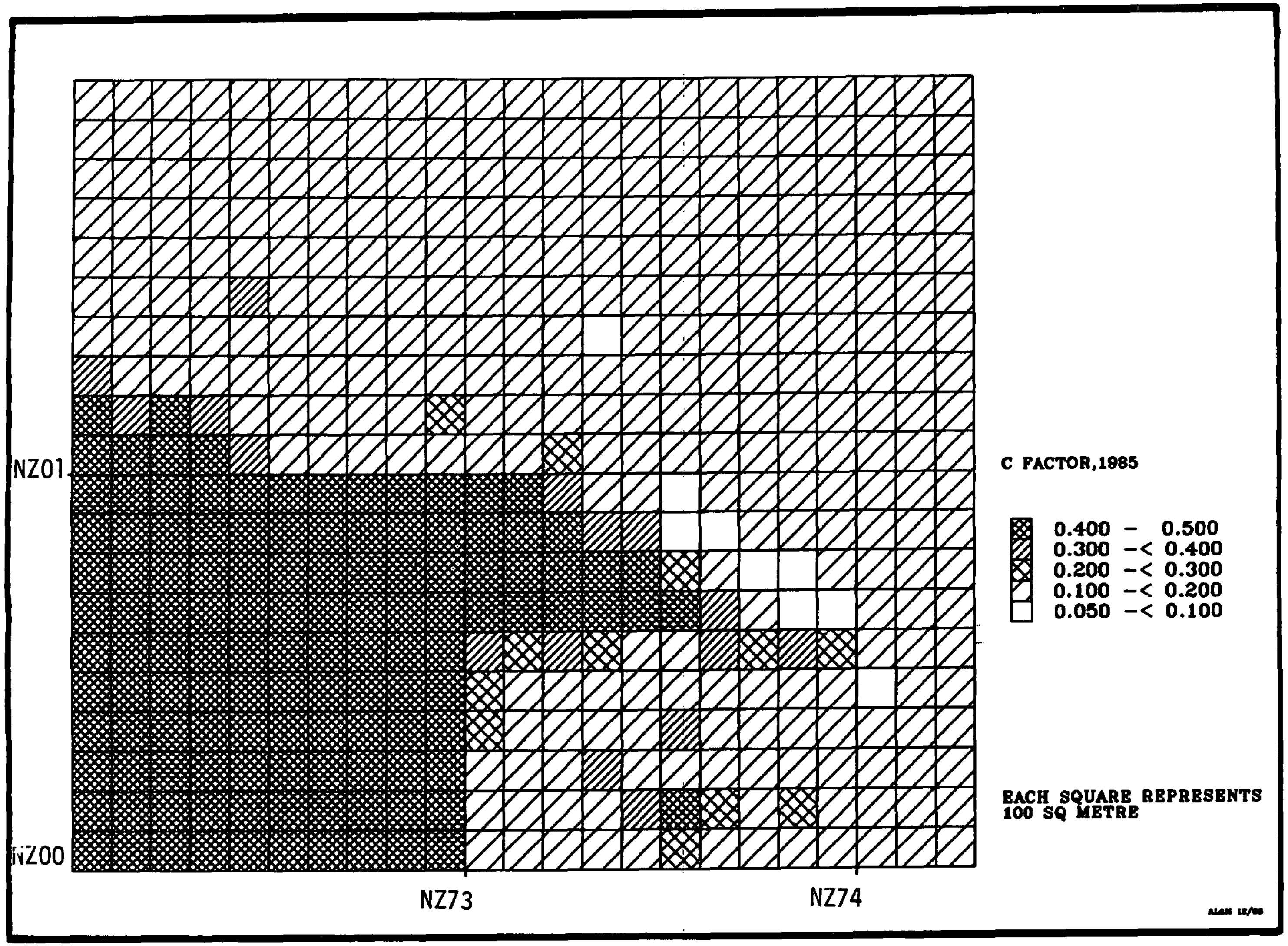


Figure 7.5a Land cover and management factor, C, of Glaisdale Moor based on aerial photograph, 1985

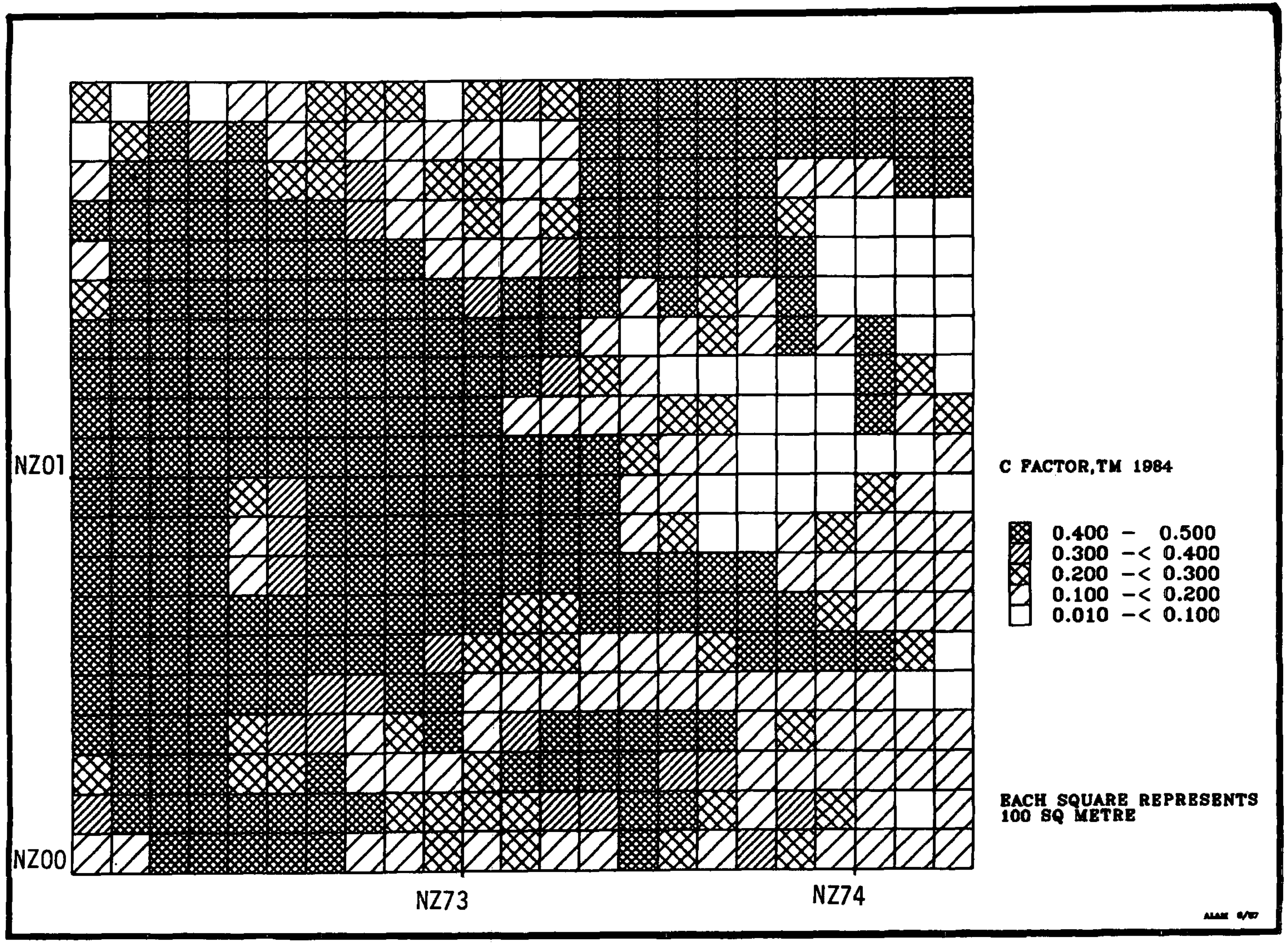


Figure 7.5b Land cover and management factor, C, of Glaisdale Moor based on Landsat Thematic Mapper image, 1984

