AN EVALUATION OF LANDSAT THEMATIC MAPPER (TM) AND SPOT-HRV DATA, IN GRASSLANDS INVENTORY IN THE U.K.

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SUMMARY

The principal aim of this project is to qualitatively and quantitatively evaluate satellite imagery for the mapping of unimproved semi-natural chalk grassland in lowland Britain and to develop a methodology that permits the classification of chalk grassland.

The rationale behind the project is to provide various governmental and independent agencies with an operational information system capable of creating quickly and inexpensively natural resource maps, specifically chalk semi-natural grassland maps, as an aid to environmental, and ecological planning and for monitoring change. Within the study areas, major land cover classifications were evaluated with the assistance of ground data and existing topographical maps.

The use of temporal and spatial features for classification of the multisensor data sets were investigated and the spectral characteristics of different chalk grassland types analysed.

Detailed chalk grass sub-community categories, as defined by English Nature (EN) for the Salisbury Plain Range, were poorly represented by the spectral classes. However, broader groupings interactively chosen with ecological significance were mapped successfully with TM and SPOT. Off the main range areas isolated Special Sites of Scientific Interest (SSSI) 'status' chalk grass fields were also successfully mapped using July TM data. SSSI classification using a earlier spring TM image was moderately successful and a June SPOT scene produced results which were of limited value.

Key Words : multispectral Landsat Thematic Mapper and SPOT-HRV imagery
remote sensing and image processing
chalk grassland mapping
Salisbury Plain

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CHAPTER ONE

INTRODUCTION

1.1 General Introduction

Grassland is a widespread vegetation type of great economic value and ecological interest. It's importance to man is well known; as an exploitable crop for both man and his domestic animals, in the provision of stability to the ground surface, for many amenity and ornamental applications and as an integral part of an attractive landscape.

Whilst the total amount of grassland in the UK has recently slightly decreased, as shown by the 1947-1980 Department of the Environment and Countryside Commission survey (Huntings, 1986), dramatic changes have taken place in the specific types of grassland which now exist. These changes reveal losses of semi-natural grassland and gains in agriculturally improved pasture. Historically, much of the lowland areas of Britain were kept as permanent pasture. Where this permanent pasture corresponded with underlying chalk bed-rock, these areas were termed 'chalk downland'; and were found to be of considerable biological richness (Duffey *et al.*, 1974). Over the past four decades much of the permanent pasture has been ploughed and converted to arable crops. Even where it has been retained as grassland there has often been fertilizing and re-seeding, which completely changes the botanical composition which has developed over centuries. Often the only pastures to escape destruction or modification have been military land and on ground too steep to plough. However, with modern implements this latter factor is no longer a constraint.

It has been estimated that during the last forty years in England, there has been a 95% loss of herbaceous species-rich meadows and an 80% loss of lowland chalk sheep walks (Adams, 1987). However, these figures are based on a poor data base and there is a genuine need to know what is happening in the countryside. It is now an urgent necessity to develop a method of accurate quantitative assessment of our natural grassland resources.

1.2 Ecological Importance of Chalk Grassland

The largest continuous areas of chalk grassland now left in the UK are in Wiltshire (Ratcliffe, 1977), namely, the military training areas of Salisbury Plain. Here security measures have debarred a relatively large tract of downland from agricultural use. Most of this is only lightly grazed by rabbits and hares and undergoes minimal management; but the balance between grasses and herbaceous plants has remained favourable (from the ecological point of view) of maintaining diversity. Still other sites in Wiltshire e.g., along the valley of the River Wylye, contribute strongly to the list of biological key sites, which are characterized by extreme species richness. There are also numerous examples of agriculturally improved pasture used for hay, silage production and intensive grazing. All these sites are included in the study area, which contains a large cross-section of the different grassland communities of lowland Britain.

Semi-natural chalk grassland of Salisbury Plain was specifically chosen for study, because these areas sustain a wide variety of flora and fauna in a dynamic and finely balanced ecosystem. However, the balance is susceptible to disturbance, particularly intervention by man in the form of agricultural improvements. The protection and preservation of these environments requires techniques for monitoring changes in the nature and species composition of the vegetation.

1.3 Brief Introduction to Remote Sensing : Definition and History

The definition of remote sensing can be said to be (Fussel *et al.*, 1986) :-

> "the non-contact recording of information from the electro-magnetic spectrum, by means of mechanical, photographic, numeric or visual sensors located on mobile or static platforms".

Satellite remote sensing can be defined by its mode of operation. Remote sensing satellites orbit the Earth at a variety of altitudes and their sensors gather electromagnetic energy reflected, emitted or backscattered from the part of the Earth-atmosphere system below the satellite

The rise of remote sensing stems from the first developments of photography (pre-1925), to the more sophisticated photogrammetric methods that were catalysed by two world wars. This has continued right up to the space age and the use of satellite digital imagery of the present day. A concise review of the major phases in the history of remote sensing is given by Barrett and Curtis (1982).

Although it would seem that remote sensing has had a long pedigree, satellite remote sensing is a relatively new and rapidly developing science. The 1970's and 1980's have seen an explosion in the advancement of the communications technology, sensor development, computing (the handling and transfer of data); and the wider application of the satellite remote sensing systems. All of this bodes well for the future of both the science and application of remote sensing.

1.4 Satellite Remote Sensing of the Earth's Resources

There are two groups of Earth resource satellites; first, the manned satellites which carry photographic and other sensors, which provide images of the Earth's surface, an example being the Space Shuttle. Second, the unmanned satellites that carry a wide range of non-photographic sensors for the production of images of the Earth's surface, an example being the Landsat generation of satellites. It is this second group of Earth observation satellites, dealing in the visible and infrared regions of the spectrum, that are now discussed. For detailed description of the characteristics of these satellites see Chapter four, section 4.1.

1.4.1 Earth Resource Satellites : Operational Criteria

Technically, an earth observation satellite system should be able to assist in the quantification of the type, amount, location and condition of land-cover resources, either in spatial (maps) or tabular (estimates) formats.

The use of satellite data in the inventory process requires that the satellite technology :-

* be implementable by the 'user' agency,
* provide consistent information with user-defined limits, and
* be cost competitive.

In addition the user should be aware of data advantages and limitations.

1.4.2 Satellite Remote Sensing : Advantages and Disadvantages

Curran and Plummer (1987), focused attention on the use of remote sensing as a potentially useful source of data from the agricultural and ecological viewpoint in the UK. They saw the main areas of application regarding inventories in the mapping of :-

(i) habitat,
(ii) land cover, and
(iii) crop types.

The benefits of producing satellite derived thematic maps would be :-

* the acquisition of relatively up-to-date vegetation maps, and
* to derive their areal extent and generate inexpensive cartographic products for field workers.

The problems incurred by such application of satellite data were also highlighted. Applications are limited by; cloud cover, the spatial resolution of current sensors, the availability of suitable sensor data, a shortage of multitemporal data, data costs and very importantly a general lack of dialogue between the remote sensing 'expert' and the potential 'user' i.e., the broader ecological and agricultural community. Curran and Plummer (1987) illustrated that over the previous three years, an average of twelve articles were published on the topic of remote sensing and ecology/agriculture, but none were published in leading biological publications, such as the *Journal of Applied Ecology*. In conclusion there was a very definite need to develop operational methodologies for the mapping of habitats, land cover and crop types (Fuller *et al.*, 1989a).

Adams and Gardner (1984), provided a critique on the shortcomings of satellite remote sensing in the ecological context. The spatial resolution of given satellites overstates the capacity of the sensor to discriminate accurately target features on the ground. In practise, ground features do not align themselves exactly to pixels and most pixels contain a mixture of cover classes. There can also be serious spillover effects from surrounding pixels, for example, a small herbaceous field in a wood might be overshadowed by the spectral response pattern of the wood and become invisible on the image. Finally, the informational land use criteria of certain land cover types are very difficult to distinguish when just using spectral information (e.g., green cereals, grass leys and herb-rich meadows will all emit similar spectral response patterns at specific points in the growing season).

1.5 Remote Sensing and Grasslands

One of the most economically and politically important vegetation application of remotely sensed data has been the discrimination of crop types and the forecasting of crop yields. The large area coverage and sequential nature of satellite imagery (and the opportunity for computer data processing) offers the potential for relatively cheap, timely and accurate agricultural/land cover inventory. For example, the Landsat Multispectral Scanner (MSS) has been employed successfully using both single date and multitemporal image sets, in crop identification and inventories (Hay, 1974; Taylor *et al.*, 1983; Wall *et al.*, 1984; Odenweller and Johnson, 1984; Belward and Taylor, 1986); with Landsat (TM) Thematic Mapper

(Townshend, 1984), and with SPOT data (Jewell, 1989).

In the context of remote sensing, grasslands have been studied less than croplands, because of their less direct economical value, and because of their greater complexity in terms of overall diversity and management practices.

Vegetation studies have generally fallen into two categories, studies concerned with vegetation types and those concerned with vegetation amount. Work on grasslands also follow this mode. Up till now, the main research work performed on grasslands concern the :-

(i) mapping of grasslands or rangeland units via aerial photography (Everitt , 1985) or satellite data using MSS (Girard, 1981; Brown and Ahern, 1983) and TM (Fuller *et al.*, 1989b; Fuller and Parsell, 1990); and the

(ii) evaluation of green biomass or forage production from; on site spectral measurements (Thalen *et al.*, 1980; Richardson *et al.*, 1983; Girard, 1986), or satellite MSS data (Carneggie *et al.*, 1977; Curran, 1983; Tucker *et al.*, 1983), airborne TM (Curran and Williamson, 1987) and TM data (Thomson *et al.*, 1985).

1.5.1 Rationale behind Present Work

Firstly, the rationale behind this study was to determine if satellite derived data, specifically data acquired by Landsat Thematic Mapper (TM) and SPOT-High Resolution Visible (HRV), could be used to inventory or assist in the mapping of chalk grassland types.

Secondly, with the difficulties of access to large tracts of Salisbury Plain, the ability to easily and safely collect the required data from orbital platforms would be desirable. The Salisbury Plain Training Areas (SPTAs), which are owned by the MoD (Ministry of Defence) are extensively used for live artillery exercises, making blanket ground sampling difficult and hazardous!

For effective management it is necessary to acquire periodic data on the boundaries, extent and condition of the resources. Remote sensing has been shown to be a useful tool for mapping tasks in delineating the boundaries and areal extent of grassland units (Carneggie *et al.*, 1983). Remote sensing also offers advantages in the collection of information, that would accrue from being synoptic, repetitive and cost effective in relation to conventional ground survey.

There is significant interest from agencies in obtaining information about the spatial distribution and amount of grasslands. The Department of the Environment (DOE) are interested in the amount of improved pasture nationally, and the former Nature Conservancy Council (NCC) now known as English Nature (EN), are interested in mapping traditionally managed meadows and semi-natural grassland. There is even more emphasis for this kind of information with the advent of the EEC's Common Agricultural Policy (CAP), incorporating 'set-aside' and a network of Environmentally Sensitive Areas (ESAs). There is therefore much scope for research into grassland mapping and surveys using remote sensing techniques. If methodologies for processing and analysing satellite data can be refined to provide an acceptable model for vegetation cover, they may gain acceptance by those with an interest in operational ecological or vegetation mapping applications (Fuller *et al.*, 1989a).

1.6 Earth Resource Satellites Role : English Nature's (EN) View Point

It is clear that the amount of unimproved lowland meadows and semi-natural grassland has fallen dramatically in recent decades. To defend against the further loss of such resources (including permanent chalk grassland), ecologists require regional and national inventories of existing sites so as to prepare an overall conservation strategy. Satellite remote sensing offers a tool with which to do this.

EN was authorised by parliament (under the 1981 Wildlife and Countryside Act) to be responsible for the appraisal and notification of Sites of Special Scientific Interest or SSSIs. The act was intended to provide a solid foundation for conservation policy in the UK. In this role, EN require the production of vegetation or habitat maps. The reasons behind this are outlined by Hume *et al.*, (1986) and they are :-

* as a basis for the designation of new reserves or SSSIs,
* as a data base for management planning and agreements and
* for monitoring exercises in response to management or external influences.

Budd (1985), used simulated SPOT (S.SPOT) data in a study of the Somerset Levels and found that the data was able to detect change in a SSSI. He stated that :-

> "the imagery was able to provide an efficient monitoring tool for SSSI habitats".

He also found that generalised descriptions of habitats with some ecological significance could be mapped and often formed basic site information for areas of conservational interest.

Detailed plant community field mapping is time consuming, expensive and often local in scope; but where this type of information is desired there is no substitute for a complete field survey. However, there are situations where more generalised information is required in the wider countryside (especially recently with CAP etc.,) so there is a real need for ecological data covering large areas. No comprehensive data sets are available on the amount and type of habitats, and it is information of this nature that is needed, if the impact of current and future planning decisions are to be efficiently evaluated. This shortage of information is particularly severe for grasslands - despite their economic importance and the fact that they cover half the farmable land (Duffey *et al.*, 1974; Girard *et al.*, 1990).

The use of satellite imagery in conservation has numerous benefits including the systematic detection and mapping of sites of ecological interest. There is a further economic advantage in that it may reduce the costs of ground survey work, by replacing the traditional ecological Phase I survey. Phase I surveys are defined as general blanket habitat survey of all cover types and are followed by a more specific Phase II survey. Phase II surveys concentrate on those habitats of ecological or conservational interest : sites are visited throughout the growing season and complete flora and fauna species lists are compiled. Alternatively, satellite imagery can be used to identify sites of ecological conservational interest and thus replace the costly Phase I stage. Field personnel can then perform a 'Phase I.5' survey (pers. comm. R. Keymer, Head of Field Unit, English Nature) to validate sites and if this is the case, ecological expertise can then be used in detailed ground Phase II habitat survey of these sites. This enables, a pin-pointing of resources and man hours to those areas of greatest importance. Satellite derived thematic maps also provide a spatial structure to an information system which might be set up. This could be important in terms of 'minimum area' needs for ecosystem preservation (Trodd, 1987). Minimum area needs for a habitat is the minimum areal extent in which that habitat ecosystem needs to be, in order to be able to exist and maintain itself independently. Remotely sensed satellite data also has the benefit that areas with difficult access can be surveyed, as can those with restricted access. This can be a problem with ground census surveys and suspicious landowners.

The spatial resolution of the newer systems are approaching 10m pixel size, such as panchromatic SPOT. This level of resolution displays spatial details equivalent to the traditional remotely sensed data source of ecological mapping, which is medium scale aerial photography. The spectral resolution of satellite sensors, with near-infra red (IR) and mid-IR bands as aids to discrimination, also improve upon aerial photography. For an account of the role and use of aerial photography in ecology and conservation see Fenton (1983). The reasons for the apparent reluctance of ecologists to embrace satellite remotely sensed data for operational use are cited as : poor spatial resolution; the resultant vegetation maps having poor accuracy and reliability, and a general unawareness of ecological 'users' in the potential of digital remote sensing techniques (Fuller *et al.*, 1989a). Conventional automated classifier's produce mapping accuracies that are typically less than 80 %, at the Anderson *et al.*, (1976) Level I and II hierarchical classification schemes.

TM and SPOT resolution ensures that the identification of an area of vegetation is dependant on the physiognomic condition and presence or absence of dominant species. These are the attributes selected in the National Vegetation Classification (NVC) scheme employed by EN in their classification of vegetation types. Dominance can be considered an appropriate discriminatory parameter for satellite sensors (Hume *et al.*, 1986; Girard *et al.*, 1990). Furthermore due to their high resolution, the ability of TM and SPOT to generate more visually realistic maps, should mean greater acceptance of digitally-derived products by field personnel, and a significant improvement in the application of remote sensing techniques as a tool in resource management.

1.7 Aims of the Research

The aim of this project is to qualitatively and quantitatively evaluate satellite imagery for the mapping of unimproved semi-natural chalk grassland in lowland Southern Britain and to develop a methodology that permits the classification of chalk grassland.

In order to achieve this aim the following objectives were identified :-

i) fully test and evaluate two different satellite sensors. The research will also focus on the multitemporal nature of the data by analysing 'spectral response patterns' of the grass cover types at key points in their growth calendar;

ii) to explore and devise methodologies in order to extract maximum information, which can be readily implemented and applied to real operational tasks;

iii) to analyse the number of bands and their 'best' combination, with respect to TM in feature selection;

iv) to examine two different supervised 'per-pixel' classification algorithms, minimum distance and maximum likelihood, by fully quantifying accuracies achieved, balanced against their performance speed. Simulated 'per-field' classification, integrating field data directly with the satellite remotely sensed data, will fully train and test the classifications. Unsupervised classification techniques will also be investigated;

v) to examine spatial post-classification modal filtering and the effects of altering the size of the filter window;

vi) compare the costs of satellite data and analysis with those of traditional survey techniques;

vii) and illustrate how satellite data can be an invaluable tool for 'users', such as ecologists, by providing information for their present mapping tasks, and for further monitoring exercises. The research also briefly discusses how the digital nature of the satellite data will allow the methodology to be relatively easily implemented with other spatial information in a Geographical Information System.

1.8 Summary

It is not anticipated that satellite remote sensing will provide a total solution to the mapping of chalk semi-natural grassland. However, it is envisaged that it will make a useful and valuable contribution to the task. It is to identify and assess this contribution which is the main interest of this research. If the findings achieve a certain reasonable accuracy (i.e., greater than 80%), then there is the possibility of extrapolating the methodology to other geographic areas and in doing so, assessing other potential sites of chalk grasslands in Southern England. Ecologists using this data could then locate these potential sites using satellite data and evaluate them in the field, using ecological criteria. These two surveying methods should then complement each other, since it would be inappropriate to determine the floristic/ecological quality of these grasslands solely by remote sensing. The role of remote sensing is to estimate the spatial distribution of grassland types, using species dominance as a spectral indicator and discriminatory factor, which is in turn a consequence of their botanical composition, phenological stage of development and management regime.

CHAPTER TWO

THE STUDY AREA AND GRASS COMMUNITY TYPES

This Chapter gives a brief description of the study area and of the three main areas of interest within the whole study area, along with descriptions of the major chalk grassland community types and their importance ecologically as a habitat.

2.1 Description of the Study Area, Salisbury Plain, Wiltshire, UK

The study area is situated around Salisbury Plain in Wiltshire, which is found in southern England. Salisbury Plain consists of several areas used by the army for training purposes. The Salisbury Plain Training Area (SPTA) consists of three major areas (see Figure 2.1) or ranges :- i) West SPTA (WSPTA); ii) Larkhill, containing the impact area for artillery training, and iii) the Eastern SPTA (ESPTA). All three ranges are used for military deployment and training and are owned by the MoD. Access to these ranges is restricted and they undergo minimal management or agricultural usage. Areas surrounding the ranges are also owned by the MoD and are termed schedule I and schedule III land (Porley, 1989). Schedule I land is tenanted to local farmers, whilst schedule III land is used predominantly for training, but with limited farming allowed. Table 2.1 gives a brief description of the agricultural use on the scheduled land.

Table 2.1: Description of the Permitted Agricultural Activities on the Scheduled Land surrounding the Three Ranges (Porley, 1989)

WSPTA	Larkhill	ESPTA
Perimeter is cropped for hay and arable crops	Grazing and cropped grasslands along narrow border in the north and extensive south of the range	Cattle grazing in pens and some arable crops

A EN botanical field survey was conducted in June/July (1985-86) for all three ranges, for further information readers are referred to Porley (1989). Only calcareous grassland (CG) and mesotrophic or neutral grass (MG1) Arrhenatherum elatius areas were considered in this survey, this included the military range areas, the scheduled land and some smaller areas off the ranges. Extensive areas of land within the SPTA were not calcareous grassland and these regions represent many land uses, but improved agricultural land was found to be the most extensive. These areas were not surveyed by the EN field unit. The SPTAs also contain some forestry, which was established for military training purposes. These plantations are generally small and scattered and consist of mixed conifer and broadleaved species.

The study area is a rectangle of approximately 630km^2, centred at 1^o 51'W -51^o 14'N in Southern Wiltshire and covering the three SPTAs. Selected test-sites of 512x512 pixel extracts were located centred at 2^o 04'W - 51^o 14'N, covering the western ranges of Salisbury Plain (WSPTA); Larkhill (SPTA), and centred around the village of Wylye 1^o 59' - 51^o 08'. These areas are covered by the Ordnance Survey (OS) 1: 50 000 Landranger series No. 184. Figure 2.1 shows the location of the study areas and the extent of the MoD ranges.

The relief for the most part is low-lying, the altitude never exceeds 200m. Geomorphologically, it is a gentle physical landscape characterized by monotonous expanses of rolling downland and grass clad escarpments formed on the chalk. The soil type being for the most part brown earths with rendzinas on the steeper ground (Jones, 1981). The area consists of gently undulating downs with cultivated fields grouped on the tops of the downs, and grassland occupying the bottoms and sides of the valleys. The MoD rangeland consists for the most part of semi-natural grasslands and scrub, situated on dry trellis valley network. Duffey *et al*., (1974) gives an account of the history of chalk grassland in Wiltshire.

2.2 Description of Chalk Grass Types

The chalk grass communities and sub-communities used in the analysis are related to the National Vegetation Classification (NVC) scheme (EN, England Field Unit publication), with adaptations to it, regarding the SPTAs specifically (Porley, 1989). These adaptions of the community level of the major chalk grassland types are described below (where CG denotes calcarious grassland and MG is mesotrophic grassland) :-

CG3a - typical sub-community as described by the NVC.

CG3a/di - sub-community not described in the NVC, but occurs as a mosaic of 3a and 3di. The floristics of the mosaic vary along a continuum from a close affinity to 3a through to the 3di sub-community. It was regarded by EN as an intermediate between these communities.

CG3di - sub-community not described by NVC, but characteristic of large areas of the SPTAs.

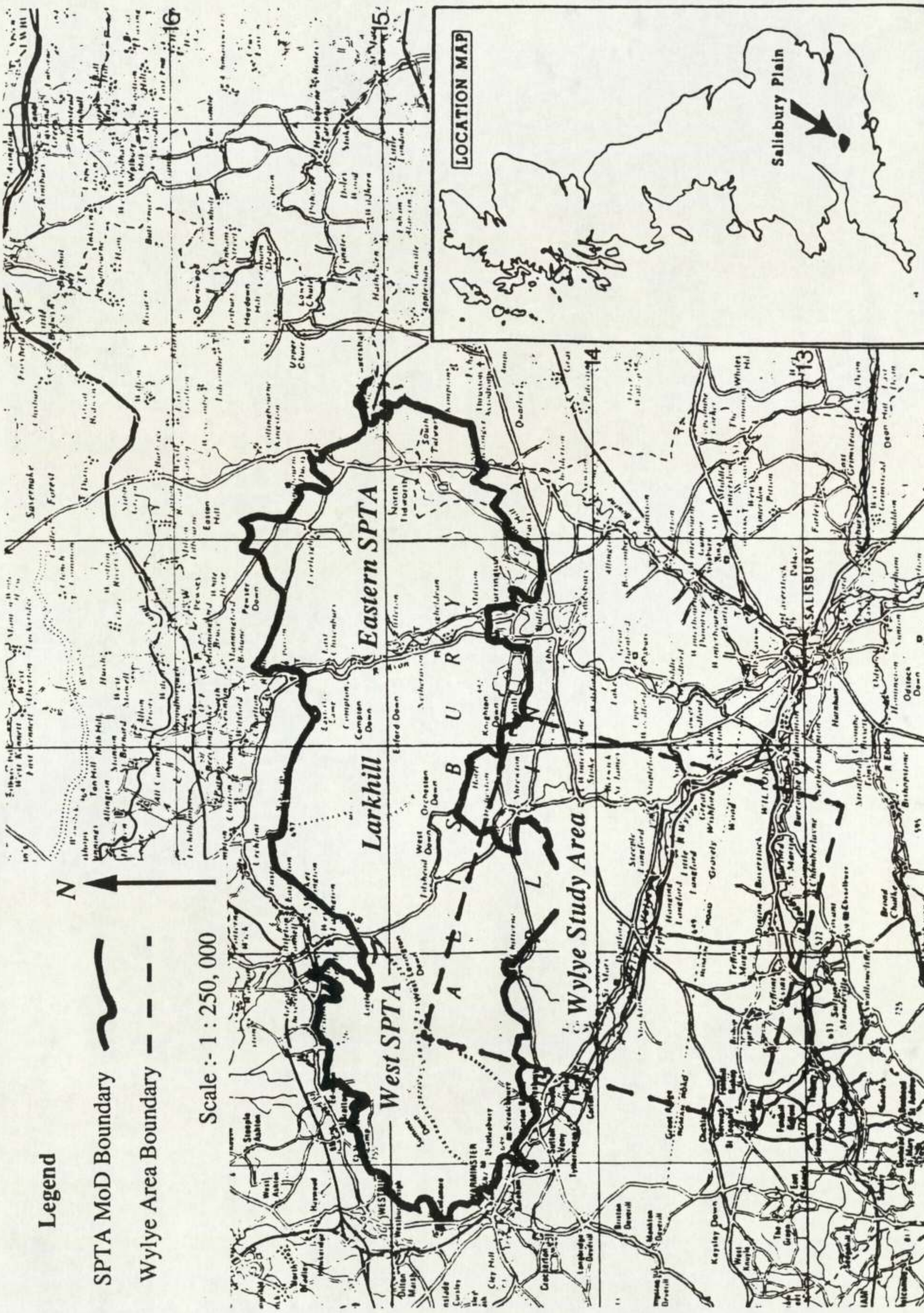


Figure 2.1 : Location of the Study Area, Salisbury Plain, Wiltshire

CG3d - sub-community described by the NVC, but when frequent associate Arrhenatherum elatius is co-dominant, it was found by EN field personnel to be difficult to separate this from MG1 grassland community type.

MG1 - community described by NVC as mesotrophic grassland (MG), dominated by Arrhenatherum elatius. Often difficult to separate from CG3d sub-community when Bromus erectus occurs at high constancy : a situation commonly encountered on the SPTA.

For a more general discussion of the vegetation classification and field data acquisition, readers are referred to the EN SPTA field survey report (Porley, 1989) and the relevant EN NVC scheme guides.

Standard vegetation classification procedures were followed. All three ranges were divided into sites using topographical references. Each site was then further divided into a grid system and a number of quadrats were selected depending on the size of the site. A total sample of 479 quadrats were analysed. As far as possible communities and sub-communities were allocated in the field using the NVC scheme. Two sub-communities were found to be distinct associations not described by the NVC, but recognised on the SPTA. B. erectus dominant (CG3a) grassland made up 82.5% of the total amount of chalk grassland present. CG3a is defined in the NVC as swards in which B. erectus makes up more than 10% of the cover. EN considered 'that the variation in vegetation on the SPTA was adequately sampled, and hence the maps accurately reflect the distribution of the community types'.

However, it should be noted that there were certain limitations within the survey. There was a time constraint of a sampling window of a couple of weeks each season in which to undertake the field work. This was because of the dangerous nature of some of the ranges and access was only possible with military escort. Problems were also found in allocating difficult sub-community associations. It was accepted that the precise point where a sward is or is not a sub-community depended largely on individual opinion and the accurate and consistent judging of cover abundance of sub-community associate or variant species presence.

A more detailed description 'down to their sub-community level' of the botanic and general physical nature of the major grassland types found on the West SPTA, is given by Table 2.2. The accuracy of the field survey in relation to the results gained in this research is discussed further in Chapter Eight, section 8.3.

Table 2.2 : Botanical Descriptions of Community Types recognised on the Western Salisbury Plain Training Area (WSPTA) Test Site (from Porley, 1989)

EN's Code	Physiognomy
CG3a	Herb rich, fine-structured turf with quite frequent scattered tussocks of Bromus erectus.
CG3a/di	This is characterised by small discrete patches of CG3a and CG3di forming a mosaic. The floristics of the mosaic can vary along a continuum from a close affinity to a CG3a to a less species-rich CG3di.
CG3di	Bromus erectus more dominant, but shows close affinities to the typical sub-community (CG3a). Contains Filipendula vulgaris variant in characteristic sub-community.
CG3d	Bromus erectus dominant forming rank tussocks, very few herbs or fine-leaved grasses. When Arrhenatherum elatius becomes co-dominant it is difficult to separate this an MG1 grassland.
MG1	Rank mesotrophic grassland community, dominated by Arrhenatherum elatius tussocks with smaller amounts of Dactylis glomerata and Holcus lanatus.

The importance of the SPTAs as given by EN are outlined below :-

i) the most important consideration is size: the SPTA can be described as three large blocks of chalk grassland. The area as a whole encompasses by far the largest continuous areas of unfragmented lowland chalk grassland in the British Isles and is of international importance in the context of North West Europe.

ii) A large proportion of the chalk grassland in the SPTA is on relatively flat ground, which is rare in Europe due to its suitability for agricultural improvement.

iii) The study area is of high scientific value, because very little management is practiced by the MoD, consequently there is considerable scope for undertaking ecological studies.

CHAPTER THREE

MULTISPECTRAL REFLECTANCE AND VEGETATION

Remote sensing offers the potential for rapidly monitoring vegetation, soil and water resources. An analysis of plants and soil tends to be complex because of their inherent characteristics, and because plants are dynamic with constantly changing conditions. A successful remote sensing application must be tailored to solve or manage this complexity and this requires an understanding of plants and soil and their interactions with the electromagnetic spectrum. The major applications of remote sensing in plant sciences are the identification of land use patterns, the inventory of types, the areal extent and yield of crops and other plant communities. The difference in reflectivity that allows discrimination of plant species or vegetation types can be traced to their leaf and canopy characteristics and these characteristics influence the leaf's optical properties and the reflection patterns received by airborne and orbital sensors, which represent the integration of their effects (Knipling, 1970).

3.1 The Physical Interaction of Multispectral Reflectance with Plants and Soil

Light reflectance from plant material is an integrated response of the plant structure and soil background. The spongy mesophyll layer of the leaf structure is important in terms of remote sensing, because it scatters near infrared (near-IR) light. A review of the literature shows that reflectance varies with cellular structure, maturity, shade, background soil, leaf area, pigmentation changes and physiological stresses.

Within the wave bands of 0.4 to 2.5μm, electromagnetic radiation reflected from vegetation can be divided into three regions :-

* the 0.4 - 0.75μm <u>visible light</u> region dominated by pigments where there is very little reflectance, however there is a reflectance peak at the green wavelength (i.e., healthy vegetation appears green);
* the 0.75 - 1.35μm <u>near-IR region</u> , a region of high reflectance due to the internal leaf structure i.e., the mesophyll region of the leaf structure. Different plant types can have very different internal structures, thereby giving different near-IR reflectance responses whilst having a similar reflectance in the visible wavelengths;
* and the 1.35-2.50μm the <u>middle-IR region</u>, is strongly influenced by water concentration in the tissue, which is a function of the total amount of water present in

the leaf and leaf thickness. Strong water absorption of the spectrum occurs at wavelengths 1.45μm and 1.95μm.

Figure 3.1 shows a typical spectral reflectance curve for green vegetation and identifies the significant spectral response regions, the physical and biological mechanisms which influence reflectance of vegetation; and the location of satellite spectral bands.

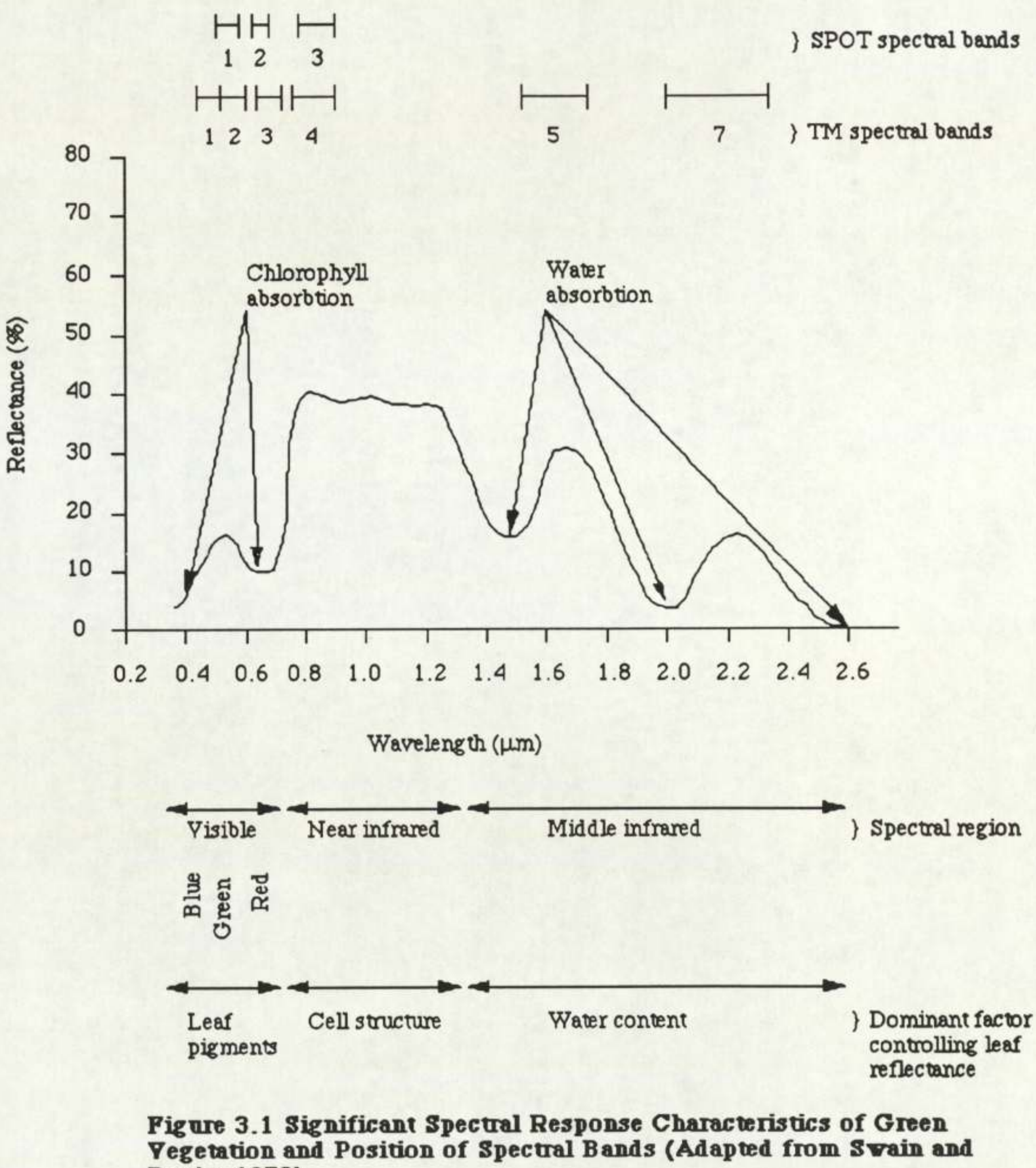


Figure 3.1 Significant Spectral Response Characteristics of Green Vegetation and Position of Spectral Bands (Adapted from Swain and Davis, 1978)

It has been found that in general the spectral reflectance curves for mature and healthy leaves are similar in that they follow these patterns of significant spectral response as in Figure 3.1, but that they differ in magnitude for different vegetation types.

Some of the parameters which influence the complete spectral response of vegetation are discussed below. All these factors must be considered when trying to interpret spectral response patterns from vegetation.

Factors shown to affect the spectral reflectance of single leaves are (Myers, 1983) :

* Leaf maturation : different spectral reflectance is attributed to the fact that young leaves are more compact with few air spaces, while old leaves are 'spongy' and have many air spaces. Furthermore, young leaves tend to contain more pigments. Hence, young leaves tend to have less reflectance in the visible region due to higher pigment levels, and significantly lower in the near-IR, because the mature leaves have more intercellular air spaces and increased reflectance in the near-IR region.
* Pigments : such as the chlorophylls and the carotenoids absorb light and hence markedly affect reflectance of plant leaves. The type and amount of the different pigments present in the leaf distinctly affect the reflective spectrum.
* Internal leaf structure : leaf mesophyll arrangements have the most influence on light reflectance over the near-IR wavelength interval. In general plants with compact mesophylls, when compared with leaves with thick mesophylls, have lower reflectance.
* Leaf damage : diseases etc., that interfere with the internal structure and thus the internal reflection of light will affect the reflectance, especially in the near-IR region.
* Leaf pubescence : it has been found that hairiness of leaves affect the reflection of visible light but the effect is not as great in reflecting infrared light.
* Leaf water content : evidence suggests that dehydration increases reflectance greatly over the entire 0.5-2.5μm wavelength interval and that in general, the correlation of leaf water content with reflectance is strongest in the near-IR region of the spectrum.
* Leaf senescence : this is the deterioration in plant leaves, flowers and roots that end their functional life. In perennial plants the above-ground vegetation dies yearly, but the crown and the roots remain alive. Herbaceous annual plants have a progressive senescence of their leaves from the older to the younger, followed by death of both stems and roots. During leaf senescence, starch, chlorophyll, protein and nucleic acid components are degraded. The change of colouration is caused by the unmasking of yellow and orange carotene when the chlorophyll is lost. As leaves senesce, their light reflectance usually increases markedly in the green visible light wavelength peaking at

0.55µm (Knipling, 1967) and to a lesser extent in the red and the blue region of the visible spectrum. There is also a slight decrease in the near-IR reflectance and a marked increase in the middle-IR, due to the decrease in tissue moisture content.

In order to fully understand the spectral response of vegetation one also needs to explore the nature of the interaction of soil as a background component with the electromagnetic spectrum. The radiant energy of the sun is partially absorbed by the soil surface and transformed chiefly into heat. A small part of this energy is diffusely reflected. The pattern of reflectance at various wavelengths is considerably different for plants. See Figure 3.2, which shows a typical soil to have considerable less peak-and-valley variations in reflectance compared to vegetation.

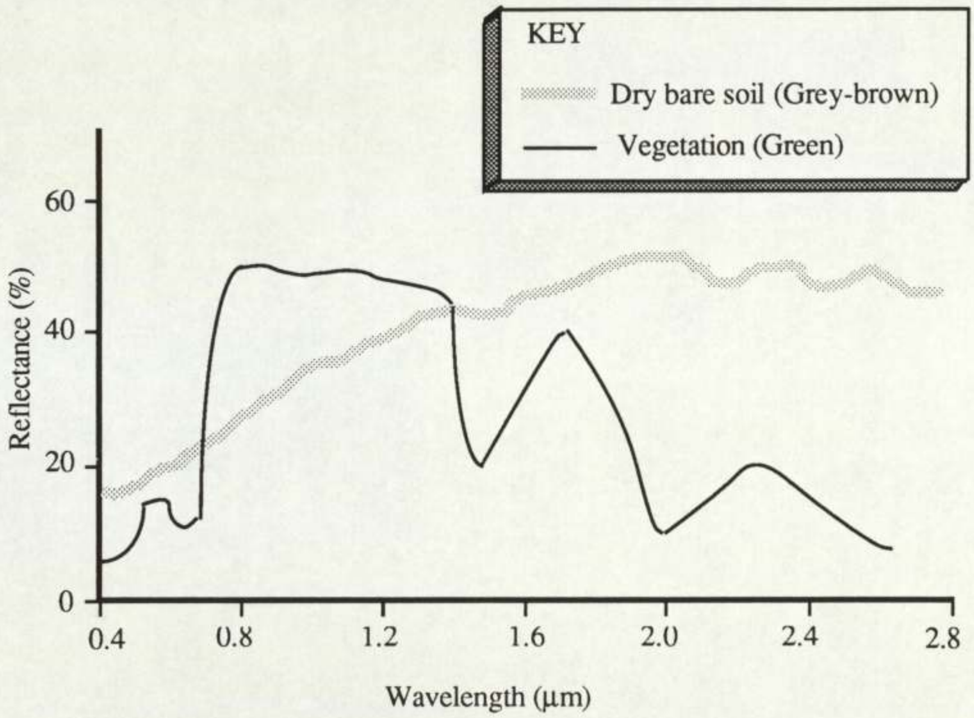


Figure 3.2 : Typical Spectral Reflectance Curves For Vegetation And Soil (Adapted From Lillesand And Kiefer, 1979)

Throughout the spectral range of reflected solar energy (0.25-2.5µm), the spectral reflectance of soils differs substantially from vegetation. Numerous soil properties influence the reflection of electro-magnetic energy : these include the mineral content, particle size, soil texture, soil colour, organic matter, chemical composition, structure and surface roughness, polarizing properties and soil moisture.

Soil moisture is one of the major factors that needs to be considered in the plant-soil-air interface. From a practical viewpoint, knowledge of soil moisture levels is important for growing crops and for estimating the impact on the spectral response of vegetation with a dry or wet soil background. Research has indicated that subtle differences in soil water can be detected with the thermal infrared and the green and red spectral bands, while the reflected near-IR shows the more severe water stress conditions (Myers, 1983). Reflectance decreases as soil moisture increases for wavelengths 0.4 - 1.3μm. Whilst this observation is valid for any soil type, it is worth noting that it can be applied only for a given soil at any one time, because of the effects produced in the soil by different grain sizes, textures and mineralogy. Probably the most appropriate and sensitive part of the electromagnetic spectrum is radar from the microwave region, for the detection of moisture content in soils (Lilliesand and Kiefer, 1979).

3.2 Vegetation Canopy Characteristics

Having briefly discussed the factors relating the reflectance responses of single leaves and background soil component, it is now necessary to consider the expanded situation of a satellite sensor remotely sensing a vegetation canopy target on the Earth's surface. Figure 3.3 shows the pathways of radiation from the sun, incident to the Earth and being detected by a passive sensor.

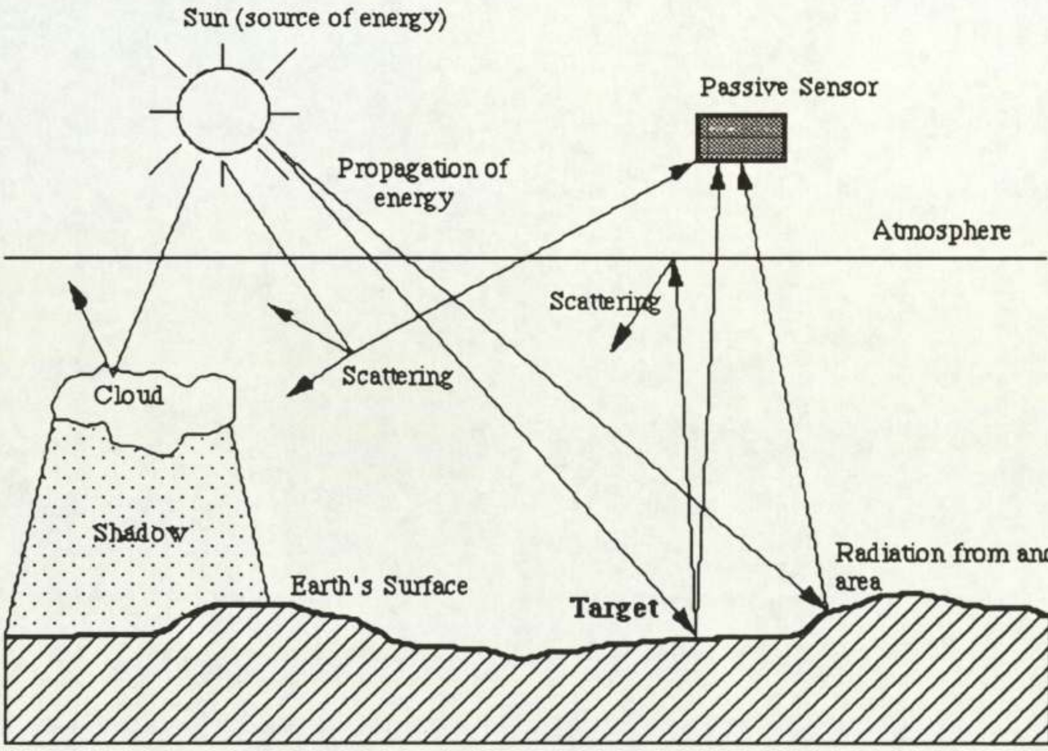


Figure 3.3 : The Pathways of Radiation to a Passive Remote Sensor (Adapted from Lillesand and Keiffer, 1979)

Figure 3.3, also illustrates that there are numerous atmospheric interactions of the radiance. All electromagnetic radiation before and after it has interacted with the Earth's surface has to pass through the atmosphere, prior to its detection by a remote sensor. As a direct result of scattering, absorption and refraction, this passage will alter the speed, frequency, intensity, spectral distribution and direction of radiation. These effects are most marked for the visible and near-IR radiation, with scattering (i.e., haze) primarily affecting the visible wavelengths. Certain molecules in the atmosphere absorb wavelengths, producing heat and longer wavelengths, such molecules include water vapour, carbon dioxide, ozone and suspended particles. They absorb radiation causing a decrease in the amount received by the sensor and also emit radiation of their own, thus adding to the radiation at the sensor.

The spectral radiant flux ($\phi\lambda$) incident on the earths surface is either reflected ($\rho\lambda$), absorbed ($\alpha\lambda$) or transmitted ($\tau\lambda$). As no energy is lost in the process then :

$$\phi\lambda = \rho\lambda + \alpha\lambda + \tau\lambda \tag{3.1}$$

This relationship is illustrated in Figure 3.4, which shows the basic interactions between electromagnetic energy, the Earth and an Earth surface feature (vegetation).

If these proportions differ for different features on the Earth's surface, then it is possible to identify such features spectrally. The angular nature of reflectance needs to be considered and it is described by two rather broad terms; hemispherical and directional. Hemispherical refers to the angle of incidence and collection of radiant flux over a hemisphere, and directional refers to the incidence or collection of radiant flux for one direction only (see Figure 3.5). In remote sensing, spectral reflectance measurements will be either bihemispherical, where the angles of incidence and collection are hemispherical, as would be the case in laboratory studies; or bidirectional where the angles of incidence and collection are directional, as would be the case with a satellite sensor.

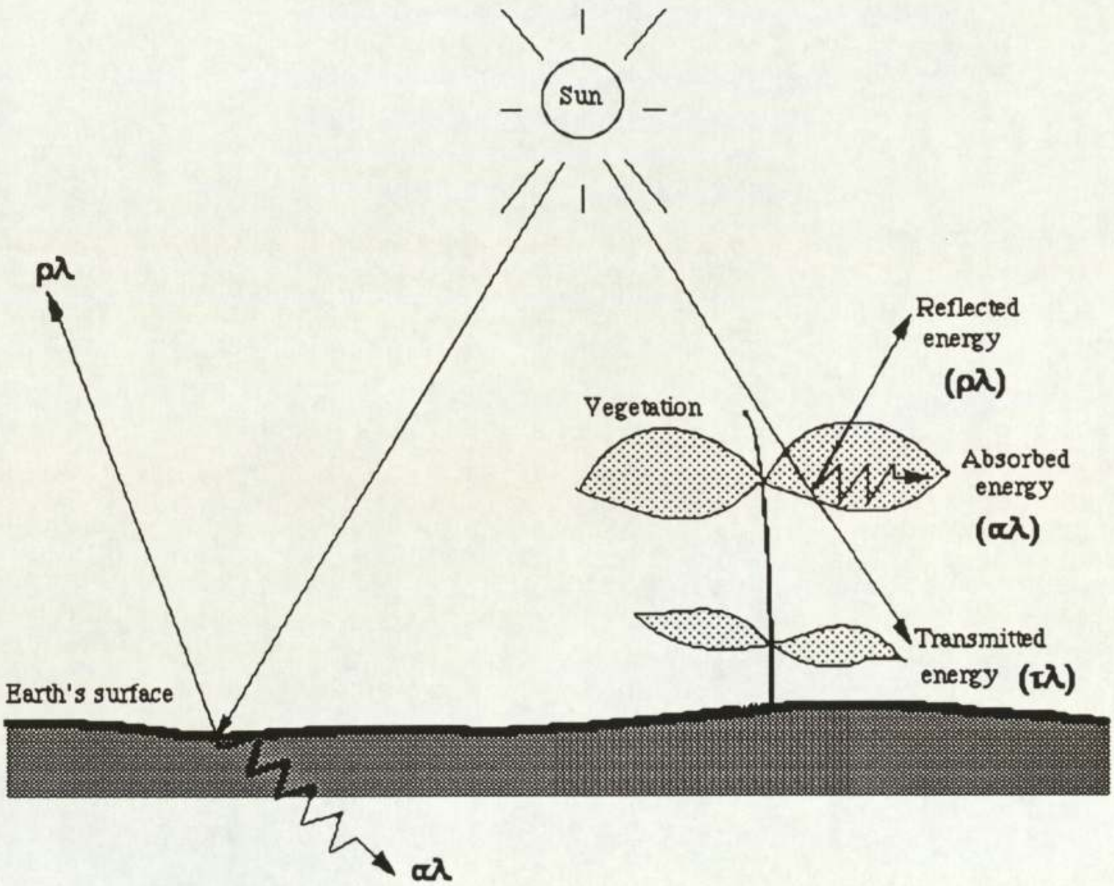


Figure 3.4 : Pathways of Spectral Radiant Flux Incident on Earth's Surface and Vegetation (Adapted from Lillesand and Keiffer, 1979)

The geometric manner in which an object reflects energy is also an important consideration. This factor is primarily a function of surface roughness of the object. There are two types of reflector : specular reflectors which are flat surfaces that produce mirrorlike reflections, (i.e., the angle of reflectance is equal to the angle of incidence), and diffuse reflectors which are rough surfaces that reflect uniformly in all directions (i.e., exhibit Lambertian properties). Surface roughness is of importance because the surface needs to be rough enough to allow radiation to interact with the surface of the objects. If the surface is smooth and radiation is reflected without interaction, then little information will be transmitted to the sensor. Fortunately, the majority of Earth's features appear rough at the visible and near-IR wavelengths. Most Earth surfaces are neither perfectly specular or diffuse reflectors. Their characteristics are somewhere in between the two extremes, the majority being diffuse and non-perfect Lambertain in nature. Figure 3.5 also illustrates the geometric character of specular reflectors, near-perfect specular reflectors, near-perfect diffuse reflectors and diffuse reflectors.

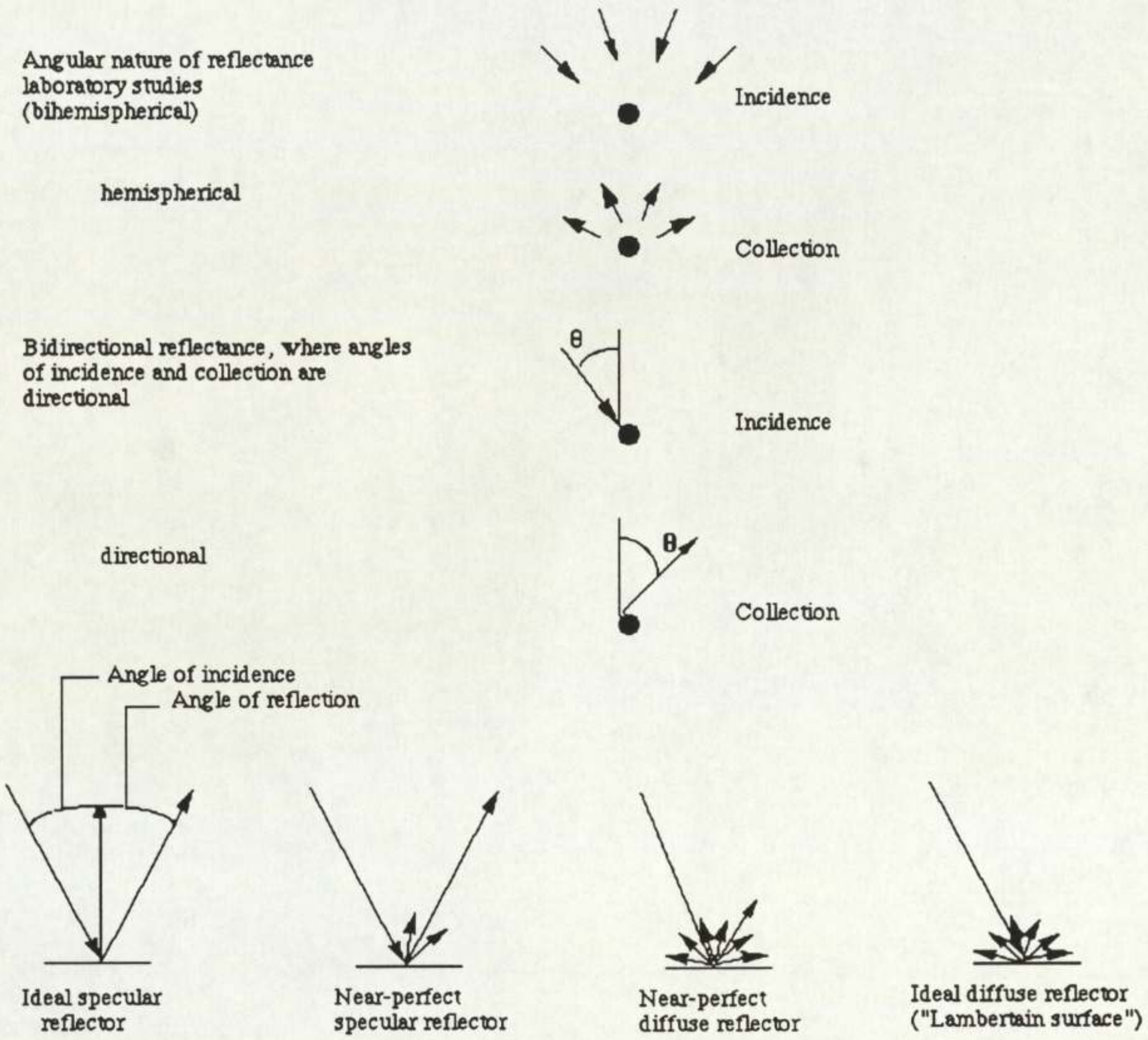


Figure 3.5 : A Graphical Description of the Angular Nature of Reflectance Measurements and the Geometric Manner of Reflectance for Specular and Diffuse Reflectors (Adapted from Lillesand and Kiefer, 1978; Curran, 1985)

Incident radiation is reflected, transmitted and absorbed by plant leaves; the response from individual leaves often being referred to as 'leaf hemispherical reflectance' (Curran, 1985). Although it is necessary to understand the reflectance properties of individual leaves, this knowledge in itself does not explain the observed response of vegetation canopies, known as canopy bidirectional reflectance (Knipling, 1970; Tucker, 1977). As vegetation canopies are mixture of leaves, other plant components, background and shadow; there may be no simple relationship between the hemispherical reflectance of individual leaves and the bidirectional reflectance of the canopy (canopy reflectance). The ideal measurement for use in remote sensing is the bidirectional distribution function (BRDF), which is the bidirectional reflectance at all possible angles of collection (Curran, 1985). As this is very difficult to measure unless in a laboratory situation, researchers use a simplified measurement - the bidirectional reflectance to measure canopy reflectance. It is the bidirectional reflectance that describes the remotely sensed reflectance of a vegetation canopy made up of its components of mosaics of leaves, other plant structures, background and shadow. Reflectance from a canopy is considerably less than that from a single leaf, because of attenuation of incident radiation by variation in leaf orientation, shadows and non-foliage background.