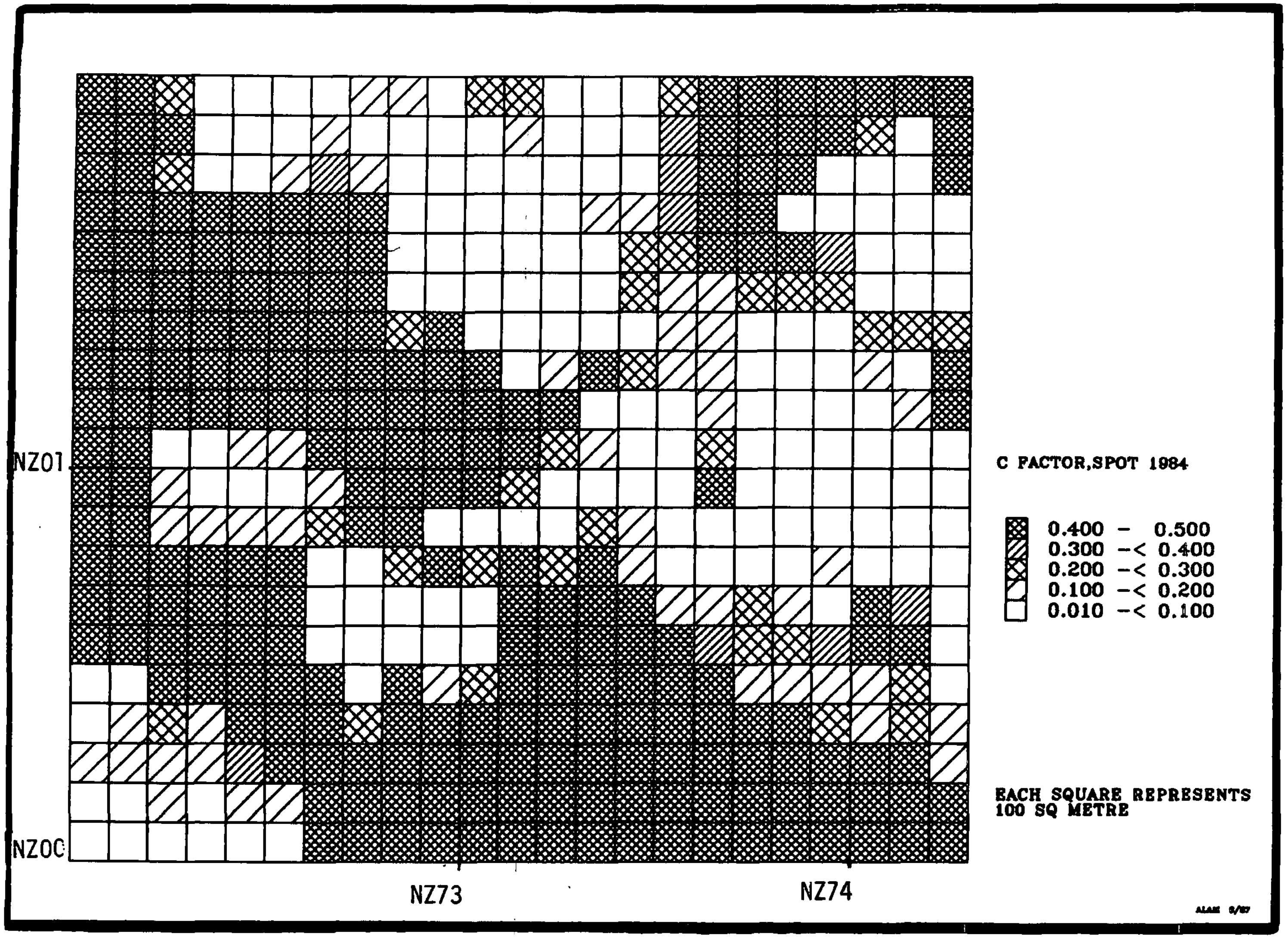


Figure 7.5c Land cover and management factor, C, of Glaisdale Moor based on SPOT simulation image, 1984

three surface types by using the mean K, C and LS values appropriate to each surface, (for vegetation K = 0.01, C = 0.08 and LS = 1.27; for bare peat K = 1, C = 1 and LS = 1.27; and for bare soil K = 0.112, C = 1 and LS = 1.27), (see table 7.3).

7.4 Results and Discussion

7.4.1 Predicted soil loss using data derived from air photos

The results of the estimation of annual rates of soil loss from Glaisdale Moor are presented in Table 7.3. At the grid square level, figure 7.6 shows that the predicted erosion rates vary considerably across the Moor. These differences are largely attributable to the variability in the vegetation cover (C factor) and soil erodibility (K factor). When tested by means of the analysis of variance, these differences were found to be very significant (Table 7.4). The erosion rates also vary considerably within each of the three surface classes, with bare peat having the greatest range (11.3 - 261.2 t ha^{-1}), vegetated area the least (0.02 - 9.5 t ha^{-1}) and bare soil the intermediate (0.5 - 3.8 t ha^{-1}). The extensive differences in the rates of peat erosion are believed to be due to variation in:- a) levels and stages of peat accumulation, b) the degree and intensity of humification, c) the nature and extent of burning (and hence the effect of the C factor), d) the local hydrological conditions and e) the variability in the LS factor. The LS factor is thought to be largely responsible for the range of erosion rates in both the vegetated and bare soil areas, although in the latter areas differences in the organic matter content of the soil effected the values of the C factor. Using the mean estimated soil loss figure derived from the

Table 7.3 Predicted soil loss from Glaisdale Moor

Cover type	Area	Estimated soil loss t ha yr^{-1}			Grand Mean
		Minimum	Maximum	Mean	
Grid Square*					
Vegetation	287	0.025	9.51	0.4	
Bare peat	140	11.31	261.13	44.7	15.4
Bare soil	33	0.04	3.83	1.1	
Areal data					
Vegetation	287			0.1	
Bare peat	140			163.0	60.5
Bare soil	33			19.5	

* for these calculations individual grid squares were allocated to one of the three vegetation types according to the dominant vegetation type -n each square.

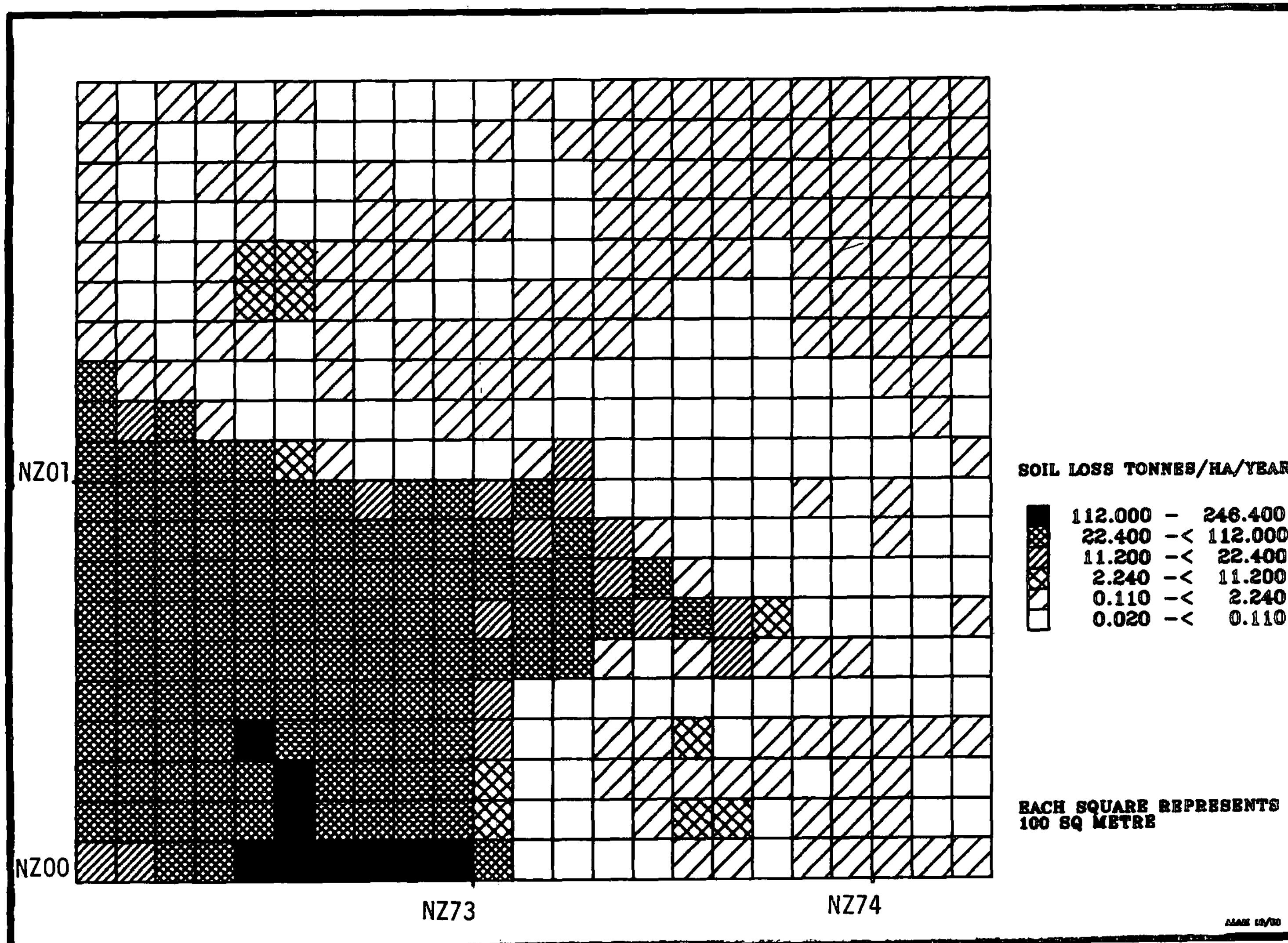


Figure 7.6a Predicted erosion pattern of Glaisdale Moor. C factor was derived from aerial photographs, 1985.