In investigating the spectral response patterns of vegetation, an awareness and understanding of the following effects is important (Swain and Davis, 1978) :

i) Temporal effects - This is where the spectral characteristics differ with time for a single type of vegetation in the same location.

ii) Spatial effects - This is where spectral response is different for a single type of vegetation in different locations.

With spatial effects differences can be due to vegetation/soil mixture over a small geographical area; or due to the different weather conditions, soil types or cultural practices over a large geographical area.

It is therefore inadvisable to ignore the impact of the temporal and broad area spatial effects on the spectral response. The fact that they exist has caused great difficulty in situations where a limited set of spectral response data (from a single geographic location and a single date) has been utilized as training data, for mapping a particular species of vegetation over a large geographic area.

Variation in spectral response for vegetation cover types can be attributed mainly to (Swain and Davis, 1978) :-

* amount of ground cover (due to cultural practises) i.e., fertilizer regimes and planting procedures, intensity and type of grazing,
* amount of ground cover (due to natural causes) i.e., differences in soil type, soil moisture,
* variations in maturity due to different varieties, growth rates, planting date.
* disease, moisture stress and insect infestations,
* geometric configuration of ground cover i.e., blowing down of crops, row direction, slope, aspects,

* environmental variables such as atmospheric conditions, wind conditions and angle of reflection and
* topographical variables i.e., elevation, slope and aspect.

It is of fundamental importance to realise that unique, unchanging spectral signatures or 'spectral response patterns' are virtually non-existent in the natural world. Although measurable and recognisable spectral response patterns of a particular vegetation type may exist, they are related to both a specific geographic area and a particular date and time. These response patterns are combinations of the reflectance and emittance from the vegetation types, which are to be identified.

The spectral variability of vegetation is a major problem when attempting to identify and map features of interest. To reduce this variation the following steps are recommended (Swain and Davis, 1978) :-

* collect data when the spectral response pattern is significantly different from other cover types (eg, oilseed rape which has a dramatic yellow colour when in bloom),
* obtain data when variations for given species are a minimum (eg, the middle of the growing season),
* collect data at intervals throughout the growing season and
* collect data under restricted environmental conditions (eg, specified sun angle, season).

A brief outline has been given of the physical nature of how electromagnetic radiation interacts with vegetation : this ranged from a consideration of single leaves to complete vegetation canopies. The importance of understanding total canopy effects, as well as single leaf spectral reflectance characteristics, is well documented. Gausman *et al*., (1973) found that individual leaf characteristics for twenty different crops revealed very little spectral differences. However, Chance (1981) found in a satellite analysis of several of the crop types, that it was evident that differences did occur, which were difficult to explain in terms of the findings of Gausman. Chance therefore argued, in light of this fact, that the actual reflective differences (for field crops detected by satellite data in the near-IR), were due mainly to species growth architecture, and not due to leaf reflectance characteristics such as size, shape and orientation. Therefore, by understanding mechanisms such as change in pigments, internal leaf structure and water content, apparent in the phenological transformation from vigorous green vegetation to senescent vegetation; together with total canopy effects such as growth architecture, soil background etc., it *is* possible to interpret multispectral reflectance of vegetation. The discussion will now be focused on semi-natural habitats and grasslands.

3.3 Semi-natural Vegetation and Grasslands

Prior to satellite studies of semi-natural vegetation and grasslands, in-situ studies were conducted in order to attempt to correlate spectral response patterns with vegetation variables; the aim being to acquire an understanding of the complex relationships between the biophysical parameters of vegetation and its reflectance. Useful data from airborne or orbital sensors can be interpreted if it is known how the energy recorded by the spectral bands interacts with the vegetation. A leading exponent of such studies is Tucker (1977; 1978; 1979), who worked on grass canopies. In the first study canopy reflectance in the near-IR was quantitatively related to physical/biotic factors, including per cent soil cover, total biomass, leaf water content and chlorophyll content. The latter study correlated red and IR ratio's to green leaf area and green leaf biomass. Senescent grass material was also analysed spectrally (Tucker, 1978; Rao *et al.*, 1979). The results gained helped to elucidate the spectral contribution of mixed live/dead canopy situations, as it was found that as material senesced, reflectances increased across the spectrum.

A literature review, has not identified the development of a 'universal' methodology for range/grassland assessment using satellite data. Common problems which hinder reliable estimates of the areal extent and condition of grasslands and semi-natural vegetation include; the wide variety of species composition, different soil backgrounds, differential growth rates of individual plants from site to site and the different spectral reflectance characteristics of green and senescent material.

These problems were confirmed in a study of rangeland production using remotely sensed techniques (Carneggie *et al.*, 1977). The production of rangeland was found to be a function of elevation, slope, aspect and various other physical, biological and chemical characteristics of the soil. Similarly with the mapping of cover types, Jones *et al.*, (1987) highlighted the fact that British semi-natural habitats are a difficult environment to study. Their ecology is both variable and complex, in that semi-natural vegetation exhibit diffuse boundaries and the land cover is spatially variable.

Semi-natural chalk grassland is a very complex habitat, even on a small scale. For instance within one-quarter square metre of semi-natural grassland, many species of green vegetation (grasses and herbaceous plants) may exist with standing senescent and dead vegetation, and sometimes bare soil. Efforts to interpret vegetated surfaces have been hampered by soil background signals, which varies with soil type, soil moisture and soil management. The literature indicates that the effects of soil reflectance, canopy structure and leaf orientation are at least as important as individual leaf characteristics in determining composite canopy reflectance.

In consideration of only canopy parameters the spectral reflectance depends upon :-

* the spectral reflectances and relative proportions of the individual components,
* the geometric arrangement of the individual components, and
* the shadow cast by canopy components.

Ahern *et al.*, (1981) conducted a detailed study in Canada of the optical characteristics of mixed grass and rough Fescue rangeland vegetation, using MSS and simulated TM. It was suggested that to simplify matters one can consider grassland as being made up of two components; the green component (healthy vegetation) and the brown component (senescent or dead material). The differences in reflectance of senescent and green tall prairie grasses over the visible and infrared part of the spectrum for the equivalent TM bands were examined. The spectral reflectance of green leaves was found to be generally low across the blue and red regions of the spectrum (because of chlorophyll absorption), and higher in the green (giving the characteristic green colour). The reflectance then rises very rapidly at about the near-IR and then slowly decreases with increasing wavelength to 2.35μm. The reflectances of brown or senescent matter in general was higher than green vegetation in the visible region, lower in the near-IR, and higher again in the mid-IR (TM-5 and 7) part of the spectrum. For a much more thorough description of the reflectance characteristics of grassland vegetation see Ahern *et al.*, (1981); and Asrar *et al.*, (1986). The third vegetation or flowering component of herbaceous vegetation can be ignored in this broad framework, as it does not usually dominate an area when viewed vertically (Ahern *et al.*, 1981).

The geometric arrangements and structure of these components is important. For example, large amounts of green grass and herbaceous matter may be completely obscured by brown carryover vegetation from the previous season, which is maintained during the early part of the growing season. Also counter examples of heavy carryover obscured by green grass and/or herbaceous material may be present. If the carryover is removed this will expose bare soil, until the green growth of the new season is established. In such cases, a remote sensing measurement will tell little about the component which cannot be seen. A related geometric effect is that the predominantly vertical structure of grass leaves contrasts with the random horizontal configuration of the leaves of herbaceous species. Unless the herbaceous species are obscured by grasses or carryover vegetation they will alter and perhaps dominate the reflectance response. Canopies of vertical orientated elements produce lower canopy reflectance than canopies of more horizontal elements. Rao *et al.*, (1979), showed that the bidirectional and angular aspects were more pronounced for a standing crop such as a cereal, than for a mown crop such as hay.

Shadows cast by individual components decrease the reflectance response throughout the spectrum. Shadowing depends on the slope, solar angle and sensor angle at the time of image acquisition, and the shadow casting efficiency of individual components. For example, in a remote sensing context, a tall headed senescent grass will cast a much more prominent shadow than a small herbaceous plant near to the ground, whose shadow is mostly obscured when viewed vertically.

Many variations can occur within this broad framework i.e., individual grass species can exhibit different senescent times and colouration. Semi-natural vegetation and grasslands can be configured in so many different ways, and made up of so many different species that many workers using satellite data (Ahern *et al.*, 1981), have found it difficult to quantitatively relate spectral reflectance and the areal extent of species and community type.

Therefore, subsequent studies of this type of habitat have become increasingly complex in their analysis. Asrar *et al.*, (1986), developed statistical procedures that allowed different grassland components of tall grass prairie to be distinguished i.e., green vegetation, senescent vegetation and the bare soil component. These were spectrally distinguished by objective discriminant and canonical discriminant analysis. It was shown that remote sensing of grasslands *could* result in quantitative information on the amount, condition and type of grassland vegetation, *provided* that the effects of physical physiological processes on spectral characteristics were understood. Using a Barnes multi-band radiometer which simulated TM performance, accuracies of 94% were achieved for estimates of areal coverage of the three components; green vegetation, senescent material and the soil factor. A simulation of MSS bands produced significantly lower accuracies.

3.3.1 Production Studies

A large number of 'production' or 'yield' studies have been conducted in N.America, where rangeland resources have been assessed by satellite imagery. Studies have linked MSS data, by exploration of band ratios and vegetation index models, to rangeland parameters in multitemporal analysis (Carneggie *et al.*, 1977; Thomson *et al.*, 1980; McDanial and Hass, 1982). Correlations were found between transformed vegetation index and greenness vegetation index with green forage production, green cover and plant moisture. The results indicated that MSS spectral radiance was sensitive to critical seasonal changes, this was in providing a quantitative measure of vegetation growth, conditions and inherent ecological characteristics for the vegetation/soil system.

An illustration of phenological development and spectral response was provided by Carneggie *et al.*, (1977), who used visual and automated techniques for information extraction on forage production, range condition and changing growth conditions.

The use of single date imagery was usually restrictive in such studies, as temporal considerations are generally of considerable importance. The presence of senescent material can mask green vegetation in the canopy and increase red reflectance MSS band-5 (Curren, 1983). Curran and Williamson (1987), used airborne MSS scanner data to map estimates of Green Leaf Area Index (GLAI) of limestone grassland. The GLAI is an accepted method for quantifying production of plant canopies of agricultural and semi-natural grasslands in the UK.

In a study of grassland canopy characteristics, Ripple (1984) used radiometer data simulating TM bands. TM-4, the near-IR band, was found to be the best indicator of total wet biomass and canopy height, whilst percentage cover correlated best with mid-IR band TM-7 and the visible bands TM-1, 2 and 3. Band ratios were more significant than individual bands, when correlations were found of spectral response and canopy variables.

A study by Thomson *et al.*, (1985), using TM on rough Fescue rangeland in Canada, provided information on rangeland condition and forage production. Quantitative biomass estimates in this type of rangeland were difficult, but correlations between TM-5 and TM-7 and senescent material were significant, whilst TM-4 showed a positive correlation with the amount of green material.

It can be seen therefore, that satellite data can provide qualitative and quantitative information on the productivity of grass/rangelands. Productivity is in turn related to the type of grassland vegetation and it is in identifying grassland types which is the main focus of this research.

3.3.2 Inventory Studies

The major problem which exists in attempting to map semi-natural vegetation is that the ground data classification legend is usually ecologically based, whilst the remote sensing classification legend is of a much more general land cover scheme. The remote sensing classification legend is commonly the Anderson *et al.*, (1976) scheme. Problems are incurred when remote sensing studies are performed, using traditionally produced vegetation maps as training data for automated classification. Semi-natural vegetation is very complex and in reality exists as a continua, rather than as a group of discrete classes. A solid line on such a vegetation map is often misinterpreted as being a sharp precise boundary, when in fact semi-natural vegetation is rarely separated by sharp distinct lines. A more ‘diffuse transition zone’, or ecotone (Watson *et al.*, 1978), which can be narrow or wide, commonly exists between units.

The classification scheme quoted frequently from the literature in this thesis, refers to the US Geological Survey (USGS), which has received a wide currency in the remote sensing community. The USGS land cover classification scheme is described by Anderson *et al.*, (1976) and is characterised by hierarchical levels, describing different scales and detail of land use and cover. Level I being the most general with increasing detail described in descending levels.

Level I classifications schemes are generally successful when using satellite data (Weaver, 1984). However, at such a very broad level ecological detail is at a minimum and therefore not really of value for the serious study of semi-natural vegetation. Level II classifications are partially successful (Everitt *et al.*, 1979; Synder and Story, 1986). Level III classifications using satellite data are more ecologically valid, however such studies often encounter problems and misclassifications, although there have been successful applications. Watson *et al.*, (1978), using MSS data was able to describe Level III grassland community units dominated by specific species and Ruth *et al.*, (1986) was able to discriminate to an adapted Level III scale of specific crops, herbaceous pasture, rangeland, scrub and range/scrubland.
The provision of land cover information, using Landsat has been successful in areas characterised by large homogeneous cover units and where cover types are composed of one or two types of plant only. Land cover description becomes more difficult, where land cover types are composed of complex mixtures of vegetation types (Townshend and Justice, 1980).

Examples of the use of remotely sensed techniques in the description of semi-natural vegetation are now presented. MSS data was applied for the mapping of the distribution of wetland vegetation communities in N. America. Barlett and Klemas (1980), demonstrated a method of discrimination that was species specific and was a function of a 'separability' measure. This was in turn a function of the effects of seasonal change i.e., separability was greatest in December and poorest in May, June and July. The application of in-situ radiometry was used in the continuing study of tidal wetland grasses (Barlett, 1981), using standard field biometric techniques. This demonstrated further that the observed variability in canopy reflectance was produced by temporal changes in canopy morphology and composition in terms of canopies dominated by specific species.

The potential of the first four bands of TM in discriminating salt marsh vegetation in the UK was studied using a portable radiometer by Budd and Milton (1982). Canonical variate analysis was performed to aid discrimination; however perfect separation into species groups was not possible although some clustering of species groups in feature space was evident. The poor results were attributed to the fact that multitemporal data was not used, as this would have improved the classification. However, the estimation of ground biomass was successful for some species groups.

Other types of semi-natural vegetation have also been the subject of study. Weaver (1984), worked on moorland communities in the UK and used MSS and airborne thematic mapper (ATM) data. The ability of using satellite imagery in monitoring different levels of detail was investigated. Broad Level I land cover groups such as water, agriculture and moorland were easily delineated with reasonable clarity using MSS data. A second finer scale break down of the moorland was attempted; four classes of moorland were discernible using ATM, with its finer spatial resolution. It was also found that at this level of detail, the optimum number and identity of bands varied for each moorland class (Weaver, 1987). Use of multispectral SPOT data for upland ecological mapping in the UK, was assessed by Jones *et al.*, (1987). A high level of discrimination of Level I land cover categories was apparent despite strong interband correlations.

Effective qualitative inventory of grassland units was achieved by the use of colour and colour infrared aerial photography (Watson *et al.*, 1978). MSS data also used in the study, provided an overview of the six major natural cover units found in the rangeland. By automatic classification of MSS data, Everitt *et al.*, (1979), successfully mapped at a Level II rangeland scale, native and improved grassland in N.America. The satellite estimates of areal extent in hectares corresponded well with the figures derived from aerial photography.

Research in France (Girard, 1981; 1984; 1986) has concerned both topics; biomass production or its agronomic value and the mapping of the spatial distribution of limestone permanent grassland, in central France. Girard (1981), mapped grassland units using MSS multitemporal data. Detailed botanical data was collected and it was found that various factors such as soil, slope and management varied the botanical composition, which in turn varied the agronomic value. The grasslands were linked to phytosociological associations comprising of dry, medium moist and wet grasslands. From these associations agronomic values were calculated, based on fodder utility. It was found that moist grazed and mown grasslands were the most productive, whilst wet and dry grassland units had the lowest production. Classification of two dates of MSS was achieved by density slicing MSS band-7, with thresholds chosen from knowledge of detailed field data. Thematic maps were manually produced from the classifications, and delineations were refined by intimate knowledge of the geology, geomorphology and botanic field data. Cross referencing of the two dates of classification, increased the accuracy of the final thematic map for most land cover categories.

On-going research on the same study area was conducted by Girard (1984a, 1984b). The 1984a study further refined the methodology by the input of in-situ field radiometer measurements. This spectral information was combined with the botanical data to provide description of the grassland units and used for input in to the MSS satellite data. This radiometer and botanic information was used to choose threshold values for the classification of a normalised difference vegetation indice of the MSS data. S.SPOT data was also assessed and evaluated for grassland mapping and estimation of production Girard (1984b). Girard (1986), then went on to model the spectral and botanical parameters of the grassland units. Eight agroecological units were characterised by species and their coverage through time. Spectral behaviour of these units were defined using the in-situ radiometer measurements from the red and near-IR part of the spectrum, to create a seasonal spectral behaviour model. Using remote sensing techniques, this could then be used in the classification and survey of grassland, and to evaluate production.

However, not all inventory studies dealing with semi-natural vegetation and grassland have proved to be so successful. To overcome the difficulties many workers have refined or suggested refinements to methodologies for automated classification and these are discussed further in Chapter Six, section 6.2.4.

CHAPTER FOUR

MATERIALS AND METHODOLOGY

The first part of this chapter deals with the satellite sensors used in this study, together with descriptions of the utility of these sensors in applied research. The second part of the chapter describes the imagery, the imaging processing hardware and the methods used in data handing.

4.1 Satellite Sensing Systems

A brief outline of the types of Earth resource satellites was given in Chapter One, section 1.4. Chapter Four provides a more detailed introduction and review of the two satellite sensor systems; Landsat Thematic Mapper (TM) and SPOT-HRV, which together provided the satellite data used in this study. This includes a description of each sensor's characteristics and each sensor's spectral band complement as pertinent to vegetation reflectance characteristics. Salomonson *et al.*, (1980), provides further discussion of Landsat TM characteristics.

4.1.1 Landsat-5 Thematic Mapper (TM)

Data from the Landsat series of satellites have been available since 1972 (Curran, 1985). The prime source of data from the first three satellites was the Multispectral System Scanner (MSS), which was a four band system with an Instantaneous Field Of View (IFOV) of 79m. The TM of Landsat-4 and Landsat-5 represented a major improvement compared with MSS in terms of the location and number of spectral bands available, the spatial resolution, and the geometric fidelity of the data.

The various characteristics of TM and its data are now briefly discussed. An overview of the main differences between TM and MSS can be seen in Table 4.1. Fundamentally, the TM and MSS operate in the same way, both being optical-mechanical scanners. Radiation from small areas of the Earth's surface is focussed on a detector and the resultant electrical signal which is generated, represents the amount of radiation reflected or emitted from the small elemental piece of ground.

The development and introduction of the Landsat-4 and -5, second generation Landsat series represented a significant advance in remote sensing data acquisition technology. Landsat-5 was launched on March 1984 and carried both MSS and TM sensors. The new TM sensor had improved pointing accuracy and stability characteristics, namely, 0.01 degree and 10^{-6}

degrees per second respectively. It consisted of a seven band, earth looking radiometer. The location and width of the seven bands were carefully chosen for sensitivity to certain natural phenomena and to minimise the attenuation of the surface energy by atmospheric water.

The TM is a scanning optical-mechanical sensor system that records reflected and emitted energy in the visible, near-infrared, middle-infrared, and thermal-infrared regions of the electromagnetic spectrum. A telescope directs the incoming radiant flux obtained along a scan line to linear arrays of detectors (sixteen for each spectral band and four for the thermal band) and the scanning mirror can operate in both forward and reverse scans.

Table 4.1: Comparison of the Landsat Thematic Mapper (TM) with Landsat Multispectral Scanner (MSS) (from Townshend *et al.*, 1988)

TM Band No. Landsat-4, 5	Thematic Mapper of Landsat-4, 5 (μm)	MSS Band No Landsat-1, 3	Multispectral scanner of Landsat-1, 3 (μm)
1	0.45-0.52		
2	0.52-0.60	4	0.50-0.60
3	0.63-0.69	5	0.60-0.70
4	0.76-0.90	6	0.70-0.80
5	1.55-1.75	7	0.80-1.1
6	10.4-12.5		
7	2.08-2.35		
Quantization levels :	8 bits, 256 levels	6 bits, 64 levels	
Field of view (FOV) :	186km	185km	
Spatial resolution :	30m bands 1-5, 7 120m band 6	79m	
Altitude of satellite :	705km	919km	
Frequency of coverage :	16 days	18 days	

Notes : The bands on the Landsat-4 and 5 MSS are numbered 1-4. Landsat-3 MSS carried a thermal infrared band, which failed shortly after launch.

Landsat-5 covers a 185km swath from an sun-synchronous orbit of 705km altitude, to provide coverage every sixteen days (Billingsley, 1984). It has an IFOV and sampling interval of 30m in the cross-track and along-track directions, for six bands in the reflective part of the spectrum. A seventh band in the thermal infrared part of the spectrum has a 120m spatial resolution. In contrast, the MSS provides a spatial resolution of approximately 80m in all bands. Finally, the radiometric resolution has been increased from 64 levels (MSS), to 256 levels (TM). This effectively corresponds to a four-fold increase in the grey scale being used to measure the intensity of Earth's radiation in each discrete spectral band.

4.1.1.1 The Characteristics of TM's Spectral Bands

TM senses more bands than MSS and the TM bands were chosen with a closer relationship to the characteristic spectral responses of vegetation and surface materials (Table 4.2). New bands of TM includes band 1 from the blue visible part of the spectrum and TM-5 and TM-7 from the middle infrared. The TM spectral bands represent important departures from the bands found on the traditional MSS also carried on board Landsat-4 and Landsat-5. The original MSS band widths were selected based on their utility for general vegetation inventories and geological studies. Conversely, most of the TM bands were after years of analysis chosen for their value in the discrimination of vegetation and vigour, measurements of plant and soil moisture, cloud and ice differentiation and geological discrimination. The TM bands are situated to make maximum use of the dominant factors controlling leaf reflectance; such as pigmentation, leaf structure, and moisture content, as discussed in Chapter Three, section 3.1.

Bands 1 and 3 were chosen to coincide with chlorophyll-absorption peaks. Band 1 can differentiate vegetation from soil and band 3 can discriminate between plant species. Band 2, with the green chlorophyll-reflectance peak can be used to assess the vigour of the vegetation. Whereas spectral response in the visible bands is controlled primarily by plant pigments, the response in the near-IR (infrared) sensed by band 4 is controlled mainly by the physical structure of the mesophyll layer of leaves, and gives some indication of the biomass. Band 5, in the middle-IR, is on a shoulder between two water-absorption bands, and gives some indication of the water content (Townshend, 1984).

The spatial resolution of TM is 30m which is finer than the 80m resolution of Landsat MSS. Therefore, for areas containing small fields the dominance of boundary effects can be reduced. Individual fields as small as 30m width can be detected and identified, which greatly aids the accuracy of land use classification for fields less than 5 hectares (DeGloria, 1984a).

Table 4.2 : Potential Vegetational Applications for Single TM Spectral Bands (adapted from Jenson, 1986; Townshend *et al.*, 1988)

TM BANDS	WAVELENGTH (μm)	APPLICATIONS
1	0.45-0.52 (blue-green)	Separation of coniferous and deciduous woodlands and differentiates soil and vegetation.
2	0.52-0.60 (green)	This band spans the region between the blue and red chlorophyll absorption bands and therefore corresponds to the green reflectance of healthy vegetation.
3	0.63-0.69 (red)	This is the red chlorophyll absorption band of healthy vegetation and represents one of the most important bands for vegetation discrimination. Used for vegetation cover mapping and identification of cropping practices. Least effected of the visible bands by atmospheric attenuation.
4	0.79-0.90 (near-IR)	Vegetation survey through reflection by mesophyll layer. Responsive to the amount of vegetation biomass present.
5	1.55-1.75 (mid-IR)	Sensitive to the turgidity or amount of water in plants, used in plant vigour studies.
7	2.08-2.35 (mid-IR)	Lithological discrimination.

The improved spatial resolution over MSS, enables the detection of greater detail, such as drainage networks, roads and localised land cover, and provides greater mapping and mensuration accuracy. The new infrared spectral bands present on TM, provide improved crop and ecological monitoring (Staenz *et al.*, 1980) and the ability to detect moisture content or stress in vegetation (DeGloria, 1984a). The increased radiometric resolution increases the scope for improved vegetation discrimination, as well as greater sensitivity to minor changes in vegetation ground cover.

In comparison with MSS there is a seven-fold areal improvement of IFOV for TM. In terms of visual analysis this improvement is undeniably beneficial. Since compared to MSS, there are a far smaller proportion of mixed pixels, automated classification is inherently likely to be more successful, though the problems of intra-target variability associated with finer spatial resolution also need to be considered.

However, with these advances of TM, there are also drawbacks present. The combined effects of increased spatial, spectral and radiometric resolution, means that the acquisition data rate of the TM is nearly ten times higher than that of MSS. Secondly, as mentioned in the preceding paragraph, for certain types of digital analysis, the improved spatial resolution can be disadvantageous for some applications unless more sophisticated types of information extraction are used.

4.1.1.2 Comparison of TM and MSS Data.

Numerous studies have been conducted comparing actual and simulated TM and MSS, both in data quality, information content and utility for applications (Ahern *et al.*, 1980; Badhwar *et al.*, 1984; DeGloria, 1984a; Owe and Ormsey, 1984). In general, the findings have been summed up by Williams *et al.*, (1984), who evaluated classification accuracies for the two sensors. It was shown that the classification accuracies were significantly improved by using TM data, because of it's increase in the number of bands and improved radiometric quantization. In contrast, the improved spatial resolution of TM did not enhance classification performance for all cover types. Williams attributed this to being a function of a 'per-point' or 'per-pixel' classification algorithm and heterogeneous cover types. This latter effect is described in more detail in Chapter Six, section 6.1.5, dealing with classification and spatial resolution.

A comparison of MSS and TM using Principle Components Analysis (PCA), which is described in more depth in Chapter Five, section 5.1.3.2, looked at the dimensionality of useful information content (Anuta *et al.*, 1984), found there were two significant dimensions in the MSS and up to four in the TM. Spectral analysis produced twice as many separable classes in TM than in MSS. Classes such as field edges, were separated out in TM, but were mixtures in MSS and in many cases not spectrally distinct.

Based on the improvements in spectral, spatial, and radiometric resolution, Solomonson (1984) suggested that :-

> "from a wide variety of analyses and results, it appears that the TM can be described as being twice as effective in providing information as the Landsat MSS".

These findings verify the high quality of TM data and suggested a significant increase in usefulness over MSS, in most earth resource applications. DeGloria (1984a), concluded that TM data would be more than sufficient for meeting most of the inventory objectives of the renewable resource specialist.

4.1.2 SPOT-1 High Resolution Visible (HRV)

The SPOT-1 (Systeme Probatoire d'Observation de la Terre) satellite was designed by the French National Space Centre (CNES) in collaboration with Belguim and Sweden. The first SPOT was launched in February, 1986 and operates in a sun-synchronous near-polar orbit at a altitude of 832km.

The SPOT satellite consists of two parts, the SPOT bus, which is a standard multipurpose platform, and a sensor system payload. The payload consists of two identical High Resolution Visible (HRV) imaging instruments. The HRV sensors can operate in one of two modes : a panchromatic (P) mode with a single broad band (similar to a typical black-and-white photograph) having a resolution of 10m; and a multispectral (XS) colour mode of three narrower spectral bands of 20m spatial resolution (Table 4.3).

In contrast to Landsat's scanning mirror, SPOT is the first satellite with 'pushbroom' sensors, where each pixel across a scan line is viewed by an individual detector (6000 in panchromatic mode, 3000 in multispectral mode). These detectors form a linear array which is moved in a forward direction by the motion of the satellite, hence the name 'pushbroom scanner'. This approach avoids problems associated with the mechanical means of moving the scanner mirror as used in TM and MSS, since the pushbroom scans electronically.

Unlike Landsat, SPOT has new capabilities, these capabilities include nadir and off-nadir viewing, up to 27^{o} from the vertical. Light reflected by the target is focused by a plane mirror onto the detector array. The mirror is steerable through a range of $\pm$ 27^{o}, allowing the instrument to view any point within a strip 475km to either side of the satellite ground track (Mather, 1987a). The off-nadir flexibility increases revisit capabilities, which are very important for observation of phenomena with short time scales or for seasonal vegetation monitoring. During the 26-day period separating two successive SPOT satellite passes over a given point on the Earth, and taking into consideration the steering capability of the instruments, a point on the Earth's surface could be observed on seven different passes if it were on the equator and on eleven occasions if at a latitude of 45^{o}.

A further important product of off-nadir viewing is the capability of recording stereoscopic pairs of images of a given scene. Stereoscopic imagery is obtained by imaging a target area from one side on day 1 and by imaging it from the same angle, but imaging it from the next orbit to the east on day 2. This assumes cloud free conditions for both days. Stereoscopic aerial photographs have been widely used over many years in photogeology and cartography, and it is in these areas that satellite applications in cartography, photointerpretation and the compilation of digital terrain models, that SPOT represents a considerable advance over Landsat products.

Table 4.3 : SPOT Sensor System Characteristics (adapted from Jenson, 1986)

HRV Sensor	Multispectral mode (μm)	Panchromatic mode (μm)
Band Number		
1	0.50-0.59	0.51-0.73
2	0.61-0.68	
3	0.79-0.89	
Quantization levels :	8 bits	6 bits
Field of view (FOV) :	60km	
Spatial resolution (IFOV) :	20m (at nadir)	10m
Altitude of satellite :	832km	
Frequency of coverage :	26 days	
Angular field of view (AFOV) :	4.13^{o}	
Off-nadir viewing :	$\pm 27^{o}$	

If off-nadir viewing is used, care must be exercised to ensure the resulting effects from a non-vertical view angle are taken into consideration. The maximum angular deviation from the vertical with Landsat MSS is 5.8^{o}, whereas the maximum viewing angle from the SPOT-HRV is 33^{o}, taking account of the Earth's curvature (Mather, 1987a). At these high viewing angles the non-Lambertain nature of the reflectance from Earth surface cover types will be a significant factor. This last point is referred to later, when viewing angle is discussed in relation to this study (section 4.2.2.2).

The mode, panchromatic or multispectral and nadir or off-nadir observations, can be programmed via the on-board computer, thus making it in theory, a very flexible system.

4.1.2.1 The Characteristics of SPOT's Spectral Bands

The three multispectral bands of SPOT were selected primarily for vegetation and biomass investigations (Table 4.4.) and as can be seen from the table they are comparable in wavelength with TM bands 2, 3 and 4. This together with the fact that SPOT currently provides the finest spatial resolution, yet available from an operational civilian satellite, indicates it is therefore likely to be of greatest value for detailed vegetation mapping.

Table 4.4 : SPOT-HRV Multispectral (XS) Vegetational Band Applications (adapted from Jones, 1987)

SPOT BANDS	WAVELENGTH (μm)	APPLICATIONS
XS-1	0.55-0.59 (green)	Region of minimum absorption due to chlorophyll in the visible part of the spectrum.
XS-2	0.61-0.68 (red)	Part of the spectrum where considerable radiation absorption due to chlorophyll.
XS-3	0.79-0.89 (near-IR)	Area of peak absorption due to mesophyll layer of leaves.

The potential capability of SPOT utility for vegetation studies as expressed by Jones *et al*., (1987) suggested that :-

> "SPOT-HRV data with its spectral bands chosen to optimise vegetation discrimination, should provide an ideal tool for the mapping of complex semi-natural vegetation. It also provides the opportunity of field pointing flexibility, which offers the possibility of obtaining high resolution multispectral data at critical times in the phenological cycle".

4.1.2.2 Comparison of SPOT and TM Data

Chavez and Bowell (1988) investigated spectral information content of TM and SPOT, using an agricultural region for the test area. Analysis and comparisons were made statistically using correlation matrices for all data sets involved, which were four bands of TM and three bands of SPOT. The results showed that original TM bands contained more spectral information and that TM band-5 revealed field/soil differences not seen in other spectral bands. A Principle Component Analysis (PCA) illustrated that the SPOT data was approximately two dimensional and the TM data was close to three dimensions (dimensions are used in statistical sense and relate to variance or informational components 'per-pixel'). The amount of correlation and percent of variance beyond the second PC, implied that there was new information in the third dimension of TM data compared with SPOT. The results imply that SPOT data for the most part duplicates the spectral information contained in TM data, whilst TM contains spectral information not present in SPOT data, even when using only four of the available six spectral TM bands.

Toll and Kennard (1984) analysed S.SPOT spatial characteristics compared with TM, for discrimination of land cover categories. It was apparent that the higher spatial resolution of SPOT significantly reduced boundary problems, whilst increasing within field variations in a 'per-pixel' procedure. The increased within-field heterogeneity at the finer spatial resolution, increased spectral variability within a class that resulted in class overlap or miscategorisation. Reduced within-class variation at coarser resolutions led to an increase in accuracy of multispectral S.SPOT from 41.2 % at 20m to 51.7% at 80m resolution. This effect would be much less with SPOT data degraded to TM's 30m resolution, although an exact quantitative measurement of this was not addressed. Spatial resolution and classification are discussed further in Chapter six, section 6.1.4, and further studies comparing SPOT and Landsat are mentioned in section 4.1.4.

4.1.3 TM Applications in the UK

There now follows a brief review of TM applications which are related to this study and located in the UK. This supplements the more wide ranging summary and literature review which is given in Chapter three, section 3.3. Numerous studies assessing the potential of TM, for vegetation studies have been made. Initial studies were made using the data from aircraft-mounted scanners, which simulated the spectral performance of the TM. This aircraft or airborne TM (ATM) data has been extensively investigated and there are numerous examples in the literature (Budd and Milton, 1982; Wardley *et al*., 1987).

The National Environmental Research Council (NERC) Daedalus campaign in 1982 using ATM, evaluated its usage in many applications. Work of interest to this study [concerned with using (ATM) in related subject matter] has been made in ecological and agricultural studies (Wardley and Curran, 1984; Townshend, 1984).

Weaver (1987), employed ATM in studies of upland semi-natural vegetation and found it a feasible way of monitoring moorland resources. Further research on upland vegetation using TM has been carried out, looking at landscape classification, vegetation communities and the mapping of upland improved pasture (see for example; Haines-Young and Mather, 1987; Williams, 1987 and Wyatt and Jones, 1987).

Preliminary analysis of lowland heath cover types was conducted using in-situ radiometer and ATM data by Wardley *et al.*, (1987). The classification of lowland heath was achieved with moderate accuracy, by using single date TM data to discriminate between the vegetation communities (Foody and Wood, 1987).

Previous work on lowland grasslands has dealt with agriculturally managed pastures, as well as semi-natural grasslands. A comparison of aerial photography, ATM and TM, was carried out for the surveying of grasslands features (Fuller *et al.*, 1989b). It was found that for generalised grassland inventories, TM proved to be the most successful in terms of accuracy, cost and flexibility. The temporal requirements for grassland classification and mapping has been investigated by many workers; using TM for upland vegetation (Morten, 1987), (Haines-Young and Mather, 1987), and for lowland vegetation (Wooding, 1987). The general consensus being that a combination of a Spring and Autumn scene, produces the best discrimination of grassland from other cover-types, and thus classification accuracy.

4.1.4 SPOT Data Applications

4.1.4.1 Introduction

Analysis of SPOT data for a wide range of applications has been undertaken. Studies investigated by the Principle Evaluation Programme or PEPS campaign, (comparing SPOT utilization with MSS and TM data) have been quite widespread. Such work includes the provision of forest inventory data (Khorram, 1987), qualitative assessment of urban and suburban fringe monitoring (Townshend, 1987), general renewable resource land cover assessment (Cilhar *et al.*, 1987) and crop and soil mapping (Buttner, 1987).

4.1.4.2 General Conclusions

General conclusions found from preliminary work with SPOT or simulated (S.SPOT) data, have found that the utility of the improved spatial resolution and therefore more informational content, lends itself more readily to visual interpretation than to the 'state of the art' automated processing techniques. Analysis of the SPOT data indicates that it is unlikely to yield any further land cover information beyond USGS Level I or II, when using machine algorithms based on spectral rather than spatial data characteristics (Milazzo and DeAngelis, 1984). The higher spatial resolution does not extract more detailed information, but rather improves the accuracy levels for those classes or features that can be readily distinguished i.e., clear boundary detail.

In the selection of training areas, the availability of greater numbers of pure pixels in homogeneous classes, such as crops, meant it was easier to interactively eliminate boundary pixels (Merrit, 1984). Cilhar *et al.*, (1987), also found SPOT data improved detection of field boundaries and that field area measurements were more accurate.

Conversely however, the higher spatial resolution introduces increased intraclass confusion in heterogeneous classes such as urban areas, which decreases the overall accuracy levels obtainable. Spatial discrimination as a function of the spatial resolution was seriously assessed using degraded SPOT data of 80m resolution (Toll and Kennard, 1984). Classification accuracy of the degraded multispectral SPOT was actually higher than the original data set. The reduced intraclass variation of the degraded data reduced spectral overlap and miscategorisation, although small homogeneous classes revealed reductions in classification accuracy in the degraded data, because of the increase in boundary pixels.

It is clear therefore that increasingly finer spatial resolutions does not automatically mean better automated classification performances; it is more a function of the defined classes of interest. Uniform homogeneous classes will benefit, but heterogeneous classes with large amounts of intraclass variation will produce confusion. Such a problem was highlighted by Sakata *et al.*, (1987), where training polygons of urban classes contained very large variances.

Having briefly discussed the spatial resolution parameter of the SPOT sensor, the spectral resolution of the multispectral mode of SPOT, as compared to other sensors will now be examined in terms of applications. It has been shown conclusively that the two visible bands of SPOT data are highly correlated (Jones *et al.*, 1987; Jewel, 1987), therefore it is effectively a two band sensor. Classification studies using two bands SPOT-2 (red) and SPOT-3 (near-IR), showed virtually no decrease in accuracy compared to using all three SPOT bands. Thus indicating that the second visible waveband contributes little to the classification and may even confuse the situation (Pedley, 1987).

Feature selection studies on TM data have found that the near-IR and wave bands such as middle-IR (TM-5) help to increase classification accuracy, especially in agricultural studies (Cilhar *et al.*, 1987). A more detailed description of feature selection and its application to TM is given in Chapter five, section 5.1. The utility of band TM-5 was illustrated in comparison studies between SPOT and TM (Toll and Kennard, 1984; Sakata *et al.*, 1987). Classification assessment was carried out using the three TM bands that corresponded with SPOT, and also with the TM spectral regions not included in SPOT. Results showed that when similar band compliment was used, comparable classification results were obtained from TM and SPOT, but the accuracy gained was significantly increased by inclusion of one of the middle-IR bands TM-5 or TM-7. Therefore, the limited spectral resolution of SPOT may limit class discrimination whatever method of classification is attempted. This point was illustrated by Cilhar *et al.*, (1987), in assessing the spatial resolution of SPOT for the detection of field boundaries. He found that it was essential that spectral contrast was evident between adjacent fields in the first place, in order to detect the boundaries. This illustrates the interlinked relationship of spectral and spatial resolution, in that there has to be spectral contrast present in order to detect spatial details, regardless of how fine the spatial resolution is.

Other workers have found however that in their specific sites, land cover classifications of SPOT data were no better or worse than TM performance (Van Kasteren and Verhoef, 1987). Buis (1984), compared S.SPOT with ATM and TM using an unsupervised approach, he actually found S.SPOT exhibited more spectral classes for their specific study area. This was attributed to the higher spatial resolution of the SPOT data and relatively homogeneous cover types. Also the overall best band for discrimination of crops in a study in Brazil was found to occupy the near-IR window of the spectrum, band 3 of SPOT and band 4 of TM (Batista *et al.*, 1987).

In a direct comparison of TM and SPOT, a quantitative and qualitative determination of the trade off between the spectral and spatial resolution, produced very varied results. This is because the spectral and spatial parameters are highly interrelated, such that spatial resolution is a function of spectral resolution and vice versa (see Table 4.5).

In order to take full advantage of the higher spatial information SPOT provides, development and incorporation of contextual algorithms is recommended, using the spatial information in an automated classification process. Results of preliminary work in this research area are now discussed, which go some way to achieving this aim. Khorram (1987), in a comparison of TM and SPOT sensors, generated textual data from the near-IR band, as an aid and improvement to forestry classification. On-going projects, such as Fernandez *et al.*, (1987) working on crop identification, are developing texture parameter extraction algorithms and Jones *et al.*, (1987), are investigating the use of contextual information in knowledge based classifiers for upland semi-natural vegetation. Improvements by the use of such an approach have been demonstrated by Pedley (1987), using S.SPOT. Contextual information was used in the form of 'per-field', as opposed to 'per-pixel' based classifier, to significantly improve classification of a low lying agricultural region.

Table 4.5 : Spatial and Spectral Characteristics of TM and SPOT

	SPOT		TM	
	Advantages	Disadvantages	Advantages	Disadvantages
Spatial resolution	More detail, clear boundaries	Greater intra-class variation	Less intra-class variation	More mixed pixels
Spectral resolution	Near-IR band	No middle-IR band	More discriminatory range	None

There are a number of general conclusions regarding SPOT's utility, which have been determined by a number of researchers, working on a variety of applications (Milazzo and DeAngelis, 1984; Sakata *et al.*, 1987; Jewel, 1987); and they can be summarised as follows :-

* the high spatial resolution of SPOT at present, lends itself to visual interpretation more readily than automated techniques,
* the spectral resolution is no better or probably worse than current sensors such as TM and
* the greater informational content of spatial detail in the SPOT is not exploited by current traditional 'per-pixel' spectral classifiers and some form of contextual data needs to be incorporated.

4.1.4.3 Semi-natural Vegetation and Grasslands

Pertinent applications related to this study, regarding the utility of S.SPOT and SPOT data are now discussed. Most initial investigations of SPOT data, or its simulation, were qualitative in nature and forecast promising results from this new sensor. Ripley (1987), reported that the improved spatial resolution was a definite advantage in mapping complex wetland communities. Qualitative analysis of S.SPOT in multispectral and panchromatic modes was investigated by DeGloria (1984b), Merrit (1984) and Sailer *et al.*, (1984) for its use in agricultural inventory. From this work, it was found that the characteristics of spectral tones and textures could be used to discriminate crop types and their different stages of growth. Small fields and boundaries, and within-field variability of canopy surface properties were identified.

Several boundary conditions were also discernible :-

* intra-field boundaries, resulting from management practices,
* inter-field boundaries independent of the contrast between fields i.e. roads, tracks, and hedges had unique tonal signatures, and
* boundaries between cultivated regions and semi-natural vegetation, where a sharp contrast occurs between the uniform tone signature of cultivated land and the variable tone signature of the semi-natural vegetated areas.

In a comparison of S.SPOT and aerial photography in mapping productivity levels of permanent pasture in France (Girard, 1984b), eight grassland units were differentiated from aerial photography, which compared to seven units classified from S.SPOT when using vegetation indices and supporting ground data. The resolution of SPOT enabled heterogeneities such as topographical effects, soil background and moisture content, as well as management practices, to be taken into account. SPOT was also found to be a useful tool in inventorying the spatial distribution of grassland units and their potential productivity level (Curren *et al.*, 1987). Curran used actual SPOT data, in which he found that the relationship of near-IR and red vegetation indices, correlated well to vegetation amount and hence productivity.

Semi-natural upland grassland communities were mapped using S.SPOT, and compared to panchromatic aerial photography (Hume *et al.*, 1986). An enhanced false colour composite of the digital SPOT data was visually interpreted by using colour tone, as the criteria for defining vegetation boundaries. As opposed to panchromatic photography or the other two bands of SPOT, the near-IR, SPOT-3 band, was shown to be important for discrimination of specific vegetation communities.

S.SPOT was compared with MSS for rangeland resource mapping (Maslanik *et al.*, 1984). The S.SPOT produced significant improvements over MSS in rangeland classification, and the finer resolution pixels produced more interpretable results. S.SPOT was used to identify rangeland types, small areas of interest and linear features. The higher spatial resolution of S.SPOT over MSS, resulted in fewer mixed pixels and clearer boundary detail, but contained more variation or noise within the cover types.

An evaluation of multispectral SPOT data for the mapping of upland semi-natural vegetation by topographical correction was assessed by Jones *et al.*, (1987). Results suggested that SPOT data exhibited good potential for the discrimination of these cover types.

4.2 Methodology

To devise a suitable methodology for the classification of semi-natural chalk grasslands, theoretical reasoning was used to consider known physical properties of the land surface and its interaction with multispectral radiance. This was used with empirical evidence from the literature.

4.2.1 Imagery

The Landsat-5 TM data used for the study, were portions of scenes 202 (path), 24 (row), acquired 9th July 1984 and the 8th May 1985. These were the most recent TM images of the study area available at the initiation of this work that corresponded with the EN ground data collection. An additional SPOT-1 multispectral image (K, J : 28, 246) dated the 15th of June 1986, was also obtained for the study. Table 4.6 gives details of the imagery used for the analysis, further scene imagery characteristics can be found in **Appendix 1**. Although, the imagery acquired is from different years, the seasonal timings May, June and July coincide with the period of maximum vegetation growth. Unimproved grasslands are by their nature permanent features and as the Salisbury Plain Training Area (SPTA) ranges are semi-natural in nature and undergo minimal management (Porley,1989). The use of multitemporal data from different years was felt to be valid. This is in contrast to an agricultural application, because of the ephemeral nature of crops, where imagery throughout the growing season would be required.

Table 4.6 : Details of the Imagery used in the Study

Scene	Sensor	Path / Row	Date	Cloud/cover*	View angle
1	TM-5	202 24.0	09.07.84	1215	Vertical
2	TM-5	202 24.0	08.05.85	0100	Vertical
3	SPOT	028 246	15.06.86	0000	Vertical

*Cloud/cover denotes the amount of cloud present in each quadrat (0 is minimum : 5 is maximum)

Reference data used to support the analysis consisted of :- i) identification by ground observation : detailed chalk grassland survey of the SPTAs carried out in the summers of 1985 - 86, by English Nature's (EN) field unit (Porley, 1989)(see **Appendix 2**); and ii) farm records (1984 - 85), the author obtained by visiting the area, showing field boundaries and crop type (see **Appendix 3**). In order to facilitate a grassland survey, the general land cover was initially assessed in the training areas. Any non-grassland cover types could be masked out of the imagery at a later stage. From farm records the land cover/crop types identified were, winter wheat, spring wheat, winter barley, spring barley, oilseed rape, woodland, urban areas and the various grassland community types.

4.2.2 Data Handling

The Landsat-5 TM and SPOT data acquired was in Royal Aircraft Establishment (RAE) format computer compatible tapes (CCTs), subscenes of which were down loaded via a host computer to the Digital Image Processing System (DIPS). The data were handled by a low cost DIPS developed inhouse.

CCTs of the imagery were down loaded on to mainframe (Vax 6510 bpi). A subsampled extract of the entire scene for one band (the near-IR band), was then transported over to DIPS via standard Kermit serial line. For all sets of imagery the near-IR band was used, since it displays good contrast without enhancement and is least affected by the atmosphere (Townshend *et al* ., 1988). Therefore by using this band it was easier to determine the location of the areas of interest and 512x512 pixel full resolution extracts centred on these study areas were extracted for further processing.

The data was not calibrated or radiometrically corrected because classification and mapping were the main objectives of the study. Such corrections become more important, when studies are addressed dealing with vegetation amount rather than type (Curran and Williamson, 1987).

For each data set a false colour composite (FCC) was created, with TM, bands 4 (red gun), 5 (green gun) and 3 (blue gun) were combined. For the SPOT imagery, band 3 (red gun), band 2 (green gun) and band 1 (blue gun) were combined. The rationale behind the FCC selection is described in Chapter five, sections 5.1 and 5.2., although some analysis of other new and traditional TM band combinations was undertaken (Chapter seven, section 7.1). The images were contrast enhanced to facilitate interpretation and processing.

Scaled FCC were produced, using TM-4, 5 and 3 band combination and SPOT-3, 2 and 1 band combination. These were used in conjunction with Ordnance Survey (OS) maps and ground data to visually identify the major and minor land uses of the study area.

Contrast enhancing, or stretching, is a transfer function via look-up tables (LUT), which alter old pixel values to new pixel values. Various stretches can be applied which basically shifts the pixel values to the full radiometric range. Fundamentally, a stretch expands the original input brightness values (BV) to make use of the total range or sensitivity of the output device, a display medium which is generally a video cathode ray tube. There are linear and nonlinear digital contrast enhancement techniques (Jensen, 1986). Linear stretches shift the pixel values by equal amounts. Nonlinear stretches reduce contrast in high and low values, but increase mid-range values and with this stretch the amount of shifting is proportional to number of pixels with specific value.

4.2.2.1 Registration and Geometric Correction

The use of two or more images of the same scene but taken at different times, i.e., multitemporal data, will generally enhance the classification of the imagery (see Chapter five, section 5.3). A fundamental pre-requisite for the use of multitemporal data is the ability to register the imagery to a common projection, i.e., image to image and/or map. This is necessary for pixel to pixel comparison from one date to another. The accuracy of any results derived from multitemporal data sets are closely related to the accuracy of registration of the original scenes (Anderson, 1985).

Geometric correction of each scene was carried out, matching image points with known ground locations, as found on 1: 50000 scale OS maps, and using the corresponding pairs of co-ordinates to generate the co-ordinate transform equations. Approximately twenty ground control points (GCPs) in the vicinity of the study area were used for each temporal subscene.

For detailed comparison, the two TM scenes and the SPOT scene were registered to the BNG (British National Grid). Geometric correction restores the image, correcting the random internal sensor distortions (systematic distortions) that the satellite imagery can contain. Most of the the digital data that the user receives have already had systematic error removed by the satellite companies (Billingsley, 1983). Random changes in the sensors orbital characteristics (non-systematic distortions), such as yaw and roll can also be corrected by this procedure, but sufficient number of GCPs are needed to do this accurately (Jensen, 1986). Generally, 'users' have to correct this latter type of geometric error, depending on the amount of image preprocessing already done before the 'user' receives the data.

An auto-linear contrast stretch was found to be the most effective for ground control pointing of features which were easily recognised on both the stretched images and the OS map. The sample and line numbers were determined from the starting image, and the BNG co-ordinates read off from the map were converted to sample and line numbers in the target image. Accurate GCPs require points with high contrast and reproducible positions. Road and rail intersections provide good control points, but care must be exercised with natural features.

Two basic procedures must be preformed to geometrically correct a remotely sensed image (Jensen, 1986) :-

* *spatial interpolation* : this is the geometric relationship between input pixel location and the associated map co-ordinate of this same point, used to rectify the output image. This interpolation uses least-squares criteria to model the corrections and transformations which correct the imagery to a geographic frame of reference. Approximately 20 control points for each scene, were used to determine the second order poynominal which describes the transformation from the starting (original image) to target (BNG map) co-ordinates. Once the transformation or T-matrix describing the transformation has been created, this can be stored and used to geometrically correct the imagery when all the processing, such as classification, has been completed.

* *intensity interpolation* : which is the process whereby pixel brightness values (BV) or digital numbers (DN) are calculated, once the spatial interpolation has been determined. There are three methods of intensity interpolation in common use, each with its own advantages and disadvantages. The practice of BV interpolation is commonly referred to as resampling. The first is termed nearest-neighbour and is the simplest to calculate. It basically takes the DN of the pixel in the input image that is closest to the computed output co-ordinates. A full mathematical explanation is given by Mather, (1987a). The advantages are that it is computer efficient and that its use ensures that the pixel values in the output image are 'real', in that they they are copied directly from the input image. They are not artificial values, such that this interpolation does not alter the pixel DN. It is often the very subtle changes in brightness value or DN that make all the difference when discriminating vegetation types, thus this method is often favoured by earth scientists (Jensen, 1986). On the other hand, it does produce a rather blocky effect, as pixels tend to be repeated (Mather, 1987a).

The other two interpolation techniques use averages to compute output intensity value and often remove valuable spectral information. The second method is termed bilinear interpolation and this takes account of the four neighbouring pixel values and computes new DN based on the weighted distances to these points. This interpolation results in a smoother output image, because it is essentially an averaging process. Thus sharp boundaries in the input image may be blurred in the output image and the computational requirements are greater than nearest-neighbour.

The third in common use, bicubic convolution, works in the same manner as bilinear interpolation, except that the weighted values of the 16 nearest pixel values in the input image, are used to estimate the new value on the output image. This technique is more complicated than the other two, but it tends to give a more natural-looking image, without the blockness of nearest-neighbour or the over-smoothing of the bilinear method (Mather, 1987a). The penalty being a considerable increase in computing requirements.

The resampling algorithm should therefore be considered carefully, and the choice of method therefore depends on the amount of computer facilities available and on the use the corrected image is put to. If it is to be used solely for classification, the replacement of raw data values with fabricated interpolated values by the last two techniques described, may have an effect on the subsequent classification.

Geometrical and resampling error of scene to scene registration of multitemporal data is substantially less than that involved in scene-to-map registration i.e., the geometrical changes of rotation are less between two scenes (Townshend *et al.*, 1988). Therefore, classification was carried out on registered scenes, and as a final step the classifications were transformed to map coordinates by bicubic convolution. By geometrically correcting after, rather than before the classification, this eliminates the need for choosing the nearest-neighbour method and it would be the most economical procedure for this type of straight classification study (Mather, 1987a).

As a formal and quantitative account of classification accuracy, an additional data set of a ground vegetation survey map was integrated with the satellite data sets. Integration of the vegetation map data and remotely sensed data can be used for quantitative and qualitative interpretation and analysis of images (Pedley, 1986). When integrating data sets from two different sources (i.e., vector cartographic data and raster satellite data), Baker and Drummond (1984), put forward requirements that the two data sets :-

* be of the same format (i.e., conversion of vector data to raster format),
* be transformed to a common co-ordinate system (i.e., the BNG in this case),
* be of compatible resolution, and
* be contemporaneous.

All of these criteria were fulfilled by the data obtained for this study.

The EN vegetation map compiled by field survey, was vector digitised and converted to raster format and transferred to the image analysis system (DIPS). The raster vegetation or cartographic data can be produced in two forms. Firstly, as an overlay showing boundary detail for visual comparison with the satellite data. Then secondly, digital cartographic data can be employed to generate solid region of interest polygons for the pertinent ground cover types : these can then be combined with the registered multitemporal satellite data This procedure can then be used to supervise the training area allocation for classification, and assess the accuracy by selection of test verification data as well. It also enables pixel-by-pixel comparisons to be made between ground data and satellite classifications.

Once the data sets have been integrated, complete images can be displayed, with near-IR on the red gun, the red visible band on the green gun and the digital vegetation map on the blue gun. It is possible to display individual components, such as the digital vegetation map, a vegetation index image and a density slice or a composite image, as an aid to image interpretation and analysis. Pedley (1986), suggested that such a set up can enable further processing, in that selected features of interest, for instance field boundaries from an OS map, can be shown and used as a basis for 'per-field' automated classification.

4.2.2.2 Environmental Variables : Atmospheric Effects, View Angle and Topographical Effects

The radiance measured by earth orbiting satellites is a combination of the energy reflected from the ground (attenuated by the atmosphere), and the radiance of the atmospheric path. The path radiance in turn, is caused by the illumination of atmospheric components by sunlight, by other components of the atmosphere and by light reflected to the ground. Due to the combined effects of attenuation and path radiance, a given pixel as seen at the orbiting sensor may appear either lighter or darker than it would at the ground. There is as yet no adequate measure of atmospheric effects (Jensen, 1986).

Certain bands will almost certainly be affected by the degree of interactions of radiation and the atmosphere. In the case of Landsat TM, the affect will be strongest for band 1 and least for band 4, and to a certain extent with TM-5 and TM-7 by the presence of water vapour. The spectral coverage of SPOT means that atmospheric effects are less significant than with TM. There is no quantitative estimate of the atmospheric contribution, however, these effects can be estimated by various methods and models in order to calculate attenuation and brightness (Jenson, 1986).

Since the sub-scenes obtained for this study area were for the most part cloud free, unhazy and that TM band 1 was not used in the colour display of imagery, the atmospheric effects were ignored.

Classification using spectral responses assumes that spectral responses are spatially independent. However, dissimilar spectral responses can be observed from areas of the same land cover class, sensed under different viewing geometries. Vegetation canopies often exhibit a rather different detected spectral response when viewed at a angle, compared to that when viewed vertically downwards i.e., nadir viewing. One of the main reasons for this is that vegetation canopies are imperfectly diffuse (non-Lambertian) reflectors and they do not reflect incident radiation equally in all directions (as previously mentioned in Chapter three, section 3.2). The magnitude of this effect is modulated by intra-class spectral variability i.e., the effect is more apparent for a homogeneous cover class covering a large spatial area, than for a heterogeneous cover class.

This effect is not thought to be significant for MSS data, which has a 11^{o} field-of-view and for TM data which has a field-of-view of $\pm$ 15^{o} from nadir. But for other sensors, such as Advanced Very High Resolution Radiometer (AVHRR), Synthetic Aperture Radar (SAR) and SPOT, the field-of-view can be up to $\pm$ 112^{o} from nadir and thus view angle-effects will be very significant (Foody and Wood, 1987). Barnsley (1984), reported that for the higher latitudes ($>50^{o}$) such as the UK, that SPOT (or other satellite) imagery collected close to the summer solstice will have minimal view-angle effects.

The SPOT imagery, acquired for this study was dated June, which is close to the summer solstice, and therefore (due to the use of TM scenes and a nadir SPOT scene of $\pm$ 16^{o} view angle all acquired in the summer season), an assumption was made that the view angle effect on spectral response for a given cover type would be insignificant.

Topographical effects of the terrain on spectral response from nadir pointing sensors have been shown comprehensively to be very significant. Holben and Juistice (1980), found that a wide range of pixel values can be associated with one cover type, due solely to variations in slope angle of the terrain and aspect, and thus influence the accuracy of information extracted from remotely sensed data. Hall-Konynes (1987), investigated topographical effects on Landsat data for three dates in gently undulating terrain in Southern Sweden. Gently undulating terrain was defined as terrain dominated by slopes between 1^{o} and 15^{o}. The relationship between Landsat MSS and TM response variation and topographic parameters within cropped areas and forest was weak, but for some pasture covers a topographical effect was identified (for April only) relating to slope aspect and slope magnitude.

Therefore, in the context of this study conducted in the Salisbury Plain area, which can be essentially described as gently undulating chalk downland, with slope angles of the range of 1^{o}-13^{o} and with a mean gradient of about 7^{o}, topographic factors, such as slope degree and slope aspect, should not unduly adversely affect spectral response, even though dealing primarily with grasslands cover types. Since the study area is gently undulating lowland, variation due to topography was less significant than variation due to real vegetational differences.

4.2.3 Digital Image Processing System (DIPS)

An inhouse workstation was used, which was based on an IBM PC-AT image processing system called 'ITS-30' (Flach and Chidley, 1987)(Flach *et al.*, 1987), which was controlled by commands from a keyboard and mouse drive. It incorporates a software package termed '*iconoclast* ', which have been integrated in a 'WIMP'S' environment to provide a user-friendly front end with pop-up menus and interactive screen update.

In addition several subsystems or peripherals were used :-

* a text character generator used to display instructions and information on a colour monitor,

* a floppy disc drive card controlling the floppy disc unit and also interfacing that unit to the system. Standard 5.25 inch, soft sectored discs were used to store and input additional software. A 230 megabyte two-sided high density laser disc storage system.

* a standard serial line interface (via Kermit) for communication with host computer (Vax 8650),

* three 0.5 Megabyte image planes (frame stores) each capable of storing 1024 x 512 x 24 bit image. Each image plane is attached separately to the Red, Green, Blue inputs of high resolution display monitor, providing 256 shades of each colour combining to give a palette of 16.8 million colours,

* the framestore on each image plane is configured as two pages of 512 x 512 pixels, eight bits deep. This means six images or bands can be held in the framestore simultaneously, although only three bands can be displayed on the monitor at any one time.

* a super VHS full colour video camera, whose output can be digitised via a frame grab module to provide a 512 x 512 x bit image and

* an Integrex colour jet 132 ink-jet plotter and A1 H.P. plotter, to provide hard copy of images displayed on the monitor.

As well as the '*iconoclast* ' image processing software, the system also incorporates video digitisation, a digital mapping system and a spatial analysis package culminating into a full Geographical Information System (GIS) environment.

4.2.4 Training and Test Area Selection

Due to the fact that comprehensive ground data or *a priori* knowledge was available, supervised classification was attempted and training data selected. Ground data in the form of EN vegetation maps incorporating the NVC scheme, were used in conjunction with remotely sensed satellite imagery.

Such information may be used for two purposes, (Bradbury and Macdonald, 1986). Firstly, 'training sites' were used for the generation of spectral statistics for each cover class. Standard statistics are generated, such as the mean ($\overline{x}$), standard deviation (s) and covariance matrices. Secondly 'test or verification' sites from the reference ground data are used to assess the land cover classification performance. 'Per-point' or 'per-pixel' sampling test areas were chosen primarily, because they enable classification confusions between cover types to be highlighted by the production of confusion matrices (Bradbury and Macdonald, 1986). By using objective 'test' areas for the assessment of classification, lower relative levels of accuracy can be expected, compared to results quoted for other references. However, the use of test areas produce classification figures that are in fact the 'real' accuracy of remote sensing results and not the higher subjective results obtained when classification performance is judged by sole usage of training area data (Congalton, 1991).

The training areas were selected at random, but stratified to avoid boundaries in cover classes. Training populations were selected that were approximately equal for each class and the number of pixels in each class were determined by the procedure put forward by Swain and Davis, (1978). This is where there are 10n to 100n pixels per class, where n is the number of bands used in the classification. It is important to represent the classes with sufficient number of pixels, and to ensure that they comprise an exhaustive and representative set of all the spectral variation for each class, within the study area. However, care must be exercised in training area selection (McMorrow and Hume, 1986). Further information on the selection and sampling of training and test sites see Chapter Seven, sections 7.3.1.1, 7.3.1.4 and 7.3.1.5.

Many classifying algorithms assume that the data exhibits a Gaussian or normal distribution, but this is not always the case. It has been shown that the method of training data selection, as much as the type of classifier used, affects classification accuracy. Hixon *et al.*, (1980) reported that the major variable affecting classification accuracy is not so much the type of classifier used, but rather the method used to generate training statistics.

Whilst a considerable amount of effort has been devoted to the analysis of the performance of classification algorithms, research into training data and its selection has largely been ignored. Adequate and representative training data with respect to their parent class are needed, since the inclusion in the training data of pixels which do not belong to the class in question can seriously distort sample statistics and hence the performance of the classifier. Most classification algorithms are parametric in nature, in which certain assumptions apply regarding the normality of data distributions.

A study by Mather (1987b), drew attention to the effects of the inclusion of atypical pixels in training data; a robust automated procedure was outlined for the removal of such pixels and such a procedure was demonstrated on model data. Glasbey (1988), took this a stage further and used actual multispectral training data of two cover types. When a more robust estimation of probability membership was applied to the training data, it was found that outlining or atypical pixels were ignored. The atypical pixels were found to correspond with boundaries of fields, the training areas had been specified too large and had included boundary pixels. Therefore, either care should be exhibited with training area selection, or the application of a robust procedure should be used to protect against atypical pixel values, which may be present in the training statistics. One such procedure could be the use of a crude form of spatial auto-correlation i.e., model filtering to remove atypical pixels in the training data. This technique is usually applied to filling in missing scan lines in digital imagery, (Mather, 1987a).

The establishment of training area polygons on the enhanced imagery from *a priori* knowledge was the initial stage in the classification procedure. Training areas were defined by means of a mouse, and from these areas the multi-dimensional pixel values were used to generate statistic files. These were used to examine and compare spatial characteristics of the data. The statistics for each cover class were then viewed by a number of quantitative image processing functions. Graphical methods allow fundamental understanding of the spectral nature of the data, rather than relying on totally abstract statistical analysis (Jenson, 1986).

However, such statistical measures, such as transformed divergence, provide a quantitative assessment of the data and are discussed in Chapter Five, section 5.1.2 on statistical separation. Frequency histograms of DN values were generated. Frequency histogram plots are basically grey level DN values plotted against the frequency of occurrence of grey levels for a specific cover type and wavelength band. Frequency histogram plots can be used to check the characteristics of training data sets for bimodel or multimodel distributions.

The multispectral response graph or coincident spectral plot is basically the mean ($\bar{x}$) spectral response for each cover type plotted against wavelength. Standard deviation (s) from the mean is calculated and displayed either side of the mean. The larger the standard deviation the greater the variance. From examination of coincident spectral plots, the relative spectral response of cover types are illustrated from one part of the spectrum to another. Specific combinations of wavelength bands, graphically illustrated by coincident spectral plots, could enable the spectral discrimination of cover types, which were probably not possible in any single wavelength band or other band combination.

Separability measures of the classes were graphically illustrated by coincident spectral plots and computed two dimensional scatter plots using two bands. Having graphically checked the training class statistic files, they were then inputted into the classifying algorithm and then the raw classified images were displayed and compared with ground reference thematic maps.

Confusion matrices were generated, which enabled classification accuracies between the cover types to be highlighted. The accuracy value for each cover class was simply taken to be the percentage of correctly identified pixels in the 'test/verification' sites for each cover class. Errors of omission are the percentage of incorrectly identified pixels in the test sites for each cover type (i.e., class x was classified as another class). Errors of commission represent the amount of over-estimation by the classifier (i.e., pixels from other classes are labelled as class x). Confusion matrices are described in more detail in Chapter seven, section 7.3.1.4.

In summary therefore, it would seem that any classification performance is only as good as the training data used. Which is in turn dependent on the skill of the analyst, his knowledge of local vegetation and land cover, and the way training areas are selected.

The basic classification procedure used in this study is an adaption based on the flexible methodology put foreword by Van Genderen and Uiterwyk (1987). Such a procedure allows efficient and reliable classification and production of thematic maps from digital data.

An overview of the procedure is outlined below and is schematically illustrated by Figure 4.1, with the various stages annotated :-

i) enhancement of the imagery by contrast stretching or spatial filtering, to facilitate digital and visual analysis;
ii) to define interactively training area locations, from which training statistics are generated;
iii) view and edit training statistics, this can be done graphically by viewing the shape of histograms of class statistics, or by generating scatterplots showing the bivariate frequency distribution for two bands, and/or by statistical methods by using some form of measure of separability, a common example being transformed divergence;
iv) the analyst selects and implements a suitable classifier;
v) the results of the classification can be viewed on the display and compared with ground data. If insufficiently accurate, it is possible to loop back in the sequence of stages to either revise the training sites, the training statistics or apply another classification algorithm;
vi) the next stage is to specify the accuracy of the results, usually by means of a confusion matrix;
vii) once acceptable classification has been obtained, post classification techniques such as logical smoothing or model filter, can be applied to increase accuracy, or present a more 'thematic map' quality to the end product.

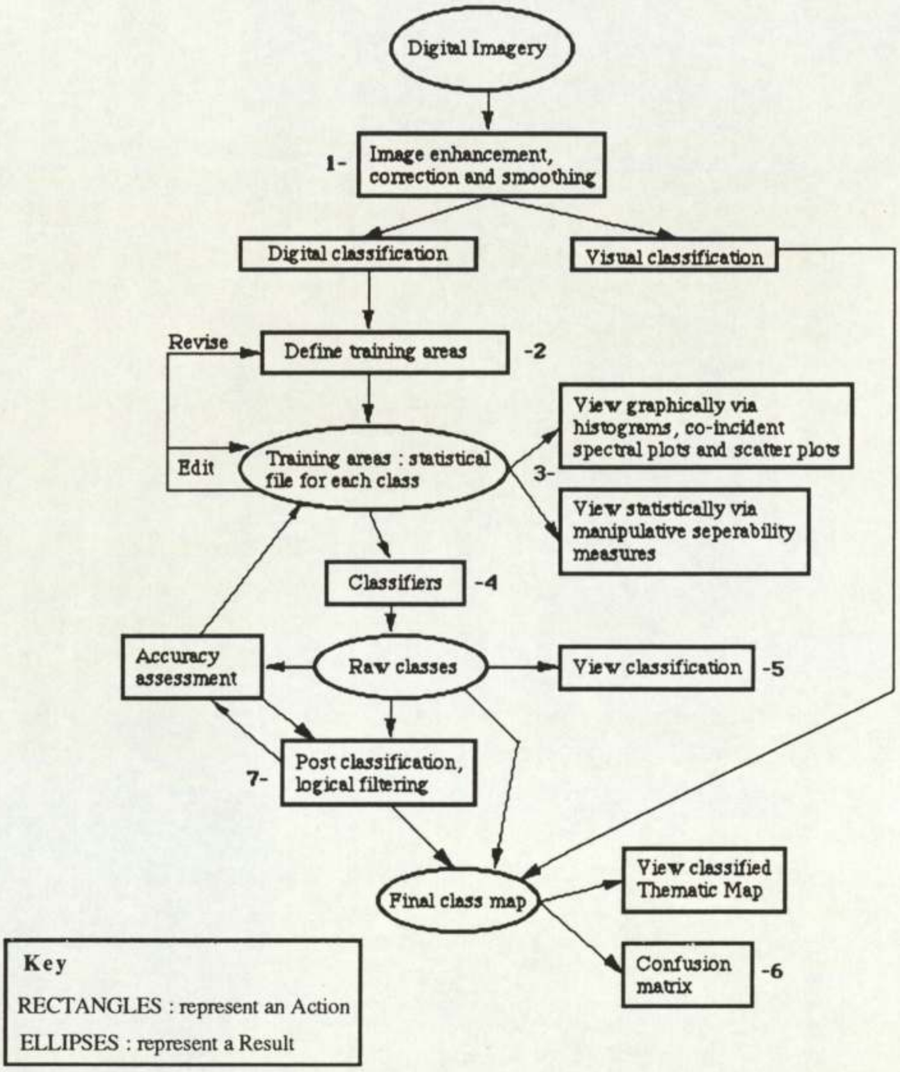


Figure 4.1 : Flow Chart of Digital Imagery Classification Procedure (adapted from Van Gerderen and Uiterwyk, 1987)

CHAPTER FIVE

IMAGE ANALYSIS TECHNIQUES

This chapter introduces the reader to some of the analysis techniques available and employed in the extraction of information from remotely sensed imagery. A detailed account is given of the background and the various options used in feature selection, and the reasons for choosing particular band combinations used in this study. This goes hand-in-hand with a review of interactive visual analysis and of the various colour displays that can be used. The final section of this chapter deals with the use of multitemporal data sets in the analysis of relevant areas of research.

5.1 Feature Selection

5.1.1 Introduction

Feature selection is the technique used to select, or otherwise combine in someway, the original bands of multidimensional data. This is done to :-

i) produce a displayable image, and
ii) reduce the volume of data that must be processed and analysed.

It is obvious that it is to the 'users' advantage to work with as few components or bands as possible, because in operational circumstances there will be limits of both time and budget for processing the data. The main objective is to remove data redundancy and efficiently extract useful information.

In the case of TM, there are seven bands available; however generally the coarser resolution thermal band is not usually used, i.e., it is frequently discarded in general mapping applications of remote sensing (Townshend *et al*., 1988). In the appropriate conditions, each of the remaining six reflective spectral bands can contribute unique information.

The prime requirement is to identify which three band subset would be optimum for a particular application. There are 180 possible three band combinations for the six spectral TM bands, when considering all band permutations and display colours. If colour assignment is resolved (see section 5.2.2 on colour assignment), there are still twenty band triplet permutations possible.

Feature selection both for the creation of colour composite imagery and for digital analysis should be carefully tailored to the results desired for a specific application. Since there is no 'best' subset of bands for all cover classes, it is important to identify what are the most significant classes of interest and which spectral bands contain the most information of interest.

Multispectral data can be expected to contain a certain degree of correlation between the different spectral bands for the same object in the band images. Therefore, these images can be said to contain a certain amount of redundant data. This can be reduced by choosing the least correlated bands, since remotely sensed multispectral data has been shown to contain high interband correlations; MSS, Staenez *et al.*, (1980); TM, Townshend and Justice (1980); SPOT, Toll and Kennard (1984). There is a redundancy of information which is source dependant, such that the intrinsic dimensionality required to characterise a specific data set is often less than the number of available bands. Research has shown that classification performance does not increase exponentially with the number of bands used. Work on TM has illustrated that for most specific tasks, three or four bands provided overall classification accuracies comparable to using all seven bands (Toll, 1984; Ahern *et al.*, 1980). The value of some sort of data compression is evident, especially in the light of on-going and future sensor development, where there is a trend of increasing spatial and radiometric quality, which results in larger volumes and dimensionality of data generation and therefore computational demand.

There are several common approaches to the reduction of the dimensionality or feature space of the data. The simplest method involves manual selection of an optimum subset based upon *a priori* knowledge. Selection can also be made upon one of a number of statistical separability measures or by reducing the dimensionality of the data by various transformations. The latter two methods are now discussed in detail.

5.1.2 Statistical Separation

5.1.2.1 Transformed Divergence

The most common and accepted statistical separability measure is the transformed divergence measure; there are numerous others, but only transformed divergence is considered here. Transformed divergence methods allow the relative worth of features to assessed in a quantitative way. This procedure determines the mathematical separability of classes; in particular, feature selection is performed by checking how separate various spectral classes remain when reduced sets of features are used. Provided separability is not lowered by the removal of features, then those features can be considered of little value in aiding discrimination and therefore should be discarded in the classification process (Richards, 1986).

Pairwise transformed divergence is a measure of two probability density distributions (Singh, 1984). The divergence statistic, measures the separability of any two classes in feature space taking into account both the differences in their mean vectors and variance-covariance matrices. It can be computed for various multispectral band groupings, in order to optimise the number and choice of waveband combinations in feature selection (Cushnie, 1984). The divergence measure of statistical separation can also indicate separability between classes, and has been used as an indirect approximation of classification performance (Thomas *et al.*, 1987).

The use of divergence or any separability index has therefore two roles :-

i) it recommends the lowest number of bands that will produce adequate accuracy (band feature selection); and
ii) it identifies classes that have poor separability for a given data set.

Thomas *et al.*, (1987), provides a review paper of most of the common multi-band statistical separability indices used in remote sensing. It is evident that such techniques can be very useful in feature selection (Richards, 1986), however this technique was not used in this study because of software limitations.

5.1.3 Transformations

For some applications it may be advisable to use new and more suitable data sets. A suitable method of data transformation can then be applied to the data.

5.1.3.1 Band Ratios

The process of dividing spectral bands of the same image is known as ratioing. It is one of the most common transformations applied to remotely sensed images. Band ratios can reduce the dimensionality of the data set, highlight differences in spectral reflectance between different cover types and can eliminate undesirable effects on the recorded radiances, such as topographical effects. The most common spectral ratio used in studies of vegetation is the simple ratio of near-infrared (IR) band over the red visible band. This ratio exploits the fact that vigorous vegetation reflects strongly in the near-IR and absorbs in the visible red. It has been found that this band ratio correlates well with vegetation amount and with Green Leaf Area Index (GLAI) by Curran, (1983). More complex ratios involve sums of, and differences between, spectral bands; for example - the Normalized Difference Vegetation Index (NDVI) has been widely used (Mather, 1987a). Such ratios are suggested to be more appropriate for use in studies over time for a single area, where comparisons of production are to be made.

5.1.3.2 Principal Component Analysis

Reduction of the dimensionality of a data set can be achieved by principal component analysis (PCA). This second systematic approach involves the linear transformation of the original bands to a set of uncorrelated new orthogonal transformed components, in which a maximum amount of spectral information is accounted for in descending order along the transformed component. One common linear transformation is called the principal component or Karhunem-Loeve transformation, in which new data sets are created. These PC generated images are then totally uncorrelated with each other. They correspond to the eigenvector of the image covariance matrix and are ordered by decreasing eigenvalues. The informational content of the multispectral bands is redistributed among these components in such a way, that most of it is concentrated in the first few principal components. Generally, a subset of the three or four higher order eigenvectors will account for almost all the information contained in the entire set of original wavelength bands, resulting in approximately the same classification performance as if all the original bands had been used.

In essence, eigenvector coefficients define the orthogonal co-ordinate system projected through the dimensions of maximum variance or information content of the data in N-dimensions. The first component has direction through the maximum variance with length proportional to the first eigenvalue. The remaining vectors and values determine the orientations and lengths respectively of the second and higher components axis, each in the direction of the maximum variance remaining in the data (for fuller mathematical explanation, see Dean and Hoffer, 1983) .

By transforming the original multi-band data set using PCA, the optimum dimensionality or information content can be determined from the eigenvalues. In addition, specific original bands can be defined using eigenvector coefficients, as being the most important in terms of information content (feature selection); for both specific cover types and for a multi-class situation. One concern is that there is potential loss of descriptive information about the relative importance of the various wavelength bands for individual cover class discrimination. In a multi-class situation, of varying *a priori* probabilities, the eigenvector coefficients will indicate only the the overall importance of the original wavelength bands for the entire data set. Individual cover classes may not be optimally represented in the eigenvectors, since some classes may have high *a priori* probabilities and/or a relatively large spectral variance and therefore exert more influence on the resulting eigenvectors.

Previous research has shown that with MSS imagery, the first two principal components contain 98% of the essential variance, or information content, present in all original spectral bands. However, PCA of TM imagery revealed that it was the first three principal components that contain 98% of the information. Therefore, it can be said that MSS data is basically two dimensional and that TM data is three dimensional. There are numerous examples in the literature of the use and application of PCA (Anuta *et al.*, 1984)(Townshend, 1984).

PC generated images of MSS data gave greater classification performance for general land cover classes, than the best three original spectral bands in feature selection (Ready and Wintz, 1973). Generation of PCs for TM data created a subset of three higher ordered eigenvectors, that when classified produced approximately the same classification performance as if all seven original bands had been used. Here, there is the added advantage on the saving of computational processing time (Dean and Hoffer, 1983).

PCs have been used in the analysis of biomass and percentage cover of monoculture grass canopy using TM. The first two principal components contained all the variation found in all the original spectral bands (Ripple, 1984). It was suggested that from PC transformation that two or possibly three PC subsets of the original bands may be sufficient for mapping grassland vegetation characteristics with TM imagery.

5.1.4 Feature Selection for Three Colour Display

Since only three bands or images can be seen on a image display at any one time, many authors have addressed the question of which three band subset to use. It has been shown convincingly from empirical evidence (Townshend, 1984), that the best combination of three bands for TM data includes one from each of three regions of the spectrum (the visible, near-IR and the middle-IR). This is most readily done by simple correlation analysis of the bands. The more complex techniques mentioned in the previous section, have also been used in feature selection for the best three band or image colour display; and these are now discussed.

Studies have used transformed divergence values, for band feature selection and for the analysis of spectral class separability of TM. In the former case, Buis (1984), used this measure to select the optimum number of bands for ATM and TM. It was found that adding a fourth, fifth and sixth spectral band did not significantly increase separability, and that a three band subset was an appropriate number with which to process.

Other workers have investigated alternative methods to transformed divergence, as a means of determining optimum band selection. Chavez *et al.*, (1984) addressed the problem in detail by using automated statistical means, since :-

> "in deciding which band combination contains the most information on the basis of visual analysis would be very difficult and a time consuming process".

A quantitative statistical technique called the Optical Index Factor (OIF) was developed. This was used to rank the twenty possible combinations of the six spectral bands, based on the amount of correlation and total variance present between the various data sets being used. The OIF algorithm generates values and the largest value generated from the OIF for a particular three band subset displays the most information and the least amount of duplication, as measured by variance. For a temperate agricultural region, it was found that a combination of one visible band (TM-1, 2 or 3, all of which provide similar information); one longer wavelength IR band (TM-5 or 7, which provide information different from the other bands, but were correlated to each other); together with TM band 4 from the near-IR region, (which contributed unique information), provided the most useful information. TM band 4 was present in five of the first six ranking triplets generated by the OIF.

Having established that TM-4 provides information not provided by other bands, there is the question of which visible band to use and which middle-IR band to choose. As this study is concerned with vegetation, specifically grasslands mapping, the relevant literature was reviewed, where it was found that precise three band triplets utility was quoted.

The literature suggests that most band selection is made rather crudely by calculating correlation coefficients for each band in the multispectral imagery and selecting the three least correlated bands. Applications, using this measure of informational content, consistently found a three band subset of TM-4, 5 and 3 was the optimum. For example, Staenez *et al.*, (1980), working on nine common crop types found that the lowest band intercorrelations were for TM bands 4, 5 and 3, and similar results were also found by Toll (1984). DeGloria (1984a) investigated crop discrimination, described the low interband correlation of TM-4, 5 and 3 in terms of physical interaction of the specific bands and surface material. The relative low correlation resulted from the combined influence of vegetated and non-vegetated surfaces absorbing red radiation TM-3; plant canopy structure and background surfaces reflecting near-IR, TM-4; and plant canopy moisture and moist surfaces absorbing mid-IR TM-5 radiation. Gorden *et al.*, (1986), used TM bands 4, 5 and 3 to separate fruit tree orchards from other vegetation cover types using multitemporal imagery.

Further studies, more relevant to this research topic, also found that a subset of bands TM-4, TM-5 and TM-3 were the best, for USGS hierarchical (Anderson *et al.*, 1976) Level I classification (Townshend *et al.*, 1983); for Level II (Synder and Story, 1986; Toll, 1984; Anuta *et al.*, 1984); for assessing rangeland conditions (Thomson *et al.*, 1984), and for mapping lowland British grasslands (Fuller and Parsell, 1990).

Thomson *et al.*, (1985), investigated three band colour displays for the visual interpretation of rangeland conditions. It was found that TM-7 had slightly more cross correlations with other bands than did TM-5, and therefore TM-5 was found to be the better middle-IR band. The least correlated three band subset was again TM-4, 5 and 3.

Other sources have suggested that TM band 1, primarily designed for water penetration, appears to be the most powerful of the visible bands, even over land areas (Chevez *et al.*, 1984; Colvacaresses, 1986). However, this might be true for general land cover categorises, but the preceding evidence suggests that the visible TM band 3 is superior for specific vegetation and range/grassland studies.

Sheffield (1985) presented a different statistical band subset selection algorithm, which was applied to the seven TM bands. This approach used an adaption of a general principle component (PC) transformation, without actually performing rotational transformation and therefore using the original band statistics. Thus, the use of this procedure provides a single preferred choice, decided uniquely by the statistics of the scene or subscene and taking into account any correlation that exists between different bands, for a particular sensor. In accordance with other workers, band combination of TM-4, 5 and 1 and band combination of 4, 5 and 3, were selected by the computer algorithm for several quite different satellite scenes, as the two 'best' triplets with the most information content. Colvocaresses (1986), reviewed the voluminous available literature on TM spectral response and band selection.

In order to make a colour display or colour composite, as mentioned before the three least correlated bands should ideally be used. However, with this method some redundant information will be retained, whilst a certain amount of information present only in the omitted bands is lost. One solution to this problem is to use all the available data and apply some form of data compression technique.

One method of display and reduction of the dimensionality of the data set can be achieved by band ratios (Jewel, 1987). There are drawbacks however; ratio images contain no brightness (albedo) information (Rothery, 1987) and secondly as with PC colour displays, colour images of band ratios are scene dependent, and interpretation of the images requires a lot of experience and knowledge of the area and its management (Thomson *et al.*, 1984). Thomson used multidate normalised difference vegetation indice (NDVI) from MSS data and concluded that it was unsuitable as a operational rangeland management tool, due to its complexity of interpretation.

A widely used method of data compression is the principal component (PC) transformation. The PC technique is arguably one of the best ways to select data to be assigned to the three fundamental colours, in order to produce colour displays of multispectral imagery for visual interpretation (refer to section 5.2.2 on colour display). In a statistical sense, the use of the first three PC images in a colour combination, presents as much information as possible using three colours, in comparison to a original three band colour composite image. However, it cannot be said beforehand that for visual interpretation of all kinds of features, the PCs of an image are exactly equivalent to the original bands. The PC images are also usually contrast enhanced in order to obtain displays suitable for visual interpretation, even though the variance or informational content is greater than any three original spectral band subset.

A problem encountered in this technique is in the display and enhancement of such transformations. Caution should be used, because when the variance of the displayed data is increased too much by means of high contrast transformations, unwanted artifacts can be introduced and identified as real features by visual interpretation. Bryant (1988), stated that with simple stretches the colours became unpredictable: small changes in the input scene, lead to wild changes in output colours. This undesirable behaviour so hampered image understanding, that the original multispectral images had to be constantly at hand in order to interpret the reduced PC image; which ironically defeats the object of the exercise in the first place.

A systematic study of the PC technique for image display in a geological application using MSS, avoided artificial artifact creation by using linear radiometric enhancement (Santisteban and Munoz, 1978). Canas and Barnett (1985), demonstrated the PC technique as a potential method for the presentation of essential information contained in multispectral imagery in the form of a FCC. Ellis (1977), found that PC data sets maximised colour differences of cover classes to a degree not possible with other data dimensionality reduction techniques, such as vegetation indices.

Another drawback however, is that the PC transformation image generated is scene dependant, this results in images to which exact physical meaning cannot easily be attributed, i.e., they are false and completely arbitrary. They cannot be related simply to surface spectral response properties; i.e., areas of shadow or under low angle illumination can be particularly confusing (Rothery, 1987). Indeed, the PC images are simply different representations of the original data, but with certain defined statistical properties. This is in contrast to a three original band composite, where assigned colours are not scene dependent. Original three band FCCs are easy to interpret, because each primary colour relates to a single spectral band and can be interpreted in terms of relative reflectance and absorption. This is useful, since many interpreters have learned the general relationships between ground cover types and colour of standard false colour composites of three bands. For a PC generated FCC, the analyst has to learn a new set of cover type to colour relations, which can be seen as a major disadvantage.

Canas and Barnett (1985) argued the case for PC colour display. Their paper dealt with an exact investigation of FCCs generated from PCA, as opposed to conventional FCC of the original bands of MSS. It was illustrated that the total variance in MSS standard FCC was 73% for their study area, whilst a FCC of the first three PC contained 98% of the variance, with very little sacrifice of information.

The fact that the PC derived colour display was scene dependent was seen as a possible benefit, in that the analyst can choose the colour scheme in such a away as to depict features of interest most clearly and that the PC FCC can be applied as a standard process in the absence of *a priori* knowledge.

5.1.5 Summary

For the framework of this study, feature selection of the TM was mainly a function of manual selection based on *a priori* knowledge from the literature. A three band subset of TM-4, 5, and 3 was chosen for overall information content in a colour display for manual interpretation, and for ease of interpretation in automated processing.

The choice of bands used in this study to discriminate cover types, stems from a solid theoretical base (Chapter Four, section 4.1.1.1), empirical evidence of fellow workers gleaned from the literature (section 5.1.4.) and qualitative results of colour displays of the data (Chapter Seven, section 7.1). The latter was based on heuristic considerations, such as intuition and experience rather than the more mathematically found techniques such as PCA or probability densities of subsets of features using divergence distance. Thus, cutting out much needless statistical manipulation in the form of computational processing time.

Original band data was chosen, as opposed to data sets created by transformations such as PCA or image ratios. It was considered that the utility of scene independent displays outweighed the advantages of the other dimensionality reduction methods. A goal of this study is to evaluate the use of satellite imagery in operational mapping of lowland semi-natural grassland types. It was envisaged that visual interpretation of the imagery, could offer as much valuable information as complex machine processing techniques to agencies such as EN. In view of this therefore, for further applications, or the long term routine monitoring of such resources, the scene independent displays could be most effectively used by visual interpretation. This will mean that with a relatively small amount of training, an analyst aware of temporal considerations could make fairly confident projections as to general cover classes of interest from their assigned colour and tone.

In all the above described methods of data dimensionality reduction and feature selection, it must be emphasised that the usefulness of the results can only be measured by each 'user' with regard to the particular features of interest in the image under consideration, e.g., 'one man's noise is another man's signal'. In general, it is recognised that PC displays are of particular benefit in geological applications, band ratios for vegetation production studies, and original three band selection procedures for general land cover category applications and mapping tasks.

5.2 Visual Analysis

The use of interactive visual interpretation of the imagery in this study was justified for the following reasons :-

* visual interpretation of the digital hardcopy images is a relatively simple exercise. On the other hand automated processing and classification requires a fairly complex procedure involving access to hardware and software development. Such equipment and expertise is not yet readily available to most organisations involved in habitat monitoring or ecological evaluation and

* the spatial resolution of the most recent sensors are not fully exploited by current classifying algorithms, which take account of spectral information but generally do not

consider spatial relationships. Visual interpretation uses both sources of information.

Visual analysis of satellite imagery, either in the form of photographic products or interactively on digitally enhanced images, has long been regarded as the 'poor relation' to automated image analysis. With the advent of more and more sophisticated image processing algorithms, visual interpretation has largely been discarded. Visual interpretation can however, produce just as reliable and accurate results. Visual interpretation relies on colour, textural and contextual information involving the use of an extremely complex and sophisticated computer the human brain; whilst most common automated techniques utilize only spectral information.

Colour monitors work in the three primary colours, red, green and blue. Multispectral imagery normally returns more than three bands of data. Therefore, since only three bands of data can be displayed simultaneously on the monitor, one problem that inevitably arises is that of making the most effective three-band colour composite image. This problem is discussed in detail in this chapter, section 5.1, with regard to TM data and feature selection. As multispectral SPOT has a complement of only three bands, colour composite formation presents no such problems.

5.2.1 Colour Composites

Since most multispectral remote sensing sensors contain more bands than SPOT, it is obvious that a number of three band combinations can be made. Using TM as an example, a number of band combinations are now discussed. By assigning bands 1, 2 and 3 to the blue, green and red guns of the monitor respectively, a natural or true colour composite (TCC) is formed. Alternatively, by assigning a infra-red band of the sensor to the primary colour guns, a false colour composite (FCC) is formed. Usually TM-4 is assigned to the red gun, TM-3 to the green gun and TM-2 to the blue gun, for forming a standard FCC (see Chapter Seven, section 7.1).

A FCC is arguably the most effective means of visual presentation of multispectral imagery. Yet if qualitative and semi-quantitative visual interpretation is to be relevant to future remote sensing systems and not be entirely displaced by numerical automated methods, some way of combining information from a number of image bands to create a single composite image needs to be employed.

Therefore, regarding the informational content of a colour composite there are two questions which need to be addressed. Which three bands to choose and to which three colours should they be assigned to produce the best match between feature space and visual colour space? As discussed in section 5.1.4 on feature selection, consideration of information content suggests that the three most uncorrelated bands will provide best results. From numerous studies dealing with feature selection the overall trend is clear; TM band 4 is the most important, secondly the importance of at least one band from the middle-IR and at least one band from the visible part of the spectrum.

Having established that the near-IR TM-4 is a required part of the three band subset for visual analysis, the question now arises concerning the choice of which visible band to choose and which of the two middle-IR bands. Townshend *et al.*, (1988) suggested TM-2 as the best representative visible band, since it is this band that usually displays the largest dynamic range of the visible bands. However, theoretical, see Chapter Four, section 4.1.1.1 on spectral characteristics of TM and empirical evidence, see section 5.1.4 on feature selection of the usage of TM visible bands in vegetation cover mapping, suggest TM-3 (red visible) as the most appropriate band. TM band 5 was chosen in preference to TM-7, for the same reasons.

Alternatively, the choice of bands can be made qualitatively by visual inspections of the bands together with *a priori* knowledge of some known features of interest, or conversely the absence of such features from the selected band triplet, the choice of bands can then be modified.

5.2.2 Colour Assignment.

Having made the choice of the best three TM band subset i.e., bands 4, 5 and 3 from the preceding section; the next question is then, to which colour on a visual display device are these bands then assigned? The allocation of a band to one of three primary colours can be governed by using the fact that the human eye is not equally sensitive to all colours. Mather (1987a), suggested that the eye is most sensitive to the red and green components and least sensitive to blue. Therefore, the band containing most potentially interesting information to the 'user', should be assigned to red or green gun so finer colour discrimination will be possible visually and the band of least importance assigned to the blue gun. Townshend *et al.*, (1988) suggested the red gun be assigned to the mid-IR TM-5, green to TM-4 and blue to TM-3. The advantage being that in the resultant image green vegetation appears green, bare surfaces or urban areas appear purple and water bodies appear blue.

However, the allocation of TM-4 to red, TM-5 to green and TM-3 to blue, where green vegetation appears bright red or pink, although more unnatural in colouration have been familiar to a wide range of 'users' for many years, working with both MSS and colour-IR photography.

The selection of three band sub-set 4, 5 and 3 assigned to R, G and B colours respectively would seem to agree with other studies, where visual interpretation were important parts of their analysis (Ahern *et al.*, 1981; Thomson *et al.*, 1984; Trolier and Philipson, 1986; Fuller *et al* ., 1989b).

For the SPOT data, bands 3, 2 and 1, were assigned to R, G, B guns respectively. This approximates the standard FCC of MSS bands (3, 2 and 1) and is equivalent to the TM band complement of (4, 3 and 2).

Although, the TM band subset of 4, 3 and 2 would complement the SPOT band data. The selection of TM (5, 4 and 3) over (4, 3 and 2) was made, because the latter is statistically only two dimensions (see section 5.1.4) i.e., using information from just the visible and near-IR part of the spectrum. Whereas, the 5, 4 and 3 band triplet uses information from the visible, near-IR and mid-IR parts of the spectrum. Hence, the resultant image display will have more spectral contrast or information.

5.2.3 Summary

In examining the evidence from the section on feature selection, together with the section on colour assignment. A FCC of TM bands 4, 5 and 3 assigned respectively to the red, green and blue guns, suggest that this specific composite is the optimum combination for the extraction of key vegetation information via visual interpretation and to facilitate automated processing in a semi-natural grass vegetation application. For the SPOT data, bands 3, 2 and 1, were assigned to R, G, B guns respectively, this approximates the standard FCC and was chosen for the same reasons as the TM combination.

5.3 Multitemporal Imagery

5.3.1 Introduction

Multitemporal imagery can be quite easily defined (Mather, 1987a) :-

> "...as a number of images of the same area taken at different times".

The main utility of multitemporal imagery has been in renewable resources assessment, in monitoring and the detection of change.

There are two types of multitemporal imagery; data from different years and data from different seasons - the latter type are particularly suitable in vegetation studies. The season will often have a strong influence on the appearance of vegetation, due to the phenological effects; cover types distinguishable readily at one time of the year may be difficult or impossible to separate at another. The season also determines sun angles, this is especially important in upland environments, where topographical effects will come into play (Townshend and Justice, 1980).

5.3.2 Agricultural Studies

There are numerous citations in the literature expressing the advantages of seasonal multitemporal imagery covering the growing period in vegetation studies, or more specifically agricultural investigations. Classification of crop cover types in the UK, using single data imagery has rarely exceeded 75% in accuracy, because the spectral characteristics of crops leads to ambiguous spectral response patterns (Taylor *et el.*, 1983; Allan, 1987). Single data images rarely possess sufficient spectral differentiation between all cover types. In effect, a single 'best time' in the growing season that can be captured by satellites does not exist, which will reliably and predictably provide crop discrimination (Badhwar *et al.*, 1987). Synder and Story (1986), stated that :-

> "multitemporal imagery was crucial, when identifying beyond the USGS Level I land cover classes".

Hay (1974), working on agricultural inventory techniques using high altitude photography, was one of the first to recognise the importance of the timing of the imagery in the study of vegetation. It was found that the most accurate inventory data was obtained using a combination of two or more dates of photography in a sequential technique, whereby the phenological differences of a crop at different times in its growth cycle were used as identification characteristics for that crop. In conjunction with this, the use of crop calendars, gave a temporal description of the condition and the state of development of specific crops (Brown *et al.*, 1980).

Sailer *et al.*, (1984) recommended at least three different dates within a single growing season in order to make with some degree of certainty unambiguous crop identification at Level II. Belward and Taylor (1986), illustrated that crop analysis problems in the UK were more easily solved by using multitemporal imagery and knowledge of the local crop calendar.

Through the use of multitemporal observations, a valuable dimension is added to remotely sensed procedures relating to agricultural feature detection and identification. Multitemporal satellite coverage allows a specific field to be sampled over the growing season, the resulting pattern of spectral values over time represents the phenological development. Using MSS data Odenweller and Johnson (1984), built up temporal-spectral profiles representing specific target crop types. It was demonstrated from these profiles that non-vegetated classes, annual crops, perennial vegetation such as pasture and rangeland could be identified based on the amplitude and distinctive shape of the profile. Badhwar *et al.*, (1987) investigated this method, using MSS data on Argentina summer crop classification and took it a stage further in classifying specific annual crops. It was found that generally each of the major annual crops were associated with specific parts of the growing season i.e., winter wheat occupied a different time scale when compared with later developing crops, such root crops like potatoes.

A study of multitemporal SPOT data for crop discrimination in the UK using vegetation indices represented as co-incident spectral plots, provided indications of the dates imagery was needed for general crop separations (Jewel, 1987). Grassland were found to be separable in April imagery, some cereals in June, and a July image was needed for separation of wheat and barley. This was a function of the fact that these two cereals have different senescent rates; there is a decrease in near-IR reflectance for winter and spring barley in relation to winter wheat, which corresponds to an earlier change in colour due to ripening and senescence of barley. In a September image, the root crops were discernible since the cereals by that stage had been harvested. Classification of the vegetation indices by simple density slice produced 75-85% accuracy of crop types using multitemporal data.

It is therefore necessary to quantify the important temporal features of agricultural scenes in a remote sensing context. De Gloria (1984a), suggested the following features :-

* the date in the growing season when the crop canopy becomes spectrally detectable,
* the date in a growing season when a crop has reached a maximum vegetative indicator value, i.e., biomass or similar variable,
* the length of growing season, and
* the date at which a crop progresses from maximum vegetative indicator value to senescence or ripening.

5.3.3 Semi-natural Vegetation and Grasslands.

As in agricultural studies, the timing of imagery is also crucial in relation to the phenology of semi-natural vegetation and grasslands. Carneggie *et al.*, (1977), was able to successfully monitor rangeland conditions using MSS data throughout a growing season. Everitt *et al.*, (1979), stated that successful Level II estimation of areal extent of rangeland required summer imagery. Moreover, multitemporal data is especially useful when certain cover types can only be discriminated at specific times of the year, i.e., Nardus and Molinia are very similar upland grasses that were separated in May, because Molinia retains its senescent material longer in the season (Hume *et al.*, 1986). Similarly bracken was found to be more easily detected in the early spring when it is brown, rather than later in the season when it turns green and can be confused spectrally with other upland cover types (Williams, 1987; Booth, 1989).

Thomson *et al.*, (1984), reported the importance of multidate imagery in Canadian rangeland assessment and for an understanding of the phenological development of the grasslands. Single date MSS data was found to be unable to provide reliable information concerning Fescue rangeland conditions. Visual interpretation of rangeland conditions was found to be a lot more successful with TM multitemporal imagery (Thomson *et al.*, 1985). Early May and early July scenes provided the most information, concerning greening up and forage production of grassland.

5.3.4 Summary

The importance of having good temporal coverage is clearly evident. The multitemporal data set used in this study consisted of a late spring May TM (1985) scene, and early summer June SPOT (1986) and July TM (1984) scenes. The imagery was from three consecutive years and corresponded with the time that the ground data was collected in the field by EN. Since the target cover type of this study was relatively static in nature, (the MoD rangeland and permanent grassland), the use of data from different years was felt to be validated, and helpful in building up an understanding of the temporal profiles of these grassland community types for the important three month period of May to July.

CHAPTER SIX

CLASSIFICATION

This chapter covers the concept of classification of remotely sensed images, and the different types of classification procedures most commonly used. It also discusses the effect of spatial resolution on the classifiers performance. It then deals with methods employed in the improvement of classifications and finally a brief account is given of how digital satellite data can be integrated with other data bases to form a Geographical Information System (GIS) and it's future potential.

6.1 Introduction

In theory, an ideal cover type or target gives a unique pixel value in each spectral band; so across a given number of spectral bands, a cover type can be identified by the pattern of pixel values. This is termed the 'spectral response pattern' of a specific land cover type. Figure 6.1a shows a scatter plot of two spectral bands plotted against each other. This figure illustrates an idealised land cover or 'target' class, which is identified by a unique point in feature space. In reality a more complex situation exists, a land cover type has inherent statistical variation in pixel values, therefore in a scatter plot pixel values form a cluster of points rather than a single unique point, as in Figure 6.1b. The land cover class or object can be identified by its cluster in feature space. A classification algorithm is simply the mathematical separation of feature space into regions, which efficiently enclose each cluster and therefore allows discrimination between land cover classes, see Figure 6.1c.

Automatic classification of pixels that make up remotely sensed images, involves associating each pixel in the image with a label describing a real-world object. There are basically two alternative methods. Supervised methods attempt to relate pixel groups with actual surface cover types and are termed informational classes. Using *a priori* knowledge, multi-training areas of specific cover types are selected throughout the area of interest. Standard statistics from the training areas are then used by the chosen classifying algorithm. With the second or unsupervised method, the identities of land cover types to be specified as classes within a scene, are not generally known *a priori*.. The computer groups or clusters pixel data into different spectral classes according to some statistically determined criteria. The analyst then labels these clusters or 'natural' groupings in multispectral feature space, as far as possible as representing informational classes. The theory of classification can be found in general remote sensing text books, such as Curran (1985), Lillesand and Keiffer (1979); or more specifically in image processing texts, such as Jensen (1986) and Mather (1987a).

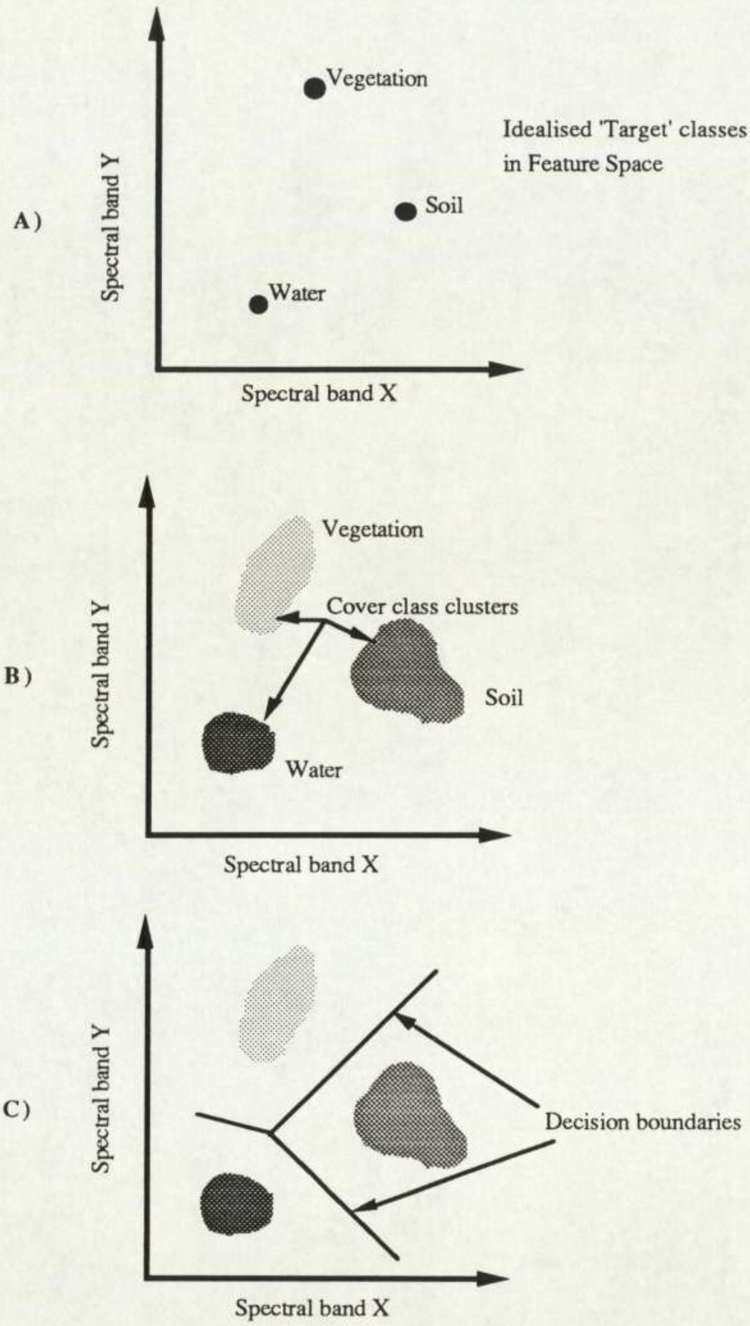


Figure 6.1 : A) Idealised Data in Two-dimensional Feature Space B) Actual Spread or Clusters of Data Points C) Decision Regions and Boundaries used by Classifying Algorithm

There are a variety of classification and clustering algorithms available. The analyst is faced with choosing the most efficient procedure for the task. It can be assumed that each classification scenario has particular advantages and disadvantages and that there is an optimum strategy for each specific land cover class.