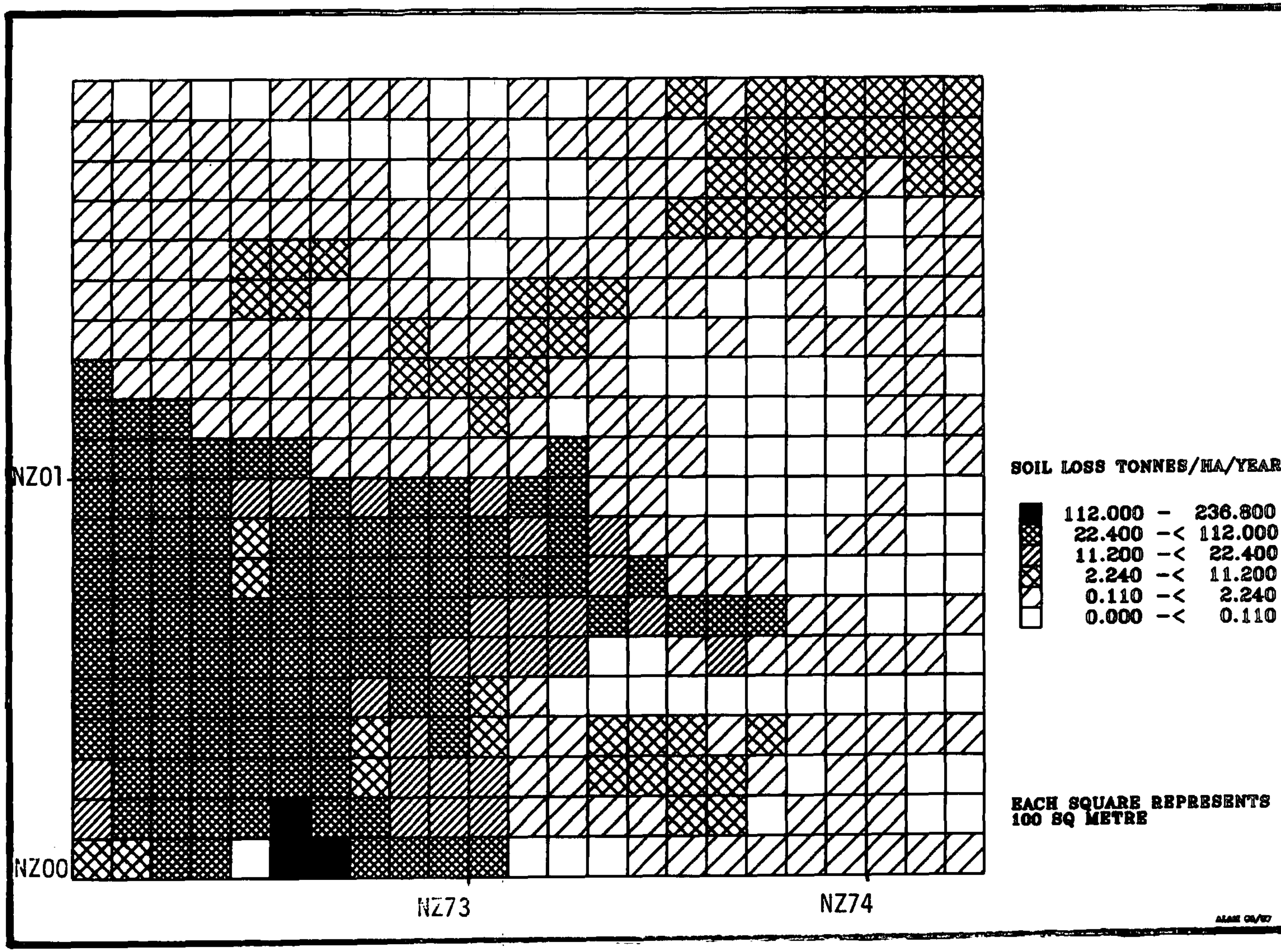


Figure 7.6b Predicted erosion pattern of Glaisdale Moor. C factor was derived from Landsat Thematic Mapper image, 1984.

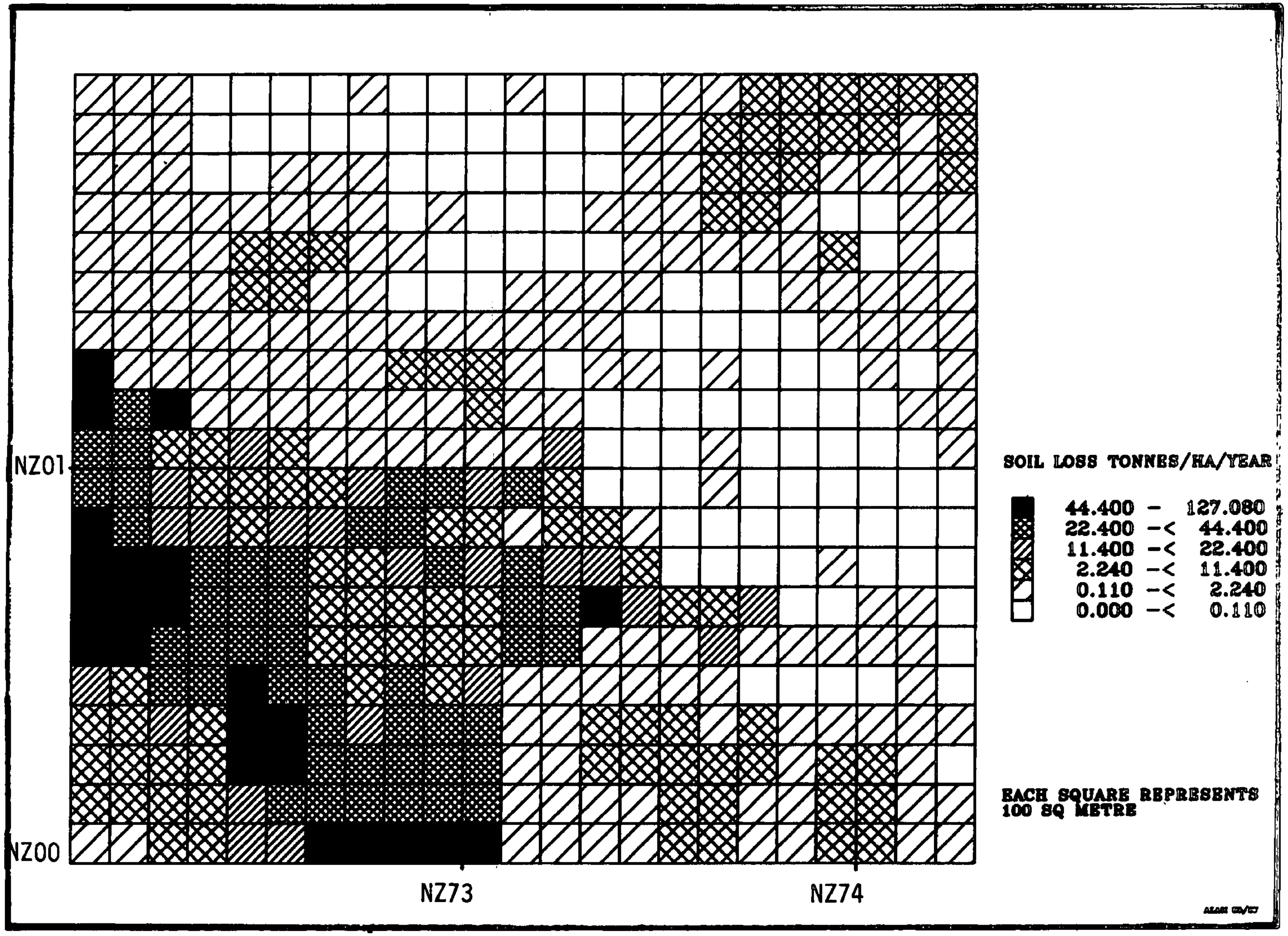


Figure 7.6c Predicted erosion pattern of Glaisdale Moor. C factor was derived from SPOT simulation image, 1984.

Table 7.4 Analysis of Variance to test the significance of the variability in soil loss derived from grid square data between vegetated, bare peat and bare soil surfaces

Source	Degrees of freedom	Sum of squares	Mean square	F Statistic	Significance at α =
Between	2	15358	7678.9	226.53	0.0001
Within	457	15491	33.898		
Total	459	30849			

grid square data and the estimated area of each surface class (Table 7.3), an overall estimate 6410 t yr^{-1} was calculated as the annual rate of soil loss from Glaisdale Moor. A crude estimate of the mean annual rate of erosion for the whole Moor can be obtained by taking, the average of the rates determined for each of the three surface types, (15.5 t ha^{-1}), this gives an annual rate of soil loss of 7084 t/yr^{-1}.

At a lower level of resolution, the predicted mean soil loss for the three surface types was estimated by using the areal mean rather than the grid data, (ie. C = 1 for both bare peat and bare soil; K = 1 and 0.12 for bare peat and bare soil respectively; C = 0.08 and K = 0.01 for vegetated surface soil and LS = 1.27 for all three surface types). This produced estimated soil loss figures of 0.13, 163.0 and 19.5 t ha/yr^{-1} for vegetated, bare peat and bare soil surfaces respectively. When these figures are applied proportionately to the area of each surface class within the confines of the Moor, and annual estimate of soil loss of 23,500 t yr^{-1} is obtained. This is almost four times the estimate derived using the grid square data.

This major discrepancy between the two estimates of the rate of annual soil loss from the Moor, is attributable to the massive differences in the mean erosion rates predicted from the areas of bare peat and the bare soil areas (44.7 and 1.1 t ha yr^{-1} and 163 and 19.5 t ha yr^{-1} respectively for the grid square and areal data). The cause of this difference lies in the fact that in no instance did any of the grid squares coincide with either a complete area of bare peat or bare soil. Thus in determining the proportional C and K factors for each square the highest C factor value used was 0.45 and the highest K factor value 0.9, as compared with a maximum of 1 for both C and K used in the areal calculation. Variation in the LS factor values were not considered important as the greatest variability in slope occurred in the vegetated areas. These differences also explain the contrast in the crude estimates of mean erosion calculated by averaging the rates for the three cover types, 15.5 and 60.5 t ha yr^{-1} for grid and areal data respectively.

These differences at once emphasise both the strengths and weaknesses of using a randomly imposed grid as a basis for the determination of the land cover factors of the USLE model. The detailed grid allows local variations in K, C, and LS to be incorporated in the model, but unless a complete grid square coincides with an area having the highest factor values, then an underestimate of the likely annual rate of erosion is an inevitable result. In the case of Glaisdale Moor, the actual annual loss of soil is somewhere between two extremes of 23,500 and 6410 t yr^{-1}.

As an attempt to provide an approximate check of the validity of predicted erosion rate for the Moor, and on particular the burnt peat area. The approximate loss of burnt peat was estimated using bulk density value 0.09 g/cm^3 (see section 7.3.3). Assuming an equal bulk density for a 20cm and 100cm depth of peat, estimated loss of burnt peat was 20.5 t/ha/yr and 102.5 t/ha/yr respectively. These depths of peat are not unrealistic because in certain places in excess of 2m of peat is thought to have been lost since the 1976 fire. These crude estimated figures of peat loss suggest that the mean predicted peat loss figures of 44.7 t/ha/yr and 163.0 t/ha/yr (see Table 7.3) are at least of the right order of magnitude.

7.4.2 Predicted soil loss using data from Landsat and SPOT simulation imagery

At the detailed grid square level, the mean estimated erosion rate obtained for the Glaisdale Moor using the Landsat TM and SPOT simulation data was 11.55 t ha yr^{-1} and 9.12 t ha yr^{-1} respectively. The estimated mean erosion rate obtained from 1985 air photographs with the similar grid square level was 15.5 t ha yr^{-1}. The estimated mean erosion rate from these three sources; air photographs, TM and SPOT simulation, therefore, seems reasonably comparable. The differences in mean estimation of the TM and SPOT simulation was possibly in part due to the differences of the timing of imagery acquisition. The TM imagery was obtained in April, 1984 when the bare soil to surface vegetation ratio remains much higher. While the SPOT data obtained at July, 1984, when, because of regeneration of marginal vegetation, the bare soil to surface vegetation ratio remains lower. Thus, the measured C value derived from the two imagery systems differ.

Further, the spatial resolution of the two imagery, TM and simulated SPOT, differs considerably, 30m and 20m respectively. With the intricate vegetation assemblages, interwoven with partially or completely burnt stems and litter, together with patchy bare soil enhancing the complexity of Glaisdale Moor surface cover. The 10m difference in spatial resolution between the two systems (TM and SPOT) appears to have had a significant effect on soil loss prediction. For such a complex feature type, 20m spatial resolution normally increase the pixel variance in feature space and thereby, possibility of misclassification among the classes increases (Townshend, 1981).

The TM data with its higher spectral resolution and with an extended spectral coverage was expected to be more effective in separating the cover types. These spectral resolution and coverage effect may have possibly contributed to the overall classification accuracy of the TM (95%) and SPOT (78%), and hence the difference in C values, (TM had a mean C value of 0.31 and SPOT a mean C value of 0.26). It is this apparently little difference in C value that has resulted in the difference in the estimated erosion rate of the two data sources.

7.4.3 Relationship between predicted rates of erosion and surface drainage density

Strong links between erosion and land use changes emerge when comparison is made between the 1985 drainage density (Figure 3.3, Chapter 3) and the erosion intensity maps (Figure 7.6). The areas of greatest erosion correspond with areas of highest drainage density. Thus, drainage density may be viewed as a crude index of the severity of erosion (Morgan, 1986) in Glaisdale Moor. With the highest potential erosion rate, the exposed peat area corresponds with the area of highest drainage density (Table 7.5). Similar relationships are apparent with the vegetated (lowest erosion - drainage density rate) and bare soil (intermediate erosion - drainage density rate) areas. Similar observations of soil and vegetation cover influencing in drainage density and erosion rate at micro-level are made by Gregory and Gardiner (1975) and Morgan (1973).

7.4.4. Comparison of predicted erosion rates from Glaisdale Moor with other studies in similar environments in Britain

Table 7.5 Comparison of drainage density and corresponding erosion intensity rate in Glaisdale Moor. Estimation is based on at the grid square level.

Surface type	Drainage density (m/m^2)	Erosion rate ($t\ ha\ yr^{-1}$)
Exposed peat	3.44	>22.4
Bare soil	2.78	<11.4
Vegetation	2.42	<2.24

Apart from the nationwide small scale survey conducted by Morgan (1980), the only other report that was found in which the USLE model has been applied to erosion in an upland environment is that by Baker _et al_ (1979) for Moel Famau Country Park. This gave a range of predicted soil loss from less than 4 t ha yr^{-1} to more than 14 t ha yr^{-1}, a range of values similar to those obtained for the vegetated and bare soil areas of Glaisdale Moor. Unfortunately the Moel Famau study did not include any areas of bare peat which could be compared with similar areas of Glaisdale Moor. In order to obtain some comparative figures for peat erosion, the results of conventional erosion studies carried out in upland environments similar to Glaisdale Moor were examined. The results of these studies, based mainly on sediment traps and erosion pins, are listed in Table 7.6.

Table 7.6 Comparative rates of soil erosion from upland Britain

Author	Year	Location	Yield ($t\ ha\ yr^{-1}$)
Al-Ansari *et al*	1977	Hill grazing land, Scotland	2-9
Baker *et al*	1979	Moel Famau, Clwyd	4-14
Evans	1977	Peak District	34.0
Imeson	1971	Hodge Beck, NYM	4.8
Morgan	1980	Britain	0.1

The Imeson (1971) and Al-Ansari et al (1977) results (4.8 and 2-9 t ha yr^{-1}), whilst comparable with the predicted rate of loss from bare soil areas of Glaisdale (1.1 - 19.5 t ha yr^{-1} grid and areal data), are much lower than the predicted figure obtained for the loss from bare peat. The mean predicted peat loss figure from the grid data for Glaisdale (44.7 t ha yr^{-1}), is very close to 34.0 t ha yr^{-1} recorded by Evans (1977) in the south Pennines. (The mean figures derived using the areal data (163 t ha yr^{-1}) is however much greater than Evans 34.0 t ha yr^{-1}, this can be explained by the fact that the peat studied by Evans had not been burnt and therefore had a much lower erodibility potential. For the well vegetated areas of the Moor the predicted loss (0.13 - 0.4 t ha yr^{-1}) is similar to the figure quoted by Morgan (1980) for the geological rate of erosion in the UK. The predicted overall mean erosion rate for Glaisdale calculated using either the grid square or areal data (15.4 and 60.5 t ha yr^{-1}), is considerably higher than the measured rates obtained by both Al-Ansari et al (1977) and Imeson (1971). The difference between Imeson's figure and the predicted Glaisdale figure is worthy of closer examination since the Imeson measurements were made in the Hodge Beck catchment which is very close to Glaisdale Moor. The divergence of the erosion rates can be attributed to major differences in the surface properties of the two areas, Hodge Beck catchment having a much smaller area of bare peat and larger area of bare soil than Glaisdale Moor.

Obviously, given the assumptions made for the USLE parameters, further work needs to be undertaken to test the predicted results with actual rates of erosion. Such an investigation could be tackled in a number of ways. Firstly, regular measurement of stream sediment loads. Work done along this line by Arnett (1978), however suggests that this approach has two serious shortcomings. a) All sediment moved downslope does not necessarily reach the stream; b) There is a time by between the movement of sediment on the slope and the final entry into stream. Because of these two problems, it is difficult to relate directly between hill side erosion rate and the sediment movements through the channel. Therefore, for the present study this method may not yield a reliable estimate of erosion rates. Secondly, estimates of erosion rate could be derived from aerial photographs by measuring the spread of bare soils or gullying over a lapse of years. This technique however would require an initial record of the depth of peat cover, something which it is not possible to estimate from air photographs. Nevertheless this probably offers the best long term method of assessing erosion rates, provided that a network of measuring stations is established, at which changes in peat depths can be monitored. The simplest approach would be to sink permanent measuring rods into the soil beneath the peat.

7.5 Conclusion

This research has demonstrated that, by using remote sensing imagery and available large scale topographic maps, prediction of soil loss can to some extent be made with a limited amount of field work. Whilst the author believes that the soil loss prediction for bare soil is realistic since all USLE parameters, particularly erodibility factor, K fall within the scope of Wischmeier and Smith's (1978) model. The soil loss values for both vegetated and burnt pear are less reliable since an arbitrary, but it is felt justifiable, assumption has been made in allocating a value for the erodibility factor, K.

By employing a grid square recording/mapping technique the maximum use is made of the available information. The size of the grid used does however effect the final estimate of soil loss, particularly where no single grid square coincides with an area of entirely similar cover of all vegetation/surface types.

Thus, this approach, which appears to require a minimum of field work, may offer a technique for rapid appraisal of areas susceptible to erosion and may also enable some assessment of the likely rates of erosion to be made. Both of which will be useful for preparing management plans for these relatively remote upland areas. This is especially valuable given the very limited budgets available to the appropriate planning authorities, such as the North York Moor National Park Authority.

Finally however, it is important to re-emphasize that, given the subjective nature of some of the assumptions made in the calculations of predicted soil loss. Too much reliance must not be placed on the exact soil loss figures determined, rather they should be taken as a first approximation, until further refinement of the assessment of the USLE parameters, particularly the erodibility of peat is made.

CHAPTER EIGHT

Conclusion

8.1 Introduction

8.2 Analyses Summary

8.3 General Conclusion

8.1 Introduction

This thesis has analysed sequential air photographs, ground radiometry, Landsat Thematic Mapper and Airborne SPOT data of the Glaisdale Moor area with a view to examining the potential of remote sensing in soil erosion studies. A series of statistical analyses were attempted in an effort to establish the relationships between the different spectral variables and the soil/ground variables. Because of the complexity of the surface types, it was expected that spectral characteristics of Glaisdale Moor would be more dominated by a composite of soil/ground variables rather than any single variable.

Discrimination of the Glaisdale Moor surface types has been attempted using the Landsat TM, airborne SPOT, sequential airphotographs and field radiometer data. Further, the Landsat TM, airborne SPOT and the aerial photographs were analysed in order to classify and map the surface types of the study area. The mapping information thus obtained from the TM, SPOT and aerial photographs were used as an input into a soil loss prediction model (USLE) to predict the soil erosion rate of the study area.

8.2 Analyses summary

The analysis using the aerial photographs of the Glaisdale Moor suggest that:

The surface cover of the Glaisdale moor has suffered a phenomenal change between 1973 and 1985. The accidental fire of August, 1976 left much of the blanket peat area completely exposed and thereafter the whole area came under immediate threat of extensive erosion and degradation.

Because of the lack of surface cover, the overall drainage density of Glaisdale Moor has increased dramatically from 1.28 m/m^2 in 1973 to 3.08 m/m^2 in 1985. A significant difference was observed in the mean drainage density rate depending on the intensity of surface cover as well as subsurface pedological condition, the highest rate being 3.44 m/m^2 for the bare blanket peat, the lowest being 2.42 m/m^2 for the vegetated area, with bare soil being the intermediate at 2.78 m/m^2.

The pedological and topographic diversity mainly dictates the erosion features of Glaisdale Moor. Extensive rilling and to some extent localised gullying were the most important erosion features of the Moor.

The analysis using the ground radiometer suggest that the three distinct surface types of Glaisdale Moor vegetation, peat and bare soils, as identified in the field do exhibit distinctive reflectance spectra.