Both supervised and unsupervised methods assume that the image data form separate groups in N-dimensional feature space, when N-bands (or features) of data are each placed on orthogonial axis and that they can be associated with observed ground cover types. Groups of data can be described by parametric or non-parametric techniques.

Parametric classification assumes that each group can be enclosed by a boundary such as a hyper-ellipsoid decision volume of maximum likelihood or the rectangular box of the simpler minimum-maximum box classifier. Non-parametric classifiers make no assumption about the shape of data distributions, except that the groups of data can be separated by some discriminant function.

Skidmore and Turner (1988), used a non-parametric classifier to inventory pine stands of different ages using SPOT data. The non-parametric supervised approach involved the collection of training data. Every pixel of the first training cover class were then assigned to a cell or vector position in N-dimensional feature space by their brightness value. The numbers of pixels (for the first class) in each cell were summed. Similarly, the pixels of the second cover class were summed into the cells of N-dimensional feature space, but were stored as separate records (to the first class). This process was continued for all the remaining training cover classes. Each cell was then tested sequentially by the classifier. The classifier found the class with the highest empirical probability in the cell and assigned that cover class identity to the cell. The highest probability for each cell was calculated by dividing the number of pixels in a cell for a specific cover class, by the total number of pixels tallied for all cover classes in the cell. This process was repeated until every cell was assigned to a cover class. The number of training area pixels were normalised and every cell in feature space was considered as separate decision rules and not function based like parametric classifiers.

A priori probabilities were found by a preliminary unsupervised classification and these probabilities were modified empirically. Test areas were chosen where empirical probabilities of correct classification of 75% or over were found. This increased the classification accuracy from 70% to 87%, and this result compared well to traditional parametric supervised maximum likelihood classifier which achieved a mapping accuracy of 56%. The disadvantages of this technique were the amount of computation time necessary, quoted as :-

> "four times the computer processing unit (CPU) time required for maximum likelihood classifier",

and is therefore more expensive and not really practical for budget orientated operational tasks, and the second disadvantage was the small pixel sample size (typically less than 50 pixels per cover type) for use as test areas with empirical probabilities of 75% and over.

6.1.1 Supervised Classification

Supervised classification can be said to contain three basic steps :-

(i) the generation of representative seed or training statistics,

(ii) input of these statistics into appropriate classifier and the subsequent assignment of non-sampled areas to informational classes, and

(iii) the output of results and assessment of accuracy.

A review of the literature suggests that supervised classification is the most widely used. The question then arises as to what supervised classifier to use? Since there are various types of classifier available, each with its own advantages and limitations. The two most accepted supervised approaches were examined for this study : minimum distance and maximum likelihood classifiers. These algorithms are readily available in most image processing systems.

The 'minimum distance to means' automated approach defines the decision boundaries of 'spheres' or clusters from training statistics. Each pixel from the whole image is examined to see which training cluster it is most closely related to. Mean vectors are needed for each class in each band from the training data. The algorithm can calculate the distance of a pixel from each mean vector training cluster, using Euclidean distance or 'round the block' distance measures based on Pythagorean theorem (Swain and Davis, 1978). Pixels with the minimum distance from the mean of each class are thus assigned to that class. The advantage of this classifier is that minimal computation is needed. The disadvantage being that this classifier relies on mean values of the training data and not on the standard deviation, which produces less accurate results when training clusters exhibit a variety of deviations.

The maximum likelihood classifier on the other hand, uses all properties of the training data i.e., variance, correlation and mean in calculating the probability of a pixel value belonging to each training cluster and being assigned to it; as long as it displays a normal or gaussian distribution. It is usually the most accurate of the classifiers, because it most efficiently delegates clusters in feature space by elliptical contours, which correspond more realistically to cluster shapes of real objects. This decision rule can be modified by Bayes decision rule, this is identical to the maximum likelihood rule, but incorporates prior probabilities concerning the encounters of specific land cover classes (Pedley and Curran, 1991). The disadvantage is that this system is computationally complex and therefore less efficient in CPU time.

Literature sources give a confusing picture about this classifier and its utility in various applications. The maximum likelihood classifier was found to be surprisingly the most accurate for an area of complex land cover patterns (Story *et al.*, 1984). Other studies have shown, that with relatively uniform classes where this classifier would be expected to perform well, the maximum likelihood classifier produced a lot of confusion. This result was attributed to it being a 'per-pixel' classifier, the similarity of cover types present and the time of year (Taylor *et al.*, 1983). Hixson *et al.*, (1980), compared five different supervised classifiers, both 'per-pixel' and 'per-field' based; for an agricultural application. It was found that similar accuracies were yielded for all five procedures, however the minimum distance was the easiest to use and cost the least per classification.

6.1.2 Unsupervised Classification

Unsupervised methods simply determine the characteristics of non-overlapping groups of pixels in terms of their spectral band values, these are termed 'spectral classes'. A clustering algorithm is used which clusters the image pixels in feature space. Pixels are allotted or rejected from a cluster based on distance from the cluster centre in terms of spectral band values. Clustering algorithms generally act in two modes, the first mode builds clusters (groups of clusters in spectral space) in which there are mean vectors associated with each cluster. The second mode is where each pixel is assigned to one of these mean vectors, this is a similar procedure to the minimum distance classifier described previously. It is this second mode which is used to reduce the number of spectral groupings generated by unsupervised approach. There are various parameters open to choice by the analyst :-

* the number of pixels to sample,
* distance used between pixels (maximum number of pixels between centriods of spectral classes),
* number of spectral classes to generate,
* and the measure of difference between spectral classes.

The usage of the unsupervised approach is well documented (Synder and Story, 1986) and has been demonstrated as a useful preliminary technique of data analysis before supervised classification (McMorrow and Hume, 1986).

As mentioned before, each classification approach is not necessarily suited for a specific application. Unsupervised classification when compared to supervised (maximum likelihood), produced lower mapping accuracies of Level II categories, when S.SPOT was analysed in an agricultural application (Sailer *et al.*, 1984). Furthermore, it was found to be very time consuming and therefore a more costly methodology to implement. Townshend and Justice (1980), found that when using MSS data, the unsupervised approach was not demonstrably superior to supervised classification in studying regions of complex terrain.

6.1.3 Hybrid Classification Approach

Hybrid methods using both unsupervised and supervised procedures have been explored and are claimed to have the best of both worlds. There are various methodologies open to the analyst; one methodology involves delineating training areas and the training data is then clustered using the unsupervised approach. Clustering strategy may produce thematic maps directly or the algorithm can generate statistics, which can be input into a supervised classifier. Initially, randomly selected training sites are grouped into spectral classes using a clustering algorithm. These clusters are then interactively edited by the analyst in terms of combination or separation. This refined statistic file is then used to classify the full data set into spectral classes using a supervised classifier; typically maximum likelihood. Finally the spectral classes can then be grouped into informational cover types by the analyst, using ground data and ancillary data. Taylor *et al.*, (1983) in a study of crop types found that by interactively editing and combining spectrally similar classes, higher accuracy levels were achieved, but at a cost of fewer informational classes. This approach was used successfully in a rangeland application using S.SPOT and MSS data (Maslanik *et al.*, 1984). Ruth *et al.*, (1986), described a typical usage of the semi-unsupervised approach using TM for a general land cover assessment.

Chuvieco and Congalton (1988), adopted a hybrid classification methodology and tested it on TM data of complex Mediterranean vegetation. The limitations of the two traditional approaches were discussed. In supervised classification, the analyst tries to classify informational categories, which can often be composed of several spectral classes. Conversely, with the unsupervised approach spectral groupings may have unclear meaning from a 'users' point of view. Therefore, Chuvieco and Congalton put forward a methodology that generated both supervised and unsupervised training statistics. Clustering analysis was then used as a tool to improve the definition of training statistics. The clustering analysis, was defined as not simply a reduction process as used in the classic unsupervised approach, but rather as a method of combining similar groupings from both supervised and unsupervised approaches. The result was to produce training statistics that are a powerful match of the two traditional methods. The strength of these new groupings, or the separability was evaluated by multivariate discriminant analysis. From these functions it was possible to regroup original training classes and to test membership in the correct grouping. The accuracy of the cluster hybrid approach was tested against the traditional supervised and unsupervised approach, by discrete multivariate statistical techniques. The cluster hybrid approach achieved 64% normalised accuracy, as opposed to 60% supervised and 48% unsupervised.

The one major benefit of such a system is that it can highlight artificial classes that have no spectral uniqueness and therefore, cannot be accurately assessed or classified. It is therefore, a useful process in training area selection, and hence in achieving reliable classification results, although the results were not significantly different from the straight forward supervised approach and employed greater computational demand.

6.1.4 Spatial Resolution and Classification

Conventional classification techniques do not automatically lend themselves to more accurate results when using TM data, compared with MSS. The increased spatial and spectral resolution of TM with respect to MSS, does not necessarily correspond with improved thematic accuracy, whilst in some cases it can actually cause a deterioration. The cause of this is now explained in more detail below.

6.1.4.1 Spatial Resolution and 'per-pixel' Classifier

Many workers have quantitatively demonstrated both with the utilisation of TM (Ahern *et al*., 1980; Townshend and Justice, 1980) and the introduction of SPOT or S.SPOT in studies of comparison with MSS (Toll and Kennard, 1984; Maslanik *et al*., 1984), that the increased spatial resolution does not necessarily give better results. The performance of 'per-pixel' maximum likelihood classifier often can not improve accuracy, but can actually diminish accuracy results. This apparent paradox can be explained in terms of two antagonistic effects :-

(i) the proportion of mixed pixels decreases with increased spatial resolution which enhances classification performance, and

(ii) the increased spatial resolution enhances the intrinsic heterogeneity or scene noise for a given theme or cover class, thus producing the increase of spectral response variance. This can then lead to a spectral overlap amongst distinct cover classes.

Irons *et al.*, (1984), worked on actual TM (30m spatial resolution) and degraded TM (80m spatial resolution). A quantitative evaluation of the consequences of increased spatial resolution of actual TM data was carried out. To detach the effects of mixed pixels from the effects of spectral variability, classification of all pixels (pure plus mixed pixels) was compared with the classification of just pure pixels at the two spatial resolutions. An analysis of variance (ANOVA) design was used for statistical evaluation of the various treatments. A 'per-pixel' maximum likelihood classifier was used. By increasing the spatial resolution from MSS to TM specification a decrease in classification performance was found for the pure pixel situation. Since only pure pixels were used, the decrease in accuracy can be attributed solely to increased within class spectral variability, incurred with the finer spatial resolution.

In the pure plus mixed pixel case, increasing the spatial resolution did not significantly affect accuracy. The reduction of mixed pixels at the finer spatial resolution counteracted the detrimental effects of increased spectral variability within cover types. The spatially degraded data was 4% more accurate over the actual TM data in the pure pixel case; this was in the main a consequence of the grassland cover type which contained a lot of variation. It was suggested that the 30m resolution of TM would be suitable for row crops and forestry classification, these are cover types that are more uniform spectrally. This agreed with findings by Synder and Story (1986), where it was found that full resolution TM benefited the classification of water, crops and forest, as opposed to degraded 60m resolution TM data.

Permanent grassland however, have been consistently found to be heterogeneous in nature, compared to monoculture intensive crops (Badwhar *et al.*, 1984). This is due largely to the fact that many species are present and to differences in physiognomy and soil moisture. In addition to differences between fields due to management and within field differences due to slope and aspect. Agriculturally improved or re-seeded grassland give a more homogeneous signal, more similar to crops. The effect of increased spatial resolution on the accuracy of classification of remotely sensed data taking account of field uniformity is illustrated by Curran and Williamson (1986), see Figure 6.2.

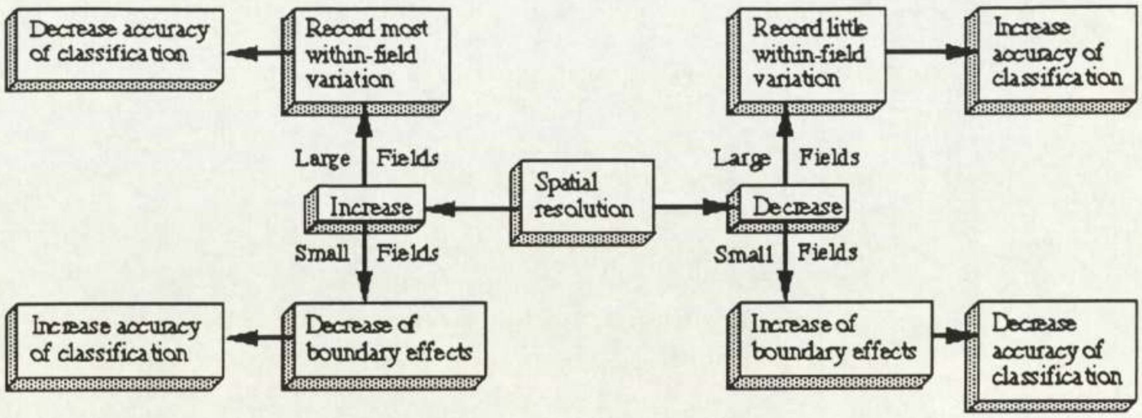


Figure 6.2 : The Relationship between Spatial Resolution and Classification Performance for Fields of Differing Size, with Regards to Satellite Data, (source Curran and Williamson, 1986)

The 'per-pixel' maximum likelihood decision rule is a commonly used algorithm. The trend for the increase in spatial resolution of sensors, has consequences not readily exploited by this algorithm. The consequences of increased resolution clarifies the shapes, boundaries and alters the textural appearance of cover classes. These are apparent on TM and SPOT imagery and facilitate visual interpretation. Therefore, new approaches to automated classification of SPOT and higher resolution sensors are needed that exploit image texture or context, and encompass spatial information.

6.1.5 Classification of Semi-natural Vegetation.

A difficulty encountered in this type of study, is the need to reconcile traditional vegetation survey methods on the ground with the objective classifiers used in remote sensing. This difficulty is compounded by the lack of clear boundaries and the heterogeneity of the vegetation.

As a consequence of field survey classifications, the type of classification scheme adopted by the remote sensing analyst can be difficult (Williamson, 1987). Traditional vegetation surveys are carried out by trained botanists/ecologists, the emphasis being on the presence or absence of species. Factors such as plant phenology (flowering, senescence), substrate background and surface moisture are of less interest in their perception of the terrain, when their objective is to produce vegetation maps. However, these factors affect the remote sensing signal, there is therefore a need to reconcile the vegetation map generalisations to the remotely sensed classification scheme. One way of generalising the spectral information to that of the generalisation of the botanical classification, would be the use of filtering or smoothing techniques, so that one achieves a closer fit, in terms of ground information and spectral information.

6.2 Strategies Used to Improve Classification

Various techniques have been developed that can improve classification accuracy. Techniques such as image smoothing, which decrease the spatial resolution of the remotely sensed data, can increase accuracy as described in the previous section. Other techniques such as increasing the information available to the classifier can also improve accuracy. This can take the form of extra spatial information from within the image, known as texture and context information; or it can be from the addition of ancillary data from other data bases. These various strategies are now discussed in more detail.

6.2.1 Application of Filters

There are two basic types of spatial filter : low-pass filters and high-pass filters. Low-pass filters suppress high frequency information i.e., lines and edges, so that detail will be blurred or noise removed. High-pass filters amplify local detail and produce sharper images; they highlight edges and linear elements.

Low-pass or smoothing filters are now considered in more detail. Filtering of images makes use of moving window algorithms. The filter window is usually made up of a 3 pixel row by 3 pixel column, termed a 'kernel'; centred at the pixel of interest. This window then moves along and down the image, until the whole image has been screened (see Figure 6.3).

There are two basic types of smoothing or spatial filter. Mean or averaging filters act on the central pixel of interest in the window, by replacing it with the mean value of the nine pixels in the 3 x 3 kernel. The effect of this filter is that it reduces the overall variability of the image. Median filters utilize the median of the kernel rather than the mean. The median filter is generally superior to the mean filter for two reasons. The median is always equal to one of the values present in the kernel and unlike the mean it is less sensitive to extremes in data value.

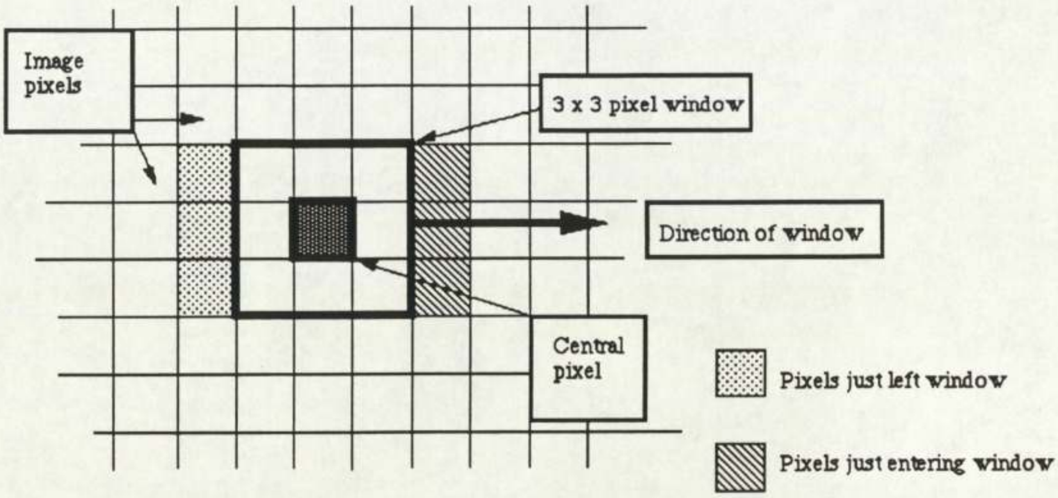


Figure 6.3 : A Moving Spatial Filter with a 3 x 3 Pixel Window

Filters can be applied at the pre-classification or post-classification stage. It is not appropriate however, to apply a meanial filter to classified images, because values of the pixels in classified images are arbitrary and intended merely to differentiate the pixels in feature space. Meanial filter procedure may produce pixels with values not previously present in the image and are therefore not representative of defined classes.

6.2.1.1 Classification and the Use of Filters

Many studies have been conducted which set out to improve computer classification results. Various options can be selected for refining the classification procedure both at pre-classification level and at post-classification stage. One such option open to the analyst is the use of filters. The use of filters is a compromise between the benefits derived from improved visual quality, more 'thematic map like', and the drawback of lost image detail or information.

The spatial resolution of TM has resulted in images which are visually more interpretable, i.e., the tonal and textural qualities of urban areas and woodland, and individual agricultural fields are easily distinguished by eye (DeGloria, 1984a). Computer classification of TM images however, has been less than satisfactory, producing typically 'salt and pepper' appearance or noise effects. The same kind of problems occur for SPOT data, with its finer 20m spatial resolution.

As discussed previously (section 6.1.5) greater spatial resolution on 'per-pixel' classifier can lead to decreasing classification accuracy. For instance, a residential cover class, comprising of grass, trees and buildings, because of the finer resolution the pixels may be assigned to their component cover types; rather than to the overall category to which they belong i.e., residential. In order to reduce this type of target variability or noise, the image may be smoothed prior to classification using various spatial filters. A 3 x 3 or 5 x 5 kernel meanial filter is usually applied. The range of digital values is reduced smoothing out scene detail, but at the expense of increasing mixed pixels at spatial boundaries i.e., they become blurred (Dutra and Mascareukas, 1984). Therefore, procedures which decrease scene noise without decreasing the proportion of boundary pixels should result in improved accuracies. This can involve using smaller kernels or windows.

A technique described by Gilmour (1987), addressed this problem, by stressing the importance of optimum window size with pre-classification averaging filters. It was found that by keeping the window as small as possible, the blurring of small regions and boundaries between cover classes was lessened.

An alternative is the use of median filters, where detail is smoothed but boundaries are better preserved. Ahern *et al*., (1980), used median filters to reduce variance within a field and still preserve field boundaries. Visual inspection confirmed that field boundaries remained sharp; only the corners were blurred. This resulted in significant increase in classification accuracy. The degree of boundary preservation is dependent on the size and shape of the filter (square or cross shape) and the orientation of the boundaries. The 3 x 3 pixel sized square filter produces the best compromise between boundary preservation and the reduction in scene noise (Townshend *et el*., 1988). Pre-classification filtering has little effect on the accuracy of homogeneous classes, but can substantially increase the discrimination of classes with a high degree of internal variance.

A different approach to the pre-classification filtering problem was adopted by Cushnie (1984), here he combined filtered data with original TM data. This was then compared to both original TM data and data that had been smoothed by averaging and median filters. The four feature combinations were then fully tested by the maximum likelihood classification technique. The original TM-5 band was used to replace filtered TM-5, to assess whether degraded (filtered) data of two other TM bands will smooth out scene noise, whilst the original TM-5 at full resolution will preserve boundary detail. Results showed that the use of average and median filters prior to classification improved accuracy as compared to raw TM, due to a reduction in scene noise. The use of median filter reduced the amount of mixed pixels by its boundary preserving properties. Classification results of the mixed resolution bands was dependent on the spatial filter used with the original TM and on the ratio of the filtered to non-filtered bands. However, the combination did reduce the effects of poor boundary resolution, whilst retaining the advantage gained by smoothing scene noise and particularly reduced the errors associated with heterogeneous cover types.

6.2.2 Spatial Information

From section 6.1.4.1, it would seem desirable that for high resolution sensors, there is a need to exploit the spatial information content. Gurney and Townshend (1983), provided a general survey of the use of spatial or contextual information in the classification of remotely sensed images and put foreword a typology of context. Context was defined as :-

> "the relationship between one pixel or a group of pixels, and the pixels or groups of pixels in the remainder of the image".

Alternative more wider ranging definitions of context can also be applied to remotely sensed data. Pattern recognition algorithms work on groups of pixels and not just individual pixels. For instance right-angle shapes, where occurring in specific alignments and specific numbers such as four, could indicate depending on the image context (i.e., urban or rural region), the presence of a building or agricultural field.

Gurney and Townshend suggested that contextual information procedures were categorised according to : whether they are applied to raw or classified data; whether they apply to individual pixels or groups of similarly classified pixels or objects; and by the form of spatial relationship between pixels.

A distinction was made between contextual information already present within an image and context derived from non-image sources. The latter includes knowledge of the geographic context of the image as a whole, and is usually gained from topographical or geological maps, (use of external ancillary data is described in section 6.2.3). In visual interpretation, the human eye senses the combination of colour, shape and proximity of associated classes and texture. In the machine processing of a remotely sensed image only one function, the 'spectral response pattern' is normally used. Therefore, there is some form of emulation of the human eye with the introduction of contextual, or spatial information.

Context of a pixel refers to its spatial relationship with other pixels in the remainder of the scene. Contextual decision rules can be applied to raw image data (spectral numerical properties), or to classified (labelled) data. In considering the single pixel situation with classified data, preliminary classification can be amended by considering classifications or labels assigned to other pixels. Therefore classification errors would probably be reduced, by the introduction of this spatial information.

Contextual procedures were categorised by Gurney and Townshend (1983) into four basic types of spatial relationship. These are i) distance; ii) direction; iii) connectivity; and iv) containment and are as shown in Figure 6.4.

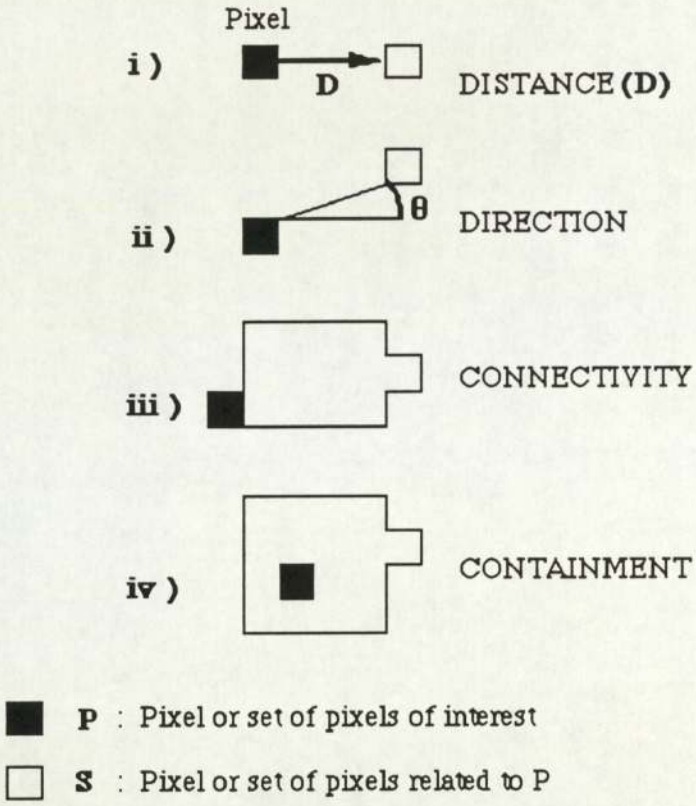


Figure 6.4 : The Four Basic Types of Spatial Relationship (From Gurney and Townshend, 1983)

Distance and direction can be applied to both single and groups of pixels (objects), and on raw or classified data. All pixels within a given distance or direction of the pixel of interest are considered and an assignment is made on the basis of spectral characteristic plus relative arrangement.

Such procedures have been successfully demonstrated in agricultural cover type studies, where 'per-field' or contextual classification algorithms were used; compared to the more traditional 'per-pixel' classification. Anuta *et al.*, (1984), used Supervised Extraction and

Classification of Homogeneous Objects (SECHO), which divided the scene to be classified into homogeneous units or fields. These fields were then classified using the maximum likelihood classifier. Homogeneous cover types were assumed to be greater than one pixel in size, therefore adjacent pixels would be highly correlated. Hence, the degree of correlation diminished with an increasing distance between pixels. With SECHO, the analyst interacted by assigning specified threshold value, below which adjacent pixels were grouped into a homogeneous field or unit. Statistics from these fields were calculated and compared to the original class statistics and a 'homogeneous field' unit was classified into a class it most closely resembled.

Connectivity and containment apply only to groups of pixels or objects and are therefore used when some form of segmentation of the data has been made i.e., this is normally classification. Pixels connected to or contained in a segment, could be reassigned or reclassified to a specific class.

6.2.2.1 Contextual Reclassifiers

Any classification results will inevitably contain error. A classifier attempts to partition feature space in regions representing different classes i.e., associate each pixel with a feature class by some unique discrimination function (in remotely sensed images this is attempted using spectral information).

Classification does not produce as a rule true homogeneous regions, but rather a 'salt and pepper' appearance consisting of noise or unwanted detail. Before description of such a classified image, it may be necessary to process it further by some segmentation method (partitioning of image space) i.e., a contextual reclassifier. Such a method would reduce image noise and produce regions or objects more representative of the features of interest.

By employing contextual information as a further segmentation process, at least a proportion of the noise or error may be corrected by reassigning classified pixels to another class. Pixel based reclassifiers are based on the use of local windows of varying sizes; they possess a similar method of operation to the spatial filtering techniques described in section 6.2.1. Logical or modal filtering operates by a decision rule that determines whether the central pixel is to retain its original value or it is to be changed to that of one of its neighbours within the window eg, in a 3 x 3 window at least five of the nine pixels must belong to one class before the central pixel's value is altered to that class. There have been numerous studies assessing pixel based reclassifiers. Initial studies investigated the spatial relationship of pixels and post classification smoothing or noise reduction. Algorithms were developed using simple majority mode functions, where individual pixels or small areas were replaced by their most frequently recurring neighbour, (Davis and Peet, 1977; Letts, 1979). The use of post classification modal filters are the simplest form of contextual reclassifier.

Different techniques have also been studied, using the majority mode theme, but incorporating different contextual procedures. One approach was taken by Thomas (1980), a minimum proximity function, with analyst specified discrimination level, was developed, which employed distance as a parameter. The spectrally classified pixel was regarded as the first dimension or 'primitive'. A second dimension pixel was created, which involved the spatial relationship between spectrally classified primitives. Noise incumbent to the target class was qualitatively defined as :-

> "the departure from the spectral response pattern homogeneity for each target cover class".

This procedure improved the spatial coherency of the spectrally classified data. The contextual reclassifying procedure was tested against raw classified data and the areal extent of forestry classes from ground data. In comparison with ground data, the results were superior for the additional spatial post processing technique.

Rothery (1982), used post classification modal filtering to help overcome the influence of topographic effects causing the misclassification of pixels in a geological application. Small areas received a typically full or oblique illumination and in consequence pixels were assigned to the wrong theme by the classifier. The contextual procedure of containment was used, in which areas that were less than eight classified pixels (minimum theme) and non-uniform were deleted and the remaining classified areas were allowed to expand to fill the vacated or misclassed spaces. The resulting classified image corresponded more realistically to ground information.

The definition of the size of the minimum theme area allowed to pass through the filter is often chosen interactively, and is a trade off between deleting small correctly classified areas and leaving too many incorrect patches. Townsend (1986), addressed this problem by refining the modal filtering of classified imagery by the development of a 'logical smoothing operator'. Any areas in a classified image, which were smaller than the smallest feature of interest, were termed elementary regions and represented noise and therefore should be removed. By constraining the logical smoothing operator, desirable information was not lost. The logical smoothing filter was constrained by a connectivity rule, such that it acted on elementary regions of the image. The constrained logical smoothing operator worked by two decision rules. The first decision rule ascertained whether the central pixel of the operator window was connected by the same value to neighbouring pixels. Connected sets of pixels were termed 'regions' i.e., they represented useful information. The second decision rule, the appliance of modal or majority filter operator, would only work if there was a 'no' answer to the first decision rule. Thereby, the logical operator would modify only elementary regions, which in effect meant the removal of noise and the retention of useful information.

In theory, a filtering window of any size could be used. Improvements in classification accuracy with increasing size of windows might be expected. However as more distant pixels were considered, it was found that a decrease in accuracy occurred when windows greater than 5 x 5 pixels were used (Gurney and Townshend, 1983). Townsend (1986), limited the window to 3 x 3 pixel kernel in order to inhibit information loss.

Gurney and Townshend (1983), considered more elegant ways of refining 'per-pixel' reclassifiers, rather than using simple majority rule. Different thresholds could be adopted for each class of interest. For example, one class might require a large number of pixels present before reassigning a pixel, whereas for another class only a few pixels would be required. Such a procedure, might be applicable where different error rates are associated with different classes.

Another refinement would be the use of some form of weighting when distance and/or direction functions are brought into play, such that the more distant pixels have proportionally less importance. It is worthy to note that such procedures are again linked to window size and potential loss of useful information.

What ever procedure is chosen, the actual degree of improvement attained will be a function of the relative sizes of the pixels and the areal extent of cover classes at ground level. Finally, the use of some form of contextual information is more important with the higher spatial resolution sensors, because of the higher internal spectral variability of classes at such a level.

6.2.3 Intelligent Procedures

A brief outline of the various methods employed in trying to improve classification by intelligent procedures are now discussed. Several refinements to the classification approach, specifically concerned with semi-natural vegetation are described in this Chapter, section 6.4.

6.2.3.1 Decision Rules

Belward and Taylor (1986), showed that despite not having data at the optimum points in the phenological cycle for the crops of their study area, a twenty per cent increase in accuracy could be achieved in classification, by using an intelligent decision rule approach based on multidate imagery. The method employed created co-incident spectral plots for all bands and all dates, from which it was possible to identify the bands most likely to provide a reliable basis for classification of the crops raised in the study area. Specific spectral data were utilized that were likely to yield reliable results, rather than the total data set for all dates. It was argued that in using the complete data set it would have introduced confusion, due to the overlapping nature of the 'spectral response patterns' of many crops in MSS feature space. As a further extension of this study, Belward and DeHoyos (1987) compared decision rules incorporated in a simple supervised binary tree classifier, with the maximum likelihood algorithm. Similar levels of accuracy were achieved with these two classifiers, but the binary decision tree classification was favoured due to the ease of training, the computational simplicity and it was found to be quicker.

A further extension of this principle was suggested by Allan (1987), who proposed that with crop studies using TM, the data required for analysis could be reduced to a tenth of the original. This would still achieve reliable classification results without significant degradation. He argued that with present farming practises in the UK, intensive farming procedures produced homogeneous crop parcels to such an extent, that very small samples of spectral data could predict crop cover type. Furthermore, small samples would reduce the variation in the data and hence reduce overlap between classes that lead to confusion and misclassification.

6.2.3.2 Knowledge Based Systems.

A further development of decision rules is knowledge based systems, where *a priori* knowledge is used. Knowledge based systems can consist of a set of rules describing each class type; or they can include ancillary data. There are three basic methods used in this approach :-

i) to stratify or segment prior to classification,

ii) incorporate ancillary information during the classification operation, and

iii) post classification incorporation, where the classified data is modified by ancillary data.

If detailed information, in the form of a complex model that characterises a given class, (eg, a detailed description of the objects or targets to be detected and the relationships amongst them), can be input to the methodology, this is in effect developing a *priori* knowledge of the real world depicted on the remotely sensed image. Blonda *et al*., (1988), developed such a knowledge based system for the classification of general land cover types of multitemporal TM imagery. *A priori* knowledge used here, was in the form of expert photointerpretation of 'spectral response patterns' and interfaced into the system, in terms of defined rules for the thematic descriptions. The approach used 'fuzzy logic' or 'uncertainty' to predict cover class, by using the rules described by expert photo-interpreter, as membership functions for fuzzy sets, defined on the image spectral values. The Knowledge Base (KB) used rules or 'facts' and was represented by an expression :-

	attribute	(object, value)	(6.1)
eg,	intensity in band 1	(pasture, x-value)	

The KB approach considers the impossibility of giving the precise definition for each real class, hence the classes are characterised only through the use of fuzzy possibility functions. This contrasts with the traditional parametric approach, which provides an estimate of the indetermination level by random statistical distributions; the variability within a class is considered as noise superimposed on the real value.

The photo-interpreter expert analysed the images and qualitative linguistic terms (such as high, low etc.,) were applied to spectral response patterns of a class, in order to describe the rules that associate the ground data to spectral characteristics of the multitemporal imagery. Using logical terms and operators eg, very, not, and, or, high and low; functions were defined by the relationship :-

$$m\,(\,Ci, X, K\,) \qquad (6.2)$$

where m, represents the measure of the possibility of belonging to the
Ci, class, for a pixel with
X, grey level, in the
K, spectral band.

Blonda *et al*., (1988), compared the fuzzy logic approach with the classical probabilistic maximum likelihood approach. It was found that the approaches gave comparable results, with fuzzy logic slightly better i.e., overall accuracy of 91% compared to maximum likelihood result of 86%. This was attributed to the fact that fuzzy logic performed better with heterogeneous classes, whereas the more uniform crops such as crop land and pasture were classified with the same precision. It was concluded that a traditional statistical maximum likelihood descriptor works well for mainly homogeneous classes, and that the fuzzy based descriptor provides a better description of the real world and its non-homogeneity.

Some form of segmentation is necessary before the classification process can take place, for instance in supervised classification, this usually takes the form of partitioning the image by eye in the selection of training areas. Segmentation partitions the image data into connected homogeneous regions. Most segmentation is achieved manually, however automated segmentation methods have been developed which use spatial and spectral data from the image (eg, edge detection). Automatic segmentation can be region or domain based, for example, a clustering procedure can be applied which splits and merges pixels to produce homogeneous regions (Cross and Mason, 1985). Automatic segmentation can use edge detection, locating points of large contrast and linking these points into connected boundaries. Parcels of land can be recognised as individual units. These units are termed 'fields', a term which is applied generally to all such parcels of land whether they are agricultural fields, forest stands or urban blocks. In effect segmentation identifies areas which are meaningful to the 'user', as opposed to areas which can be distinguished from the image on spectral grounds alone.

In a segmentation procedure, ancillary data can be used together with remote sensing data. Ancillary data is any type of information used in the classification process, not directly obtainable from either spatial or spectral characteristics of the remotely sensed data. Tailor *et al.*, (1987), described the use of automated segmentation of remotely sensed images. Knowledge based automated segmentation as used by Tailor *et al.*, supplemented the information by *a priori* knowledge in the form of digitised map boundary data. In this way the segmentation was refined using a rule base derived from domain data; this acted as a series of constraints on region properties, i.e., the variance of pixels in the region. The image was then classified using the segmented data by a 'per-field' classifier as opposed to a 'per-pixel' classifier.

Pedley (1987), also used boundary data gleaned from digitised map data, in which statistics for each field were then generated and imputed to classifying algorithm. The standard maximum likelihood 'per-pixel' classifier was used as well as the equivalent 'per-field' classifier. The latter was further modified by two refinements, i) to include a measure of spatial variation for each class by the input of one band of standard deviation and ii) by including a measure of prior probabilities. The resultant classification accuracies were significantly greater than the 'per-pixel' method and the resultant thematic images were more easily interpretable. Such 'per-field' classification systems are directed principally towards applications of crop monitoring, where their use with regular shaped agricultural fields of relatively homogeneous cover types will be of most benefit.

Other forms of ancillary data can be input into classifications of remote sensing data. Raster elevation data was included together with SPOT imagery by Sakata *et al.*, (1987). The elevation data was input in the form of a digital terrain model (DTM) to reduce topographic effects on the classification procedures. Slope and aspect terrain components were incorporated into the classification algorithms in the form of prior probabilities, decision rules and image segmentation using contextual information.

6.2.3.3 Probability Measures

Early work on probability measures could be a promising new approach with regards to the classification of semi-natural vegetation. Wood (1988), discussed ways in which to analysis and display ecological continuum of semi-natural vegetation using TM data. It was suggested that probability measures would be a more realistic way of mapping semi-natural vegetation. The resultant image would indicate changing levels of confidence in the cover type selected by the classifier. Alternatively, posterior probabilities could be used. Within regions of classified cover type, the variations in probability could be mapped using zones of membership. The resultant image then indicates gradients of group membership likelihood and illustrate the direction of likely confusion. However, this is an area of research where there is much scope for further investigation.

6.2.4 Methodology Refinements for Semi-natural Classification and Grasslands

The need to refine methodologies is perhaps more important when considering complex semi-natural vegetation, as opposed to monoculture crop canopies, when attempting conventional automated classification techniques. Since there is extreme diversity in the species composition of semi-natural vegetation communities and boundaries between these communities are commonly diffuse in nature (see Chapter Three, section 3.3 on the problems of semi-natural vegetation). It is worthy to note that the adequacy of improvements on the classification depends on the 'users' end requirements. For instance, whether is it more important for the accurate mapping of semi-natural vegetation or is the priority tabular results in the form of statistics.

Foody and Wood(1987), investigated the use of TM for ecological monitoring of lowland semi-natural heathland, where classification accuracies of around 70% overall, were achieved using automated classifiers. He suggested various refinements to the classifying procedure in order to improve results that would be needed for a more realistic mapping exercise, such as input into a geographical information system (GIS) data base. Four types of refinement proposed by Foody and Wood, and implemented by other workers are briefly discussed below :

* Hierarchical method :- this is the removal of classes that are accurately classified i.e., classes with low commission errors can be removed. McMorrow and Hume (1986) used a graphics mask to mask out areas that had been successfully classified. Another method is by the input of ancillary data in the form of discrimination variables such as slope, aspect or elevation data from topographical maps (Jones *et al.*, 1987); or other forms of ancillary data (Blazye, 1987).

* Rule modification :- this is where the classification rules are modified on the basis of misclassification error in the classification of training areas. The training classification can be used to provide information on potential misclassification which can then be incorporated into the classification proper (Belward and Taylor, 1986). In effect *a priori* knowledge of misclassification is gained and the classification rules can be modified accordingly.

* The creation of 'fuzzy' or 'uncertain' classes :- where a class may contain proportions of other classes, not too dissimilar to mixels (mixed pixels). It is apparent that semi-natural vegetation does not exist as discrete units, consequently the spectral difference between two classes can be very variable. If a sample of each class were obtained at the end point of the continua along which they lie, they may well be spectrally dissimilar. However, near the arbitrary defined break point between the two classes the difference may be so insignificant, as to make spectral classification very difficult. With an ordinary classifying algorithm, a sample may be allocated to one class when it reflects the qualities of two classes. In such circumstances it could be more appropriate to allocate a 'fuzzy' class, which shows it to have marginal properties of two classes. Fuzzy set approaches do not make rigid assumptions about the characteristics of the data, they allow for natural variation or 'fuzzyness' of the scene to be mapped (Foody, 1992).This is more realistic for the representation of prevailing ground conditions. Ancillary data or field investigation could then be used to reconcile the uncertainty or create a intermediate class.

* Ordination or probability mapping :- This approach could be used where the concept of classification into discrete classes is inappropriate, because of the continuum of vegetation types in semi-natural vegetation. The adoption of ordination techniques could be more suitable, with the replacement of classification with probability contours, derived from the Mahalanobis distance between the sample areas and the

class (group) centroids. The Mahalanobis function is crudely a measure of the distance of an observation from the class mean, corrected for variance and covariance of that class, and takes account of the probability of membership (Mather, 1987a). The mapping of probabilities of group membership of different vegetation communities would indicate their spatial distribution and thus models their continua.

Alternatively, quite simple measures can be adopted for the improvement of classification. Topographical effects on the classification of upland semi-natural vegetation can be ameliorated by dividing classes into terrain related sub-classes (McMorrow and Hume,1986; Williams, 1987).

More elaborate and elegant methodology refinements can be used, such as in a study conducted by Jones *et al.*, (1987), who used various parameters to improve discrimination and accuracy of automated classification algorithms, whilst using SPOT data for upland semi-natural vegetation mapping. Incorporation of ancillary data in the form of Digital Elevation Model (DEM) has already been mentioned. Further refinement of the classification procedure was achieved by assigning prior probabilities in maximum likelihood classifications, based on a knowledge of the general ecological principles which determine the likely distribution of the observed vegetation.

Blazye (1987), used ancillary data from the Institute of Terrestrial Ecology (ITE) land classification system, which provided a rich source of information about the spatial patterns of land cover types and their relationship to the physical attributes of the landscape. The whole of the UK has been classified according to one of thirty-two ITE land classes. Blazyes study site in N. Wales contained upland semi-natural vegetation and contained four of the ITE land classes. From TM imagery, nineteen spectral classes were extracted to train and test a maximum likelihood classifier. This data set was then stratified according to the four ITE land classes and reclassified. By this stratification of the image data, confusion was decreased between classes with similar spectral responses, but were from different ITE land classes and were thus not present together in the reclassification. The mean classification accuracy improved by twenty percent after the stratification using the ancillary data.

6.3 Geographical Information Systems (G.I.S.): the future !

Effective environmental or renewable resource management is limited by the quality and quantity of present available data. The lack of standardised surveying procedures, makes comparisons, integration and analysis of habitat data recorded from different sources, a difficult task. Furthermore, the surveys to-date have been irregular and inconsistent both in time and space. Consequently, survey effort may be lacking in some areas, but may be duplicated in others. Data quality is likely to be both spatially and temporally variable owing to the range of survey personnel expertise. The logistics and cost of surveys and the management of data generated are further problems.

A possible solution to these problems would be remotely sensed surveys and classifications incorporating ancillary data. The most suitable sensor data at present for a county and regional level, would appear to be TM (Foody and Wood, 1987; Young, 1986).

The digital form of satellite data, allows automatic classification and transformation by means of a Geographical Information System (GIS). Extensive ground data can be compared with images by means of such a system. Image feature files, ground data and classification results can be input to the GIS.

The end products of the GIS being thematic maps, which could be one of various forms, dictated by the analyst to show salient features of interest. At base level a thematic map is divided into polygons or regions, according to categories of the theme, i.e., a land cover map showing cultivated land, woodland and urban areas. From the GIS thematic maps of different emphasis can also be readily produced i.e., land productivity, or lines of communications.

With the increasing informational content of successive sensor platforms, the development of GIS, capable of handling multidate, multiplatform remotely sensed data and sophisticated geographical data bases, can take advantage of the more detailed and reliable description of the Earth's surface.

CHAPTER SEVEN

RESULTS

This Chapter gives the findings of the interactive visual analysis of the study area, together with initial supervised classification results and the final results gained from the application of a refined methodology. Results are given both for the Salisbury Plain Training Areas (SPTAs) range grass analysis and for permanent chalk grasslands of Special Sites of Scientific Interest (SSSI) status off the immediate Salisbury Plain MoD ranges.

7.1 Qualitative Assessment for Feature Selection

The various methods for feature selection have been discussed in Chapter Five, section 5.1 and 5.2. In conjunction with this, a brief account of the qualitative assessment of various band subset combinations of TM is provided and the results are given below. Although a subjective process, if specific features of interest, as in this case the SPTA ranges are easily identified from the imagery; a relatively quick look at the various band combinations and colour permutations can produce interesting results and be a valid input into the analysis (Table 7.1).

Various three band combinations were assessed for the utility and potential operational usage. All combinations were displayed on the colour guns in red, green and blue order respectively and enhanced by contrast stretching.

In conclusion, it was found that the most readily interpretable image was with TM bands 4, 5, and 3, in which vigorous green vegetation appears as bright red tones. This result further supports the conclusions drawn from Chapter Five on feature selection, where theoretical and empirical evidence is regarded. However, as with all remote sensing data, the user has to recognise that the utility of such composites cannot be assessed independent of the spatial, spectral and temporal characteristics of the scene being imaged (Townshend *et al.*, 1988).

7.2 Qualitative Interpretation of Multitemporal Single and Composite Multispectral Data Sets

This section refers to visual discrimination of features of interest from the multisensor, multitemporal data set. The reasons for the choice of the three bands of the TM have already been outlined in Chapter Five, section 5.2 and in the previous section. An appreciation of the utility of their resultant images and an introduction to their analysis, can be obtained through the examination of single bands and their combinations in relating image properties

Table 7.1 : Three Band Thematic Mapper (TM) Combinations and their Information Content

Band combination	Comments on Colour Composite
4 5 3	Best overall contrast and largest range of variation, was found to contain most informational content of the study area. Although the resultant colours are unnatural, statistically the data is three dimensional in nature and it follows colour perceptions familiar to 'users'. It is also the three band subset most quoted in UK grassland studies, using TM (Fuller and Parsell, 1990; Fuller *et al.*, 1989b; Belward *et al.*, 1990; Foody and Wood, 1987).
4 5 1	This composite was found to be similar to 4 5 3, but with slightly less variation present for this study area. It is referred to by many sources both qualitatively and quantitatively as the best combination for many applications (Trolier and Philipson, 1986; Chavez and Bowell, 1988)
4 3 2	Not as satisfactory as 4 5 3, much less variation present and hence of lesser value for feature extraction. Known as the standard FCC (SFCC), which is familiar to users of Landsat MSS and colour IR photography for it's land cover and tonal associations. Also equivalent to the best FCC of SPOT.
3 2 1	Quite a narrow range of contrast, needs the extra dimension of the IR bands for vegetation discrimination. This band combination, termed the natural colour composite, it is the closest in terms of the human perception of the terrain i.e., vegetation appears green and bare fields brown, grey etc.. It has much less informational value for vegetation studies than do false-colour presentations.
5 4 3	This variation of the best three band subset has been quoted as the most useful by some users (Townshend *et al.*, 1988; CCRS, 1987). This is because in the resultant image, green vegetation does indeed appear green, bare surfaces and buildings appear purple, and water bodies appear blue. However, for discrimination of vegetation types the 4, 5, 3 subset was judged by the author to be superior to the 5, 4, 3 permutation.

* In general the best band combination for vegetation use involves one of the three bands in the visible spectrum in combination, with the near-IR band and one of the two middle IR bands.

to ground conditions. For all three sets of imagery, original data was enhanced by auto-linear median contrast stretch function. The listing of imagery follows a seasonal sequence, rather than the year it was acquired so as to follow the phenological development of vegetation.

Belward *et al.*, (1990) suggested with semi-natural vegetation application, primary analysis by eye of the FCC can help to define classes by :-

* identification of subdivisions in broad ecological classes such as croplands,
* identifying classes that show poor spectral separation from ecological related groups and
* identifying cover types of no direct interest to the ecologist, which are nevertheless spectrally important.

Additional collaborative information was gathered from existing UK TM imagery of the same three band subset and colour display (Hilton *et al.*, 1988). Seven such images were available which Hilton *et al.*, had used in FCC analysis (mainly for teaching purposes) and of these, there were four southern lowland agricultural scenes which were applicable to this study area. These scenes were multitemporal in nature, mainly from 1984-85 and covered the majority of the crop calender. From visually analysing these scenes, it was possible to construct a summary of scene independent cover type, and colour associations for scenes of similar topography and nature to that of the study area. The results are given below in Table 7.2 and provide further comparative information and guidance on the visual analysis and training area selection used in this research project.

Using SPOT data a similar FCC evaluation carried out by the NRSC (1983), can also be used for comparative purposes. The visual appearance of several different agricultural cover types for a single date (May 1983) using a Derbyshire test site, is given by Table 7.3. The semi-natural grassland found in this study was on limestone and not chalk, but it was felt it did provide some useful information.

All subsequent descriptive analysis relate to 512 x 512 extracts of West SPTA and of extracts centred around the village of Wylye. This is an area south of the Salisbury Plain training areas which includes a large selection of the various land cover types and uses that occur in the region : it is also the location of the study site used in the permanent chalk SSSI analysis.

Table 7.2 : The Seasonal Visual Appearance of Vegetation Cover Types for 4, 5, 3 TM Band Composite for Lowland UK (from Hilton *et al.*, 1988)

Cover type	Month					
	January	April	May	June	July	August
Ploughed or bare	Blue	Blue or white (chalk)	Blue	Blue		Blue tones
Cereals		Orange, pale red	Red	Bright red	Purple	
Unimproved grassland			Pale orange , yellow & green tones	Pale orange , yellow & green tones	Orange	Greenish orange & yellow
Improved grassland			Tans, gold orange	Orange		Red
Oilseed rape			Pink	Magenta, pink	Magenta, pink	
Mixed woodland	Black/ brown	Green/ brown	Light brown, red			Brown, red
Coniferous woodland	Black	Black	Black	Dark brown /black		Dark brown /black

Table 7.3 : The Spectral Responses of Cover Types for May, using S.SPOT SFCC Bands 3, 2 and 1 (NRSC, 1983)

Cover type or feature	Description of feature on SFCC
Winter cereal	Bright red/pink
Spring cereal	Light red, pink, light brown/grey, light red/green
Broadleaved/mixed woodland	Dark red/green (coarse texture)
Coniferous woodland	Black/very dark green
Grass leys (improved)	Bright red
Rough grassland (unimproved/semi-natural)	Blue/green or blue pink
Bare or low vegetation	White to cyan/grey

7.2.1 TM May 1985

Band 4 (0.76-0.90μm)
Water bodies were very apparent, they appeared black due to absorption of the near-IR. Linear features such as major roads were visible. The MoD rangeland was quite distinct, such that it was darker in appearance than the surrounding farmland. Woodland appeared even darker and there were two tones apparent; broadleaved woodland was darker, whilst coniferous was slightly lighter in tone. Vigorous vegetation appeared very bright and this related to the fact that by May, winter cereals and improved grasslands were well established and growing vigorously. Permanent chalk grassland of SSSI status, revealed within field differences with this band.

Band 5 (1.55-1.75μm)
Again water bodies appear very black, band 5 even picked out a small river system (the River Wylye). Linear features such as roads were not as clear as on TM-4. Chalk tracks used by tanks on the rangeland and bare ground were very bright and distinctive. The rangeland was less distinct and quite light in appearance, reflecting the carry over of senescent material from the previous season. Woodland features were not as apparent as on the previous band, although coniferous woodland did appear darker and with broadleaved woodland now appearing as a lighter tone, a reversal from band 4. Vigorous vegetation was very dark in appearance, this was attributed to the fact that band 5 (mid-IR) produces a lower response due to its absorption by foliar moisture. Permanent grassland exhibited uniform tones within fields, but between fields there were differences.

Band 3 (0.63-0.69μm)
Water bodies were very indistinct, but linear features such as roads and tracks were detectable. The response of chalk tracks, bare fields and areas of low vegetation were very reflective and was similar to that as found with TM-5. This occurred because the red visible part of the spectrum was being reflected by these cover types. The rangeland produced a similar response to that found with TM-5. Woodland and vigorous vegetation were dark in appearance, but they were very similar in tone and not as discernible as with TM-5. Overall there were more general tones for all the cover types, but there was not the spectral contrast of the IR bands.

A FCC image was then generated from these three bands of TM (see Figure 7.1) on the Digital Image Processing (DIP) workstation, as described in section 7.1 (Table 7.1). The spectral response patterns of the various cover types were noted and are given by Table 7.4.