Although the spectral variables were statistically correlated with selected ground properties, the relationships, however, are neither simple nor direct. Within the limited 1 m field-of-view of the sensors indicates that no one ground property is dominant in determining the reflectance spectra. Because of the high spatial resolution of the ground radiometer (1m) it was expected to resolve the internal heterogeneity of the main cover types studied. This was manifest in the spectral variance determined for each cover type. However, there was a wavelength dependancy in the relationship, with the infrared bands exhibiting a greater variation compared with the visible exhibiting a greater variation compared with the visible wavebands.

The high spectral variability measured by the radiometer resulted in a greater overlap between cover types in spectral feature space. A decrease in spectral separability results in a lower classification accuracy. The MSS bandpass equivalents as measured by the radiometer were only marginally successful (i.e. overall classification accuracy = 61%) in discriminating between bare peat, vegetated peat, and bare mineral soils.

As with the field radiometer, both bivariate and multivariate analyses of the simulated SPOT data for the Moor suggested that no single ground variable can be said to have dominance over others in terms of accountable spectral variation. The ground variables in a group can better explain the spectral variation, the highest being 58% for the May and 68% for the July data. Such a comparison of accountable spectral variation, however, should be treated with caution given the fact the images were not calibrated to some common reference and some of the ground variables considered (e.g. soil moisture) are dynamic phenomena.

The overall classification accuracies achieved for the three surface types of the Glaisdale Moor are 74.1% for the May simulated SPOT data and 78.3% for the July equivalent. The difference between the figure may be attributed to the contrasting spatial resolution between the two data sets (20 m for the May and 10 m for the July data). Changes in classification accuracy with spatial resolution arise from two conflicting trends (Townshend 1981). First, the variance of the spectral response with decrease with an increase in spatial resolution which should help to improve classification accuracy. The degree of improvement will be controlled by the nature of the spatial heterogeneity within a given cover type. Second, the proportion of boundary pixels will increase with coarsening resolution and this will lead to lower classification accuracies. These conflicting trends are controlled primarily by the spatial properties of the cover types being observed. Cover types with high boundary densities, as in the case of Glaisdale Moor would suggest that the coarser spatial resolution data might contain a greater number of boundary pixels. Sampling the higher spatial resolution data is more likely to result in pixels falling within individual cover types and not on their boundaries. Decreasing the spatial resolution to 20m may have resulted in more boundary pixels being sampled, with each pixel containing a mixed response from the two or possibly three cover types. Assigning these mixed or boundary pixels to particular classes have led to the increased errors arising during the classification process. Mixed pixels labelled as one class during their selection may be classified as another thereby giving rise to higher errors of omission.

Differences in the figures for overall classification accuracy may also reflect a change in the spectral contrast between the cover types over the May to July time period. Vegetation cover over the peat was likely to be greater in July compared with May. Spectral differences between vegetated peat and bare peat would be increased as a direct result. Examination of the classification confusion matrix (Table 5.6) indicated that the vegetation class was classified with a higher accuracy in July compared with May, and that errors or omission between the vegetation and peat classes decreased by over 15%.

The recult of the imagery analyses implied that although the increased spatial resolution of the SPOT was sufficient enough to expose the details of Glaisdale Moor, because of the very minute detail of the spectral variation, it was difficult to map clearly the eroded surface. The enhanced image whilst making the identification of the broad surface types more straight forward, failed to increase the accuracy of the classification. Interpretation of the False colour Composite indicates that exposed peat would be recognised with ease, although some difficulty remains in separating dry peat from bare soil. A band ratio 3/2 (near infrared/red) was useful in delimiting the blanket exposed peat from the bare soil and vegetation. An interpretation of the maximum likelihood result suggests that broad categories : vegetation, peat and bare soils are separable although in few cases misclassification between vegetation and peat might occur. The FCC's, the ratio image and maximum likelihood classification map provided a very general guide to the spatial distribution of the main cover types. However, the interpretation and comparisons should only be considered as subjective.

As far as moorland erosion is concerned it appears that the simulated SPOT data is less satisfactory for the clear identification and accurate delimitation of the eroded area, more specifically the separation of bare blanket peat from vegetation. Apparently, it seems that for a successful identification and discrimination of bare peat from vegetation of moorland, such as the Glaisdale Moor, the SPOT system needs:

a) More integration of spectral information within the spectral class so that internal variations remain at minimum, which would enhance the class variation and hence improve the classification accuracy;

b) More spectral bands at the longer wavelength, such as the Landsat TM band 5 and 7, are essential. The present SPOT wavebands 1 and 2 provide almost similar information. Therefore, one of them is effectively redundant. The increased number of spectral bands would increase the possible number of band combinations that might help in better identification and delimitation of blanket peat and hence would reduce the misclassification between bare peat and vegetation.

Analyses of the Landsat Thematic Mapper data suggests that this is the most useful imagery in the identification of vegetation types on Glaisdale Moor. The TM bands were better correlated than either the radiometer or SPOT imagery with the grouped ground data. Amongst others, the soil moisture, organic matter and surface silt were significantly correlated with most of the TM bands. Because of dynamic nature of soil moisture, the significance of correlation must be treated with considerable caution. The relationship may only be valid, if we assume that moisture conditions in May 1985 were exactly the same as April 1984 when the images were acquired. For the effective surface type discrimination of Glaisdale Moor, the useful waveband combinations include at least one band from the visible, near infrared and middle infrared spectral regions. The near infrared band (TM 4) proved to be the most useful for discriminating the surface types. The blue band TM1 in combination with band 5 and 7 proved to be the most useful classifier, particularly for the peat and bare soil.

The TM spectral and spatial resolution was sufficient enough to expose the detail spectral class variation of the Glaisdale Moor but not too detailed to cause confusion. Because of spectral and spatial diversity of the surface types in the study area, different TM band combinations would be essential for effective delimitation of the major surface categories.

The overall classification accuracy achieved for the three surface types of Glaisdale Moor with the TM data was 95%. Because of coarser spatial resolution of the TM data (30m) incomparable with the SPOT simulated data (20m and 10m) an increase in the number of boundary pixels, thereby decrease in classification accuracy was expected. However, that trend may have been significantly offset by the improved spectral separability offset by the improved spectral separability of the cover types arising from the improved spectral resolution and coverage. It may be that the sampling process in selecting pixels from each cover type avoided many boundary pixels. The real determining factors for the increase in overall classification accuracy compared with the SPOT data sets remain undetermined.

The maximum likelihood classification was most useful in classifying the bare peat and moderate for the bare soil and least effective for the vegetation.

The most effective TM bands (1, 5 & 7) for the discrimination of Glaisdale Moor surface types are not available in either the SPOT or Landsat Multispectral Scanner (similar to ground radiometer as used here). Therefore, significant improvements may be expected in the ability to spectrally differentiate the open moorland surface types using TM data.

The generation of classification accuracy figures, classification maps from image processing, maps from aerial photographs, require some independent means for checking their corrections. Otherwise the validity of these results are thrown into doubt. The role of field work is particularly important in checking the interpretations from the aerial photographs and the classification of the imagery.

In the present study, extensive field work was done in checking 1985 aerial photointerpretation. In certain cases changes to boundaries were made, but the original interpretation remains largely unchanged. In only very few cases was it necessary to alter the attributed classes. This suggests the conventional aerial photointerpretation is a viable approach to mapping cover types in this area and that only a limited amount of field work was necessary to check the results. It also suggests that the results arising from a comparison of maps derived from the interpretation of aerial photographs for different dates can be viewed with some confidence.

The availability of aerial photographs and the high level of confidence attributed to their interpretation permits their use as a surrogate to field checking when interpreting the results from the airborne and satellite multispectral data sets. In their absence however, the role of field studies would assume a greater significance. In this study the interpretation of false colour composites, ratio and classified images for the simulated SPOT and the Landsat TM data sets were bakced up by comparisons with the aerial photointerpretations and a limited amount of field work. A similar methodology has been adopted in other studies to determine the accuracy of remote sensing data for classifying land cover types (e.g. Justice and Townshend 1981). Nevertheless, the results presented here should be treated with some caution. An independent check of the likely success of the various remote sensing data sets for classifying the main cover types is given with the results from the discriminant analysis. Whilst these figures are likely to overestimate the accuracies derived from a completely independent data set they do provide a guide as to the likely levels of misclassification between the main cover types found on Glaisdale Moor.

Given the limitation of the assumptions, particularly (relating to the derivations) the K factor, the prediction of soil erosion rate from Glaisdale Moor by using remote sensing and other collateral information as an input into the USLE model was reasonably achieved. The mean annual erosion rate obtained with 1985 aerial photographs for the vegetation, peat and bare soil was 15.4 t ha yr^{-1} and an overall estimate of the annual rate of soil loss from the Glaisdale Moor was 6410 t yr^{-1}. The mean annual erosion rate obtained at the grid square level using the Landsat TM and SPOT data was 11.55 t ha yr^{-1} and 9.12 t ha yr^{-1} respectively.

The estimated mean erosion rate based on Landsat TM (11.5 t ha yr^{-1}) is reasonably comparable with the rate obtained at the corresponding level from the aerial photographs (15.4 t h yr^{-1}), while the rate obtained with the SPOT simulation is marginally lower. The poor estimated erosion rate based on SPOT simulation is directly attributable to its low effectiveness in clearly separating the bare peat from the vegetation in comparison with the Landsat TM image.

Adoption of a grid square recording mapping technique has enabled the maximum use to be made of the available information. The size of the grid used however does affect the final estimate of soil loss. More specifically, problems arise when a grid square does not coincide with areas of uniform cover. A weighted c factor was derived for this type of mixed grid squares, thus solving the problem to some extent. However, the fact does remain that a reorientated grid and/or one of smaller size may well produce a higher estimate of erosion rates, particularly if the complete squares coincided with an area of bare peat.

However, in addressing the role of remote sensing data for soil loss estimation it must be emphasised that it is by no means a definitive study. Errors arise particularly in measuring the USLEC values due to errors involved in cover type classification. Therefore, figures on actual erosion must be treated with caution. It is suggested that further work is required to tackle this issue.

8.3 General conclusion

Remote sensing information offers significant advantages over traditional methods in detecting, inventoring, monitoring and measuring various parameters of natural environmental hazards, such as soil erosion. However, very few of the remote sensing studies carried out have attempted to quantify the amount of soil erosion occurring in upland areas.

The moors which often consisted of highly erosive blanket peat, with a high potential fire risk when poorly managed, can lead to a critical soil erosion problem. The ability to quickly identify the problem areas and to quantify soil loss are vital for the proper management plans.

The present study suggests that remote sensing can be used to make a rapid first approximation of the erosion in an area and to rank different parts of a water-shed according to the potential for erosion, thus saving the need for extensive field investigations and maximising the use of limited resources.

Furthermore, this research demonstrates the potential of remote sensing to identify soil loss and cover factors over time and to obtain an approximate estimation of long term erosion problems. This technique can provide National Park Authorities with continuous information on land cover changes that effect erosion.

A grid mesh based Universal Soil Loss Equation proved to be useful in the estimation of the rate of soil erosion for the upland moors. Further, the grid mesh approach is valuable as the grid squares are geographically referenced. Therefore, all the relevant collateral and derived data files can be spatially overlaid and compared square by square, which has great implications to the land management practices and erosion control. Moreover, once a USLE data base has been established, periodic reevaluation of erosion within a water-shed can be performed using sequential remotely sensed imagery and hence the effectiveness of management strategy reviewed. It must be emphasised however, that the effectiveness of spectral discrimination of surface cover types by a specific remote sensing data source must be checked for each new study area, be it in lowland England or elsewhere in the world. It cannot be assumed that the system and wave bands of value on Glaisdale Moor have similar utility elsewhere.

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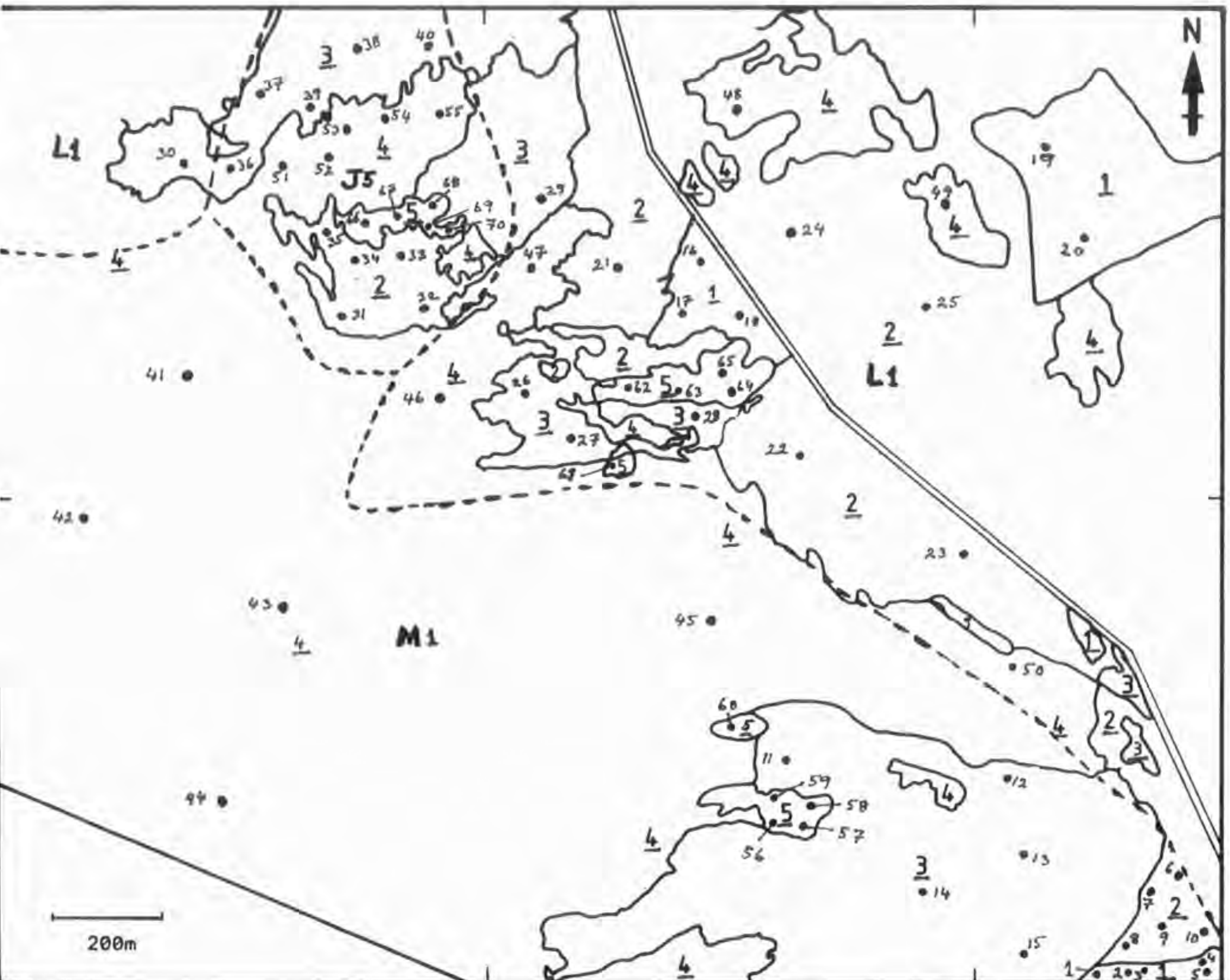
Appendix 1 Fortran program, GRID.FOR, to create Polygons

```
      ORIGIN FOR COORDS OF ENDS OF SEGMENTS = SW CORNER
      ARRAY LOCATIONS(Labels) ORIGIN= NW
      OUTPUT ON CHANNEL 12 !!
      Ian Shennan/Danny Donoghue  1/3/85

      DATA K /1000/
      WRITE(6,101)
      READ(5/300)N
      WRITE(6,200)
      READ(5,300)M
C
C     N - ROWS  AND  M - COLUMNS
C
101     FORMAT('INPUT NO OF ROWS REQUIRED')
200     FORMAT('INPUT NO OF COLUMNS REQUIRED')
300     FORMAT(I2)
      N=N+1
      M=M+1
      DATA SL/'/'/
      INTEGER LL,LR,IX,IY,IXX,IYY
C
C     BY ROW
C
        DO 1 IR=2,N
C
C     BY COLUMN
C
        DO 2 IC=2,M
C
C     TOP SIDE
      IF(IR.NE.2)GOTO 10
      LL=1001
      LR=IR*100+IC+K
      IX=IC-1
      IY=(N+2)-IR
      IXX=IC
      IYY=IY
      WRITE(12,100)LL,LR,IX,IY,IXX,IYY,SL
C
C     FORMAT WILL ONLY ALLOW SEGMENT LABELS TO BE
C     GENERATED FOR 80 ROWS OR COLUMN WITHOUT
C     INCREASING THE VALUE OF CONSTANT K
C
100     FORMAT('Z',I4,2X,'2',I4,1X,4I5,1X,A1)
10    CONTINUE
C
C     RIGHT HAND SIDE
C
      IF(IC.NE.M) GOTO 20
      LR=IR*100+IC+K
      LL=1001

      IX=IC
      IXX=IC
      IY=(N+1)-IR)+1
      IYY=IY-1
      WRITE(12,100)LL,LR,IX,IY,IXX,IYY,SL
20    CONTINUE
C
```

```
C       BASE ALWAYS DRAWN
C
        LR=IR*100+IC+K
        LL=(IR+1)*100+IC+K
        IF(IR.EQ.N) LL=1001
C       IF(IC.EQ.N) LL=1001
        IX=IC
        IY=(N-IR)+1
        IXX=IC-1
        IYY=IY
        WRITE(12,100)LL,LR,IX,IY,IXX,IYY,SL
C
C       LEFT HAND SIDE ALWAYS DRAWN
C
        LR=IR*100+IC+K
        IF(IC.EQ.2) LL=1001
        IX=IC-1
        IY=(N-IR)+1
        IXX=IC-1
        IYY=((N+1)-IR)+1
        WRITE(12,100)LL,LR,IX,IY,IXX,IYY,SL
C
C       END
C
2       CONTINUE
1       CONTINUE
        STOP
        END
```

Appendix 2 GIMMS Comand file used for map production

```
SR *GIMMS 9=-MAP 6=-6 15=SL.DATA4 4=ZONES

LANDSAT MAPPING - D.DONOGHUE FEB/MARCH 85>

CHANNEL 4 = OUTPUT FROM poly1>

CHANNELL 15 = OUTPUT FROM RS.MAST>
*FILEIN DATAFILE
 FILEIN=15
 FILENAME=DATAFILE
 ZONES=460
 VARS=1
 BEGIN
*PLOTPARM PLOTTER
*TEXTPARM ALPHABET=61,SHADE
*PLOTPROG
*NEWMAP 25,18.5 FRAME NOLOGO
*TEXT POSITION=4,17.5 SIZE=0.5 TEXT='PEAT EROSION GLAISDALE N.Y.MOORS'
*TEXT POSITION=19.5,9.0 SIZE=0.2
TEXT='SOIL LOSS TONS/ACRE/YEAR' ALPHABET=14
*TEXT POSITION=19.5,2.5 SIZE=0.2
TEXT='EACH SQUARE REPRESENTS

00 SQ METRE' ALPHABET=14
*TEXT POSITION=23.5,0.3 SIZE=.1YEXT='ALAM 10/86' ALPHABET=14
*SYMBOLISM AREA

.12,135,0,2/

.08,45,0,2/

.04,45,0,2/

.08,45,0,4&0.08,135,0,4/

.05,0,0,4&0.05,90,0,4/

.02,0,0,3&0.02,90,0,4/*
*GIMMSFILE=4 F=0.77 PLOT=0.5,0.5
*LEVELS=6
*INTERVALS VAR=1 USER=0.000,0.05,1.0,5.0,10.0,50.0,100.0 MIN=.000 MAX=100.0
*LEGEND POSITION=19.7,6.0 SIZE=0.4 ALPHABET=14 DAFPT=3
*MAP VAR=1 AREA
*END
*STOP
```