Scale 1: 100000

N

Figure 7.1 : WSPTA Study Area, May 1985 TM (Bands 4 5 and 3) FCC

Table 7.4 : The Spectral Responses of Cover Types for May, using TM 4, 5 and 3 False Colour Composite

Cover type	Description of the unit on FCC
Winter Cereals	Ranges from dark red (most developed), bright red (growing well), dirty purple (vegetation developing) to white (the influence of chalk soil background)
Spring Cereals	Light purple to white (spring cereal growth is thin and patchy, which has produced a mosaic of tones in this late spring imagery)
Oil seed rape	Bright pink in appearance, quite distinct
Root crops	Light blue to grey tones
Bare fields	Light blue to white
Urban	Dirty blue and textured
Broadleaved woodland	Dark green to black
Coniferous woodland	Brown to dark red
Permanent grassland	Orange/green to grey
Rangeland	Grey/green and blue mottled tones

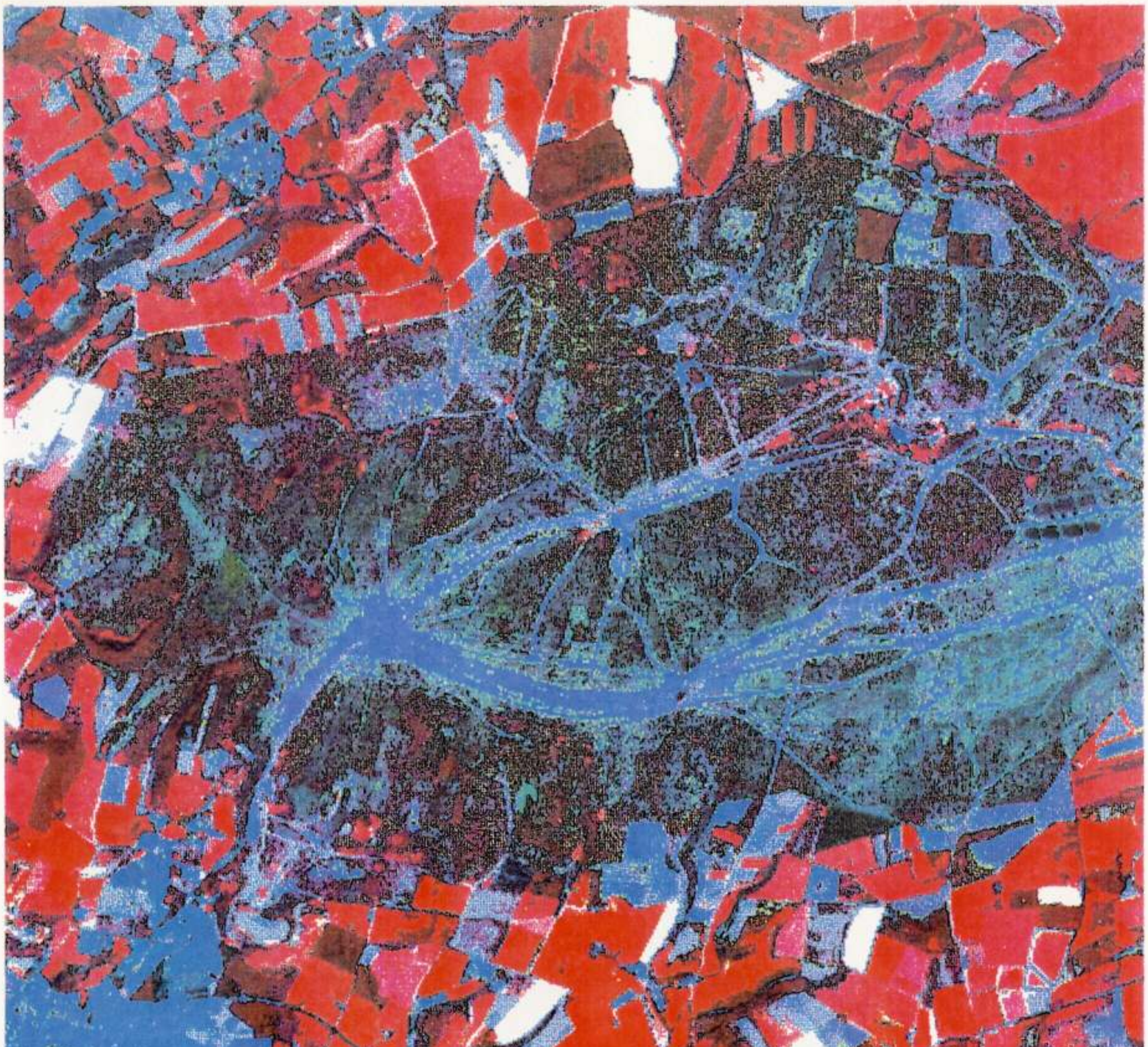
7.2.2 SPOT June 1986

Band 3 (0.79-0.89μm)

Linear features such as road and railways were more evident with this near-IR band than the equivalent TM band, which is attributed to SPOT's increased spatial resolution. The extent of the rangeland was easily discernible, with the rangeland being quite dark in appearance, compared to the surrounding agricultural fields which were comprised of more lighter tones. Urban areas were distinguishable with a characteristic mottled tone and texture.

Band 2 (0.61-0.68μm)

Field boundaries were identified and thus small field patterns could be distinguished. Chalk tracks, bare fields, or fields with low vegetation amount were very apparent with bright tones. Conversely, with this band the rangeland appeared lighter in tone than the surrounding agricultural land compared with SPOT's near-IR band. This is due to the red visible part of the spectrum being absorbed by vigorously growing vegetation of crops in early summer.



Scale 1: 66500

N

Figure 7.2 : WSPTA Study Area, June 1986 SPOT (Bands 3 2 and 1) Standard FCC

Band 1 (0.5-0.59μm)

This band was very similar to band 2 in terms of tones regarding cover types. However, there were subtle differences within the rangeland and certain field types were lighter in tone compared with band 2.

A Standard FCC (SFCC) was generated (see Figure 7.2), since SPOT only contains three multispectral bands. This FCC is similar to the general composite formation found with Landsat MSS, due to the choice of spectral wavelengths. It thus provides a picture for interpretation that is familiar to 'users' (see Table 7.5 for a description of the cover types).

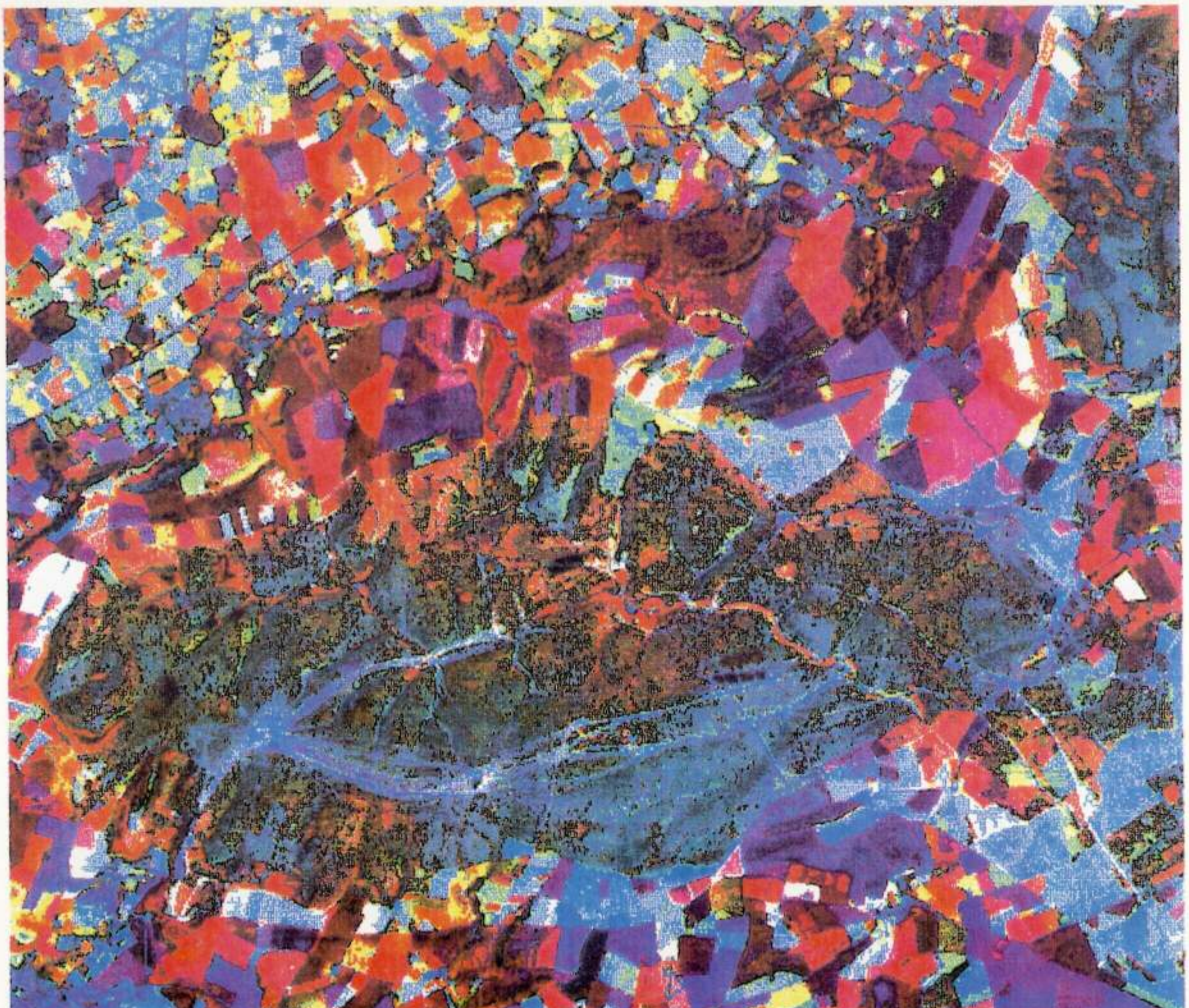
Table 7.5 : The Spectral Responses of Cover Types for June using SPOT Standard False Colour Composite

Cover type	Description of the unit on FCC
Winter cereals	Bright red and red tones
Spring cereals	Light red and pink tones
Bare fields	Cyan to blue/grey to white tones
Urban	Dirty blue (coarse texture)
Broadleaved woodland	Red/black (some confusion with cereals)
Coniferous woodland	Green/black
Permanent grassland	Dirty pink/grey
Rangeland	Greenish grey and pinkish grey, together with mottled green, grey and pink

7.2.3 TM July 1984

Band 4

Water bodies were very distinct, as were linear features such as major roads. Urban areas were very dark in tone. The rangeland appeared dark, as did areas of coniferous woodland and winter cereals. In the case of the winter cereals, the absorption of the near-IR can be explained by the fact that the crops have ripened and senesced. The decrease in reflectance is caused by the reduction of moisture in ripe crops. The situation of the coniferous areas could be explained by the fact that 1984 was a hot and dry summer and that these woodland areas were experiencing water stress. However, most woodland areas were quite light in tone (easily identified by their textural quality), as were areas of continuing vigorous vegetation growth. The June/July period is the period of maximum vegetation growth and



Scale 1: 100000

N

Figure 7.3 : WSPTA Study Area, July 1984 TM (Bands 4 5 and 3) FCC

production.

Band 5

Water bodies were quite clear, but linear features such as roads were not so discernible as compared with TM-4. Chalk tracks were very evident being bright in tone, as were bare fields and fields with low vegetation amount, such as fields cut for hay etc,. The rangeland was less distinct with a light grey tone. Coniferous woodland ranged from a dark tone to mid grey, whilst mixed and broadleaved woodland exhibited a mid grey tone with highly discernible textural quality. Crops exhibited a range of colouration from black, to dark medium and light grey tones. This reflected the various growth stages and phenological development of the various crops present. Permanent grassland was light grey in tone and showed within field variation, this was thought to be attributed to differences in soil moisture.

Band 3

Water bodies were indistinct in this band and linear features were only moderately detectable. The chalk tracks were visible and the rangeland was of similar appearance to that as in TM-5, but just a shade darker. Woodland was very distinct, both coniferous and broadleaved appeared black. Broadleaved areas not distinguishable on the other two bands were clearly illustrated with this band. With crops, the various grey tones seem to correspond to their growth stages. Mid grey tones corresponded well with established growing crops and grassland, and light grey to white areas corresponded to permanent grassland and mature ripening cereals. A FCC image was again generated in the same way as the previous TM image (see Figure 7.3), and description of the cover types is given by Table 7.6.

It is apparent that there was a lot more colour variation present in the July 1984 TM image compared to the other two images, and this can be explained by the fact that crop phenology factors comes into play. The winter and spring cereals were for the most part ripe by this stage and exhibited different spectral responses in relation to the May 1985 TM imagery. In the May image spring and winter cereals were green and just beginning to grow vigorously and exhibit more similar spectral responses. Hence, the colour variation found in the 1984 July image is a function of crop calender, different growth stages of specific crops and intra-crop differences from field to field.

Table 7.6 : The Spectral Responses of Cover Types for July using TM 4, 5 and 3 False Colour Composite

Cover type	Description of the unit on FCC
Winter cereals	Purple to redish purple
Spring cereals	Dirty red
Oil seed rape	Bright pink
Root crops	Brick red
Bare fields	White to very light green
Urban	Dirty blue (textured)
Broadleaved woodland	Brownish orange to bright red (textured)
Coniferous woodland	Black to brown with dark green
Permanent grassland	Bright orange to greyish green
Rangeland	Green, greyish green and dull orange

7.2.4 Summary

Evaluation of the FCCs illustrated the various land cover categories present, by the wide variety of spectral response patterns evident in the imagery. These were markedly different within, and between the imagery and were readily distinguishable. It was also noted that there was within field tonal variation present in the TM imagery (a function of its spectral resolution) and with the SPOT data (a function of its spatial resolution), which was less easy to differentiate and interpret.

It is clearly evident from the FCC stretched images that the TM contained much more information than the SPOT imagery from a qualitative point of view (see Figures 7.1 to 7.3). This phenomenon was even more apparent when the TM-84 July image was assessed. This was for the most part a factor of crop phenology in that cereals were spectrally distinguishable by that time of the growing season.

Areas under arable crops are regularly ploughed, resulting in a disturbed soil profile with chalk flints at the surface. Examples of such were clearly evident in the imagery, where the darker soils and the chalk flints produced a mottled 'salt and pepper' appearance.

In summary, the following points can be made :-

i) As anticipated each individual band of the TM 4, 5, 3 composite when viewed singly contributed useful information. This confirmed previous work that stated that one band from each of the three sections of the spectrum, visible, near-IR and mid-IR, provides the most useful general information, without too much redundancy or duplication.

ii) The two visible bands of SPOT were very similar and in marked contrast to the near-IR, which provided independent new information. However, it must be noted that the two visible bands did provide some information, as there were subtle differences evident. Therefore, depending on the analysts interest, this information may be important.

iii) The FCC of the SPOT imagery clearly demonstrated a much poorer range of spectral variation, as compared to both TM composites.

iv) The rangeland was very distinct on all three sets of imagery and could easily be visually delineated from the surrounding agricultural land. However any attempt to further subdivide the rangeland by visual means into homogeneous units proved impossible. The imagery of the rangeland proved to be too complex in approximating the general grassland thematic map provided by EN. This was not surprising considering the informational classes present, since they are :-

a) very similar in dominant species composition and physiognomy,

b) that trained botanical field personnel had difficulty in identifying and delineating the classes, and

c) the semi-natural nature of the vegetation meant it occurs as a continuum, rather than discrete classes.

These results did not bode well for the application of automatic classification algorithms for the mapping of the semi-natural range grassland types.

7.3 Automated Classification Results

7.3.1 Initial Supervised Classification

All classifications were carried out using the maximum likelihood and the minimum distance classifiers. The first classifications used all range grass units of major areal extent. All results relate to WSPTA and both the TM and SPOT imagery were resampled and registered together at 25m spatial resolution for a direct comparison, using the nearest neighbour transformation. The classifications were then performed and then the classified overlays were then warped to British National Grid (BNG), using the bicubic convolution (see

Chapter Four, section 4.2.2.1.). Twenty one ground control points (GCP) were used to geometrically correct both the TM image files, and nineteen were used to correct the SPOT image file.

As an indication of the geometric accuracy, the root mean square (RMS) error was calculated for a number of points in each image file using the following formula (Jensen, 1986) :

$$RMS_{error} = \sqrt{(x - x_{orig})^2 - (y - y_{orig})^2} \qquad (7.1)$$

where x and y are the actual pixel locations on the image (in terms of BNG coordinates), and x_{orig} and y_{orig} are the theoretical (accurate) BNG coordinates.

These data sets were then reduced to the 'best fit' sixteen GCPs and a RMS error for the whole data sets were calculated as $\pm$ 1.27 pixels (see **Appendix 4**). All three imagery data sets could then be directly compared and contrasted, since they all have the same spatial resolution (25m). The classification statistics generated were obtained using the same training and test sites for all three data sets. Therefore, the only variables between the three data sets were the spectral resolution between the SPOT and the TM; and the image temporal characteristics in terms of vegetation phenology between the three dates. The cover types used in the training procedure for the whole WSPTA extracts are described in Table 7.7.

Minimum Distance Classifier :
The minimum distance used the Euclidean distance measure with a threshold of 16. This classifier is described in more detail in Chapter Six, section 6.1.1. The larger the threshold the more likely that there will be no unclassified pixels, however the confidence limits for each class are much reduced. The normal threshold is about three times the standard deviation for each class i.e., a normal figure of between 6 - 16. The figure of 16 was chosen as a result of examination of the training data statistics, primarily the standard deviation and through the analysts experience. The computer processing unit (CPU) time involved in operating this process was 14.6 minutes, for the best three band classification. With the inclusion of two further visible bands of TM, in a five band classification, the CPU time rose to 24 minutes, the significance of this will be discussed later.

Table 7.7 : Grassland Communities and Cover Types occurring on the whole Western Salisbury Plain Training Area (WSPTA)

Class	Classification colour code	Description of the land cover types	
1	Red	CG3a	(Calcarious range grassland)
2	Green	CG3a/di	(" " ")
3	Blue	CG3d	(" " ")
4	Cyan	CG3di	(" " ")
5	Yellow	MG1	(Mesotrophic range grassland)
6	Magenta	Wheat	(mainly winter)
7	Light Red	Barley	(mainly winter)
8	Light Green	Agricultural I calcarious grassland	
9	Light Blue	Urban	
10	Light Cyan	Agricultural II calcarious grassland	
11	Light Yellow	Open-cast Quarry (Chalk)	
12	Light Magenta	Chalk tank tracks	
13	Brown	Coniferous woodland	
14	Orange	Broadleaved or mixed woodland	

Maximum Likelihood Classifier :

The maximum likelihood classifier was used with a probability threshold of 90%. This is the likelihood that pixel x belongs to class n, and it is the minimum acceptable probability for inclusion into that class. By increasing the percentage probability this will lower the acceptable range of standard deviation, and thus the more homogeneous the class brightness values will be. It is thus standard for a normal percentage probability figure being 90% and above. The CPU time involved in this process is significantly increased when compared to minimum distance. It was recorded as being 81.4 minutes, an increased factor of over five, for the best three band classification. For five band classification it increased to 182.4 minutes, an increased factor of over twelve. This could be an important consideration with regard to the costs of processing and this would have to be balanced with the benefit of increased accuracy this algorithm has been suggested to have (see Chapter Six, section 6.1.1)

7.3.1.1 TM May 1985

A five band classification scheme using bands 4, 5, 3, 2, and 1 was first attempted. Fourteen informational classes were identified and used to train the classifier (see Chapter Four, section 4.2.4 on training and test site selection). Evidence from the previous analysis (section 7.2), it was apparent from the imagery that certain cover types were a potential source of error and that this was a direct result of the temporal development of the vegetation.

For the rangeland of West SPTA (WSPTA), five semi-natural grassland units were initially chosen with which to train the classifier. These were not the most important botanically as far as informational classes useful to English Nature (EN), but they were chosen because they covered the largest areal extent necessary for the required number of pixels to train and assess the classification (Swain and Davis, 1978). This applied to all three data sets and Chapter Two Table 2.2 gives the description of the major grassland types found on the WSPTA and used initially in the supervised classification procedure. Only pure swards of grass type were used in all the selection of training and test areas, this was because the EN survey also found areas that were mixed i.e., there were areas that contained CG3d and MG1 grassland units. This in effect reduced the areal extent of homogeneous areas that could be utilised in sampling, this therefore meant that any random sampling strategy was biased/limited to these areas. Pure sward areas were used, because it was necessary to ascertain if any unique spectral response patterns were revealed in the chalk grassland types.

7.3.1.1.1 Analysis of Training Statistics

It is necessary to examine the statistical properties, because when using parametric classifiers, such as maximum likelihood, there are certain inherent assumptions that must be fulfilled by the statistical parameters of the training data. This can be done by graphical processes as described in Chapter Four, section 4.2.4. These can greatly aid the analyst in checking the characteristics of potential training data sets (Swain and Davis, 1978).

However, this assumption of normality can easily be departed from, depending on the cover types. Grasslands are one such cover type, because of their complexity and different management regimes (Glasbey, 1988). It was recommended that attention is given to the amount of variability within-fields, particularly in the way that it relates to between-field variability of pixel values. Glasbey showed that between-field variability of the same grass cover type invalidated the assumption of normal distribution, as did within-field variability.

Histogram plots can be used to check that the data utilized have a 'Gaussian' or normal distribution. Data may be normally distributed in different wavelength bands, yet in certain spectral bands it could have a bimodal or multimodal distribution. Failure to separate a bimodal training informational class into two spectral classes may cause classification errors which could have been avoided.

Coincident spectral plots plot the mean in spectral response for each class of interest for each wavelength band. The standard deviation from the mean is also plotted and thus give an indication of the variance of the data. The small values of standard deviation relative to mean values indicate a marked degree of spectral separation of the clusters in feature space.

Table 7.8 : Training Area Statistics for Classification of WSPTA, TM-85 Data (Bands 4, 5, 3, 2, and 1)

	Class Statistics (mean and ± one standard deviation)						
Band	CG3a	CG3a/di	CG3d	CG3di	MG1	Agri I* grass	Agri II* grass
4	113.3	80.0	84.4	82.7	95.9	144.8	117.4
	5.3	6.4	5.9	4.5	4.5	4.6	3.9
5	105.1	110.3	101.5	111.1	104.8	69.1	96.5
	3.4	3.5	3.1	4.3	4.7	4.1	2.9
3	32.7	40.5	38.5	40.2	36.0	24.2	31.6
	2.5	1.5	1.2	1.6	1.4	4.2	4.0
2	36.9	39.0	38.3	38.5	37.4	31.9	36.6
	0.8	2.0	0.9	1.1	0.9	0.9	0.9
1	83.9	90.2	88.5	89.6	85.7	78.6	82.5
	1.5	3.1	2.3	2.0	1.8	1.4	1.4

* Agric I & II denotes agricultural calcareous grasslands outside the immediate range area

Scatter plots allow the analyst to plot the pixel brightness values of spectral bands in feature space. Usually two spectral bands are plotted against each other to give a two-dimensional plot, but it can be more. The usefulness of this to the analyst is that it can illustrate certain band combinations where virtually complete spectral discrimination is apparent, even though such discrimination is not possible in any single wavelength band. It is a good graphical way at looking at spectral overlap of training class statistics. An example of the results of the statistical data generated from TM-85 are given by Table 7.8.

7.3.1.1.2 Qualitative Interactive Supervised Classification Results - Maximum Likelihood

This is where the analyst can interactively display individual classified class components of the classification overlay, over the FCC image. This process aids the effective analysis of multispectral data by increasing the in-depth understanding of the spectral characteristics of the cover types involved, particularly the temporal and spatial effects on vegetation which are significant (Swain and Davis, 1978).

Each individual class or theme can then be viewed in isolation and qualitatively compared to the ground information. An example of the results of this form of analysis is given below :-

CG 3a - Off the range some known CG3a areas were correctly classified partially or fully. Small areas in the schedule III land were also classified (light yellow/green on FCC).

CG 3a/di - classified large areas of WSPTA and Larkhill, the pixels being for the most part confined to the ranges (light green on FCC). A good general correspondence to the EN survey three areas correctly labelled, however over classified in CG3d and MG1 areas.

CG 3d - exclusive to ranges (blue/green on FCC), a good general correspondence to the EN survey, however confusion with CG3d especially along chalk tracks.

CG 3di - classified most of WSPTA (grey/green on FCC), apart from major areas of other grass classes.

MG1 - very good general correspondence to the EN survey on the range, also classified a large portion of the schedule III agricultural grassland to the south east of the range. It also picked out the remaining CG3a areas and a few areas in north western pastoral agricultural region (orange/green on FCC).

Wheat - picked out all the brown/dark reds areas on FCC, that field data indicated as winter and spring wheat fields.

Barley - picked out all the bright orange areas on FCC, that field data indicated were mostly winter barley. However, large amounts of confusion with vigorously growing agricultural grassland, especially in the north western pastoral region i.e., airport verges were classified as barley.

Agricultural grass I - bright brick red areas on FCC, confusion with cereal growth stage, however picked out fields in the north western pastoral region.

Urban - classified all of the urban areas, but also large misclassifications with coniferous woodland (dirty blue/black on FCC) and areas of wheat/cereal (also dirty blue/black on FCC).

Agricultural grass II - orange on FCC, picked out areas of the schedule III land areas, around the airport and scattered fields in the rest of the agricultural areas.

Quarry - 100% classification i.e., just picked out the quarry.

Chalk tracks - picked out the larger bare chalk track areas on range and bare fields in agricultural areas.

Coniferous woodland - picked out the remaining coniferous areas, not classified as urban.

Broadleaved woodland - picked out some scrub and broadleaved areas, but also within the range classified dirty blue/purple areas on FCC and cereal growth stage in agricultural areas.

7.3.1.2 SPOT June 1986

Thirteen spectral/informational classes were used to train the classifier. It was evident that there were less spectral classes present, as compared to TM especially with regards to crop types.

7.3.1.2.1 Analysis of Training Statistics

Inspection of the class statistics (Table 7.9) reveals the mean and standard deviation for the five classes of grass selected for the study.

Standard graphical processes (section 7.3.1.1.1) are now described. Examples of this type of analysis are presented later in the results in section 7.3.2.1. Inspection of the class statistics via histogram plots revealed normal distributions and an adequate degree of class separation in SPOT's near-infrared band 3. SPOT's two visible bands both exhibited normal distributions for the classes, but they also showed a high degree of class overlapping as a result of the classes having similar means.

Coincident spectral plots, show that as expected the urban class has a high variance and it was also noted that the bare dry chalk quarry had a high reflectance and variance in all three bands.

Table 7.9 : Training Area Statistics for Classification of WSPTA, SPOT-86 Data (Bands 3, 2 and 1)

	Class Statistics (mean and ± one standard deviation)				
Band	CG3a	CG3a/di	CG3d	CG3di	MG1
3	126.2	97.4	112.1	102.1	114.7
	4.0	5.0	3.8	4.0	5.1
2	30.3	32.7	31.3	32.0	32.1
	0.9	1.3	1.1	1.0	1.1
1	47.1	47.5	47.4	47.2	48.4
	0.9	1.0	1.4	0.8	1.0

A spectral scatter plot of just the five chalk grass classes show the spectral separation in 2-dimensional feature space, using the more highly discriminatory SPOT-3 band verses SPOT-2. It gives a good indication of the relationship of reflectance, with CG3a/di being the least reflective followed by CG3di, CG3d, MG1 and CG3a being the most reflective. This being in part due to the shorter more productive swards absorbing more of the radiance in a June situation .

Both maximum likelihood and minimum distance algorithms were tested with the SPOT data, to see if there was significant difference in quantifiable results in accuracy. This is to see if the faster minimum distance classifier would produce an equivalent accuracy to the supposedly superior maximum likelihood algorithm. For results of the minimum distance classification see Figure 7.4, and for maximum likelihood results see Figure 7.5.

7.3.1.2.2 Qualitative Interactive Supervised Classification Results - Minimum Distance

CG 3a - small amounts of the range and areas of scrub within the range were classified. Off the range a known CG3a area was correctly classified, however large amounts of crop areas (dull red on the FCC) were misclassified as CG3a.

CG 3a/di - on the range one large area was correctly classified (grey/green on the FCC), however large amounts of CG 3di and 3d were incorrectly classified as 3adi. There were also confusions with urban and coniferous classes.

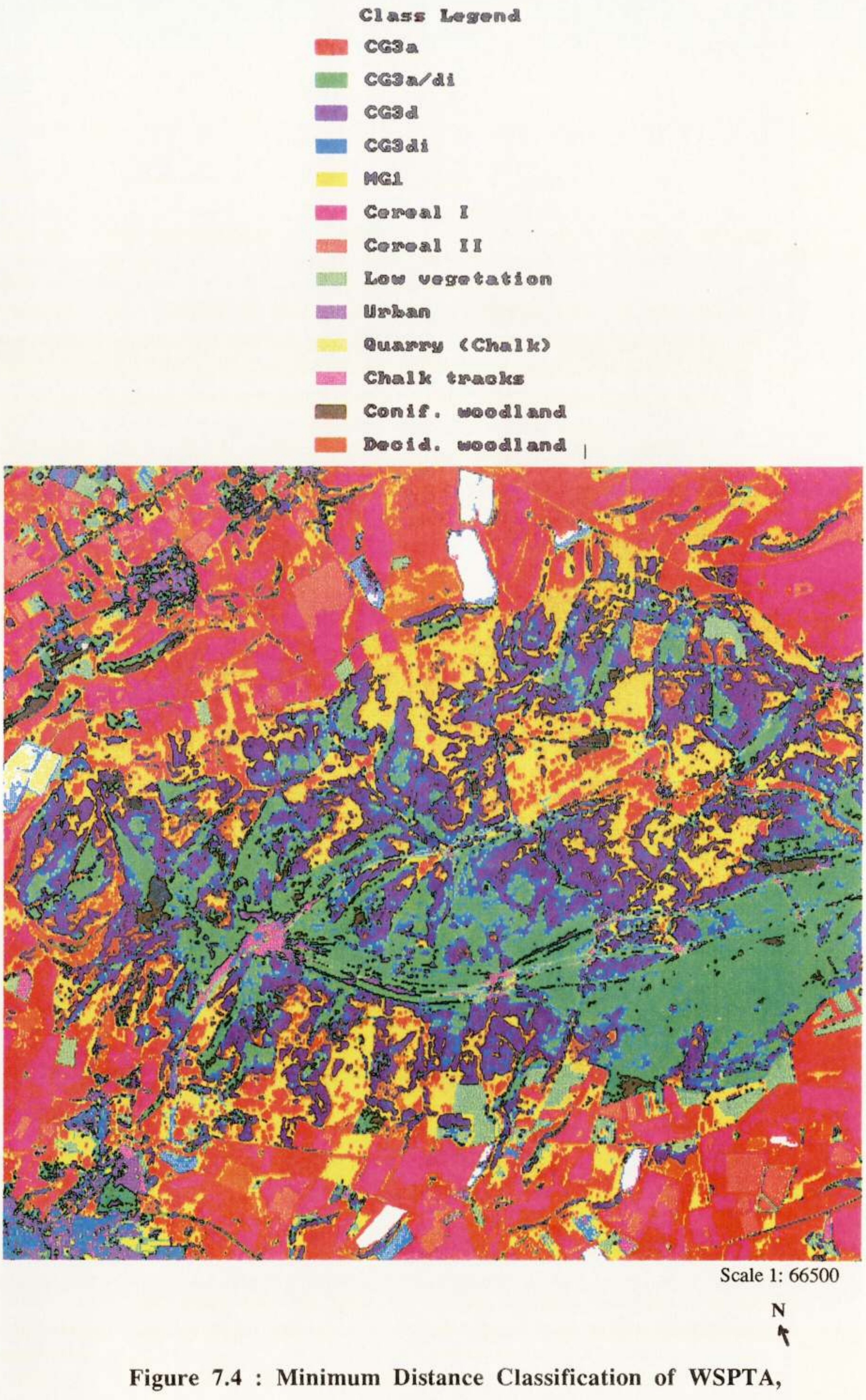


Figure 7.4 : Minimum Distance Classification of WSPTA, June 1986 SPOT Data

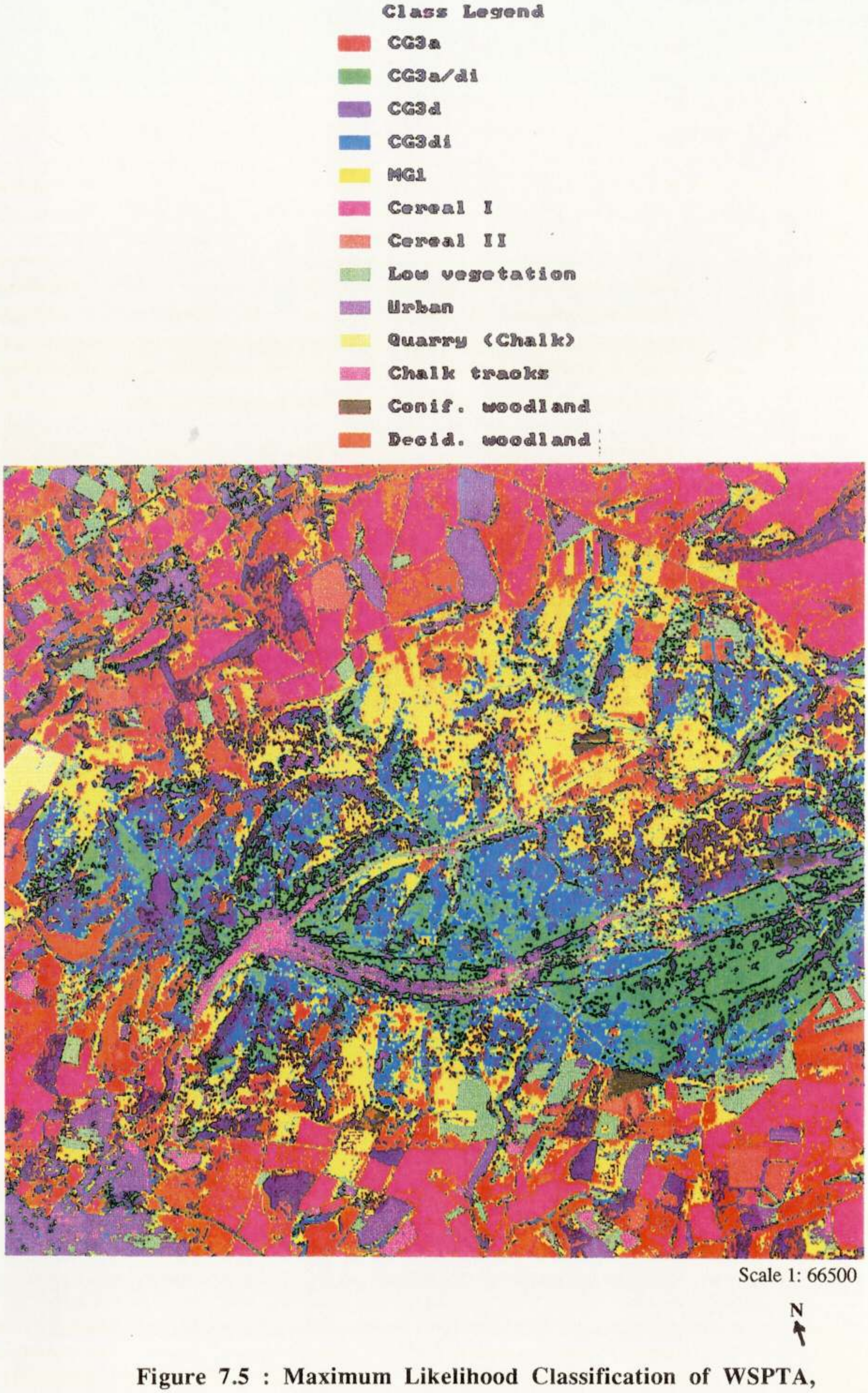


Figure 7.5 : Maximum Likelihood Classification of WSPTA, June 1986 SPOT Data

CG 3d - scattered distribution on the range (blue/grey on FCC), some correspondence with the EN field map, but confusion with CG3di.

CG 3di - small amount classified, large omission error with CG 3d (grey on FCC).

MG1 - good correspondence with EN field map, but some confusion with CG 3d and 3di. Off the range, fields of low vegetation (pink/grey on FCC) were also picked up.

Cereal 1 - classified 100% all the bright red areas on FCC. The remaining dirty or dull red areas being misclassified as CG 3a.

Cereal 2 - classified 100% all the bright pink areas on FCC (barley or cereal growth stage).

Low vegetation - classified 100% all the light grey areas on FCC. These correspond to areas of low vegetation, cut silage or hay where the background substrate affects the reflectance. Also picked up some of the smaller tracks within the range.

Urban - classified the majority of urban areas (blue/grey on FCC). As well as some track areas within the range.

Quarry - the chalk quarry present in the extract (bright white on the FCC) was correctly classified.

Chalk tracks - the classifier picked out the remaining larger track areas within the range (cyan on FCC) and some bare areas off the range.

Coniferous woodland - majority of coniferous woods and plantations were classified correctly (black on FCC).

Broadleaved woodland - majority of broadleaved woods were classified correctly (dark red on FCC), however large amounts of confusion were apparent with a crop growth stage.

7.3.1.2.3 Qualitative Interactive Supervised Classification Results - Maximum Likelihood

CG 3a - classified small isolated areas of the range and areas of scrub within the range valley. Again off the range a known 3a area was correctly classified, however smaller amounts of crop areas (dull red on the FCC) were misclassified, as compared to the minimum distance classifier.

CG 3a/di - similar result to the minimum distance classifier, the pixels being for the most part confined to the range. There were also less confusions with urban and coniferous classes.

CG 3d - a lot more scattered in distribution and less in amount on the range (very much more salt and pepper in appearance) compared to the minimum distance. Large amounts of confusion with CG3a/di and CG3di. CG3d was also classified off the range in agricultural fields, which were correctly classified as crops with the minimum distance classifier.

CG 3di - 70% of the range, large amount classified compared to minimum distance. Much better correspondence to the EN field map. However, still error with CG3a/di and 3d.

MG1 - similar result to the minimum distance classifier.

Cereal 1 - similar result to the minimum distance classifier. However, also picked out the dirty or dull red crop areas being misclassified as CG3a with the minimum distance classifier..

Cereal 2 - similar result to the minimum distance classifier.

Low vegetation - similar result to the minimum distance classifier.

Urban - classified much more of the urban areas, but also classified all the bare areas as well as much more of the track areas within the range.

Quarry - similar result to the minimum distance classifier.

Chalk tracks - similar result to the minimum distance classifier.

Coniferous woodland - similar result to the minimum distance classifier.

Broadleaved woodland - similar result to the minimum distance classifier, but classified more of the dark red crop growth stage as broadleaved woodland.

Generally, the difference between the two classifiers for most of the classes were minimal, except for four classes. Overall, the minimum distance gave a much more thematic map like quality compared to the maximum likelihood classifier. The maximum likelihood classifier did however give a much more accurate representation of the grass class CG3di, but at the expense of misclassifying the grass class CG3d. The surprisingly good performance of these qualitative results, belies the disadvantage of SPOT's spectral resolution.

7.3.1.3 TM July 1984

A five band classification and a three best band (4, 5 and 3) classification were undertaken for this date of imagery. Fourteen informational cover classes were again used to train the classifier.

7.3.1.3.1 Analysis of Training Statistics

Inspection of the class statistics (Table 7.10) shows the mean and standard deviation for the seven classes of grass type selected for the study.

A comparison of the statistics files generated for the five band and the three band classification were very similar. This serves as a good cross checking process, since both files were independently generated, but the training areas were selected at approximately the same locations.

Table 7.10 : Training Area Statistics for Classification of WSPTA, TM-84 Data (Bands 4, 5, 3, 2, and 1)

	Class Statistics (mean and ± one standard deviation)						
Band	CG3a	CG3a/di	CG3d	CG3di	MG1	Agri I grass	Agri II grass
4	108.7	88.2	101.8	96.9	106.4	98.6	107.4
	5.5	4.3	3.3	6.2	3.2	3.2	9.5
5	100.9	92.7	87.3	89.5	89.8	141.2	110.7
	9.6	2.6	2.8	3.2	3.1	4.7	7.1
3	39.7	40.8	38.2	37.4	38.6	65.1	43.2
	2.5	1.5	1.2	1.6	1.4	4.2	4.0
2	41.0	40.9	40.8	39.2	40.6	52.0	43.3
	1.5	1.1	0.8	1.3	0.9	1.9	1.6
1	93.6	93.8	93.3	91.8	93.9	108.5	97.9
	1.8	1.8	1.5	1.4	1.4	2.2	2.3

7.3.1.3.2 Qualitative Interactive Supervised Classification Results - Maximum Likelihood

CG 3a - classified small isolated areas of the range, also small areas of Larkhill range. Off the range some known CG3a areas were correctly classified, but not all. North west of WSPTA partial and whole fields were classified (dull green on FCC). This area is predominantly pastoral with much smaller fields, compared to the rest of the arable land surrounding the WSPTA.

CG 3a/di - classified large areas of WSPTA and Larkhill, the pixels being for the most part confined to the range (green/blue on FCC). A good general correspondence to the EN survey i.e., three areas correctly labelled, however over classified in CG3di and 3d areas.

CG 3d - exclusive to ranges (green/orange on FCC), a good general correspondence to the EN survey, however confusion with CG3di.

CG 3di - some good general correspondence to the EN survey, however confusion with

CG3d.

MG1 - very good general correspondence to the EN survey, even in mixed areas of CG3d. Some agricultural areas were also picked out, these had the same tone and colour on the FCC as MG1 areas on the range (dull orange).

Wheat - picked out all the dark blue/purple/red areas on FCC, that field data indicated were winter and spring wheat.

Barley - picked out all the pale blue areas on FCC, that field data indicated were mostly winter barley.

Agricultural grass I - picked out all grass areas that have been cut, where there is low dry vegetation and soil background. These are mostly areas in schedule III land on the edge of the range, small fields in the north western pastoral region and cut areas around runways of a local airport.

Urban - classified all of the urban areas, but also classified track areas within the range (dirty blue on FCC) and small areas of wheat (also dirty blue on FCC).

Quarry - 100% classification of the quarry.

Chalk tracks - picked out the larger bare chalk track areas.

Coniferous woodland - picked out most of the coniferous areas, but also small cereal areas that appeared black on FCC.

Broadleaved woodland - picked out scrub and broadleaved areas, but also classified bright red crop growth stage as broadleaved woodland.

7.3.1.4 Initial Quantitative Classification Results

Since it is primarily the range grasslands which are of interest, test verification areas were selected from ground data for the five range/grassland units.

* The first test areas were selected subjectively, these were linked to the training area locations. This was performed as a preliminary exercise to ascertain the spectral uniqueness of the grassland units and give some indication of the usefulness of the classifier.

Results are normally presented by a confusion matrix (Chapter four, section 4.2.4). In this matrix the number of pixels in the training or test data correctly classified are represented along the leading diagonal. Off diagonal elements represent the misclassified pixels, either incorrectly omitted from the class (vertical direction), or incorrectly included from another class (horizontal direction) errors of commission. The overall accuracy is then calculated by summing the leading diagonal and dividing by the total number of pixels tested. Errors only in commission are not as significant as errors of omission, for instance where low or no omission errors the classes can be said to be identified with reasonable high accuracy.

An example confusion matrix is given by Table 7.11, for the initial classification using TM-85 data. As shown in Table 7.11, classification accuracy for individual classes varied widely, CG3a/di was most accurately identified (98%), and CG3di the least (17%), whilst MG1 and CG3d achieved less than 50% accuracy. The greatest amount of confusion occurs where CG3di has a large omission error and was misclassified as CG3a/di and conversely a lot of MG1 has been incorrectly omitted and was misclassified as CG3di. The greatest commission error occurred with CG3a/di, where pixels from all the other classes have been labelled as CG3a/di.

Table 7.11 : Accuracy of Maximum Likelihood Initial Classification of WSPTA, May 1985 TM Data (Bands 4, 5, 3, 2 and 1)

		True (Test Data) Class				
		CG3a	CG3a/di	CG3d	CG3di	MG1
No. of Pixels		267	239	251	226	229
	CG3a	108	0	0	0	0
		(0.40)	(0.00)	(0.00)	(0.00)	(0.00)
	CG3a/di	48	235	17	162	12
		(0.18)	**(0.98)**	(0.07)	(0.72)	(0.04)
Predicted	CG3d	4	0	234	26	36
Class		(0.01)	(0.00)	**(0.93)**	(0.11)	(0.16)
	CG3di	14	4	0	38	118
		(0.05)	(0.02)	(0.00)	**(0.17)**	(0.52)
	MG1	44	0	0	0	63
		(0.16)	(0.00)	(0.00)	(0.00)	**(0.28)**
		Overall Normalised Accuracy			:	**55.3 %**

* figures in the brackets denote normalised accuracy where each column in the matrix sum to one

The overall results of this classification for all the data sets is given by Table 7.12 for the five grassland units.

A 3 x 3 kernel modal filter was applied as a post classification process (see Chapter Six, section 6.2.2.1), this a simple way of introducing contextual information and to produce a more 'thematic map like' product and hence have more correspondence to the EN's field vegetation map.

Table 7.12 : Initial Normalised Classification Accuracy of the Five Semi-natural Grassland Units of WSPTA for the Three Data Sets

Data set	Overall accuracy (%)	
	Normalised	Normalised plus model filter
TM 85	55.3	57.1
SPOT 86	65.2	70.9
TM 84	68.0	70.8

A summary of individual unfiltered class results and sources of error for all the three data sets is given below :-

	Normalised % Accuracy			
Class	TM-84	TM-85	SPOT-86	
CG3a	54	40	61	- low omission errors in all data sets, some commission error in TM-85 with 3a/di
CG3a/di	100	98	98	- no omission errors, high commission errors in all three data sets with 3di
CG3d	88	93	75	- low omission errors in all data sets, some commission errors with MG1
CG3di	68	17	30	- high omission errors with 3a/di in all dates, some commission error in TM-85 with MG1
MG1	30	28	62	- omission errors with 3d and 3di in all dates, some commission error in SPOT-86 with 3d

In general, modal filtering increased the accuracy by between 2-5%, with the greatest increase for the SPOT imagery.

7.3.1.5 Secondary Quantitative Classification Results

* The second stage of this process was a more realistic test, whereby objective test area selection was made. This will give a real and more accurate assessment of the classification. The test areas were chosen totally independent of the training areas.

The overall results showed that only class CG3a/di was successfully classified (> 60%), all the other classes were less than 20% correctly classified. CG3a, CG3d and CG3di were all misclassified as CG3a/di, whilst MG1 was generally misclassified as CG3di. The overall results of this procedure for all three data sets are given by Table 7.13.

Table 7.13 : Secondary Normalised Classification Accuracy of the Five Semi-natural Grassland Units of WSPTA for the Three Data Sets

Data set	Overall accuracy normalised (%)
TM 85	27.0
SPOT 86	43.1
TM 84	32.3

In summary, with the more objective test data CG3a/di still classified the most accurately with a range of 90-98% for all three dates. All the other classes were very confused i.e., none of the classes achieved an accuracy over 20% with the TM imagery, whilst no class had an accuracy over 45% with the SPOT data.

The secondary quantitative analysis of the grassland units was to test the hypothesis that it was possible to discriminate the grassland communities using reflectance data alone, since both the TM and SPOT have the same spatial resolution (25m). However, as seen from Table 7.14, the results are very much poorer and give a more realistic indication of the ability of satellite data in mapping specific grassland types and its complex subdivisions. It is unclear why SPOT should produce higher accuracies with its two statistical dimensional data, compared to the the five bands of TM which has three statistical dimensions, from the inclusion of the mid-IR band (Townshend, 1984). Modal filtering was not attempted, because where the accuracies are below 50-60%, it is very unlikely to improve the results.

A comparison between the two classifying algorithms with the SPOT data, with both the initial classification test data and the more objective secondary test data was also undertaken. The SPOT data achieved overall the best results, so it was chosen to assess minimum distance and maximum likelihood classifiers using the same training and test areas, and with regard to the CPU time of each process (Table 7.14).

As can be seen the maximum likelihood performed better compared to the minimum distance classifier, however at a cost of over five times more CPU time.

Table 7.14 : The Comparison in Accuracy and Time taken for the Two Classifying Algorithms using SPOT Data

	Overall Normalised % Accuracy			
	Initial Test Areas		Secondary Test Areas	
	Min. Dist.	Maxi. Likeli.	Min. Dist.	Maxi.Likeli.
	57.1	65.2	38.8	43.1
Modal Filter	59.5	70.9	39.1	45.5
CPU time (mins.)	14.6	81.4		

A comparison between the five band TM classification and the best three band classification was also undertaken for the July 1984 data. The results gained showed that the inclusion of a further two visible bands of TM did not significantly increase the accuracy, if anything it was slightly better with the best three band subset. The overall normalized accuracy using the more objective test data, using five bands of data was 32.3%, the best three band subset result was 34.1%. Therefore, the far greater CPU time involved (see section 7.3.1) with the five band classification did not merit its usage in further analysis. The best three TM bands 4, 5, and 3 were therefore used in all subsequent processing, with the advantage of considerable time saving. An important consideration for a routine operational methodology that will have limits in both time and money.

7.3.2 Revised Classification Procedure : Application of a Mask

7.3.2.1 TM July 1984

The July TM 1984 data was chosen to test this refinement in the analysis, because of the greater variation and thus spectral information present compared to the other two data sets. All subsequent refined classifications were carried out using the original spatial resolution of TM (30m) and SPOT (20m). In the previous two classifications (sections 7.3.1.4 and 7.3.1.5), the two types of sensor were resampled to a common 25m spatial resolution. This did not have any significant effect on the classification.

The next stage of the analysis was the introduction of refinements to the methodology, this was in the form of a graphics mask of just the rangeland area. It has been suggested that such a mask is of benefit when attempting to classify semi-natural vegetation (McMorrow and Hume, 1986). The masked area of interest was then contrast stretched, this highlighted more spectral and spatial variation or information within the rangeland area (Belward *et al.*, 1990). This was then qualitatively viewed to see if it had any meaningful representation with the EN informational classes from their field maps of the range.

Eight informational classes were identified and used to train the classifier. Of these eight classes, four classes were made up of grassland units, two of woodland cover types, one of bare soil and one of chalk tracks used by military vehicles (Table 7.15). The grassland unit CG3a was removed from this part of the analysis, because this particular class occurred mainly in the MoD schedule I and III land and only within the range in a limited spatial distribution.

Table 7.15 : Grassland Community Types and Cover Types occurring on the Masked WSPTA

Class	Classification Colour Code	Cover type description	
1	Red	CG3a/di	(Calcarious grassland)
2	Green	CG3di	(" ")
3	Blue	CG3d	(" ")
4	Cyan	MG1	(Mesotrophic grassland)
5	Yellow	Bare ground/low vegetation	
6	Magenta	Exposed chalk/tracks	
7	Brown	Coniferous Woodland	
8	Orange	Deciduous or Mixed Woodland	

Training statistics analysis via frequency histograms for TM band 4, illustrated that the eight classes were unimodal. There were quite distinct peaks, but some overlap was evident between all the grass units (Figure 7.6). Band 4 gave the best discrimination of the classes and shows nicely the increase in reflectance from species rich CG3a/di to the more reflective species poor MG1 at the other end of the spectrum. Band 5 showed all the grass classes were unimodal in nature, but there was a lot more overlap evident. Coincident spectral plots for the three bands illustrate the degree of spectral overlap for all the classes (Figure 7.7).