Key : 1 Vegetation, 40-80 % cover
3 Vegetation, less than 10 % cover
2 Vegetation, 10-40 % cover
4 Exposed peat
5 Bare soil
--- Soil series boundary
J5 Coarse loamy soil
L1 Fine loamy soil
• Sample points
M1 Peat soils

Appendix 3 Location of ground sample points, Glaisdale Moor

Appendix 4a Ground data analysed for the Glaisdale Moor, 1985

Cover Type	Soil moisture %	Organic matter %	Slope in Degree	Biomass gm/m2
1. Vegetation	1.36	5.41	27.75	1525.86
2.	10.64	24.15	42.27	1975.60
3.	1.39	22.73	27.75	1242.10
4.	10.00	84.09	27.75	1329.20
5.	11.13	87.97	27.75	881.89
6.	12.60	35.13	42.27	209.69
7.	14.03	46.91	26.56	1154.50
8.	3.22	91.61	26.56	614.68
9.	10.00	85.00	26.56	492.46
10.	9.58	75.08	26.56	1416.48
11.	2.24	11.62	27.75	1602.36
12.	.70	4.93	17.87	1757.98
13.	10.90	6.09	18.43	1298.38
14.	2.42	16.35	20.32	1599.70
15.	1.72	13.96	14.38	2095.68
16.	8.29	47.39	20.32	2155.59
17.	8.15	23.31	22.61	2115.59
18.	4.43	44.09	25.46	2097.40
19.	27.17	53.38	37.56	2245.90
20.	10.72	18.93	21.03	1605.76
21.	.14	8.32	33.69	2144.06
22.	2.97	2.29	29.05	1403.84
23.	1.35	3.24	10.30	1998.88
24.	2.04	28.57	13.70	2061.08
25.	4.00	5.60	27.75	1781.32
26.	6.51	68.75	19.02	1717.26
27.	12.92	30.12	12.80	2206.00
28.	7.76	21.55	19.02	1332.84
29.	16.53	42.04	30.46	1444.30
30.	4.93	23.13	19.65	1039.66
31.	1.23	34.09	26.56	1826.78
32.	2.66	39.32	21.80	1372.78
33.	.66	37.95	51.34	1100.46
34.	1.48	28.81	48.00	1408.76
35.	14.08	33.76	51.34	864.46
36.	4.29	57.36	32.00	1264.30
37.	4.39	68.92	30.46	1261.15
38.	2.56	68.26	27.75	1257.62
39.	2.94	66.17	24.44	1469.66
40.	1.78	56.54	22.62	691.70
41. Peat	9.54	82.68	23.49	
42.	9.21	77.07	33.69	
43.	10.34	78.38	19.02	
44.	7.85	68.75	12.26	
45.	10.23	75.06	27.75	
46.	18.14	72.15	26.56	
47.	3.32	45.70	10.80	
48.	8.75	62.36	12.52	
49.	6.66	54.66	27.75	
50.	29.90	63.16	15.94	
51.	4.16	61.45	33.69	
52.	11.77	53.28	16.38	
53.	2.53	53.69	21.80	
54.	.42	56.90	23.49	
55.	2.27	54.54	23.49	
56. Bare soils	.61	3.17	21.80	
57.	1.23	2.96	20.32	
58.	.99	2.86	16.85	
59.	1.37	3.16	14.74	
60.	.61	2.56	14.38	
61.	1.26	3.14	19.65	
62.	4.33	2.64	17.87	
63.	1.04	2.86	17.87	
64.	.38	2.50	21.80	
65	8.06	2.40	14.03	
66.	.12	3.68	27.75	
67.	.61	3.68	30.46	
68.	2.37	3.92	33.69	
69.	.49	4.34	48.00	
70.	.35	3.53	26.56	

Appendix 4b Ground data analysed for the Glaisdale moor,1985

Cover Types	Surface sand %	silt %	clay %	Subsurface sand %	silt %	clay %
1. Vegetation	75.69	16.20	8.11	87.83	8.12	4.05
2.	66.43	22.38	11.19	86.57	8.96	4.47
3.	87.83	10.14	2.03	89.85	6.14	4.01
4.	88.88	8.80	2.22	86.66	6.68	6.66
5.	70.74	20.26	9.00	88.74	6.75	4.50
6.	70.25	20.60	9.15	77.11	13.73	9.15
7.	62.77	20.90	16.28	79.06	11.63	9.31
8.	77.26	6.21	16.53	81.40	8.27	10.33
9.	73.33	13.33	13.33	77.77	11.12	11.11
10.	55.76	40.28	15.48	82.30	8.85	8.84
11.	83.63	12.28	4.09	79.54	14.33	6.13
12.	83.88	12.09	4.03	81.87	14.10	4.03
13.	82.04	13.48	4.48	79.79	15.72	4.48
14.	81.55	12.30	6.15	81.55	10.24	8.20
15.	81.68	12.21	6.10	91.85	.01	8.14
16.	71.65	19.65	8.72	71.64	15.28	13.08
17.	67.35	21.77	10.88	69.51	15.25	15.24
18.	70.71	18.83	10.46	70.69	14.66	14.65
19.	64.30	21.97	13.73	64.29	19.24	16.47
20.	70.87	20.17	8.96	70.87	15.69	13.44
21.	73.98	16.01	10.01	73.96	8.02	18.02
22.	73.20	16.49	10.31	73.20	10.31	16.49
23.	75.67	16.22	8.11	73.64	6.08	20.27
24.	71.43	18.37	10.20	75.50	4.08	20.42
25.	72.92	16.67	10.41	77.08	4.17	18.75
26.	82.89	10.70	6.41	85.02	6.43	8.55
27.	83.93	9.18	6.89	88.11	5.00	6.89
28.	82.66	13.06	4.28	93.49	2.17	4.33
29.	85.63	4.79	9.58	92.81	2.39	4.79
30.	87.37	6.31	6.31	92.79	3.00	4.21
31.	71.65	18.22	10.12	53.42	18.23	28.35
32.	75.34	16.44	8.22	46.57	32.88	20.54
33.	75.84	18.12	6.04	55.71	20.13	24.16
34.	75.64	18.26	6.09	55.33	26.40	18.27
35.	69.74	23.27	6.98	39.47	37.25	23.27
36.	77.01	14.63	8.35	39.39	29.26	31.35
37.	74.89	16.74	8.36	35.15	29.28	35.56
38.	73.32	14.36	12.31	38.42	28.75	32.84
39.	60.85	24.72	14.42	44.36	26.79	28.84
40.	73.53	6.11	20.36	38.91	26.47	34.62
41.	73.13	17.10	9.77	75.56	12.22	12.21
42.	79.33	12.40	8.27	79.31	10.35	10.34
43.	75.90	15.34	8.76	78.09	13.15	8.76
44.	80.73	12.85	6.42	80.71	10.72	8.57
45.	77.19	14.26	8.55	71.46	14.27	14.26
46. Bare soils	91.95	4.03	4.02	91.95	.01	8.04
47.	91.90	6.07	2.02	83.79	10.14	6.07
48.	91.92	6.06	2.02	77.78	18.18	4.04
49.	89.86	8.11	2.03	83.77	8.12	8.11
50.	91.95	4.03	4.02	87.92	10.06	2.01
51.	55.43	10.13	34.43	53.41	10.13	36.45
52.	48.63	14.01	37.35	53.70	6.61	36.69
53.	57.55	10.11	32.34	55.53	10.11	34.35
54.	57.84	12.04	30.11	51.82	12.04	36.14
55.	52.14	13.06	34.80	54.38	6.47	39.15
56.	73.96	12.02	14.02	79.97	10.02	10.01
57.	73.36	12.29	14.34	77.86	12.08	10.06
58.	75.41	18.56	6.03	77.46	14.34	8.19
59.	75.87	8.05	16.08	75.87	16.09	8.04
60.	75.91	10.04	14.07	75.91	14.05	10.03