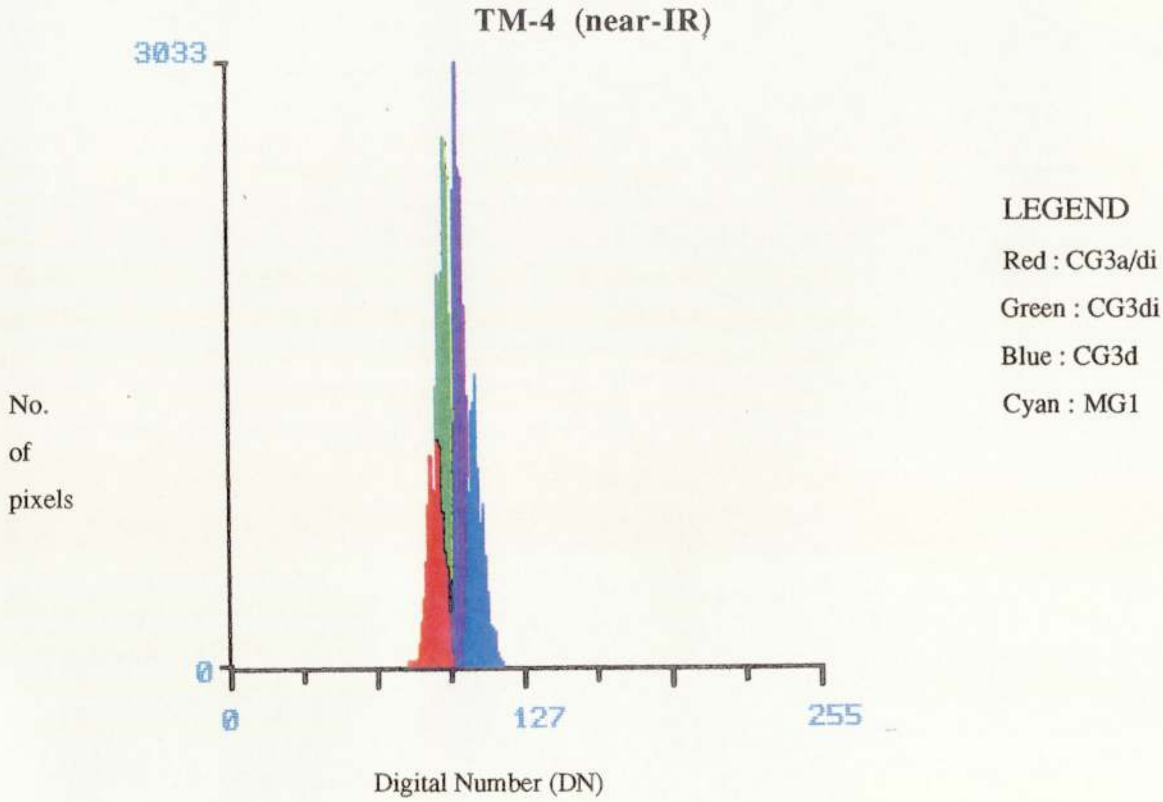


Figure 7.6 : Frequency Histogram of Four Range Grass Classes,WSPTA, TM Band-4, July 1984

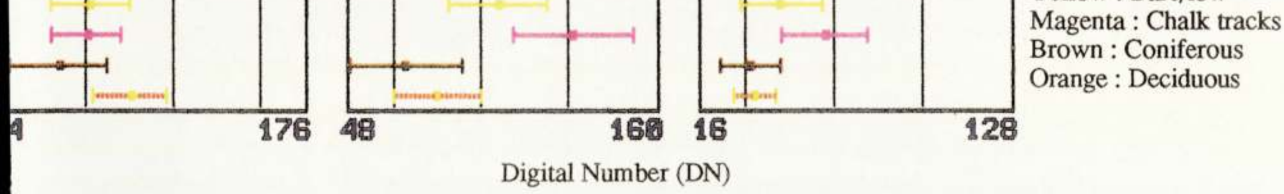


Figure 7.7 : Coincident Spectral Plots of Seven Cover Classes for WSPTA, July 1984 TM Data (mean value $\pm$ one standard deviation)

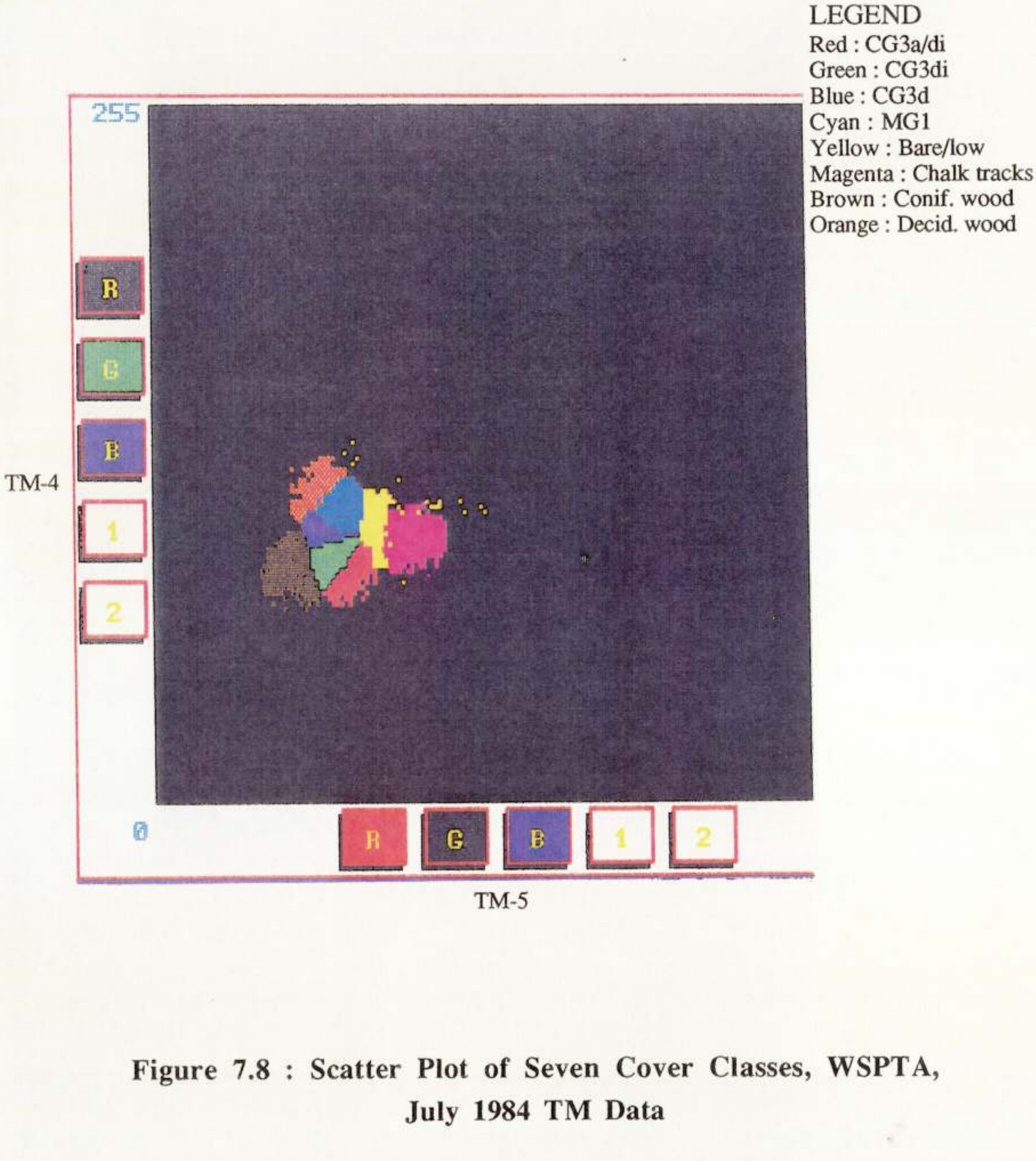


Figure 7.8 : Scatter Plot of Seven Cover Classes, WSPTA, July 1984 TM Data

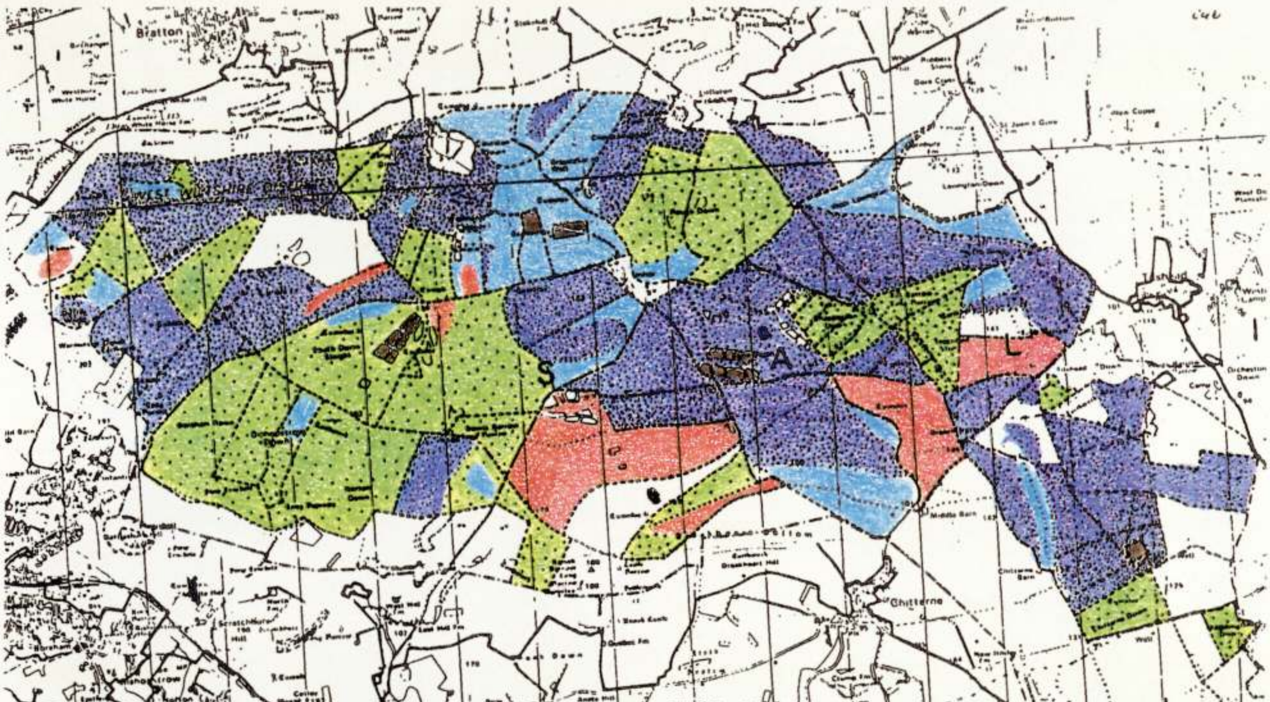
Two dimensional scatterplots of bands TM-4 verses TM-5 illustrate the spread of class clusters in spectral feature space (Figure 7.8). This shows overlap between CG3a/di and CG3di and also between CG3d and MG1. There also could be confusion between this latter pair and deciduous woodland and all the grass units and the bare/low vegetation class.

Objective test areas were used and the number of pixels used to test the classification for each class is given by Table 7.16.

Qualitative analysis of the data with EN field vegetation maps (Figure 7.9), indicated some good general correspondence, the minimum distance classifier being slightly better in performance (Figures 7.10 and 7.11). However, it was also apparent that there were some misclassification and confusion between classes.

LEGEND
Red : CG3a/di
Green : CG3di
Blue : CG3d
Cyan : MG1

Brown : Conif. wood



N

Scale 1 : 100000

Figure 7.9 : Field Data Map of the Distribution of Vegetation Communities for the Masked Range Classification

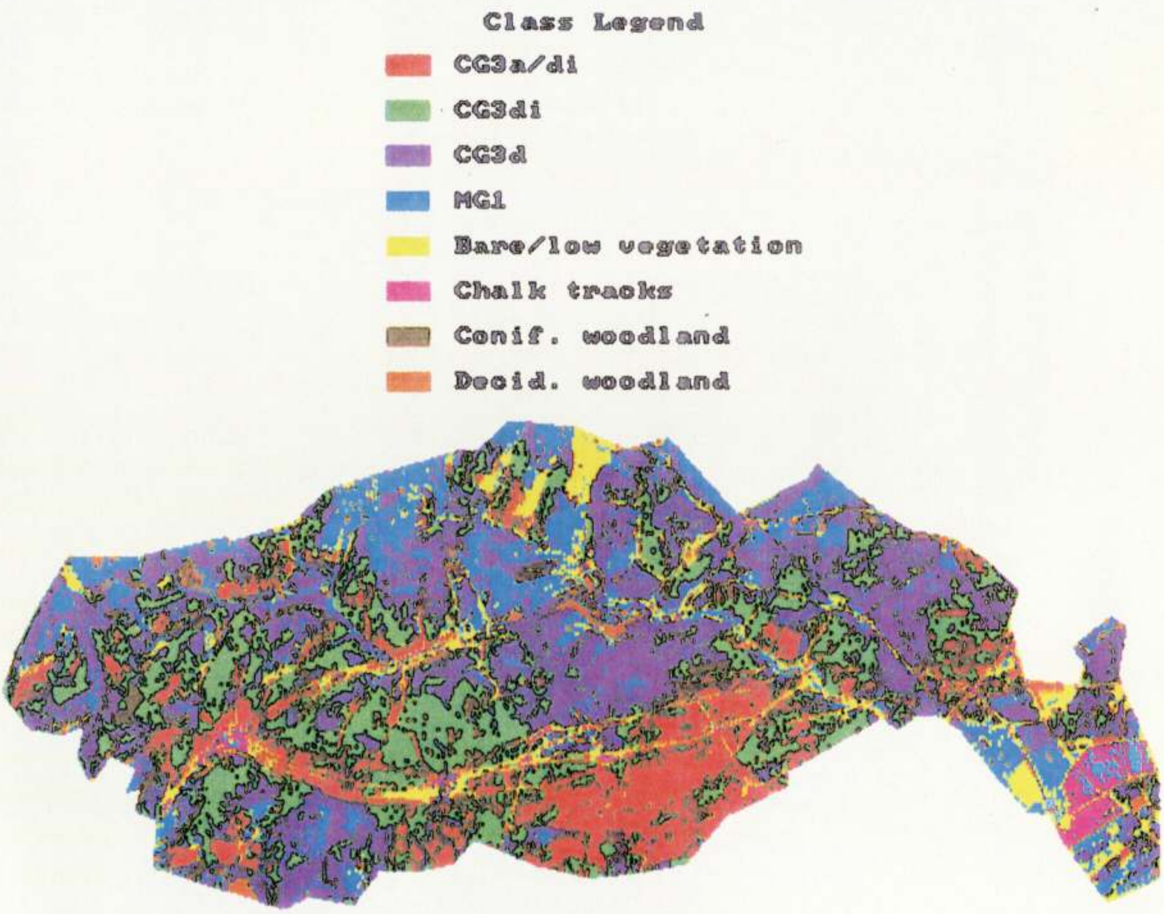


Figure 7.10 : Minimum Distance Classification of Masked WSPTA, July 1984 TM

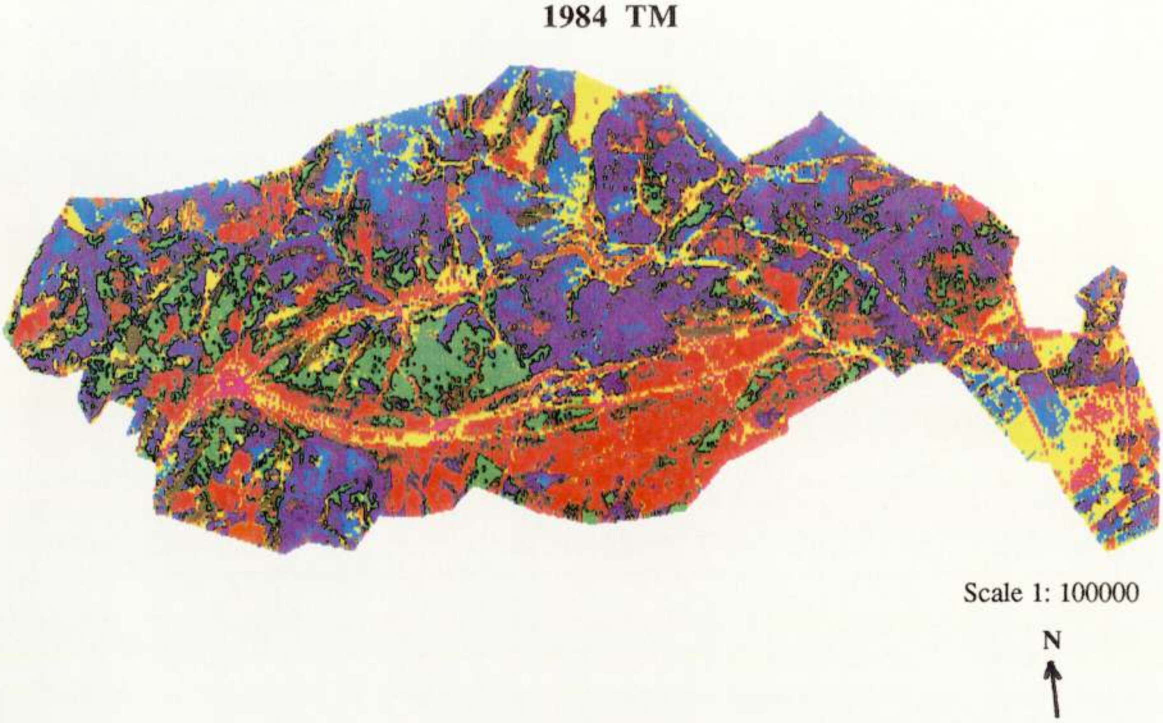


Figure 7.11 : Maximum Likelihood Classification of Masked WSPTA, July 1984 TM

Table 7.16 : Number of Pixels used for the Test on Classification Accuracy, July 1984 TM

Number of pixels :

Class	1	2	3	4	5	6	7	8
Pixels	446	500	479	500	282	149	72	88

The overall accuracy for TM-84 achieved with maximum likelihood was 79.9% (Table 7.17), compared to 34.1% without the graphics mask in the proceeding classification. Thus the improvement in accuracy was found to be quite significant. It was also noted that use of the CPU was greatly reduced by the application of the mask, since the algorithm is only processing the area inside the mask and not the whole extract.

Table 7.17 : Accuracies of the two classifiers with Graphics Mask of WSPTA, July 1984 TM Data (Bands 4, 5, and 3)

	Normalised Percentage Accuracy (%)			
Class	Min. dist.	modal filter (3x3)	Max. likeli.	modal filter (3x3)
1.CG3a/di	90	94	88	97
2.CG3di	71	75	67	71
3.CG3d	48	52	53	57
4.MG1	72	80	59	66
Overall accuracy for all classes	72.3	76.9	75.8	79.9

The mean increase in accuracy by the introduction of post-classification modal filtering was 4 - 5%. The mean increase in accuracy by using the maximum likelihood classifier was 3.5%. Some classes were more accurately represented by the minimum distance classifier, for example MG1 and CG3di, which would account for the better qualitative appearance of the minimum distance result (Figure 7.10).

Examination of the confusion matrixes in detail reveal the following general trends in all the data. CG3a/di, bare/low vegetation, chalk tracks, and the two woodland classes were identified with high accuracy. CG3di had some omission errors with CG3d, CG3d had a lot of omission errors with 3a/di and with some errors with MG1. MG1 exhibited omission errors with CG3d.

With the apparent more successful results achieved with the application of a mask on the TM-84 data. The next stage of the analysis was to incorporate the graphics mask in the classification of all data sets, and further refine the methodology with additional knowledge both from within the data set and from ancillary information to use in a tertiary or final refinement of the methodology classification (see section 7.3.4).

7.3.3 Simulated 'Per-Field' Classification

In order to see how well satellite multispectral data can discriminate and map the specific Salisbury Plain grassland community and sub-community types, a simulated 'per-field' as opposed to a 'per-pixel' classification was performed. This can be said to be the theoretical quantifiable 'acid test', in which every pixel will be tested by a correspondence matrix of the classified overlay and the EN field vegetation map.

This was achieved by video frame grabbing the EN field thematic map, this is where the map image is captured by a video camera. Once the image has been grabbed and saved on the image processing work station, it was transformed to the BNG. The vegetation boundaries on the map were then delineated and saved in the digital mapping and spatial analysis component of *'iconsys '* software package. The next stage was to then infill the various parcels with a theme, taken from the field map. This results in a colour coded thematic map (Figure 7.12), that can be compared directly with the supervised classification overlays on a per-parcel or 'per-field' basis (Pedley, 1986). To do this the classified overlays were geometrically corrected to the rasterised field map (see Chapter Four, section 4.2.2.1).

This analysis was performed on the four major grassland types found on WSPTA and used in the analysis described in section 7.3.2. The classes and classification colours are described below, along with the total number of pixels for all the fields and the number of fields per class that were used to test the classification :-

Class No.	Class	Colour code	Total No. of pixels	No. of fields or parcels per class
2.	CG3a/di	Green	3969	3
3.	CG3d	Blue	20415	6
4.	CG3di	Cyan	19498	8
5.	MG1	Yellow	6705	6

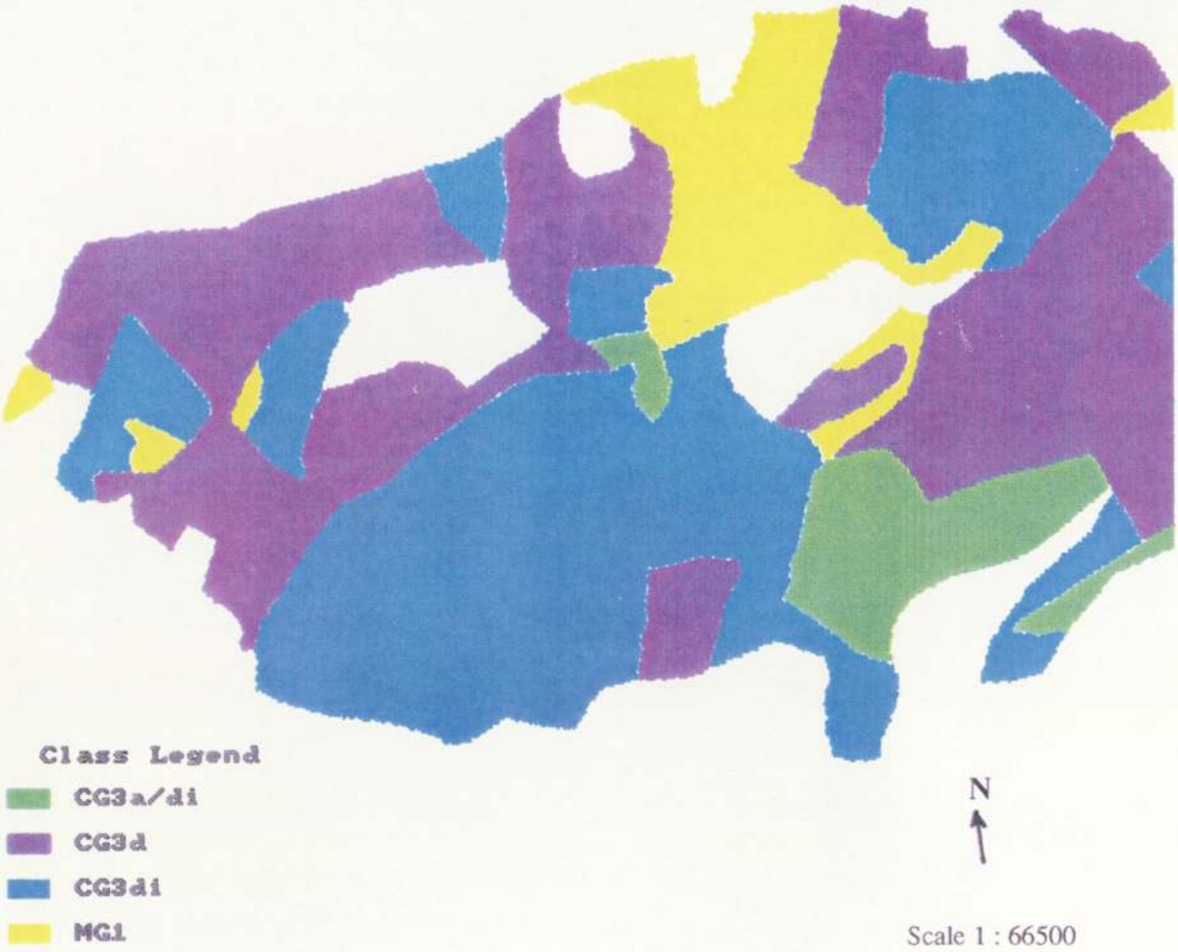


Figure 7.12 Thematic Map of Ground Data Registered to WSPTA SPOT Data

(Note : the Classification Legend is the same as in Section 7.3.1)

The classification results for all three data sets are summarised below in Table 7.18.

Table 7.18 : Supervised Classification Results for the Simulated 'per-field' Classification for all Data Sets (WSPTA)

Class	TM-84		TM-85		SPOT-86			
	Maxi. Likeli.	Filter	Maxi. Likeli.	Filter	Min. Dist.	Filter	Maxi. Likeli.	Filter
2.	57.0	66.0	42.0	45.2	58.7	63.6	46.4	51.3
3.	19.0	20.3	18.0	17.3	23.8	25.2	13.8	8.2
4.	30.0	34.6	42.0	49.4	17.0	14.0	30.2	35.6
5.	27.7	36.0	27.7	34.0	46.6	55.4	49.0	61.7
Overall	33.4	39.2	32.3	36.4	36.5	39.6	34.8	39.2

These results give a 'true' indication of the ability of satellite data to spectrally discriminate the grasslands units at this sub-community level, since every available pixel was used in the test verification process. The overall results for all the data sets are similar despite the differences in year and using two different sensors of different spectral band combinations. Figure 7.13, shows the simulated 'per-field' classification accuracies for the three data sets and with filters applied. Class 3 (CG3d) was constantly the poorest in classification accuracy, whilst class 2 (CG3a/di) achieved the best result. In every case each class suffered quite high omission and commission errors with every other class. A test comparing the two different type of classifiers with the SPOT data did not significantly alter the end result.

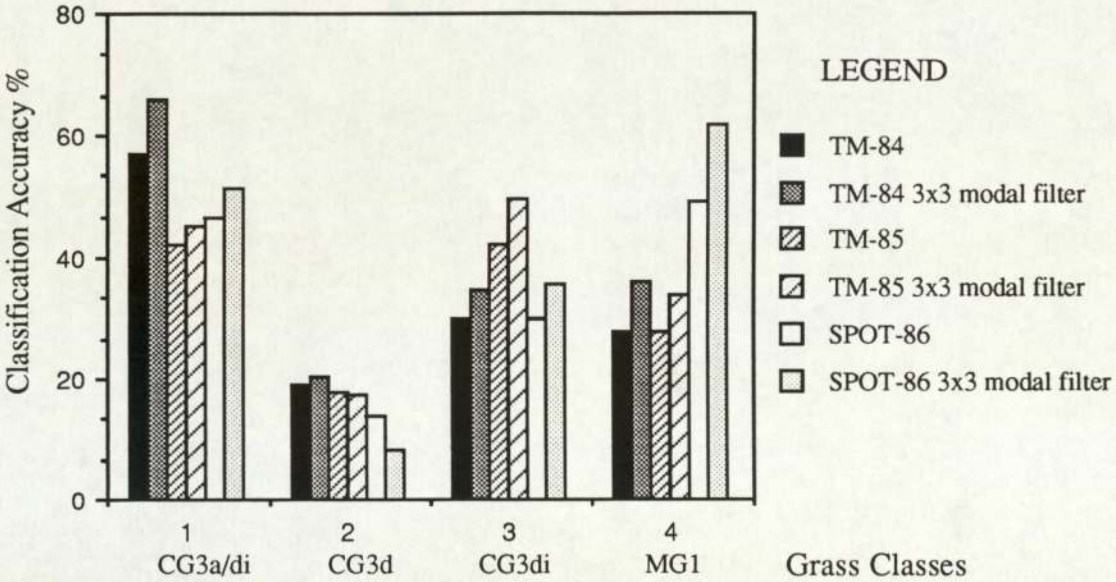


Figure 7.13 : Simulated 'Per-field' Maximum Likelihood Classification Accuracies for the Three Data Sets

The results do show however, that at this detailed specific level of grassland community type, satellite data does not discriminate with sufficient reliability or accuracy. The next stage was to further refine the methodology to see if the classification accuracy could be further improved.

It is also necessary to be made aware of the following errors implicit in this particular analysis (these are discussed in more detail in Chapter eight). These include :-

i) errors by field workers,

ii) errors in parcels where mixtures of grass types not described by EN's field thematic map,

iii) errors where other cover types present i.e., woodland, chalk tracks, etc and

iv) where at the edge of the range especially the schedule III land, farmers have managed the land such that it alters the spectral response, but the informational class is still the same. For example, where the EN field map has classified an area as MG1, the imagery clearly shows that the farmer has cut the grass for hay or silage and the imagery therefore displays it as a different spectral class of low vegetation or stubble.

7.3.4 Tertiary Classification : Final Refinements to Methodology

As a final stage to the methodology, further refinements were introduced by editing the informational classes using the input of three types of information :-

* input of information from unsupervised classification regarding spectral classes present,
* empirical evidence from statistical analysis from EN, and
* the analysis of confusion errors from initial supervised classifications.

7.3.4.1 Unsupervised Classification

As part of the training procedure it is advisable (Curran, 1985) to instigate an unsupervised classification of the whole data set, to determine if the number of classes chosen during training bear anything more than scant relation to the number of statistically separable spectral classes in the whole data set. This can be achieved by dividing the image data into its natural groupings or clusters in feature space. The results of this classification are dependent upon the number of classes that are initially chosen by the analyst. This procedure is described in more detail in Chapter Six, section 6.1.2.

7.3.4.1.1 TM July 84

All available classes were chosen, which were fourteen in number (Table 7.19).

Such an exploratory technique gives a good indication of how the spectral classes relate to informational classes. One major range spectral class and two agricultural grassland classes were found. Also four cereal, two woodland classes, two bare or low vegetation, two minor quarry classes and one urban class were distinguished. This process also provides clues as to where spectral confusions, hence misclassifications are going to occur.

Table 7.19 : Unsupervised Classification WSPTA whole Extract, July 1984 TM (Bands 4, 5, and 3)

Class	Peak No. of Pixels	Mean value per band 4	5	3	Colour *	Land cover types classified
1	10561	96	80	36	R	- 90% of the range. Some confusion with cereals (dark purple/red on FCC)
2	2729	96	40	30	G	- coniferous woodland. Some confusion with cereals (very dark red on FCC)
3	1726	96	112	48	B	- bare fields or low vegetation (light blue on FCC). Large extent in north western pastoral region (hay cut)
4	891	120	72	36	C	- areas of SSSIs (orange on FCC) and bright pink (rape) on FCC
5	529	96	144	60	Y	- bare fields no vegetation (light blue to whites on FCC)
6	450	78	80	48	M	- cereal I (purple on FCC). Slight confusion with some range and urban
7	349	120	32	36	Lr	- cereal II (bright red on FCC)
8	287	120	104	36	Lg	- areas of SSSIs (yellow/green on FCC) and permanent pasture in north western region
9	134	102	80	60	Lb	- cereal III (blue/purple on FCC) growth stage
10	87	144	80	30	Lc	- cereal or improved grassland (very bright orange on FCC)
11	43	60	96	48	Ly	- urban areas, airport runways, however large errors of omission with non-urban cover types
12	40	54	48	30	Lm	- coniferous woodland II
13	25	162	112	162	Br	- chalk quarry
14	17	108	112	72	O	- small area within quarry even brighter pixels

* for explanation of the annotated colour symbols see Table 7.7, where R equals red, G equals green etc.

The next relevant step is to repeat the process with the graphics mask applied, so only the range area is subjected to the unsupervised classification. This is where choosing the number of classes becomes important and shows how many significant spectral classes within the range are present (Table 7.20).

Table 7.20 : Unsupervised Classification WSPTA Rangeland, July 1984 TM (Bands 4, 5, and 3)

Class No.	Peak of Pixels	Mean value per band 4	5	3	Colour *	Land cover types classified
1	2710	92	85	36	R	- 70% of the range (blue/green areas on FCC)
2	778	104	90	39	G	- 25% of the range (orange areas on FCC), some rough approximation to class MG1.
3	122	92	105	48	B	- 2-3% of range corresponds to low or dry vegetation (grey on FCC). Also picked out chalk track areas
4	70	96	130	57	C	- low vegetation or bare areas i.e., larger track areas and where rangeland has been cut in schedule III region
5	25	84	60	30	Y	- coniferous woodland
6	15	72	80	39	M	- very small part of the range (dark green on FCC)
7	12	108	70	30	Lr	- bright orange/red on FCC, scrub mixed/broad leaved woodland
8	11	100	135	69	Lg	- grey/white on FCC, minor areas of chalk track and bare land

* for explanation of the annotated colour symbols see Table 7.7, where R equals red, G equals green etc.

The number of classes chosen was eight. This was the maximum number of classes that could be chosen with a more than adequate peak number of pixels represented. The threshold for the number of pixels being ten or less, since classes 9 - 14 contained very small peak number of pixels and could not be easily identified on the unsupervised classification overlay. This result confirms the number of training classes chosen in the secondary rangeland masked classification (section 7.3.2). The unsupervised spectral classes comprised three range classes, three low vegetation, bare and track classes, and two woodland classes. The previous supervised classification (section 7.3.2) which used informational classes comprised four range classes, two bare/low vegetation and two woodland classes.

As a method of cross checking it was thought prudent to compare the mean statistics found in the unsupervised classification and used in the previous supervised classifications for the range grass units. These figures are shown below :-

Class	Supervised training class means			Unsupervised natural class means			
	4	5	3	4	5	3	
CG3a/di	89.9	92.3	40.6	92	105	48	Class 3
CG3di	94.4	89.5	37.6	92	85	36	Class 1
CG3d	101.7	87.8	38.3				
MG1	106.1	89.7	38.8	104	90	39	Class 2

As it can be seen the three natural unsupervised classes roughly match the supervised training class means, which adds some validity to the spectral discriminatory potential of the data.

7.3.4.1.2 TM April 1985

In a fourteen class unsupervised classification of the whole extract, the range was well discriminated again from the surrounding agricultural land. The range was made up of two major classes. The rest of the classes were made up of woodland classes and a large number of crop growth stages and vigorously growing green vegetation. This was a reflection of the date of the imagery i.e., April being the beginning of the rapid growth period. Of note was a spectral class that picked out SSSI areas (yellow/green on FCC) and large expanses of the agriculturally managed schedule III land adjacent to the range.

Again the next stage was to repeat the process with the graphics mask applied. The results of the unsupervised analysis are given by Table 7.21.

Eight spectral classes were chosen interactively above the threshold of the peak number of pixels (i.e., greater than 10). Of these there were four significant range classes, one woodland class, one bare class and one crop class. The first three of the unsupervised grass classes means compared well with CG3a/di, CG3di and MG1 supervised training statistic means. The fourth unsupervised range (class 4) mean did not relate to the remaining CG3d supervised class, however the unsupervised class 4 had also picked out the bare chalk areas which will bias the mean values in the three bands away from the mean values used to train the classifier in recognising the CG3d class.

Table 7.21 : Unsupervised Classification WSPTA Rangeland, April 1985 TM (Bands 4, 5, and 3)

Class	Peak No. of Pixels	Mean value per band 4	5	3	Colour *	Land cover types classified
1	1709	80	105	39	R	- 75% of the range (blue/grey areas on FCC)
2	426	96	100	33	G	- 10% of the range (orange/grey areas on FCC), some rough approximation to class MG1.
3	62	76	115	51	B	- 10% of range (light blue/green on FCC). Also picked out a lot of the chalk track areas
4	50	68	80	33	C	- 5% of range (yellow/green on FCC)
5	35	92	120	42	Y	- small area bright red on FCC, cereal or improved pasture
6	31	116	80	27	M	- coniferous or mixed woodland
7	16	60	95	39	LR	- remaining larger chalk track areas
8	12	60	55	27	LG	- very small part of the range (blue on FCC)

* for explanation of the annotated colour symbols see Table 7.7, where R equals red, G equals green etc.

7.3.4.1.3 SPOT June 1986

In the unsupervised classification of the whole extract, thirteen classes were identified showing that there are less spectral classes present compared to TM, even though it is June the period of most vegetation growth. Most of the whole extract was described by the first six classes. Class 1 represented 99% of the range (red/grey & green/grey on FCC), but it also picked out woodland, urban areas and crop areas off the range. The rest of the classification categories were made up of two crop classes, one urban class and two classes representing bare, chalk tracks and low vegetation.

Again the next stage was to repeat the process with the graphics mask applied. The results are given by Table 7.22.

Table 7.22 : Unsupervised Classification WSPTA Rangeland, June 1986 SPOT (Bands 3, 2 and 1)

Class	Peak No. of Pixels	Mean value per band 4	5	3	Colour *	Land cover types classified
1	8578	100	30	45	R	- 85% of the range (blue/green grey areas on FCC) also red/black woodland
2	1721	120	27	45	G	- 10% of the range (red/pink grey areas on FCC),
3	423	95	42	54	B	- chalk track areas
4	116	70	30	42	C	- black/green coniferous woodland and burnt areas of the range
5	61	115	42	57	Y	- chalk track II areas (grey on FCC)
6	46	90	51	63	M	- chalk track III areas (white on FCC)
7	27	140	27	45	Lr	- scrub broadleaved woodland (bright red on FCC)
8	12	90	72	75	Lg	- very small area linked to chalk tracks

* for explanation of the annotated colour symbols see Table 7.7, where R equals red, G equals green etc.

The unsupervised classification produced two range spectral classes, four classes associated with the bare chalk tracks and two woodland classes. A comparison between the two spectral range class band means and the informational range class means used in the supervised classification is shown below :-

SPOT bands (mean)

Informational range class	Supervised 3	2	1	Unsupervised 3	2	1	Spectral range class
CG3a/di	97.4	32.7	47.5	100	30	45	1
CG3di	102.1	32.0	47.2	120	27	45	2
CG3d	112.1	31.2	47.4				
MG1	114.7	32.1	48.4				

This shows that most of the discriminatory information is contained in the near-infared band 3, and that the informational classes fall in between the two spectral natural clusters found by the unsupervised classifier.

7.3.4.2 Class Editing

Having gained useful information on the composition of natural spectral classes present within the data sets. The next stage was the further final refinement of the procedure which was comprised of two parts, these were :-

i) the editing of classes to statistically significant noda or points on continuum based on species richness and on canopy structure, and
ii) the analysis of confusion errors from initial supervised classifications.

EN undertook some statistical analysis from their ground data based on sample quadrats. A comparison of means of samples was conducted on the community types to see if differences between the species-richness of communities were statistically different using TWINSPAN. They found that three groups were apparent, these were i) CG3a and CG3a/di; ii) CG3d and CG3di, and iii) MG1. There were significant differences in species-richness between these groups but not within them. It was noted that the variation of the community types was as a continuum from short species rich swards to taller mesotrophic species poor swards and that these three groups existed as noda on this continuum (Porley, 1989).

By careful examination of the confusions errors experienced most commonly from the previous classifications, it was possible to observe repeated classification errors between pairs of classes suggesting the following systematic trends for all data sets in all classifications. This arose from the fact that each pair were physiognomically similar and hence spectrally related. Whilst keeping in mind that it is the omission errors that are most the most significant :-

Common general error trends from previous analysis

omission errors :-	commission errors :-
	Some CG3a/di labelled as 3di
CG3di confused with 3a/di	A lot of CG3di labelled as 3a/di
CG3d confused with 3a/di	A lot of CG3d labelled as MG1
MG1 confused with CG3d and 3di	MG1 labelled as 3d.

This knowledge was combined with the statistical results that EN conducted, together with the information of the spectral classes present from the unsupervised classification, to produce a final edited training set of three range grassland units.

Three groupings were formed, the grassland units CG3a and CG3a/di were combined; as were CG3di and CG3d, whilst MG1 remained by its self. These edited grassland groups were then used in the final classifications.

7.3.4.2.1 TM July 1984

The whole extract was first classified to see if the edited range classes were confined to the range areas and that if this were the case, that would mean there would be little confusion with the other land cover types that occur in the mainly agricultural surrounding area. This would show that the range classes were indeed spectrally valid. After this analysis, the next stage was the application of the mask and to quantitatively assess how accurately the three edited range classes were represented. The training area statistics for the complete extract and for all the classes are given by Table 7.23.

Table 7.23 : Edited Grassland Communities and Cover Types found on the WSPTA and their Training Statistics, July 1984 TM (bands 4, 5, and 3)

CLASS	CLASSIFICATION COLOUR CODE	DESCRIPTION	TRAINING STATISTICS 4 Mean	4 Std. dev	5 Mean	5 Std. dev	3 Mean	3 Std. dev
1	Red	MG1	105	2.4	88	2.0	38	1.1
2	Green	CG3di & CG3d	94	3.7	89	2.2	38	0.9
3	Blue	CG3a & CG3a/di	88	3.2	93	2.6	41	1.5
4	Cyan	Agri I grass (SSSI)	111	3.9	104	6.3	40	2.0
5	Yellow	Agri II grass (SSSI)	124	2.6	91	2.7	35	0.9
6	Magenta	Winter barley	88	2.3	89	5.2	60	1.7
7	Light Red	Winter wheat I	101	2.6	56	2.6	34	1.5
8	Light Green	Oil seed rape	127	0.3	72	2.2	43	1.6
9	Light Blue	Winter wheat II	90	2.6	61	2.3	40	1.6
10	Light Cyan	Bare / stubble	97	2.5	127	0.3	65	3.8
11	Light Magenta	Urban	76	8.4	82	6.2	44	4.5
12	Brown	Coniferous Woodland	79	3.0	47	2.1	32	1.1
13	Orange	Deciduous or Mixed Woodland	109	13.0	69	9.4	30	1.8
14	White	Open cast quarry (chalk)	124	2.9	134	0.9	72	3.9

Analysis of the class statistics by the methods used earlier (section 7.3.1.1.1) was undertaken for the three range grass units and for two agricultural chalk grass types that were identified from field data as of SSSI status. These two chalk grass types are referred to as SSSI I and SSSI II.

Examination of frequency histogram plot of TM band 4, showed that all five grass classes are unimodal, but that there was some overlap between MG1 and SSSI I. A coincident spectral plot of all fourteen classes showed that in band 5, class SSSI I exhibited quite a large standard deviation. This was further illustrated by examination of a scatter plot of TM band 4 verses band 5, where class SSSI I has a much larger spread of data and more overlap with other classes. Whilst of the other non-grass classes winter wheat class I, the urban class and broadleaved woodland all displayed large standard deviations in all three bands.

From a visual 'quick-look' qualitative inspection, the classified thematic maps, displayed a certain degree of overall correspondence with the EN ground survey data and that this correspondence was more accentuated for the crop land. For the qualitative assessment of both minimum distance and maximum likelihood classifiers performance for all classes for the whole WSPTA extract refer to **Appendix 6.**

By observing the training statistics, the high standard deviations present in some of the classes, were seen to cause some problems in the finished classification overlays (see Table 7.23), where there were confusions in the classification of winter wheat, broadleaved woodland and the urban classes. Overall however, the classification can be said to be the best so far, with the minimum distance, which does not rely on the statistical standard deviations parameters as much as the maximum likelihood, being qualitatively the superior.

The next stage of the analysis is to be able to quantify whether the accuracy of the rangeland classes is increased or not by the additional knowledge used to edit the classes for all three data sets. The range was masked off again even though the range classes were not confused with the other mainly agricultural land cover classes. Training and test sites were chosen carefully and were kept the same in location and in number of pixels for all three data sets.

7.3.4.2.1.1 Masked TM July 1984

Seven classes were used to train the classifiers, both classifiers were again assessed, (for the complete statistics of the training file [**ctrain84.csd**] see **Appendix 5**). The seven classes consisted of : the three edited grass groupings (referred to as class 1, 2, and 3), bare/stubble class, cereal class and two woodland classes. In the selection of test and training areas all the large areas of homogeneous grass sward as found by EN, were used in this analysis. For instance, three large areas were used as test sites for each class. This amounts to an almost complete test, since all possible areas were used, except those areas that were not surveyed by EN, that were chalk tracks and the immediate areas associated with them and areas that were found to contain a mixture of classes from the field survey.

Analysis of the training class statistics by the histograms etc, were satisfactory. Class standard deviations were relatively small and there were no indications that the classifications would not be satisfactory.

The classified thematic map produced by minimum distance classifier can be seen in Figure 7.14, and it can be compared with EN's field vegetation map with corresponding edited grassland classes (Figure 7.15). Note that from a visual qualitative inspection, the classified thematic maps, showed a certain degree of overall correspondence with EN ground survey data.

Whilst a confusion matrix gives an indication of the accuracy of the classification, they do not give any estimate of the level of confidence in the results. To do this and to determine the accuracy of individual categories, the true 95% confidence limits for each category the following two-tailed test was applied (Jensen, 1986) :

$$p = p\sim \pm \left[1.96 \sqrt{(p\sim)\,(q\sim)/n} + 50/n \right] \qquad (7.2)$$

where :- p = actual class accuracy expressed as a %,

$p\sim$ = the percent of a class calculated as being accurately classified (the number of pixels correctly identified divided by the total number of pixels),

$q\sim$ = to $100 - p\sim$, and n = the number of pixels in each class.

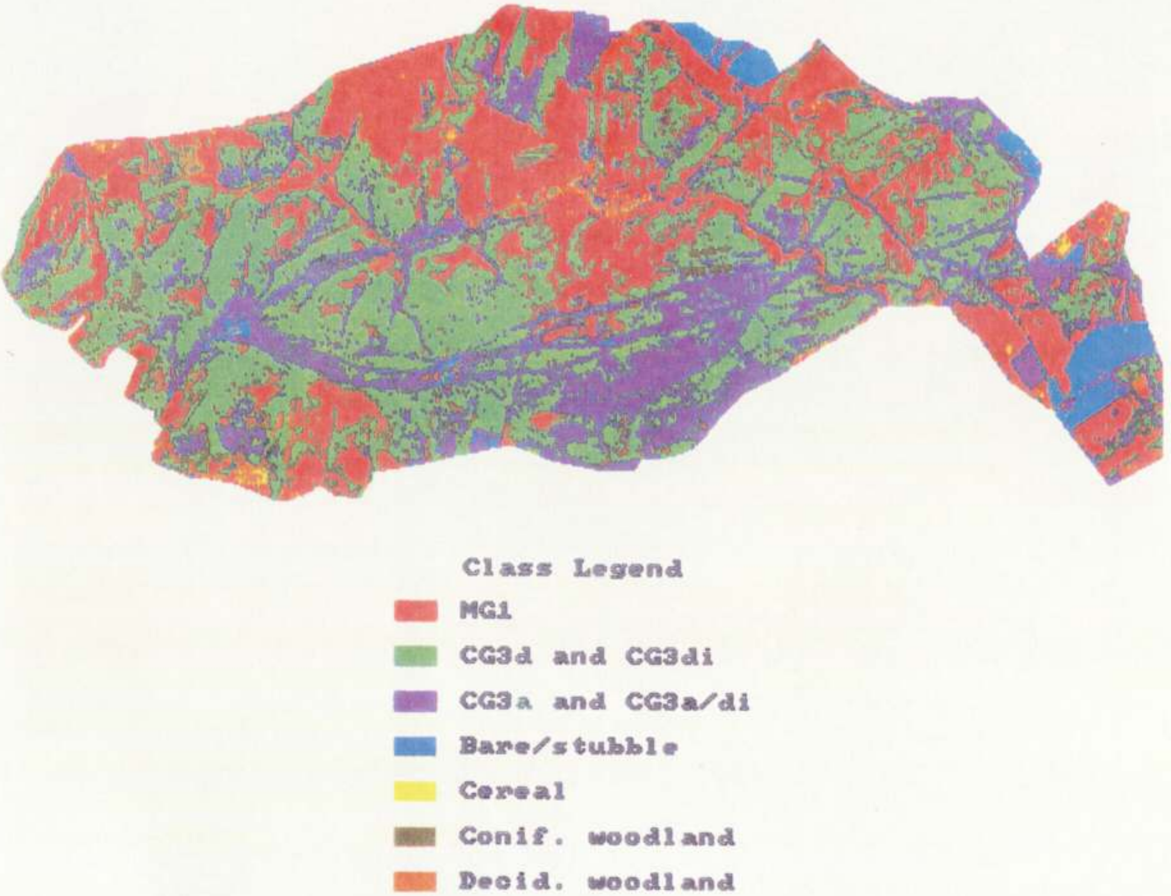


Figure 7.14 : Minimum Distance Classification of WSPTA, with Edited Grass Classes July 1984 TM

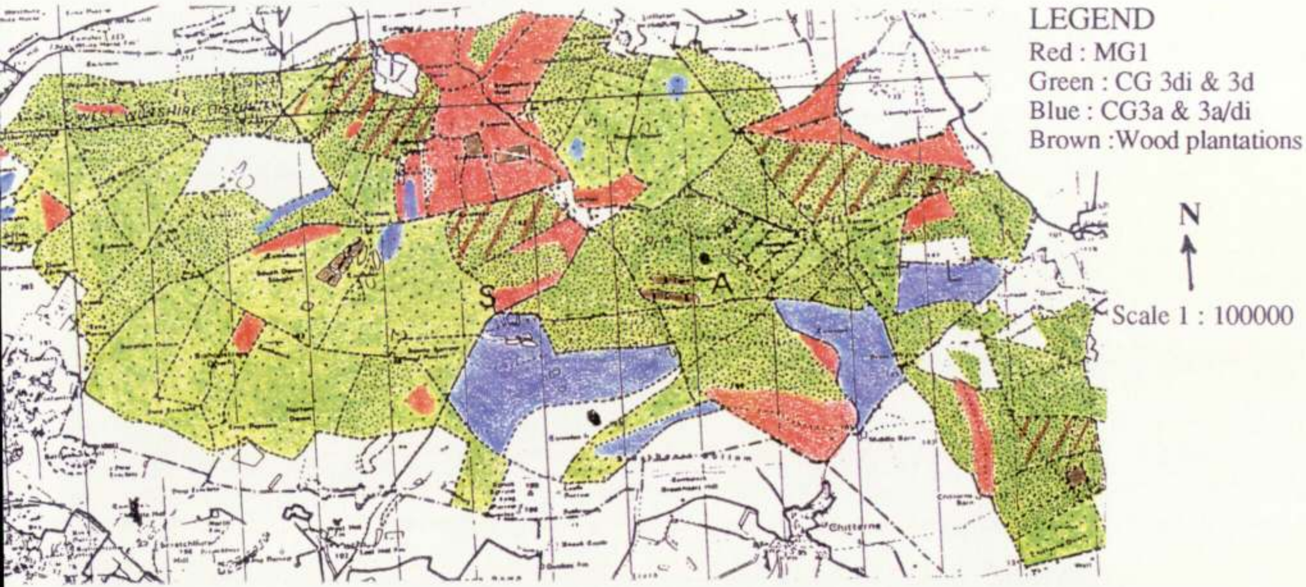


Figure 7.15 : Field Data Map of the Distribution of Edited Grassland Classes used in the Tertiary Classification

(Note : areas of red hatch denote where two classes are mixed. These areas were not used in the training and testing of the classification)

A summary of the results for the three edited classes are given below :-

	Normalised Accuracy %				
Class	Min. Dist.	plus filter * (3x3)	Max. Likeli.	plus filter (3x3)	**Confidence limits (95%)**
1 MG1	90.6	92.2	84.3	87.5	90.1 - 93.9
2 CG3d & 3di	81.3	87.0	83.7	88.1	84.6 - 89.4
3 CG3a & 3a/di	36.1	36.0	28.9	28.2	32.1 - 39.9
OVERALL	69.3	71.6	65.6	68.0	70.5 - 73.5

* The confidence limits for each data set were calculated by using the best results achieved; in this case this was the minimum distance classifier with 3 x 3 modal post classification filter.

The results of the edited grass class supervised classification are shown by Figure 7.16.

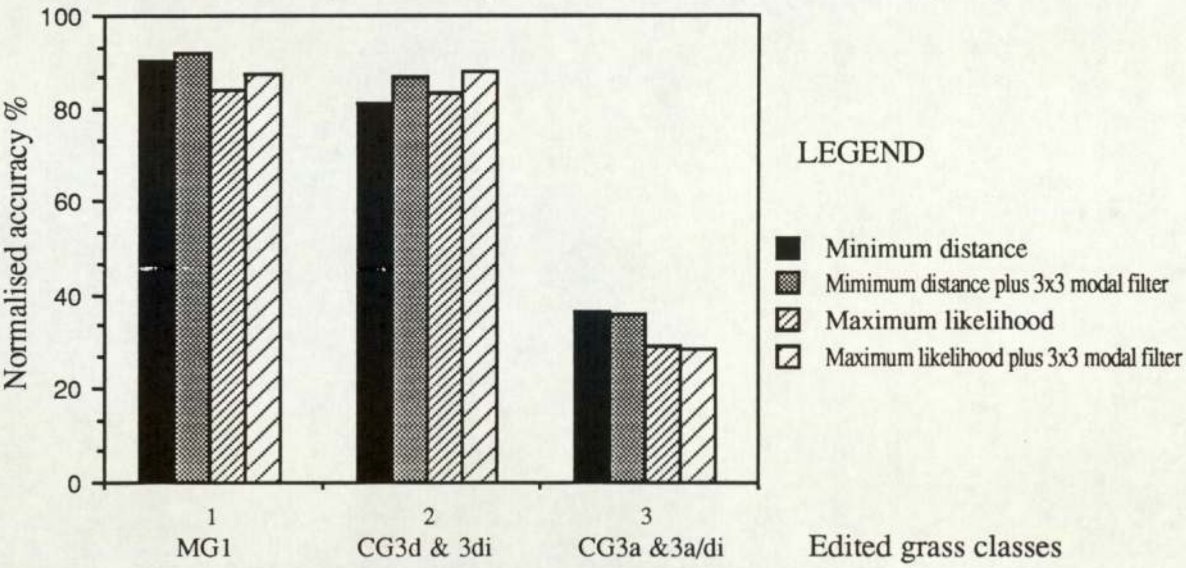


Figure 7.16 : Classification Accuracies for the Edited Grass Classes, July 1984 TM

Examination of all the confusion errors show in general that there were small omission errors between class 1 and 2, and between 2 and 3. However, large omission errors were evident between class 3 and 2, where what should be CG3a and 3a/di was being classified as CG3d and 3di. This result was contrary to all previous results, since CG3a/di consistently achieved greatest accuracy. The component of CG3a in class 3 can be ignored as being a contributing factor, due its very small spatial extent within the range. These results perhaps give a truer picture of the accuracy of classifying CG3a/di, since in previous classifications test areas were selected from the one very large pure area of CG3a/di. In this classification however, all the other much smaller regions were included in the test/verification site selection process (in conclusion this shows how important test training selection is in the final outcome of result i.e., need at least one test site for each reasonable large pure sward area), which gave a much lower overall result for class 3.

Minimum distance classifier performed slightly better than the maximum likelihood classifier, whilst application of post classification smoothing filter increased accuracy from 2 - 6%.

7.3.4.2.2 Masked TM May 1985

Examination of the statistics showed that they fulfilled all the necessary assumptions regarding the normality of the data, good separation of clusters etc,. The classified thematic map produced by minimum distance classification can be seen in Figure 7.17.

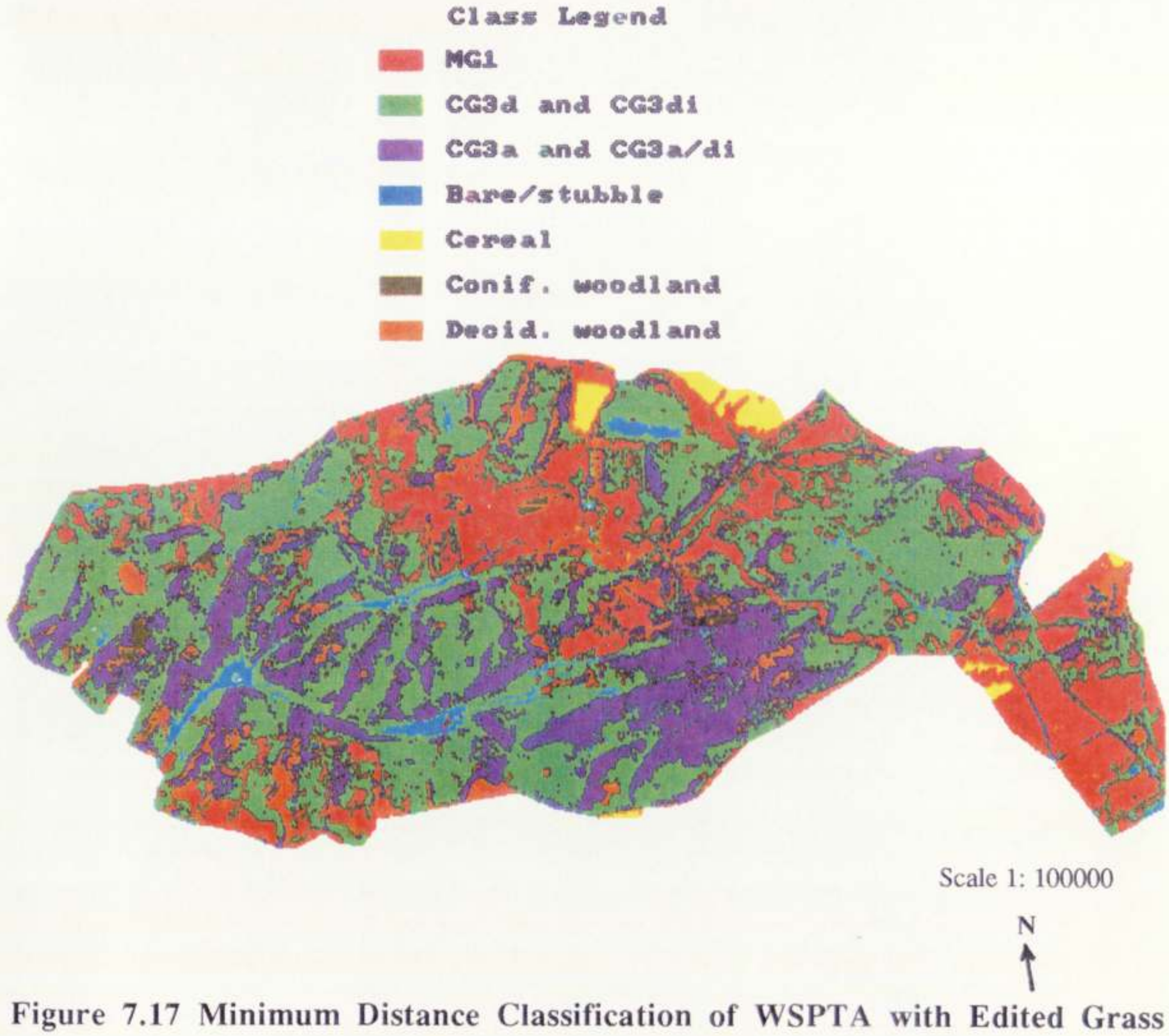


Figure 7.17 Minimum Distance Classification of WSPTA with Edited Grass Classes May 1985 TM

A summary of the results for the three edited classes are given below :-

	Normalised Accuracy %				
Class	Min. Dist.	plus filter (3x3)	Max. Likeli.	plus filter* (3x3)	**Confidence limits (95%)**
1 MG1	48.0	47.5	75.1	76.6	74.1 - 79.9
2 CG3d & 3di	45.3	46.2	46.1	52.0	48.4 - 55.6
3 CG3a & 3a/di	34.6	34.4	33.0	32.8	30.0 - 36.0
OVERALL	42.6	42.7	51.4	53.8	52.1 - 55.9

* The maximum likelihood plus modal filter results were used to calculate the the 95% confidence limits.

The results of the edited grass class supervised classification are shown by Figure 7.18.

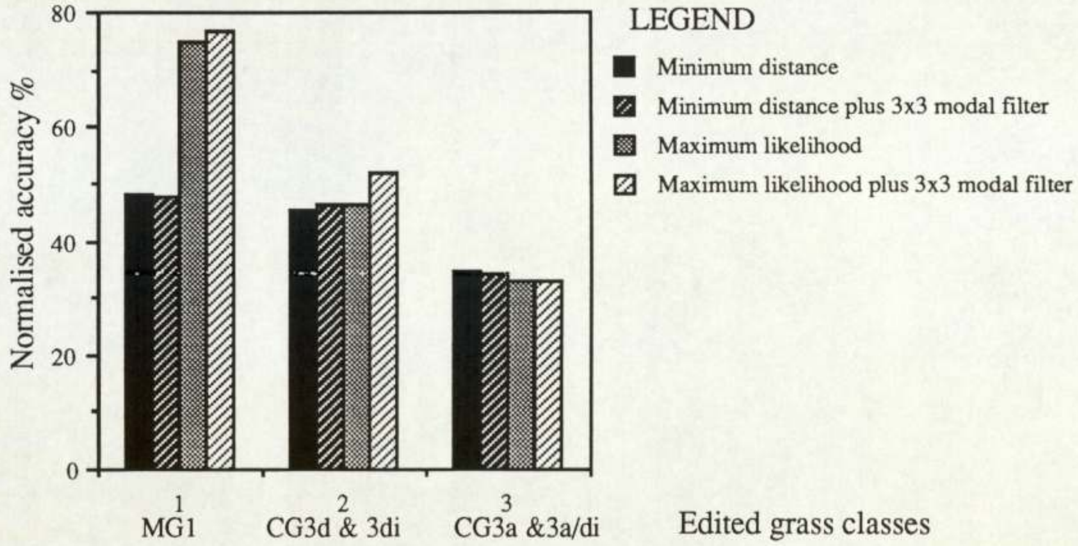


Figure 7.18 : Classification Accuracies of the Edited Grass Classes, May 1985 TM

Again class 3 had the poorest results. Large omission errors occurred between class 1 and 2 (this was not so large with the maximum likelihood), and between class 2 and 3. Class 3 showed even larger omission errors with class 2.

Here the individual class and overall accuracies are lower than the 1984 data. The maximum likelihood produced better results and where the class has been classified with over 50% success then filtering further increased the accuracy.

Figure 7.19 : Minimum Distance Classification with Edited Grass Classes June 1986 SPOT

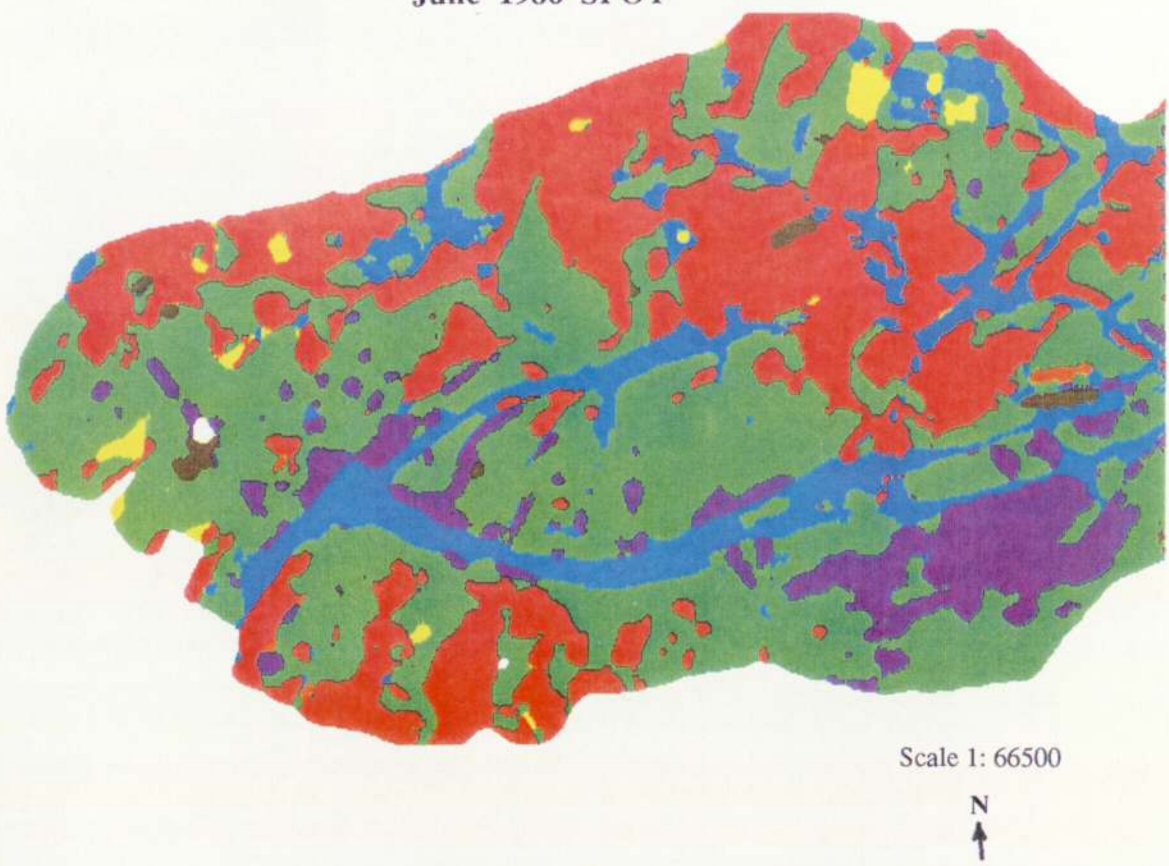


Figure 7.20 : Minimum Distance Classification of SPOT with 7x7 Modal Post-Classification Filter

7.3.4.2.3 Masked SPOT June 1986

It was noticed in the supervised training process, that all the grass classes were made up of complete mixtures of pixel tones, they all contained red, pink, green and grey pixels. Unlike the more tonally distinct situation found with the TM data, where it was found that there was generally distinct general tonal associations for the various specific grass classes.

Examination of the statistics as before proved satisfactory, however there did seem to be some evidence of spectral overlap between the vigorously growing grass class 1 (MG1), the crop class and broadleaved/mixed woodland.

A summary of the results for the three edited classes are given below :-

	Normalised Accuracy %						
Class	Min. Dist.	plus filter (3x3)	Max. Likeli.	(3x3)*	plus filter (5x5)	(7x7)	**Confidence limits (95%)**
1 MG1	63.7	66.9	70.3	72.4	75.9	77.9	69.5 - 74.5
2 CG3d & 3di	70.9	74.0	67.6	71.2	74.7	80.9	69.1 - 72.9
3 CG3a & 3a/di	66.9	68.3	70.3	72.6	73.4	74.4	70.3 - 75.7
OVERALL	67.1	69.7	69.4	72.1	74.6	77.7	70.7 - 73.3

* The maximum likelihood plus 3 x 3 modal filter results were used to calculate the 95% confidence limits.

The classified thematic map produced by minimum distance classification can be seen in Figure 7.19 with an overall accuracy of 69.4% . Figure 7.20 shows the same classification but with a much larger filter kernel (of 7 x 7 pixels) and an overall result of 77.7%. The effects of post-classification modal filtering on the accuracy of the classification of the edited grass classes is shown by Figure 7.21.

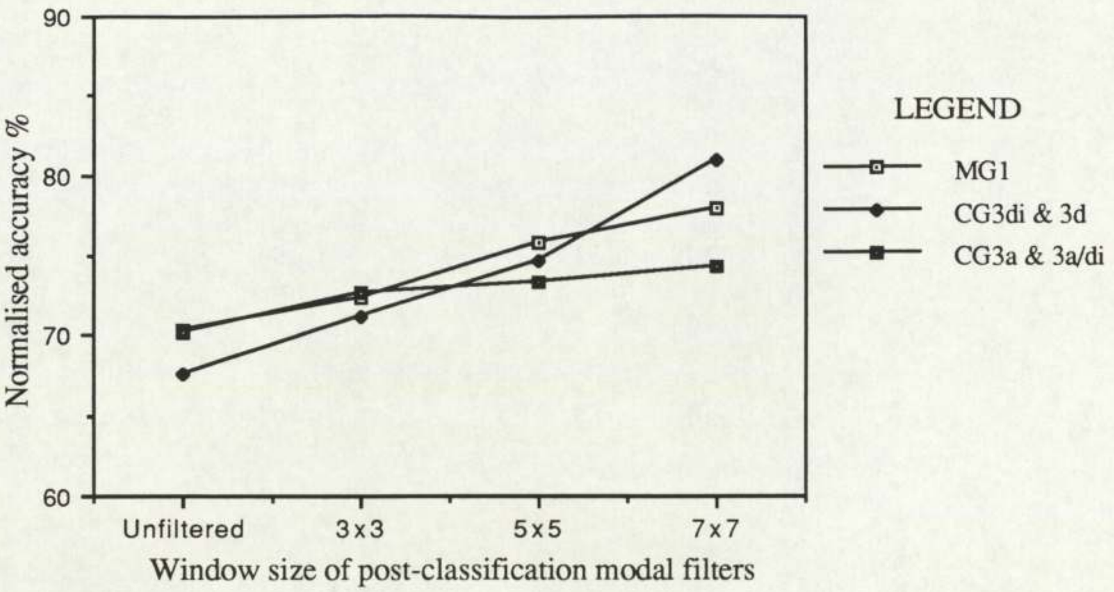


Figure 7.21 : Effects of Post-Classification Modal Filtering on the Accuracy of the Edited Grass Classes

The results of the edited grass class supervised classification are shown by Figure 7.22. All grass classes were classified with roughly equivalent accuracy. Confusion occurred between class 1 and class 2, each showed omission errors with each other. Whilst class 3 showed confusion errors with class 2.

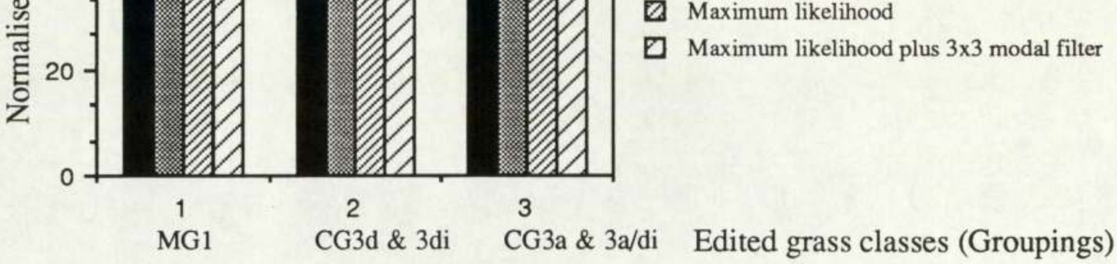


Figure 7.22 : Classification Accuracies of the Edited Grass Classes, June 1986 SPOT

The SPOT maximum likelihood results were slightly better than the best TM results. This was mainly because class 3 was identified more accurately with the SPOT data. The maximum likelihood was 3% more accurate than the minimum distance and filtering progressively increased accuracy with increased kernal size. The overall accuracy increased by 8.3% after application of the 7 x 7 pixel smoothing post classification filter.

As a further test of the accuracy, the areas of each grass unit on the Salisbury Plain was measured by EN, and these can be compared directly to the WSPTA figures calculated by the satellite classifications (Table 7.24).

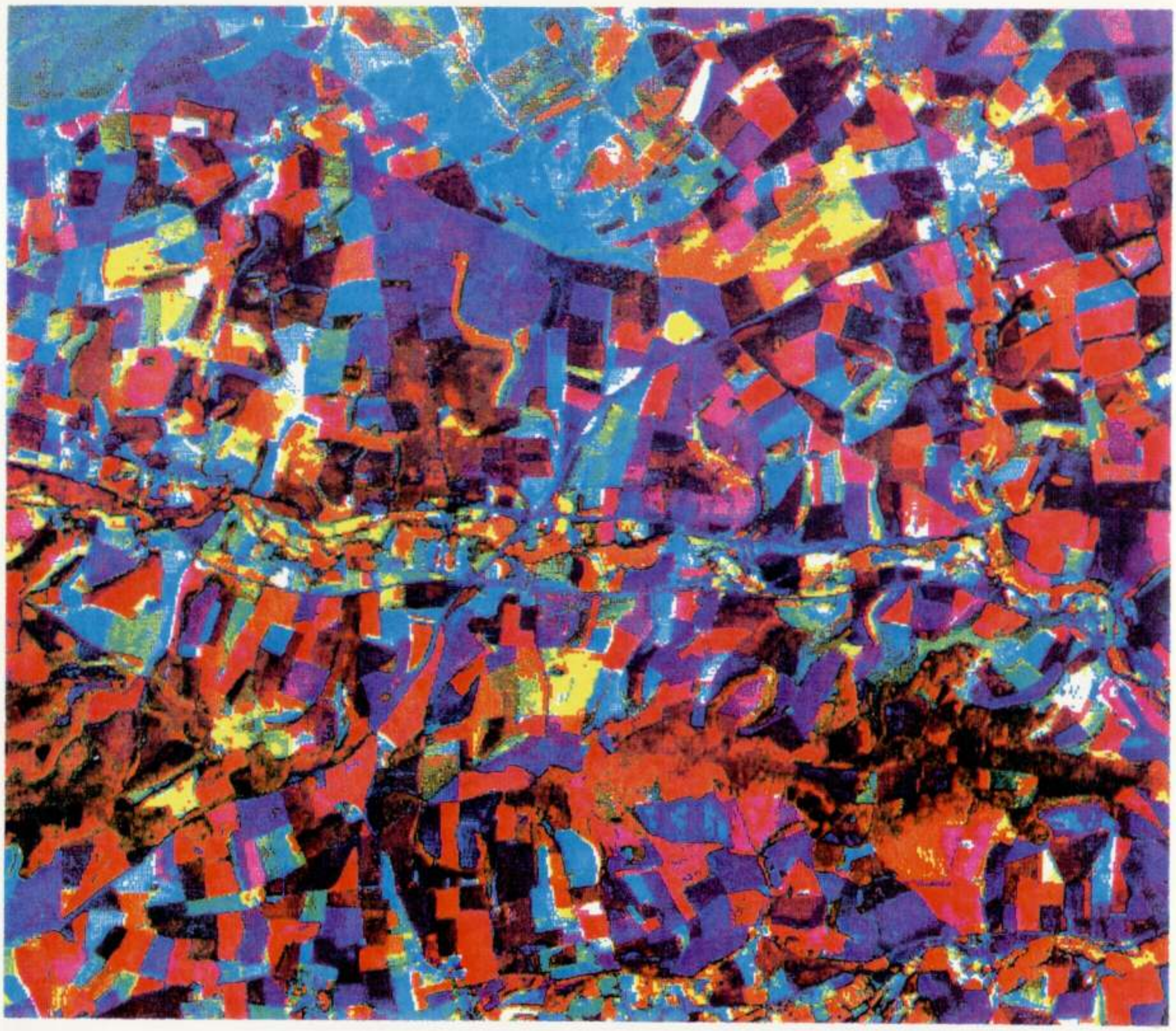
Table 7.24 : The Classified Percentage and Areas of the Land Cover Types found on WSPTA for all Three Data Sets, Compared to English Nature (EN) Ground Estimates

	TM-84 (30m)			TM-85 (30m)			SPOT-86 (20m)			EN Estimates	
Class	No of Pixels	% of area	Area (Ha)	No of Pixels	% of area	Area (Ha)	No of Pixels	% of area	Area (Ha)	% of area	Area (Ha)
MG1	24414	34.7	2,197	16448	23.4	1,480	41606	26.1	1,664	22	1,367
CG3di & 3d	27894	39.6	2,510	30560	43.4	2,751	77357	48.4	3,094	66	4,104
CG3a & 3a/di	12811	18.2	1,153	14251	20.3	1,283	16050	10.2	642	12	744
Bare/ Stubble	2434	3.5	219	2025	3.0	182	14367	9.3	575		
Crop	618	0.8	56	1431	2.0	129	11015	7.4	440		
Coniferous woodland	983	1.4	88	714	1.0	64	1071	0.9	43		
Broadleaved woodland	707	1.0	64	4840	6.8	436	778	0.6	32		
Totals of grasses (Ha)		**6,080**				**6,056**			**6,415**		**6,215**

The results show a comparable overall total amount (Ha) of grass types between the three data sets and EN figures (Porley, 1989). However, individual categories varied widely in comparison to EN estimates. Overall, the SPOT data gave the best results, with the two TM data sets over estimating the CG3a and 3a/di group. Both the TM-85 overall grass figure had to be adjusted to compensate for over classification of broadleaved/mixed woodland; as did the SPOT-86 figure due to over classification of crop/arable areas in schedule III areas, that were really grass areas waiting to be cropped for hay.

7.4. Classification of the Wylye Study Area

As a secondary part of the research programme, as well as looking at the capability of satellite sensors in mapping and inventory of the chalk rangeland, the ability to detect the unimproved agricultural chalk grassland that occurs in the surrounding agricultural land was also investigated. The study area is shown by Figure 7.23, the example data set is of July 1984 TM data (bands 4, 5 and 3). EN provided field data on SSSIs present in the area and the Wylye region was chosen as the study area, because it contained numerous examples with which to train and test the classification (see **Appendix 8**).



Scale 1 : 100000 N

Figure 7.23 Wylye Study Area Extract, July 1984 TM Data (Bands 4 5 and 3)

7.4.1 TM July 1984

7.4.1.1 Unsupervised Classification

An unsupervised classification was first performed to give an indication of the number of spectral classes present in the imagery. Fourteen classes were chosen for the analysis and the resultant classes are described in terms of informational cover classes (**Appendix 7,** Table A7.1) :-

The major classes comprised of six crop growth stages (mainly spring and winter cereals), however these were totally confused with woodland. Two classes of SSSIs or permanent pasture, one class of semi-natural rangeland, one class of low vegetation or stubble, and one class of bare ground. This information was then used as a aid in a supervised approach.

7.4.1.2 Supervised Classification

As well as EN field data, general agricultural information was used to train the classifiers, this information can be found in the form of farm maps that are in **Appendix 3**. Classification of arable land cover classes eg, crops were not an important aspect of the projects objectives, so no attempts were made to refine the arable land classification except where such refinements improved the classification of the grassland communities. Thirteen informational land cover classes were identified for the supervised classification, which was performed using the two classifiers. The crop growth stages were used, as were the SSSI and range classes, however the bare and low vegetation class was combined and water and two woodland classes were introduced (see Table 7.25).

Analysis of the training class statistics proved satisfactory and the classifications were performed. Qualitatively with the maximum likelihood, the SSSI, range, bare, four crop, and the coniferous classes were generally identified correctly. Confusions were apparent between two of the crop classes and also between broadleaved/mixed woodland, the water class and a few crop areas that appeared very dark on the FCC. In comparison, the minimum distance classified a lot more of the range class throughout the whole extract, for instance in SSSI areas, along road fringes and along river valleys. There was less misclassification between two crop types, but this was countered by far more misclassification of broadleaved/mixed woodland as a crop type.

Table 7.25 : Class Types and Number of Test Pixels, Wylye classification July 1984 TM

Class No.	Class cover type	No. of test pixels
1	SSSI I permanent chalk grassland	203
2	SSSI II permanent chalk grassland	194
3	semi-natural range grassland	212
4	bare or low vegetation	231
5	crop or improved grassland	230
6	cereal growth stage I	335
7	winter cereals I	263
8	winter cereals II	348
9	oil seed rape I	66
10	water	220
11	oil seed rape II	236
12	coniferous woodland	196
13	broadleaved mixed woodland	352

An example of a whole confusion matrix for the supervised minimum distance classification of the Wylye region using TM-84 data is given by Table 7.26.

Table 7.26 : Supervised Minimum Distance Classification of Wylye, July 1984 TM (Bands 4, 5, and 3)

		Class (true)												
C														
l		1	2	3	4	5	6	7	8	9	10	11	12	13
a	1	**96.5**	9.3	27.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
s	2	2.0	**90.0**	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
s	3	0.0	1.0	**70.3**	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
	4	0.0	0.0	0.0	**70.0**	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
p	5	0.0	0.0	0.0	0.0	**95.0**	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0
r	6	0.0	0.0	0.0	0.0	0.0	**97.0**	1.0	0.0	0.0	0.0	0.0	25.0	20.0
e	7	0.0	0.0	0.0	0.0	0.0	0.3	**50.2**	0.0	0.0	0.5	0.0	0.0	1.0
d	8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**91.0**	0.0	0.0	0.0	0.0	0.0
i	9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**76.0**	0.0	0.0	0.0	0.0
c	10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**99.0**	0.0	0.0	0.0
t	11	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**100.0**	0.0	0.0
e	12	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	20.0	0.0	0.0	**74.0**	2.0
d	13	0.0	0.0	0.0	0.0	5.0	0.0	48.0	0.0	0.0	0.0	0.0	2.0	**77.0**

Overall normalised accuracy 70.12%

Note : unclassified pixels are not included in this matrix

As anticipated the major sources of error were between class 6 and 7 (cereal classes) and 12 and 13 (the two woodland classes) in both omission and commission. Class 7 had the lowest accuracy 50%, whilst class 10 crop II (rape) was classified at 100% accuracy. There was also some confusion between coniferous woodland and water. The two SSSI chalk grasslands had minor errors with each other and with the rangeland, where 27% of the range was misclassified as the SSSI grass class 1.

A summary of the other results pertaining to use of filtering and maximum likelihood are given below in Table 7.27 for the grass classes of interest and the overall accuracy for all classes.

Table 7.27 : Classification Accuracy of the Grass Classes, Wylye Extract July 1984 TM

	Normalised accuracy %					
Class	Min Dist	Filter		Maxi. Likeli.	Filter	
		(3x3)	(5x5)		(3x3)	(5x5)
1. SSSI I	97.0	97.0	97.5	89.7	90.6	92.1
2. SSSI II	90.2	94.0	97.0	97.0	99.0	100.0
3. Range	70.3	75.0	75.5	95.8	100.0	98.6
Overall*	70.1	72.1	73.1	67.2	67.6	67.4

* the overall figure is given for all classes in the classification

The results show for the grass classes of interest that the maximum likelihood classifier performed better, however overall the minimum distance was more accurate, and the introduction of filtering generally increased the accuracy. The same sources of error were apparent in the maximum likelihood i.e., woodland and cereals, but there were slightly more intra-cereal confusions (class 6 and 7).

7.4.2 TM May 1985

7.4.2.1 Unsupervised classification

An unsupervised classification was first performed to give an indication of the number of spectral classes present in the imagery. Fourteen classes were chosen with an adequate number of peak value pixels to represent the natural clusters for the analysis and are described in **Appendix 7,** Table A7.2.

The major classes comprised of three cereal growth stages, two classes of emerging cereals (low vegetation/bare), and two crop growth stages (vigorous green growth). Two classes of SSSIs or permanent pasture, one major class of semi-natural rangeland, one class of bare ground and two classes of woodland, with one of these being confused with water. Again this information was then used as an aid in a supervised approach.

7.4.2.2 Supervised classification

Thirteen informational land cover classes were identified for the supervised classification, which was performed using the two classifiers. The cereal crop growth stages and one crop class were used, as were the SSSI and range classes, two bare and low/emerging vegetation classes, two woodland classes and a water class was introduced (Table 7.28).

Analysis of the training class statistics proved satisfactory although class 4 (bare) exhibited large standard deviation especially in TM band 5. The classifications were then performed with the two classifiers. Qualitatively, the maximum likelihood appeared to be the better of the two classifiers, the minimum distance over classified SSSI class II in crop areas and over classified the range in areas that were agriculturally managed crops.

Table 7.28 : Class Types and Number of Test Pixels, Wylye Classification May 1985 TM

Class No.	Class cover type	No. of test pixels
1	SSSI I permanent chalk grassland	65
2	SSSI II permanent chalk grassland	81
3	semi-natural range grassland	177
4	bare or low vegetation I	64
5	crop or improved grassland	78
6	cereal growth stage I	88
7	winter cereals I	85
8	winter/spring cereals	111
9	oil seed rape	88
10	water	47
11	low vegetation/bare II	107
12	coniferous woodland	62
13	broadleaved mixed woodland	126

There was a different emphasise compared to the July 1984 TM imagery, with more emerging crop/soil background classes in the May 1985 imagery, this being a function of the season. It was also noted that the woodland classes were much more apparent compared to the 1984 image.

A summary of the results (Table 7.29) shows that there was no confusion between the woodland and the crops this time. With unfiltered minimum distance, seven classes were correctly classified over 90%, the lowest accuracy was with crop class 9 (63%), which was confused with another crop class 7. The overall result was 87%. There were relatively small confusions between the two SSSI classes and between the range class 3 and the bare/low vegetation class 11. The unfiltered maximum likelihood classifier in comparison correctly classified nine classes over 90%. The overall result was 85.5%. However, the lowest accuracy was 36% with class 5, which had large omission errors with SSSI class 1, these two classes did exhibit similar tones on the FCC. There was also greater confusion evident between the two SSSI classes with the maximum likelihood classifier. There was also omission errors in class 7, with classes 6 and 8, which are all cereal growth stages. However unlike, the minimum distance, the range class was correctly classified.

Table 7.29 : Classification Accuracy of the Grass Classes, Wylye Extract May 1985 TM

	Normalised accuracy %					
Class	Min. Dist.	Filter (3x3)	(5x5)	Maxi. Likeli.	Filter (3x3)	(5x5)
1. SSSI I	100.0	100.0	100.0	100.0	100.0	100.0
2. SSSI II	71.6	77.8	89.0	52.0	61.0	68.0
3. Range	71.8	78.0	84.2	100.0	100.0	100.0
Overall*	87.0	87.6	90.1	85.5	87.1	88.5

* the overall figure is for all classes in the classification

7.4.3 SPOT June 1986

7.4.3.1 Unsupervised Classification

An unsupervised classification was first performed to give an indication of the number of spectral classes present in the imagery. Eleven classes were chosen with an adequate number of peak value pixels to represent the natural clusters for the analysis (see **Appendix 7** Table A7.3).

Major spectral classes consisted of three cereal, three bare/low vegetation, two woodland, two SSSI chalk grasslands and one range. In attempting a supervised procedure, analysis of the FCC and the unsupervised result illustrated the difficulty in separating grasslands from crops. It was clear that only three major land cover groups were any thing like spectrally discernible, and these were the bare/low vegetation group, growing vegetation and woodland groups.

7.4.3.2 Supervised classification

Thirteen informational land cover classes were identified for the supervised classification, which was performed using the two classifiers. Two winter cereal and two cereal crop growth stages were used, as were the SSSI and range classes, three bare and low/emerging vegetation classes, two woodland classes and a water class was introduced (Table 7.30).

Analysis of the training class statistics proved satisfactory. The statistics did show that the similarity of the two visible bands and their near complete spectral overlap for all the classes. The classifications were then performed using the two classifiers. Qualitatively, the minimum distance and to a greater extent the maximum likelihood both over classified the SSSI classes in cereal areas. Generally however, the bare and some of the crop classes were identified correctly. Confusions were apparent between range and woodland, and also between crop classes and woodland.

Table 7.30 : Class Types and Number of Test Pixels, Wylye Classification June 1986 SPOT

Class No.	Class cover type	No. of test pixels
1	SSSI I permanent chalk grassland	213
2	SSSI II permanent chalk grassland	255
3	semi-natural range grassland	249
4	bare	97
5	cereal growth stage I	142
6	cereal growth stage II	150
7	winter cereals I	170
8	winter cereals II	225
9	low vegetation/bare I	133
10	water	112
11	low vegetation/bare II	132
12	coniferous woodland	165
13	broadleaved mixed woodland	333

The classification results are summarised and are given by Table 7.31.

Table 7.31 : Classification Accuracy of the Grass Classes, Wylye Extract June 1986 SPOT

	Normalised accuracy %					
Class	Min Dist	Filter		Maxi. Likeli.	Filter	
		(3x3)	(5x5)		(3x3)	(5x5)
1. SSSI I	55.8	53.1	52.6	83.5	86.4	89.2
2. SSSI II	64.7	72.9	78.8	79.0	81.2	83.1
3. Range	69.1	74.7	78.0	55.0	65.1	74.7
Overall*	77.6	79.8	81.4	79.7	82.1	83.8

* the overall figure is for all classes in the classification

Overall with the minimum distance classifier, five classes were classified over 90%, these were bare, cereal I and II, winter cereal I and II, and coniferous woodland. Class 9, low vegetation/bare I was totally misclassified as low vegetation/bare II (class 11). There were large omission errors with SSSI class 1 being classified as class 5 (cereal I), SSSI class 2 being misclassified as SSSI class 1, winter cereal class 8 and low vegetation class 9. The range (class 3) was also confused with classes 8, 9 and 11. Finally mixed/broadleaved woodland was confused with the range, and two cereal classes (class 6 and 8).

The results were generally a bit better with maximum likelihood, there was a similar trend in errors except that there was more misclassification of the range and mixed/broadleaved woodland classes.

7.4.4 Permanent Chalk (SSSI) Grassland Classification

It was evident that the two spectral SSSI classes were adequately mapped in two of image dates by supervised classification, however it was also clear that there was serious over classification in areas that were obviously crops with the TM and that there were more serious problems with the SPOT data. Therefore in an attempt to fine tune the procedure only the two SSSI classes were used as training input, this together with the careful selection of training and test data would allow a more accurate assessment of the ability of satellite imagery in the mapping of chalk grasslands of SSSI status.

The training class statistics are given by Table 7.32 for the two spectral classes for TM 1984.

Analysis of the training statistics proved satisfactory and classification took place with more stringent thresholds. A trial and error process was undertaken whereby with the minimum euclidian distance threshold was decreased to a threshold of 15 and the probability of class membership in the maximum likelihood was increased probability 95%, such that any pixels classified as either class 1 or 2 would be very likely to be that class with regard to their training data statistical parameters.

Table 7.32 : Training Statistics for SSSI Spectral Classes, July 1984 TM (Bands 4, 5, and 3)

		Mean and ± one standard deviation		
Class	Colour on FCC	4	5	3
Class 1	Yellow/green	112.6	110.4	41.4
		2.5	5.9	1.5
Class 2	Orange	124.6	95.2	36.3
		2.8	5.8	1.4

The overall best classification result was 90% with minimum distance classifier and modal filtering. Class 1 had an accuracy of 86% and class 2 a figure of 94%, there were small omission errors i.e., 12% of class 1 was classified as class 2 and 5% of class 2 was classified as class 1. Figure 7.24, shows the spatial distribution of the two spectral classes of SSSI 'status' chalk grassland in the Wylye region. The same process was then repeated for the two other data sets.

With the TM 1985 data set the best overall classification result was 84.2% with modal filtering and maximum likelihood. This time class 1 was more accurately identified with 92%, whilst class 2 had an accuracy level of 76%. The errors being 8% of class 1 being misclassified as class 2 and 12% of class 2 being classified as class 1.

Application of the same process to the SPOT data proved to be problematic, there was no degree of spectral uniqueness evident as in the two dates of TM. The best overall result was 28.4%, with the two classes achieving results of 36% and 21% respectively. It was apparent from interpretation of the SPOT image, that there was no spectral separability between the permanent chalk grassland and actively growing crops, and this was borne out by the previous unsupervised procedure. The reasons put forward to account for this being both the spectral resolution of SPOT and the phenology of vegetation in a June situation.

Figure 7.24 : Supervised Classification of the Spatial Distribution of Permanent Chalk Grassland

7.5. Larkhill Range Test Area Data Set

The last stage of the analysis was to test the final revised methodology on a different data set. For this the Larkhill range training area was chosen, this is described in Chapter two, section 2.1. Larkhill although smaller in area than WSPTA, was a continuous block and contained sufficient areal extent of grassland units to provide adequate numbers of pixels for training and testing of the same grassland units found in WSPTA. The Eastern range or ESPTA was much more discontinuous, smaller in areal extent and made up of more complex grassland units, which were unique to it (Porley, 1989).

The same procedure as used in section 7.3.4 classification was repeated. Just the 1984 data set was used, time constraints did not permit the further testing of the 1985 and 1986 data sets or the selective testing of the ESPTA.

7.5.1 Unsupervised Classification

First the Larkhill range was masked off and an unsupervised classification undertaken to give an idea of the number of spectral classes present and to see how they related to WSPTA. Seven significant peak number of classes were found. The statistics and how they relate to the ground cover types are given by **Appendix 7** Table A7.4.

From this it can be seen that these natural spectral classes correspond for the most part with the WSPTA unsupervised classes and with the edited seven training classes from the supervised 7.3.4 classification, except that is for the replacement of the scrub/broadleaved woodland with a new 'burnt' range class. This is because unlike WSPTA, the Larkhill range is mainly used as a artillery range and that by July the ground would be very dry and since 1984 was a hot summer, the explosion of artillery shells would very likely ignite the range locally.

7.5.2 Supervised Classification

The same training statistic file [**ctrain84.csd**] (see **Appendix 5**), generated from WSPTA section 7.3.4.2.1 classification with the edited three major grassland units, was used to train both minimum distance and maximum likelihood classifiers.

Qualitatively, the two classifiers performed as such (where there are major differences between the classifiers this is commented on) :-

No.	Class	Comments
1R	MG1	classified areas mainly confined to northern periphery of the range (light orange on FCC) and green/orange areas on schedule III land
2G	CG3di & 3d	classified 90% of the range that is not schedule III land (blue/green/grey on FCC)
3B	CG3a/di & 3a	5% of the range classified (light blue/grey on FCC), however the minimum distance classified most of the bare/low vegetation on the schedule III land

4C	Bare or low vegetation	minimum distance just classified the bare areas, whilst the maximum likelihood classified low vegetation areas as well
5Y	Cereal	virtually none found with minimum distance, a few areas of bright orange with the maximum likelihood classifier were mapped
6Br	Coniferous woodland	minimum distance picked out some plantations, whilst the maximum likelihood classified plantations, valley shadow and areas linked to burnt areas
7O	Scrub/broad woodland	classified scrub areas on the range, but also orange/red areas on schedule III land, which were vigorously growing green vegetation (improved grasslands/cereals).

The majority of the burnt areas were unclassified, because it was not a significant class in WSPTA and thus was not represented in the training data and input into the classifier.

Test verification areas were then selected from the EN field survey on the distribution of community types and confusion matrixes were generated. A summary of the results of percentage correctly classified for all seven classes is given by Table 7.33.

In the case of the minimum distance classifier, classes 4 and 7 were successfully classified. Concentrating on the first three range grass classes, there were errors between class 1 and class 7. Class 2 was confused with class 1 and 3. Class 3 was totally confused (82% omission error) with class 2 and class 6 was to some degree confused with class 2 and class 7.

In the case of maximum likelihood where there were differences, it was classes 4 and 5 that were successfully classified. Class 2 was confused with class 3, and again class 3 was totally confused (87% omission error) with class 2. Class 6 was confused with class 7 and class 7 was confused with class 5.

Overall, maximum likelihood performed slightly better and filtering increased the accuracy where a class was sufficiently correctly identified in the first place.

In comparison with the WSPTA data set, class 1 was again identified most successfully, class 2 was slightly less successfully mapped and class 3 was for both WSPTA and Larkhill data sets poorly represented. The overall trend for both was the same, with the test data set (Larkhill) giving credence to the validity of the results gained from the WSPTA data set. This gives some indication of the level of discriminatory ability of the satellite sensors (albeit just TM in this case) in the mapping of these specific chalk grass groupings.

Table 7.33 : Supervised Classification Results of the Larkhill Range, July 1984 TM (Bands 4, 5 and 3)

Class	Min Dist	Filter (3x3)	Maxi. Likeli.	Filter (3x3)
1. MG1	78.2	93.0	77.6	90.1
2. CG3di & 3d	60.0	62.7	65.1	69.1
3. CG3a/di & 3a	16.5	12.0	11.0	7.1
4. Bare & low vegetation	100.0	100.0	100.0	100.0
5. Cereal	0.0	0.0	100.0	100.0
6. Coniferous woodland	68.2	86.4	47.7	45.5
7. Scrub/broadleaved woodland	90.0	100.0	72.5	90.0
Overall	60.0	64.8	67.7	71.6

CHAPTER EIGHT

DISCUSSION

8.1 Summary of Research

This chapter discusses the findings of this research and attempts to define the positive and negative elements found in terms of temporal, spatial and spectral characteristics of the target classes and the imagery.

In feature selection with the TM imagery, the best three band subset was found to be 4, 5 and 3 on the red, green and blue colour guns for discriminating key target vegetation classes. The July 1984 TM image provided the most qualitative information, this was a consequence of the vegetation phenology when compared with the earlier in the season May TM imagery; and the superior spectral resolution of July TM scene when compared with the June SPOT imagery.

The next stage was to quantify the amount of information extraction for all three data sets, this was achieved by automated supervised classification.

8.1.1 Supervised Classification

A comparable application (Trodd, 1987) used multidate Landsat TM to detect ecological important unimproved neutral grassland, but it was found that the traditional supervised classification techniques were inappropriate; therefore this study used an alternative approach. A methodology was developed using a binary decision tree, where relevant vegetation indices were used as decision rules. From this it was possible to detect a single land use category of unimproved pasture. Initial attempts using supervised maximum likelihood failed to positively identify any of the unimproved grassland.

Referring to Chapter Seven, section 7.2, it was evident that unlike Trodd's study, the range and the ecologically significant individual chalk grass SSSI fields around Wylye village were consistently spectrally (tonally) distinct by eye, compared to surrounding cover types (McGuire and Collins, 1988; McGuire *et al.*, 1989). Therefore, it was envisaged that traditional supervised classification procedures would work (Fuller and Parsell, 1990) and these were used in all subsequent classifications and procedures.

The initial full extract supervised classification results, using objective test data, gave overall accuracy results of the WSPTA range classes of 43% for the SPOT-86 data, 32% for TM-84 and 27% for TM-85 data. This analysis compared directly TM and SPOT, as both data sets were resampled to 25m pixel spatial resolution (Chapter Seven, section 7.3.1). The reason for SPOT's apparent better performance was unclear, it was expected that the inclusion of the mid-IR dimension of the TM data would make it a superior tool in mapping these types of vegetation. The overall poor performance in all three dates indicates the inability of satellite spectral data to discriminate the full complement of all five sub-community range grassland types as found on the Salisbury Plain Training Areas (SPTAs) by the English Nature (EN) ground survey.

Specific classifier performance was evaluated for the two algorithms using SPOT data. Maximum likelihood was on average 4% more accurate compared with minimum distance classifier, this increased to 7% when modal post-classification filtering was applied. This is off-set by the fact that the more complex maximum likelihood algorithm, used five times more computational time. Similar findings were obtained by Booth and Oldfield (1989), where speed and accuracy were tested for four different classification algorithms. Although maximum likelihood produced slightly higher accuracies, minimum distance plus post-classification modal filtering was recommended, because of the reduced time needed to run this classifier.

A quantitative comparison of feature selection of the TM data, showed that using five bands of data did not increase the accuracy compared with a best three band classification. The Computer processing unit (CPU) time was also halved when just using three bands.

In the secondary classification a graphics mask was applied, such that only the range areas were used in the analysis (Chapter Seven, section 7.3.2). There was a significant improvement in accuracy with the TM-84 data. Application of the mask reduced the number of grass classes to four. Overall accuracy levels of 80% was achieved with the application of a modal filter, compared to just 32% achieved with the previous initial classification, using the full complement of grass classes and all other cover types.

A digital vegetation map was created from the EN ground survey data and was used as an input to test the classification; this would in effect produce a 'per-field' classification or its simulation of it. The digital EN vegetation map allowed the delineation of training and test areas, such an objective process places implicit trust in the ground survey, and avoids the influence of colour variation on the FCC data sets (Williams, 1987). This equivalent of a 'per-field' classification (Chapter Seven, section 7.3.3) using the total range area and four grass classes to test the classification, produced overall accuracy levels of 39% for TM-84, 36% for TM-85 and 39% for the SPOT-86 data. The performance of the two classifiers was comparable. These results were similar to the initial objective classification (Chapter Seven, section 7.3.1), but a lot poorer than the masked secondary classification (Chapter Seven, section 7.3.2). This was because the masked classification used a much lower population of test pixels compared to the total test population used in the simulated 'per-field' classification, and because of other reasons put forward in section 7.3.3. However, this result did give an indication of the ability of satellite sensors to spectrally discriminate, at this ecological level, the different Bromus erectus dominant sub-community vegetation types.

Having established that this was the level of accuracy likely to be attained in attempting to map the grassland units at this level of detail, the next stage of the analysis was to intelligently edit the grassland units to see if improvement in accuracy could be achieved.

One part of this process was the unsupervised classification of the WSPTA. Belward *et al.*, (1990) argued that because semi-natural habitat classes consist of many species, soil types etc., they therefore exhibit multimodal probability distributions. Unsupervised classification overcomes this problem of distribution assumptions and was therefore better for mapping and inventory of heterogeneous ground cover types.

In this study it was found that unsupervised classification on both the whole extract, and of just the masked range for all three data sets, failed to create thematic maps showing ecological units to the level of detail found in the ground survey. This procedure however, was found to provide valuable information regarding how the informational classes used in supervised classification related to the spectral classes present within the imagery at any one point of time.

The unsupervised classification information, together with other refinements of the methodology, were then used in the tertiary classification scheme (Chapter Seven, section 7.3.4), where the range grassland units were amalgamated into three groupings (groups 1 to 3). With the TM-84 data, the first two groups were classified with over 80% accuracy, this is about the figure stipulated as the acceptable level of reliability in land cover classification (Anderson *et al.*, 1976). The third class made up of CG3a and CG3a/di achieved a best result of only 36%. One component of this grouping had previously been identified with the most accuracy in the initial and secondary classifications. This disparity in results was thought to be explained by inclusion of all the significant areas of this class in the test analysis, since in the previous two classification schemes only one large area had been used to test the accuracy.

Analysis of the TM-85 data produced somewhat poorer overall results. Class accuracies ranged from 33% to 77%, again group three was poorly identified. The maximum likelihood classifier performed significantly better compared with the minimum distance algorithm, especially with group one containing the MG1 grassland class.

The SPOT data was overall only slightly better than the TM-84 data; this was because with the SPOT data all three classes were identified with similar range of accuracy i.e., between 60 to 70%. Modal filtering and increasing the kernel size also improved the accuracies. Wilson (1992), compared different procedures for classifying remotely sensed data using simulated data sets and recommended using single or multiple pass smoothing post-classification modal filters, as a simple effective way of yielding improvements in accuracy.

For operational digital classification there is a need to fully assess the reliability of the results. Confidence limits at 95% were calculated for the tertiary classification results (Chapter Seven, section 7.3.4) and these give an indication of accuracy assessment of the three data sets and of the cover types used in the analysis. Methods of computing accuracy for automated classification are the subject of much discussion (Congleton *et al.*, 1983; Pedley, 1987). Previously in this study, accuracy figures quoted are the overall accuracy and the normalised class accuracy for accuracy assessment between different dates, classifiers and sensors.

As well as the traditional overall accuracy figures, 'normalised' accuracy levels were also quoted throughout Chapter seven. This technique standardises the error matricies, it uses an iterative proportional fitting procedure which forces each row and column in the matrix to sum to one. In this way individual cell values within the matrix are directly comparable, since differences in sample sizes are eliminated. It is thus a better representation of accuracy, because it contains information about the off-diagonal cell values (Congalton, 1991).

However, there is another statistical technique of use in accuracy assessment and this is called KAPPA. The result of performing a KAPPA analysis is a KHAT statistic (an estimate of KAPPA). The KHAT statistic is computed as follows (Congalton *et al.*, 1983) :-

$$\hat{K} = \frac{N\sum_{i=1}^{r} X_{ii} - (X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^{r} (X_{i+} * X_{+i})} \qquad (8.1)$$

where r = No. of rows in matrix , X_{ii} = No. of observations in row i and column i X_{i+} = marginal totals row i , $X_{x\,i}$ = marginal totals column i, and N = total observations

Table 8.1 provides a comparison of the overall accuracy, the normalised accuracy, and the

KHAT statistic for the two classification algorithms and the application of filters used in the three different multitemporal multisensor data sets for the tertiary classification results (Chapter Seven, section 7.3.4).

Table 8.1 : A Comparison of the Overall Three Accuracy Measures for the Two Classification Approaches for each Multitemporal Data Set

Data set	Classification approach	Overall accuracy (%)	Normalised accuracy (%)	KHAT accuracy (%)
TM-84	Min. Dist	68	69	52
	Min. Dist + filter	70	72	55
	Max.Likeli	64	66	47
	Max. Likeli + filter	66	68	50
TM-85	Min. Dist	42	43	15
	Min. Dist + filter	42	43	15
	Max. Likeli	51	51	30
	Max. Likeli + filter	53	54	33
SPOT-86	Min. Dist	68	67	51
	Min. Dist + filter	71	70	54
	Max. Likeli	69	69	54
	Max. Likeli + filter (3x3)	72	72	56
	Max. Likeli + filter (5x5)	75	75	60
	Max. Likeli + filter (7x7)	79	78	66

As can be seen all three accuracy measures agree about the relative ranking of the results. Normalised accuracy generally gave the highest results, followed by overall accuracy and with the KHAT estimate of accuracy being the lowest, since each accuracy measure incorporates different information about the error matrix. As already described, overall accuracy only incorporates the major diagonal, normalised accuracy directly includes the off-diagonal elements and the KHAT accuracy indirectly incorporates the off-diagonal elements as a product of the row and column marginals. Congalton (1991) recommended that all three accuracy measures be used to glean as much information from the error confusion matrices

Formulation for estimated large sample variances of KAPPA is given by (Hudson and Ramm, 1987) :

$$\hat{\sigma}(\hat{K}) = \frac{1}{N}\left[\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4-4\theta_2^2)}{(1-\theta_2)^4}\right] \tag{8.2}$$

where

$$\theta_1 = \sum_{i=1}^{r} \frac{X_{ii}}{N}$$

$$\theta_2 = \sum_{i=1}^{r} \frac{X_{i+} + X_{+i}}{N^2}$$

$$\theta_3 = \sum_{i=1}^{r} \frac{X_{ii}}{N}\left(\frac{X_{i+}}{N} + \frac{X_{+i}}{N}\right)$$

$$\theta_4 = \sum_{\substack{i=1 \\ j=1}}^{r} \frac{X_{ij}}{N}\left(\frac{X_{j+}}{N} + \frac{X_{+i}}{N}\right)$$

The test statistic for significant difference in large sample between two independent KAPPA's is given by (Rosenfield and Fitzpatrick-Lins, 1986) :

$$Z = \frac{(\hat{K}_1 - \hat{K}_2)}{\sqrt{\sigma_1^2 + \sigma_2^2}} \tag{8.3}$$

where Z is the standard normal deviate and σ is the variance of KAPPA. If Z exceeds 1.96

then the difference is significant at the 95% probability level.

KAPPA is a powerful technique in its ability to provide information about single matrix, as well as to statistically compare matrices. Table 8.2 presents the results of the KAPPA analysis to test the significance of each matrix alone. This test determines whether the results presented in the confusion matrix are significantly better than a random result (i.e., the null hypothesis : KHAT = 0).

Table 8.2 : Results of the KAPPA Analysis Test of Significance for Individual Error Matrices

Test of Significance for each confusion matrix

Max. Likeli + filter result for each data set	*KHAT Statistic*	*Z Statistic*	*Results* [a]
TM-84	0.4972	36.26	S [b]
TM-85	0.3266	21.77	S
SPOT-86	0.5609	51.86	S

[a] *At the 95% Confidence Level*

[b] *S= Significant*

This indicates that the refinement of the amalgamation of the original classes into three groupings in the tertiary classification was a valid exercise, since Table 8.2 shows that all three individual data sets have produced significant results.

The next series of tables presents the results of the KAPPA analysis that compares the confusion matrices two at a time to determine if they are significantly different. Table 8.3 shows the results of the KAPPA analysis on the significance of using different classifying algorithms and the impact of using post-classification smoothing filters of different kernal size.