Appendix 4c Raw ground radiometer data for the Glaisdale Moor, 1985

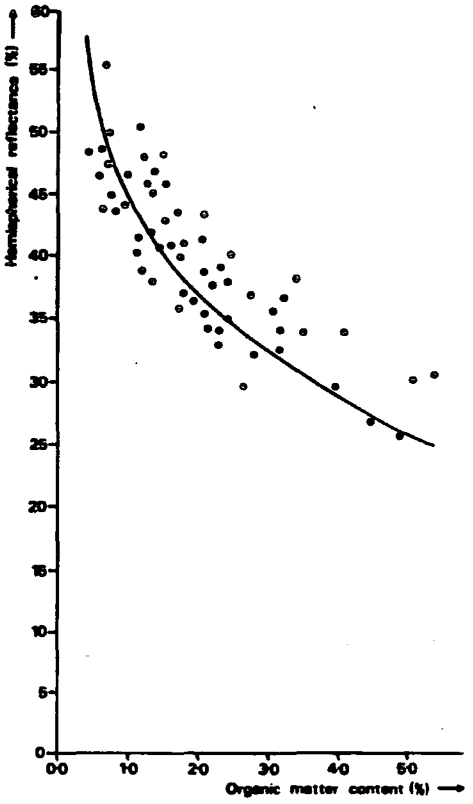
Cover type	Channel 1	Channel 2	channel 3	Channel 4
1. Vegetation	3.22	5.27	13.29	50.58
2.	6.30	12.94	27.47	51.03
3.	5.31	11.05	54.44	35.20
4.	13.03	11.97	55.66	58.29
5.	4.22	10.87	17.58	43.75
6.	22.12	28.12	75.12	111.82
7.	31.44	46.48	67.86	88.65
8.	18.46	65.45	60.09	89.47
9.	19.35	28.77	85.44	90.19
10.	22.81	55.95	62.70	93.47
11.	6.36	8.86	28.39	70.43
12.	14.43	15.50	25.77	22.41
13.	5.67	14.96	18.02	53.75
14.	5.47	5.48	32.13	56.58
15.	13.71	23.66	19.96	43.77
16.	21.47	46.90	49.32	64.21
17.	36.91	23.69	30.31	69.83
18.	31.66	28.19	24.58	60.46
19.	32.33	32.00	24.24	74.63
20.	29.12	69.18	43.18	72.95
21.	27.20	27.36	67.10	63.71
22.	45.55	41.21	56.22	126.00
23.	22.96	40.07	68.80	94.68
24.	60.89	37.49	85.00	102.28
25.	53.43	54.68	106.70	101.80
26.	60.24	60.44	64.95	57.25
27.	43.81	59.00	47.19	52.53
28.	59.36	47.26	70.33	65.79
29.	51.01	71.40	46.77	76.80
30.	82.54	67.96	67.75	70.52
31.	2.97	3.65	15.03	29.63
32.	2.97	5.22	17.77	56.61
33.	5.76	2.77	16.45	60.84
34.	6.95	2.86	24.77	58.81
35.	3.11	3.20	18.55	52.89
36.	23.18	48.99	24.73	20.10
37.	11.27	29.74	38.19	49.07
38.	26.52	46.82	44.65	32.08
39.	3.42	45.02	9.68	55.85
40.	11.82	48.88	21.94	45.76
41. Peat	3.81	6.05	20.42	26.01
42.	20.46	23.88	23.11	42.03
43.	7.79	15.55	13.92	16.64
44.	6.18	7.67	13.15	15.82
45.	15.36	12.11	27.02	18.25
46.	10.15	5.22	14.88	31.92
47.	21.52	30.83	17.67	43.57
48.	20.34	28.55	13.24	28.12
49.	23.91	50.83	43.85	53.31
50.	19.05	34.44	15.08	32.56
51.	36.91	28.82	25.48	65.77
52.	31.02	59.85	38.38	51.22
53.	37.41	31.12	25.52	65.06
54.	34.37	38.73	44.53	50.52
55.	18.42	35.98	34.48	45.64
56. Bare soils	16.31	12.75	26.59	45.86
57.	16.39	18.56	19.02	48.25
58.	17.40	12.59	29.95	48.51
59.	24.04	21.96	42.72	59.83
60.	26.60	16.05	35.86	59.13
61.	60.30	98.65	61.28	85.14
62.	49.63	53.21	52.30	64.62
63.	55.76	50.57	59.25	85.32
64.	55.42	59.05	78.53	80.22
65.	62.72	72.49	54.52	60.21
66.	66.88	72.07	159.00	212.83
67.	36.37	62.21	176.18	178.74
68.	50.76	64.37	155.88	145.37
69.	41.54	65.57	117.13	128.34
70.	62.29	76.62	150.63	123.66

Appendix 5 *SPOT : Principal characteristics.*

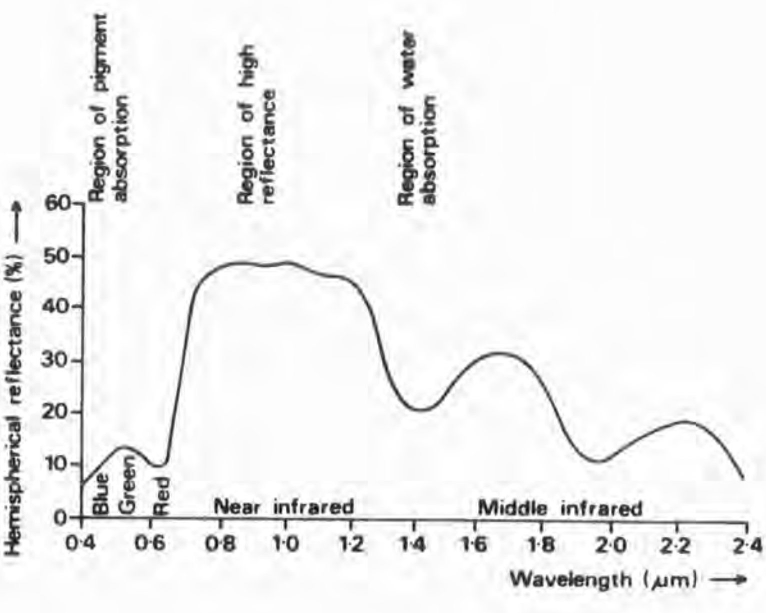
Orbit	circular at 832 km inclination : 98.7 degrees descending node at 10h 30mn a.m. orbital cycle: 26 days
Haute resolution visible (HRV)	two identical instruments pointing capability: ± 27° east or west of the Orbital plane ground swath: 60 km each at vertical incidence pixel size: 10 m in panchromatic mode 20 m in multispectral mode spectral channels: panchromatic: 0.51 — 0.73 μm multispectral: 0.50 — 0.59 μm 0.61 — 0.68 μm 0.79 — 0.89 μm
Images transmission	two on board recorders with 23 min capacity each direct broadcast at 8 GHz (50 Mbits/s)
Weight	1750 kg
Size	2 × 2 × 3.5 m plus solar panel (9 m)

(Source: Brochet 1986)

Appendix 6 The relationship between organic matter and hemispherical reflectance in visible wavelengths(Modified from Page 1974)



Appendix 7 The hemispherical reflectance of a Rhododendron leaf (Source: Curran 1985)



Appendix 8 Estimation of erosion index (E I) from daily rainfall amount

Erosion Index (E I) has been calculated for two years of daily rainfall amounts of Glaisdale Moor using the Richardson et al (1983) formula

$$EI = a\ p^{b} + e$$

where P is the rainfall amount, a and b are equation parameters, e is the random component of the relationship.

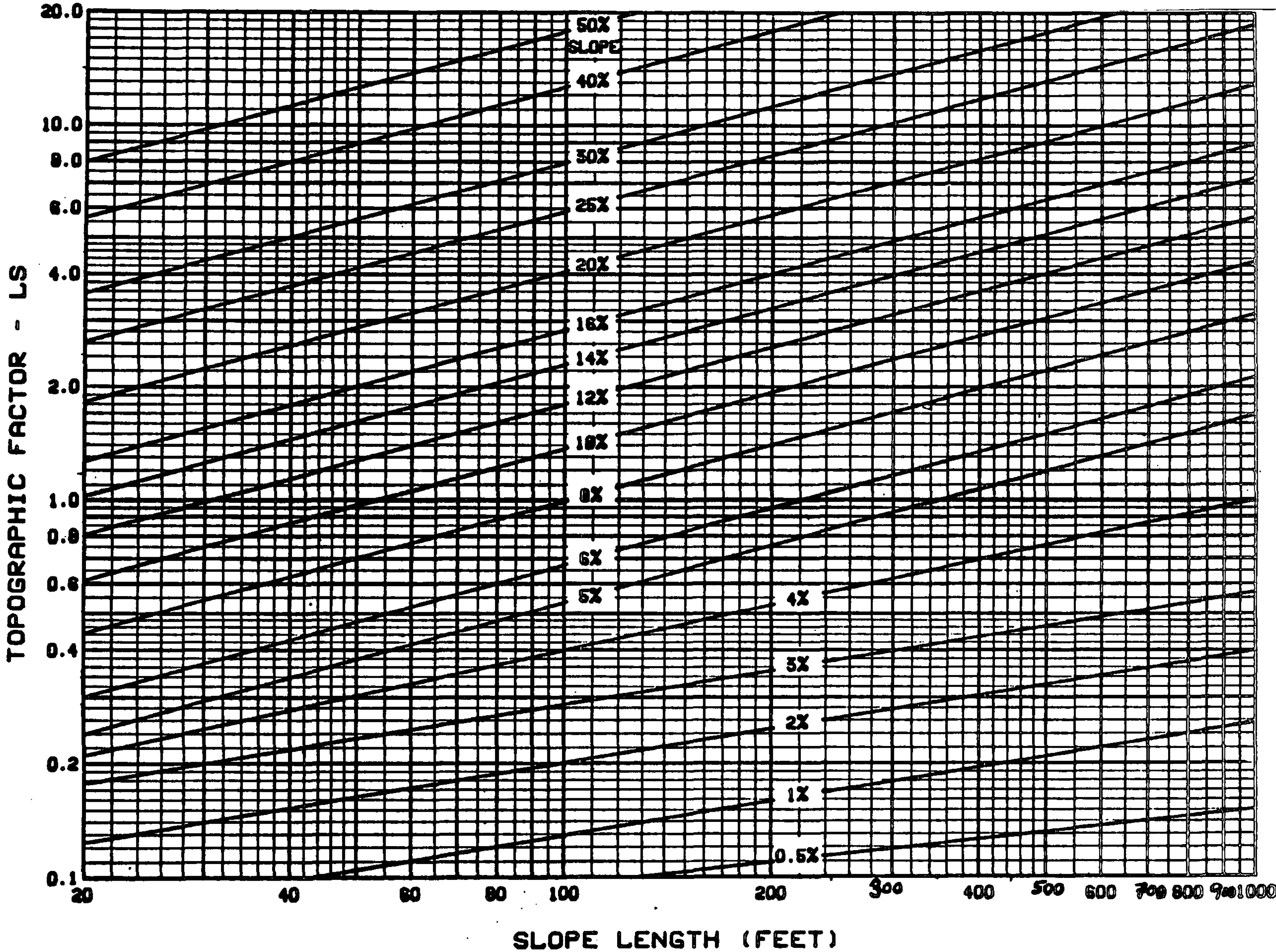
For 15 mm rainfall, derived EI value	= 56 x 41 (No. of events)		= 2296
For 25 mm	"	= 125 x 11	= 1375
For 35 mm	"	= 225 x 5	= 1125
For 50 mm	"	= 400 x 4	= 1600
	for 24 months		= 6396
	for 12 months		= 3198

To convert EI = 3198 $MJ.mm^{-1}.ha\ h^{-1}$ in to R (Erosivity index) in USLE

divide by 17.02

$$R = 3194 \div 17.02$$

$$= 187.89$$



Appendix 9 Slope-effect chart to derive USLE-LS factor
(Soure: Wischmeier and Smith 1978)