Table 8.3 : Results of the KAPPA Analysis for Comparison between Confusion Matrices for different Classification Algorithms and for Post-classification Modal Filtering, using SPOT-86 Data

Test of Significant differences between confusion matrices

Comparison	*Z Statistic*	*Results* [a]
Min. Dist. vs. Max. Likeli.	1.767	NS [b]
Min. Dist. vs. Max. Likeli. + 3x3 filter	1.287	NS
Min. Dist. vs. Max. Likeli. + 7x7 filter	7.780	S

[a] *At the 95% Confidence Level*

[b] *S= Significant, NS= Not Significant*

The result of the KAPPA analysis show that the there was no significant difference between minimum distance and maximum likelihood algorithms and therefore, given the choice of these two approaches, one should use the easier, quicker, or more efficient approach because accuracy will not be the deciding factor. On the other hand post-classification modal filtering was found to be important, increasing the kernal size of the filter was found to have a significant effect on the increase in the overall accuracy.

Similar results are presented in Table 8.4 comparing the maximum likelihood classification results for the three dates of the data. Each result shows that each date is significantly different and it therefore shows the importance of the timing of the imagery in this type of analysis.

Table 8.4 : Results of the KAPPA Analysis for Comparison between Confusion Matrices for the Three Dates of Imagery

Test of Significant differences between confusion matrices

Multitemporal Comparison	*Z Statistic*	*Results* [a]
July 84 vs. May 85	8.45	S [b]
July 84 vs. June 86	3.74	S
May 85 vs. June 86	12.89	S

[a] *At the 95% Confidence Level*

[b] *S= Significant, NS= Not Significant*

The last part of this analysis was to see if there was any statistical significant difference in the results relative to the type of sensor used. The 'best' result of TM (TM-84, July) was compared with the 'best' result achieved from the SPOT data. The KAPPA analysis (see Table 8.5) illustrated that there was no significant difference between the 'best' results of the two different sensors. It was envisaged that the TM sensor with its superior spectral resolution would have been the better remote sensing platform, however as it can be seen the use of SPOT produces equally promising results. This result can probably be explained by the fact that SPOT's 20m spatial resolution represents more accurately the spatial heterogeneity of the semi-natural range chalk grassland groups and that the coarser resolution of the TM sensor is compensated by it's greater dynamic spectral range. Due to this, and despite the findings of the KAPPA analysis, TM would be the sensor recommended for similar study applications. Provided that is, that the ground cover types one is attempting to map are not so closely related and heterogeneous in nature as in the case of the SPTA range chalk grassland types found in this study.

Table 8.5 : Results of the KAPPA Analysis for Comparison between the 'best' Supervised Classification Results for TM Sensor *1 and SPOT Sensor *2

Test of Significant differences between confusion matrices

Sensor Comparison	*Z Statistic*	*Results* [a]
TM-84 *1 vs. SPOT-86 *2	0.477	NS [b]

[a] *At the 95% Confidence Level*

[b] *S= Significant, NS= Not Significant*

It is therefore, recommended that KAPPA statistic be adopted by the remote sensing community, as the standard measure of accuracy for thematic classification as a whole and for individual categories. This is endorsed by a large number of fellow workers (Congalton *et al.*, 1983; Rosenfield and Fitzpatrick-Lins, 1986; Hudson and Ram, 1987; Congalton, 1991; Pedley and Curran, 1991).

It is therefore apparent that a classification needs to be assessed. For only then can the decision made on that information from the classification have any validity in management tasks. In addition, it is critical for the use of quantitative analysis of remotely sensed data to continue, since remotely sensed data is just a small subset of the vast amounts of spatial data used in GIS, and the techniques described here can be applied and integrated with all the spatial data used in such systems.

As a further test, the amount of each class in hectares, generated from the classification was compared with EN statistics from their ground survey. It was expected that the satellite figures would be less than the EN figures, due to the presence of other cover types present within the range area. Figure 8.1 shows the percentage of areas in hectares for the main three groups present on the WSPTA. The differences can be explained by the fact that for no obvious reason some areas of the range were not surveyed by EN and that therefore the EN statistics could be underestimated compared with the satellite derived findings. Also, an attempt was made to match as closely as possible the manual construction of the mask with the extent of the range from the EN field map, differences were likely to have occurred. Conversely, overestimation may have occurred compared to the satellite figures, due to EN including areas in the scheduled MoD land off the immediate range, which were areas ignored by this analysis. Also by the inclusion of other cover types present within the range but not surveyed by the EN field unit; for example, chalk-tracks, crops and woodland plantations, which were land cover classes picked out by the satellite analysis.

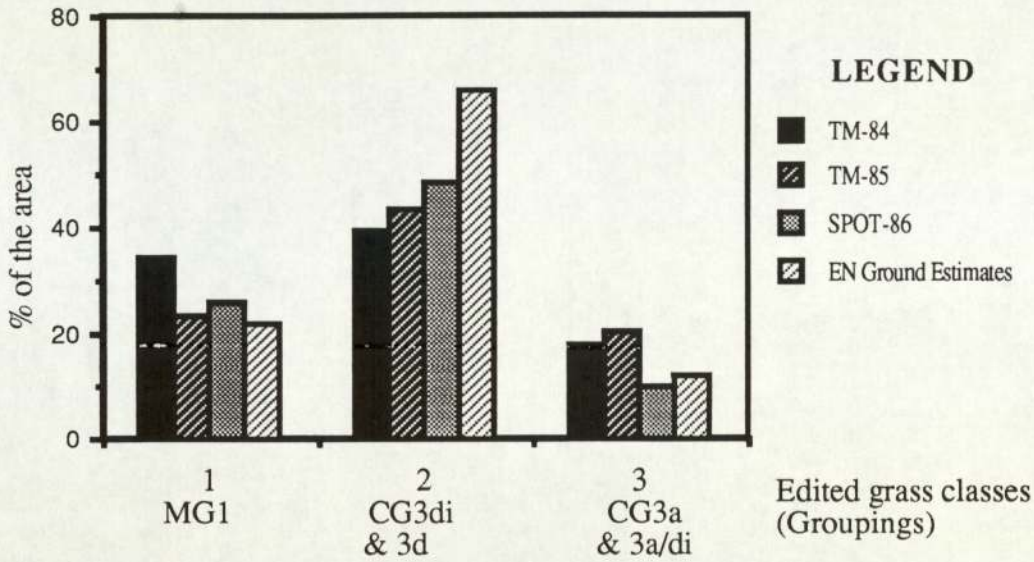


Fig 8.1: The Classified Percentage of Grass Cover Types found on WSPTA, Compared to English Nature Ground Estimates

The last stage of the range class analysis, and as a final test of the methodology, the edited range groups training class results were applied to a different data set : this was carried out on the TM-84 data only (Chapter Seven, section 7.5). The statistics derived from the training procedure of WSPTA tertiary classification were used to classify the different study area of Larkhill range and an accuracy assessment was carried out. The overall results were comparable to those achieved with WSPTA. The best overall minimum distance result was 64% : group 1 (93%) and to a lesser extent group 2 (63%) were successfully identified. The best maximum likelihood overall result was 72%, with group 1 (90%) and group 2 (70%) respectively. However, as with the WSPTA results, the group 3 class was very poorly identified in both cases, it never achieved a greater correspondence than 17% with identified in both cases, it never achieved a greater correspondence than 17% with the ground data. The results suggest that the grouping of class 1 and 2 can be identified and mapped from satellite data with reasonable success. However the class 3 group (CG3a and CG3a/di), which is the more botanically important sub-community type in ecological terms of species richness, could not be reliably mapped.

8.2. Rationale Behind the Editing of the Range Classes into Groupings

The grasslands were divided into units or communities and sub-communities by the national vegetation classification (NVC) scheme. In reality no such clear cut divisions exist. Rather the grasslands units form a continuum and grassland species rarely exist in large homogeneous stands. Blazye (1987), stated that :-

> "since grassland exists as a continuum any arbitrary division of it is likely to lead to errors of commission and omission in classification".

Therefore improved classification accuracy was achieved by amalgamation of the grass classes, due to their similar spectral response exhibited by such closely related cover types.

EN conducted a statistical comparison of the means of species richness on the SPTA grassland types. Three groupings of the grassland types were found to be statistically significant. It was found that there was a difference between the three groups, but not within them regarding species richness and structure. The groupings were; (i) MG1; (ii) CG3d & CG3di, and (iii) CG3a & CG3a/di. These groupings reflected distinct noda along a continuum, relating from left to right, taller rank mesotrophic species poor communities to short turf species rich communities and therefore were less of an arbitrary division. It was therefore on this basis that the different sub-community types were amalgamated into these three groupings to be used in the supervised training procedure and hence improve their automated classification.

8.3 Sources of Error and Problems Encountered in the Classifications

8.3.1 WSPTA Range Grass Classes

The first attempt at a national study of land cover using satellite derived data (Huntings, 1986) dealt with five major cover types. These were cultivated land, which covered all crops and included grass leys; grassland which comprised of improved and permanent grassland;

woodland; semi-natural vegetation and finally developed land. Considerable misclassification occurred between the crops and the improved grassland. In addition to this, large errors existed in the classification of permanent and improved grassland, and it was concluded that the degree of misclassification was directly related to the season that the imagery was acquired.

Spectral classification of satellite imagery, for the identification of semi-natural vegetation classes, was found to be difficult due to the fact that within-class variance was often greater than the variance between classes. Blazye (1987), in attempting to map semi-natural vegetation found that the overall accuracy was low. It was suggested that the 30m resolution of TM whilst sufficient for the classification of homogeneous vegetation i.e., arable crops; was insufficient in areas such as grassland where the accuracy was less reliable, since the vegetation cover varies considerably within the 30m pixel area. The semi-natural nature of the SPTA grasslands meant that the range classes were very heterogeneous and therefore difficult to extract in classification. The complex nature of grasslands have been addressed in several previous chapters of this thesis (see Chapter Three, section 3.3; Chapter Six, section 6.1.4.1 and Chapter Seven, section 7.3.3.1.1.1.).

The ground survey itself was not without its own difficulties; the rangeland grass vegetation sub-communities were found to be very complex, with subtle variations not easily explained by EN's own National Vegetation Classification Scheme developed for ground surveys. It was apparent that EN field operatives found that there was considerable variation within the CG3d sub-community i.e., that this association sometimes approached class CG3a floristics in the field and at other times the observation in the field matched well the text book NVC CG3d description. Field observations also found that the floristic boundaries between calcareous grassland CG3d and the mesotrophic or neutral MG1 grass type, were somewhat blurred (Porley, 1989). The collection of ground data is a subjective process, the influence of operator error of the survey personnel is not usually addressed (Curran and Williamson, 1985). Curran and Williamson, found error associated with the ground data exceeded the estimated error contained in the remotely sensed data. Therefore, the field map is itself a subjective document based on apparent dominance rather than quantitatively defined classes. Field operator error was not assessed in this study.

Also few studies have been conducted that attempt to discriminate grasslands down to specific species dominant type from satellite sensors, this is because of the complex nature of grasslands. However, a few such studies have been attempted. It was shown by Girard *et al.*, (1990), that it was possible to successfully differentiate calcareous grass range classes, using multi-seasonal SPOT data in France. Floristically different grass units were distinguished according to seasonal change in reflectance. A Bromus erectus dominant phytosociological range class was identified, as were seven other phytosociological classes dominated by other completely different grass species. The SPTA ranges of this study however, had just the equivalent of just two such classes; the Bromus erectus dominant (CG3) association and the neutral class (MG1) Arrhenatherum elatius, since all the other classes used in the analysis were Bromus erectus dominated sub-communities of this association. Such a detailed discrimination level may be well beyond the scope of space-borne sensors using spectral data alone. It is important to consider that to-date nearly all the land cover satellite classification applications found in the literature consider results successful if broad general land cover classes such as water, soil, woodland, crops and urban; achieve greater than overall 85% accuracy (Taylor *et al.*, 1983; Huntings, 1986; Pedley and Curran, 1991).

8.3.2 Unimproved Chalk (SSSI) Grassland : Wylye Study Area

Although few UK satellite studies have been conducted in relating grassland botanical parameters with spectral reflectance, other studies have attempted to map and classify grasslands with the emphasise on the landuse of grasslands. Previous attempts have been successful in differentiating between such grassland landuse types, however imagery was available from all the critical times spread out throughout the growing season. Fuller and Parsell (1990), were able with TM to distinguish between different grassland types under different management practises in lowland Britain. Managed, hay cut, grazed, standing hay and unmanaged non-agricultural rough grassland were all distinguished using multi-seasonal imagery. This study had only imagery from the late spring/early summer part of the season, and to make matters worse each date was from different years.

In attempting to classify the unimproved chalk grasslands in the Wylye study area, it was necessary to be able to discriminate them from improved grasslands present within the study area, as well as from other cover types. Improved grassland and grass leys in the scheduled MoD land in general, had a higher green component (Green Leaf Area Index) in May than the unimproved grassland. This was the predicted result (Trodd, 1987), when one considers management practises, such as fertilizer application, should produce a more vigorous growth. In the May TM image, unimproved grassland especially noticeable on the unmanaged range had a more persistent senescent component to their 'top or blanket cover'. It was too late in the growing season however, for the higher component of senescent vegetation or 'blanket cover' to be spectrally significant (Morten, 1986), for some of the SSSI sites which were agriculturally managed.

In the July TM image, it was possible to distinguish between the improved and unimproved grassland. In theory this is to be expected due to the red edge effect (Trodd, 1987), as a result of the interpretation of the 'spectral response pattern' in terms of the physical properties, which would be more pronounced for improved grassland. This is because of the greater vitality, less senescent cover and because soil moisture decreases the mid-infrared (IR) reflectance for improved grassland. The improved grassland has a more open canopy, such that background soil component influences the spectral reflectance. Unimproved grassland has a more closed canopy due to senescent material underlying the green leaf top cover.

In a NRSC study (1983), it was suggested that the blue/grey appearance on SPOT false colour composite (FCC) in May of rough grassland, was so because of the high proportion of dead senescent material within it. This type of grassland would be equivalent to the military rangeland of the SPTAs. Tones of pink/grey indicated the new seasons growth coming up through the dead material. Improved grassland displayed bright red tones, representing tall densely growing vegetation, dull darker red tones indicated shorter swards; whilst dark pink to blue/grey tones represented grass types under different management practises such as :- i) high proportion of senescent material, ii) recently grazed or iii) mown, and that these cover types showed quite large within-field variation. All these tones were present within the Wylye extract of the June SPOT imagery used in this study, but the later date meant that there was increased confusion with other crops, mainly cereals.

In the Wylye whole extract classification (Chapter Seven, section 7.4), the unsupervised procedure found two spectral classes relating to the informational cover class of chalk grass SSSI areas. Therefore, these two classes were used in the training procedure of the supervised analysis. The spectral classes occurred within the same field and/or between different fields; for the former this was probably due to local variables within fields; such as amount of herbaceous species, soil moisture, slope, aspect etc.; and for the latter these differences reflect the different management regimes imposed on them. The two spectral classes both achieved accuracies of 90% or over for the July TM-84 data. Usage of the two classifiers was comparable in terms of accuracy. This July period seems to be the optimum time of the year for this particular cover type. Watson (1979), used aerial photography and found that the best separation of herb-rich meadows from other cover types, was when all or most of the major herbaceous species of grasslands had reached their phenological peak. Milton and Rollin (1990), showed the importance of flowers as a canopy component in mid-summer and this could account for the discriminatory factor of the July TM data.

With TM-85 data, the unsupervised classification showed confusion problems with improved grassland. This was reflected in the supervised result where one class (SSSI I) was identified with 100% accuracy, whilst the other spectral class (SSSI II) produced a range of accuracy of between 52 to 77%. The SSSI II class was confused with improved grassland because it had less senescent carryover material from the previous season and a more pronounced green vigorous growth. In May therefore, the SSSI II class was confused with similarly growing improved grassland and growth stages of cereals.

Unsupervised classification of the SPOT data showed it was reasonably easy to separate the broader land cover classes such as bare/low vegetation, vigorously growing vegetation and woodland. Specific vegetation types such as grasslands and crops were confused with each other. Overall classification accuracy of the two SSSI classes was poorer compared to the TM results for supervised classification, because of confusions with agricultural crops. Grasses have been separated from other crops with multitemporal SPOT in early spring scenes of April and May imagery (Jewel, 1987). However, it was found that June and September scenes revealed confusion and overlap of reflectance with other crops eg, with cereals in June and root crops in September.

As a secondary part of this analysis of the Wylye study area (see Chapter Seven, section 7.4.1), it was attempted to classify just the single land cover category of the SSSI areas, by using the two spectral classes found by manual interpretation (McGuire *et al.*, 1989) and evident in the unsupervised analysis. TM-84 data gave an overall accuracy of 90% for the two classes, they were both above the generally accepted minimum accuracy level (85%). The TM-85 data had an overall accuracy of 84%, just under the minimum and the SPOT data failed completely in giving a good correspondence. SPOT's overall accuracy was 28%, due in part to the spectral resolution of the sensor, combined with problems of similar crop vegetation phenology in a June situation.

In the classification of the single category SSSI sites, this analysis used satellite images to locate all the unimproved chalk grassland provided by ground data and identified numerous other potential areas, which are areas for subsequent field survey, thus rejecting vast areas of arable land without the need for a full field reconnaissance.

8.3.3 Other Non-grass Cover Class Results

There is theoretical evidence (Chapter Three) that the structure of the canopy should provide discriminatory information. Deciduous trees have large umbrella canopies, whilst grasses exhibit shorter linear canopies. However, the strongly correlated growth phases in the leaves of grasses and deciduous trees provided some automated classification confusion. Visual interpretation using textual and contextual information, was more successful in the discrimination of these two cover types. With the June SPOT data broadleaved/mixed woodlands were highly confused with improved grasslands and winter cereals, there were also confusions between spring cereals and permanent chalk grasslands, due to the variability of growth of these cover classes. Similar findings were reported using S.SPOT May imagery by the NRSC (1983). TM bands 4 and 5, were found to be best in woodland discrimination and the May TM image was found to be the best in identifying woodland areas.

The May TM-85, the June SPOT and to some extent the July TM-84 images all showed confusions that were apparent between actively growing crops and grassland. Fuller and Parsell (1990) found that by incorporating October data, where there was stark spectral contrast between these two cover types, the problem was solved. It would therefore have been preferable to have multitemporal imagery from the different seasons, instead of data from three different years.

8.3.4 Summary

The classification errors incurred with the SPTA range grass units can be attributed to their closely resembling 'spectral response patterns'. However, high classification accuracies for non-grass and grass cover types, indicate the suitability of the classification approach in periodic grassland area updating. Taking into account the spatial complexity of the SPTAs, the obtained results can be viewed as acceptable for the inventory and subsequent management and monitoring of the SPTA ranges. The results of the evaluation of satellite imagery for the classification and mapping of the chalk grassland SSSIs in the Wylye study area were highly successful for the July TM-84 data, moderately successful for May TM-85 data, and limited when using SPOT data dated June.

8.4 Costs of Alternative Surveying Methods

As previously mentioned, ecological resource inventories are needed by agencies like EN, local authorities etc., who use these data through the planning process to allocate financial assets to present and future policies and management proposals. The 'soundness' of any conservation policy depends on the accuracy, detail, source and timeliness of this natural resource information.

A major problem facing resource managers is the lack of inventory data covering large areas; for instance, regional or national data bases (Krebs, 1978). Existing inventory data where available lack uniform and robust survey methodologies and do not have standardised accuracy levels.

Application of remote sensing technology can efficiently and cost effectively fill the data gaps. One key question therefore is the relative cost of remote sensing compared with other more traditional survey methods. A cost assessment should include work hours, travel, field work; and all the materials necessary for analysis/interpretation, accuracy assessment and production of final products.

Alternative natural resource surveying methods have traditionally been : i) conventional ground survey, and ii) aerial photography :-

i) Conventional ground survey : local, county or regional ecological ground survey tend to be intuitive, from local knowledge of enthusiasts, limited by means of access; but scientifically sound due to detailed botanical survey dealing with indicator species. More general national census ground surveys on land cover types are no longer logistically possible, the last such survey in England was performed in 1963 (Coleman and Maggs, 1965);

ii) Aerial photography : usually panchromatic and limited in areal extent, this format can be expensive for regional inventories.

With traditional manual air-photo interpretation all the information in map format has to be hand digitised if it is to be entered into a digital database. This increases cost and is very time consuming. The cost trade-off point between the manual analysis of aerial photography and the computer aided digital analysis of satellite imagery, depends upon the amount of area that needs to be covered, and the level of detail required by the user. For example, it makes sense to use satellite derived data the larger the area and the broader the classification legend.

The costs of the various survey methods are examined in detail for the Wylye SSSI analysis (Table 8.6), compiled for one 512 x 512 pixel extract which covers 225km^2 (2,250Ha). The costs are given for conventional ground survey, and the equivalent survey based on the interpretation of aerial photographs. The costs are also compared between the manual interpretation of satellite imagery and machine supervised classification of the digital data (McGuire *et al*., 1990).

In terms of cost per area, Fuller *et al*., (1989b) stated that :-

"the cost of TM imagery was equivalent to £ 0.10 per km^2".

In terms of EN economic objectives as mentioned in Chapter One, section 1.7, such an operational remotely sensed survey could replace the traditional phase I blanket survey. This could be done by initially stratifying the landscape and highlighting the specific cover types of interest : in this case, the identification of potential ecologically rich grassland. This results in the efficient pin-pointing of resources in terms of expertise of field personnel and time. Once these sites have been identified, field workers could be sent to do detailed botanical survey and assess potential sites not previously recorded, but classified from remotely sensed products.

In addition, the full field survey of the SPTA ranges took trained personnel two years to complete (Porley, 1989). Once the imagery was in-house, the satellite analysis would take much less time to process the images and interpret the results. Therefore, after initial field survey for botanical detail, the ranges could be monitored in the future using stratified field work derived from satellite imagery, for a fraction of the cost of subsequent full field surveys.

Table 8.6 : Cost of Ground and Remote Sensing Surveys

	Ground Survey *	Aerial Photography *	Satellite Data * Digital format (CCT)	Satellite Data * Photographic format (Prints)
Availability	Commissioned	Commissioned	Widely available	
Cost of Imagery	N/A	£ 525 - 750	£ 1,125 (Quarter scene)	£ 500
Time taken	2 - 3 man months survey & interpretation	3 weeks interpretation	4 - 6 Hrs (CPU) time	8 - 10 Hrs interpretation
Equipment	Survey materials & maps	Stereoscope Zoom transfer scope	Tape reader image processing system	Data transfer equipment
Total costs	£ 5 - 6000	£ 3 - 4000	£ 1500 - 1850	£ 900 - 1300

* Figures from the NRSC Ltd, 1992; and standard consultancy rates.

CHAPTER NINE

CONCLUSIONS

9.1 Introduction

There is a large body of published research in the USA, relating to crop/land cover classification using remote sensing techniques. However, this information does not transfer well in the context of the UK situation, due to different crops, farming practices, climate, geology and soils. Griffiths and Smith (1988) stated :-

> "that as yet there is little published research on cultivated land classification from high resolution satellite imagery in the UK".

Also UK studies of semi-natural environments have all tended to be focused in the highland areas and not in the lowland areas. Therefore, any further information on semi-natural cover types in lowland areas, that relate to identifying optimal image dates and image processing techniques, will help develop an effective methodology for routine and systematic monitoring and mapping.

It is apparent that more and more agencies interested in natural resources (from English Nature (EN) and local authorities, to county based natural trusts) have decided to develop and apply biological data bases. The digital nature of remotely sensed data makes it ideal for incorporation into a GIS, which is the ultimate data base for spatial information.

It is apparent that no comprehensive natural resource data bases exist in the UK (Fuller *et al* ., 1990; Fuller *et al* ., 1989a; Belward *et al* ., 1990). The few UK county phase I or census studies performed have had to use volunteers (wild-life trusts) or part-time MSC teams of variable expertise. The logistics and costs of these surveys impose a severe burden on national organisations (such as EN). Suitable baseline studies, using remotely sensed data of standard format, are needed to evaluate land cover and habitat changes on a local and county scale in the UK (Foody and Wood, 1987).

9.2 Aims of the Thesis

The prime aim was first to evaluate the extent to which satellite derived data could be used to compile an inventory of different range chalk grassland types in the Salisbury Plain area. The principle objective was to derive a methodology to classify chalk grasslands. This classification was based mainly on the 'spectral response patterns' of the different chalk grassland types.

The results show that satellite analysis did provide some contribution to the mapping of the very detailed sub-community categories, as defined by EN for the Salisbury Plain range areas, although the classification was limited in accuracy. By refining the methodology however, broader groupings interactively chosen with ecological significance, were successfully mapped with TM and SPOT data. Off the main range areas, isolated SSSI unimproved chalk grass fields were successfully mapped using July TM data, the other two dates (May TM and June SPOT) were of limited value.

9.3 Satellite Remote Sensing of Semi-natural Lowland Chalk Grassland

9.3.1 Image Band Selection

Qualitative, interactive, manual assessment of scene independent, original band FCCs is a good means of getting the 'user' to gain an understanding of target spectral characteristics and the associated sensor characteristics.

For visual display; and to facilitate image processing, the best three bands of TM were found to be a 4, 5 and 3, and SPOT 3, 2 and 1 FCC displayed on R, G and B colour guns. This allowed a detailed study of lowland semi-natural range vegetation communities and also of unimproved chalk SSSI grassland.

9.3.2 Classification Accuracy

The classification accuracy was assessed by comparison with the SSSI ground census by scoring the classification on a field-by-field basis. The range area class maps were assessed by a fully quantitative pixel-by-pixel approach with field verification vegetation maps.

9.3.2.1 WSPTA Range Study Area

The use of training areas as test verification areas give biased results (Pedley and Curran, 1991; Congalton, 1991). Therefore, for all subsequent classifications independent objective test verification areas were used.

The two most commonly used and widely available classification algorithms were tested in this study. With the two classifiers it could not be said categorically that one was better than the other. This study found that they generally gave comparable results : on occasions minimum distance performed better and at other times the maximum likelihood proved to be slightly more accurate. However, in a research situation maximum likelihood is recommended, but in an operational cost/benefit situation, minimum distance is suggested because of the savings in computer processing unit (CPU) time and thus expense. It may be that the extra improvement brought about by the use of maximum likelihood classifier is not considered sufficient to justify the increased complexity.

An application of a graphics mask over other non-rangeland cover types, was found to increase the accuracy of the classification of semi-natural grassland vegetation community types.

A 'per-field' classification (whereby every pixel is tested) is recommended where the appropriate amount of ground data information exists. The negative findings of this analysis (i.e., never greater than 40% classification accuracy overall) give a true indication of the ability of satellite senors, to map and inventory such closely inter-related grassland types, when using traditional supervised classification techniques. These grassland types were all inter-linked, differing only at specific sub-community level, and some of the sub-classes were unique to the Salisbury Plain MoD training areas (Porley, 1988).

The negative findings made it necessary to further refine the methodology. This was achieved by the application of a mask of agricultural cover types; by the addition of unsupervised classification information; editing of the classes according to confusion matrix errors, and by using ancillary statistical information provided by EN. By doing this, both the individual edited classes and the overall results were generally significantly improved. However, group class 3 comprising of the sub-community classes CG3a and CG3a/di, could not be reliably mapped.

It was found that in a comparison of the two sensors TM and SPOT, in the tertiary classification, that for lowland chalk range grass types the accuracy levels were not too dissimilar. This was rather unexpected : what was expected was that the better spectral resolution of TM (i.e., the inclusion of a mid-IR band) would out weigh the better spatial resolution of the SPOT sensor. The apparent success of the SPOT data could be explained in terms of the semi-natural grass classes heterogeneity and it's natural variation, in terms of it existing as a continuum. The classification results of the May TM imagery were less accurate than that for the other two dates, because in the spring scene the grassland cover types were not as discernible from other vegetation cover types as later on in the season.

9.3.2.2 Wylye Study Area

Individual SSSIs were generally found to be spectrally distinct on TM imagery; however with the May TM image some SSSI fields were confused with improved grasslands and cereals. The absence of spectral contrast present in the SPOT image meant that by automatic classification individual SSSI fields were not so readily discernible and therefore not so accurately mapped.

SSSI informational cover class classifications for the three data sets were found to be best with the July TM imagery, adequate with the May TM and unsuccessful with the SPOT June data. The application of SPOT data in monitoring SSSI chalk grasslands was found to be limited.

The use of automated supervised techniques to detect fields of permanent chalk grassland has been shown to be successful for practical operational purposes. However, it must be noted that with such a remote sensing study it is inappropriate to identify the ecological quality of these fields : such a survey would go hand in hand with the follow up complementary botanical field survey. The satellite survey is a method of segmenting the study area, detecting existing chalk grassland and also indicating potential sites of ecological interest.

From this part of the study the following conclusions are drawn. Using a relatively simple operational procedure the method of analysis using TM produced acceptable levels of accuracy for this study area. There is also the added advantage that if visual analysis is undertaken using satellite photographic prints, this is a simple exercise and does not require digital image processing equipment. Also it was found with the Wylye SSSI analysis, that the superior spatial resolution of SPOT does not override the better spectral resolution of TM.

It must be noted that just a single informational class was being identified, and that since the area of study was predominantly arable, TM spectral contrast with the grassland was high in July, as the cereals were ripening. The identification of other classes, or working in different geographical locations, may complicate the situation. This study was specific to the identification and mapping of potential and existing chalk grassland SSSIs only. However, the basic principles of the methodology are valid and simple adaptations of the proposed methodology could be easily implemented for other applications of direct interest to other agencies. Taylor *et al.*, (1983) discussed briefly the commercial market for operational programs in agricultural applications.

The evaluation of advanced sensor systems is needed now for operational applications by resource professionals, because the future will bring the development of low-cost image processing systems (Elgy and Chidley, 1987). This will mean that image processing facilities will become increasingly available to organisations with limited financial resources and, provided that the cost of remotely sensed products remain relatively low, there will be a much greater demand for satellite products.

9.3.2.3 Larkhill Study Area

Using the TM-84 data, the Larkhill test data set just produced comparable results with the WSPTA analysis, these results validate the spectral 'uniqueness' of the edited final classes used in the tertiary classification. However, the edited class group 3, made up of sub-community classes CG3a and CG3a/di, were unsuccessfully classified. This was in agreement with the results found with the WSPTA analysis and therefore suggests that when using traditional processing techniques with satellite data, these more species-rich, shorter sward range grass types do not have sufficient spectral discrimination to be reliably mapped.

9.4 Classification Problems Encountered

From these research findings, the main problems encountered in the classification of semi-natural vegetation using satellite imagery, appear to stem from the complex nature of many of the cover types. Their boundaries are not sharp distinct entities, but are more zones of transition and that traditional classifiers can be said to be inappropriate for their classification.

Belward *et al.*, (1990), remarked that :-

> "the satellite's view of Earth is not the same as that of the ecologist".

It is inappropriate to try to match classified satellite data with traditional field ecological division. If satellite data is used cover types must be identified such that they have both ecological significance and have some degree of spectral homogeneity.

Although there was some overlap between the species poor Arrhenatherum dominated (i) MG1 class; and the species richer Bromus dominated grassland groups (ii) CG3di & CG3d; and (iii) CG3a & CG3a/di : there was sufficient separation to justify keeping them as individual grassland groupings. The overall results suggest that the classification to the level of three grassland groupings as recognised by EN is a realistic goal.

This study found that, due to the inherent nature of semi-natural vegetation existing as a continuum, the different SPTA chalk original sub-community types could not be reliably separated using Landsat TM or SPOT data. Despite the negative findings regarding the separability of these specific chalk sub-community range classes, the range area itself was sufficiently spectrally unique in all three dates of imagery. The areal extent could be easily identified and this could used to serve as a base in future monitoring exercises by EN, by identifying reduction or fragmentation of the range by agricultural incursions. By amalgamating the original range classes into three groupings the classification was more successful, and this was tested to validate the results by using a different study range area (Larkhill). Finally, it was also found that the spatial distribution of chalk grass SSSIs could be isolated and mapped using satellite sensors, providing it was an appropriate sensor and the correct date of imagery.

9.5 Summary of the Findings

It was not the aim of this research to identify new functions that are needed for improving image processing, but rather the improvement of a robust methodology needed for operational systems in mapping of land use and cover.

It is apparent that the accuracy of the final classification maps is largely dependent upon a wide range of factors relating to the spectral contrast between the cover types to be classified and the spatial and spectral resolution of the sensor. The pertinent findings are summarised below :

* Use of training areas as test areas give biased results, as quoted in Literature.
* Overall classification accuracy is poor at the original class level; this is not really surprising when considering that most of the range grass units were <u>Bromus erectus</u> dominant and therefore very similar in physiognomy, type and structure.
* When overall accuracies were less than 50%, the application of a post-classification smoothing filter could reduce the accuracies and was therefore not a useful process.
* With the direct comparison between the TM and SPOT sensors, where the spatial resolution was the same (Chapter Seven, section 7.3.1), it was found that the SPOT data produced equivalent results in the range analysis. The data suggests that SPOT's three bands were as good as the best three TM bands, and that TM-5, the mid-IR band may be superfluous when discriminating chalk range grassland units dominated by one major species of grass. These results are difficult to explain, it was expected that the TM with its superior spectral

resolution would give significantly greater accuracy. When the two sensors were compared in their original format in the tertiary classification (Chapter Seven, section 7.3.4), the 20m spatial resolution of SPOT verses the 30m resolution of the TM data, no significance statistical difference was found.

* When investigating the dimensionality of the data in terms of the number of bands needed (referring specifically to the TM sensor) it was evident that the best three band subset was all that is needed, rather than the full compliment of available bands.

* By intelligent editing of the original classes in the refined tertiary classification groupings, classification accuracies were improved and this classification scheme was tested on a different study area.

* The careful selection of training and test areas was found to be very important, eg, with the initial and secondary classifications, very good results were achieved for the sub-community class of CG3a/di. In contrast, the accuracy level was very much poorer in the final tertiary classification, where different, more comprehensive test areas were used to assess this class's classification.

* Overall the performance of the two classifiers : maximum likelihood and minimum distance were comparable, however it was evident that individual classes varied in accuracy according to the classifier used.

* It was possible to identify and map unimproved chalk grass SSSI fields using July TM imagery.

In conclusion this study has found that satellite derived data can be used for :-

i) directing detailed botanical field survey and generating inexpensive cartographic documents (hardcopy) for field workers;
ii) the routine monitoring and change assessments in areas such as the SPTAs, because of the repeatable systematic coverage offered by satellites;
iii) it could also be possible that classified satellite images could be used by EN to review their own mapping. The assumption that their field maps are 'definitive' can be questioned with regard to the associated error inherent in the field survey and that satellite mapping might provide a 'truer' picture in a generalised sense.

These findings support the claim that TM provides accurate cover and distribution data at a scale of individual fields for most major land uses. Fuller and Parsell (1990), stated that :-

"no other method could realistically do this".

The general principles of the methodology outlined in this project should apply to the classification of other environmental features using multispectral remotely sensed imagery.

Applied 'users' need to be aware, that if successful operational procedures are to be made, then the image analyst needs to :-

* understand the characteristics of the target features,
* be familiar with the characteristics of the imagery and with image processing techniques.

As mentioned previously in Chapter One and Chapter Eight, there are considerable advantages to satellite remote sensing, these are now briefly summarised :

* That traditional data sources of information are often found to be inadequate; be it survey maps, aerial photography, or specialised data bases. Some data may be out of date, information may be lacking in certain themes, and data from different sources are often unsuitable for direct comparison. However, satellite data offers itself as a single-source data and this is recognised as a major step foreword in environmental studies (Hersan, 1991).

* Field work can be substantially reduced when using satellite data, and great savings in cost can be made over conventional ground surveys.

* More importantly, satellite data is digitally based and permits ready incorporation into a GIS and other data bases which include :-

i) new information from image analysis giving an up-to-date overview on land cover information on the distribution of major cover types including farmland, semi-natural vegetation and woodland;
ii) digital geocoded data : the information is extensive and accurate; it can be overlaid on standard topographical maps; it is easy to combine ancillary data; scales can be varied without loss of information quality, and map updating is greatly facilitated;
iii) the data can, subject to cloud cover be thoroughly up-to-date, acquired in real time, and finally
vi) follow up environmental monitoring studies can be quickly completed by acquiring additional imagery at a later date.

9.6 Recommendations for Future Work

Further testing is recommended of the two other temporal data sets (TM-85 and SPOT-86) on the other range areas on Salisbury Plain and/or the further testing of the methodology on other areas in lowland Britain where chalk grasslands occur.

It is further recommended that panchromatic (P) SPOT data of 10m resolution be acquired and merged with Landsat TM bands 4, 5 and 3, via an Intensity, Hue and Saturation (IHS) transformation. Thereby combining the merits of both sensors for a truly powerful tool of spatial and spectral information (Chavez *et al.*, 1991). With such imagery, in a field-by-field survey as used in the SSSI analysis, it is envisaged that such a natural resource survey tool would be of great benefit for county or regional biological databases and as a base-line input into environmental GIS applications.

A brief exploration of the more sophisticated classification techniques currently being researched was given in Chapter Three and Chapter Six with regard to semi-natural vegetation. Recent work has been published (Foody and Wood, 1987; Trodd *et al.*, 1989; Foody and Trodd, 1990), which suggest that successful development of probability measurements are more in tune with what is the true situation on the ground - with regards to semi-natural vegetation existing as a continuum. Other approaches along the same lines are currently being investigated. Foody (1992) evaluated a 'fuzzy' set algorithm to model semi-natural heathland through its continua. It was found to be more appropriate than a conventional image classification. The fuzzy membership functions derived from the analysis were related to canopy composition and were suggested to be a more useful input into GIS, because it reveals gradual transitions between classes, not the sharp artificial boundaries characteristic of most classified scenes and thematic maps. These forms of analysis will probably be used in the future with regard to these types of vegetation communities and remotely sensed data.

Finally, it is recommended that 'per-field' analysis be undertaken with specific single category class classifications, such as with the fragmented unimproved chalk grass SSSI sites. Also that probability measurements or fuzzy set approaches be used in the classification of semi-natural vegetation as in the SPTA range areas, where no arbitrary borders exist, but rather ecozones of transitions occur along continua and not as mutually exclusive discrete classes.

In the general sense of remote sensing research and development Townshend (1992), provided a recent review of the European effort in remote sensing and described the research challenges of the future. A brief summary of the main points stressed were :-

* the need for improving methods of information extraction by contextual information and per-field based methods;
* the much more wider use of new sensors such Earth Resources Satellite (ERS-1) and the micro-wave sensors;
* the matching of sensor characteristics to informational needs for land cover applications;
* and the moving towards more operational uses of remotely sensed data.

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APPENDIX 1

IMAGERY CHARACTERISTICS :-

Table A1.1 : SUBSCENE DATA SET DETAILS

Imagery	Origin	Size (No of pixels)	No of bands
TM-84	x-5 y-126	1250 750	5
TM-85	x-0 y-0	1250 750	5
SPOT-86	x-0 y-0	1850 850	3

Table A1.2 : EXTRACT (WSPTA) DATA SET DETAILS

Imagery	Origin x y	Size (No of pixels)	Spatial resolution
TM-84	90 236	512 512	30m
TM-85	85 110	512 512	30m
SPOT-86	35 320	512 512	20m
SPOT-86	540 320	512 512	20m

APPENDIX 2

GROUND REFERENCE DATA :-

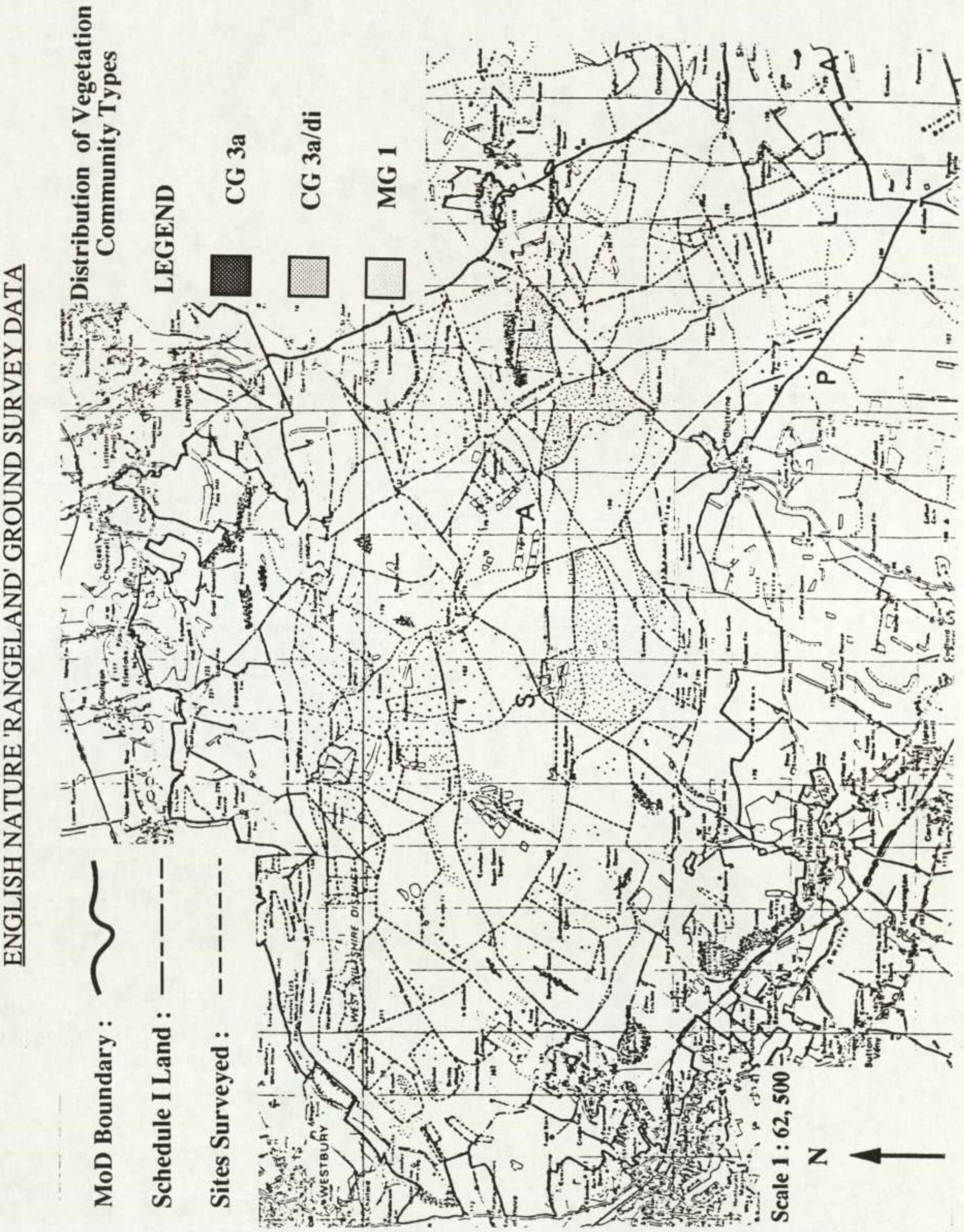

Figure A2.1 : Field Data on the Distribution of Grass Community Types, WEST SPTA

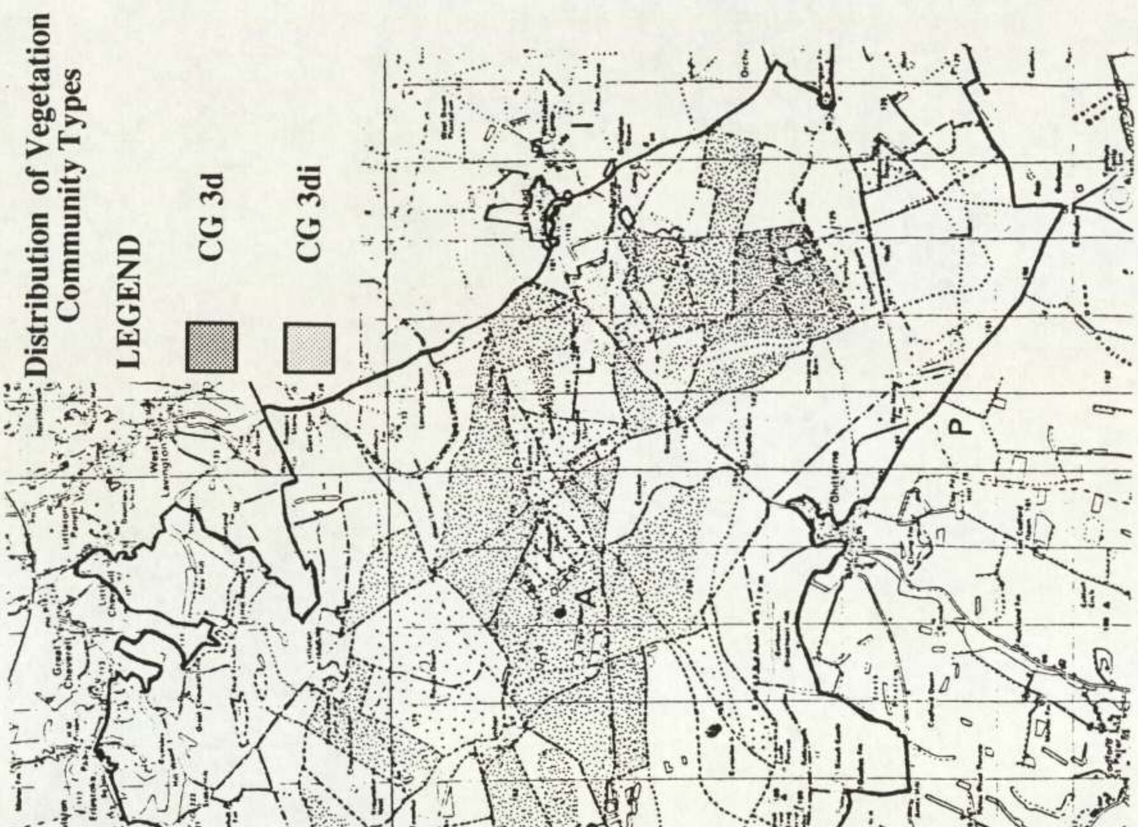

Figure A2.2 : Field Data on the Distribution of Grass Community Types, WEST SPTA

APPENDIX 3

GROUND REFERENCE DATA :-

AGRICULTURAL 'GROUND DATA' IN THE FORM OF FARM RECORDS

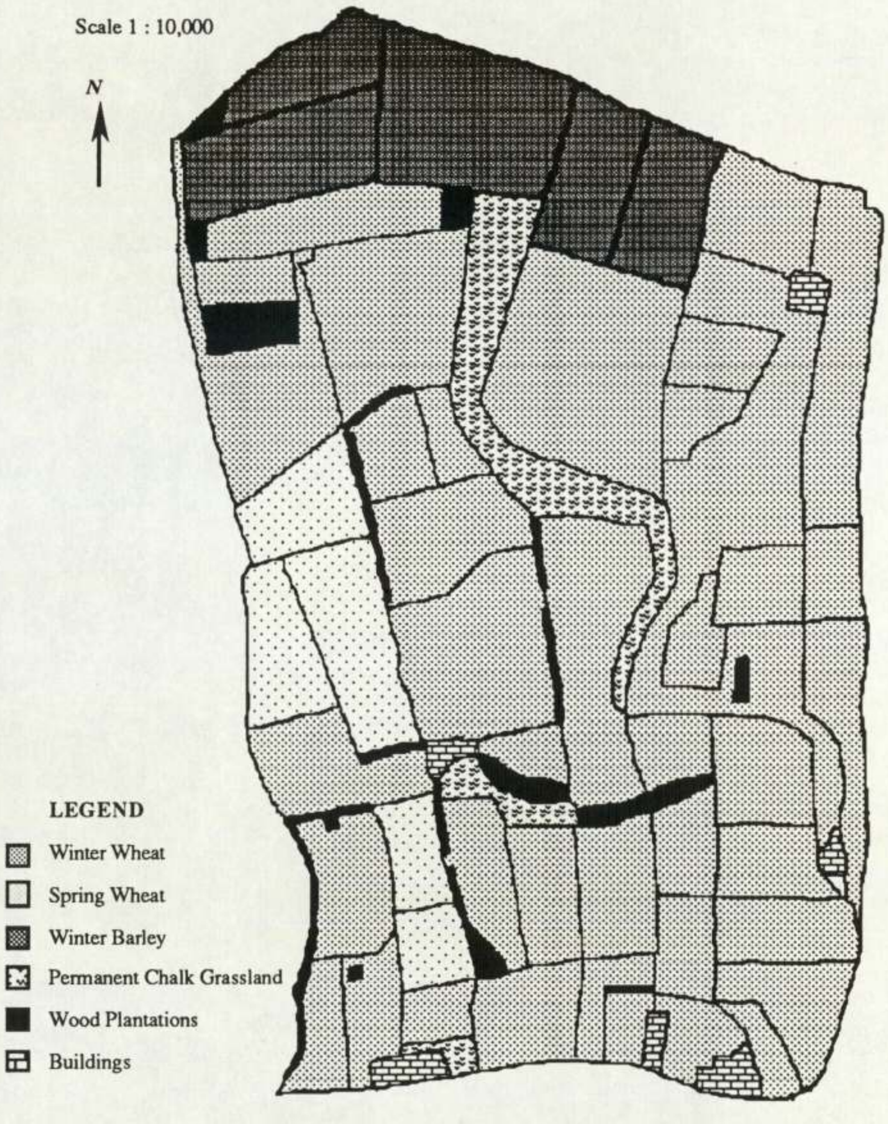

Figure A3.1 : Map of Crops Grown, Manor Farm, Wylye, Wiltshire, 1984.

APPENDIX 4

CORRECTION OF THE IMAGERY :-

GEOMETRIC CORRECTION

The correction was carried out using a least squares fit to a polynomial of the form (Jensen, 1986) :-

$$x = a + bX + cY + dXY \qquad \text{(A2.1)}$$

$$y = e + fX + gY + hXY \qquad \text{(A2.2)}$$

where : a - h are constants

(x,y) are the old image pixel co-ordinates and

(X,Y) are the new image pixel co-ordinates (measured in metres)

Table A4.1 : THE EQUATION COEFFICIENTS, GCPs AND THE RMS ERROR

T Matrix

X	Y
-37.58203	160.3408
0.9791622	-0.2168493
0.2247314	0.9758749
-5.5544078E-06	-2.5816262E-06

POINT	REAL X	REAL Y	PREDICT X	PREDICT Y	ERROR
1	165.0000	246.0000	167.0811	245.1850	2.2350
2	150.0000	260.0000	148.9958	260.4759	1.1112
3	165.0000	266.0000	163.7290	266.4311	1.3422
4	179.0000	232.0000	179.5215	232.1737	0.5496
5	44.0000	248.0000	44.2807	247.8290	0.3287
6	282.0000	497.0000	282.4217	497.3201	0.5294
7	639.0000	700.0000	638.8839	701.4540	1.4586
8	666.0000	723.0000	666.3268	722.9545	0.3299
9	260.0000	726.0000	259.6745	724.8987	1.1484
10	1164.0000	245.0000	1163.3464	244.6709	0.7318
11	1186.0000	325.0000	1186.5713	325.3052	0.6477
12	1156.0000	624.0000	1158.3159	623.8908	2.3185
13	1167.0000	671.0000	1164.7013	670.5034	2.3517
14	1073.0000	689.0000	1072.6180	689.1249	0.4019
15	914.0000	561.0000	914.5619	560.9006	0.5706
16	304.0000	210.0000	302.9503	209.9050	1.0540
RMS error for the whole data set					**1.26827**

APPENDIX 5

SUPERVISED CLASSIFICATION, TRAINING INPUT :-

TRAINING AREA STATISTICS

An example of a training area file with the standard statistics generated is now given. The file is [ctrain84.csd] and was used in the Tertiary supervised classification, Chapter seven, section 7.3.4.2.1.1 and also used in the test area (Larkhill) supervised classification, section 7.5.2. The classification was carried out using TM-84 data, bands 4, 5 and 3, on the masked WSPTA range study area, where the grass classes were edited into three groupings. Altogether *a priori* input knowledge for seven land cover classes were input, with which to train the classifier.

[**Ctrain84.csd**] : FILE

7 No. of Classes   3 No. of Bands

0 Class No. (Class 1 : MG1)   0 Colour assigned class (Red)
387 No. of pixels in training class
0 Band on Red display store (TM-4)
106.077519 Mean pixel value 2.917552 Standard deviation
99 Minimum 115 Maximum values
1 Band on Green display store (TM-5)
88.679587 Mean pixel value 2.650774 Standard deviation
83 98 Min - Max values
2 Band on Blue display store (TM-3)
38.687339 Mean pixel value 1.564807 Standard deviation
35 46 Min - Max values

Bands	TM-4	TM-5	TM-3	
TM-4	8.5	0.6	-0.3	Covariance Matrix
TM-5	0.6	7.0	1.8	
TM-3	-0.3	1.8	2.4	

1 Class No. (Class 2 : CG3di & CG3d) 1 Colour assigned class (G)
450 (No. of Pixels)
0 (TM-4)
92.486667 (Mean) 4.245375 (Std.dev)
86 108 (Min - Max)
1 (TM-5)
90.046667 2.586594
83 100
2 (TM-3)
38.335556 1.462471
35 44

18.0	0.0	0.2	Covariance Matrix
0.0	6.7	1.4	
0.2	1.4	2.1	

2 (Class 2 : CG3a/di & CG3a) 2 (Colour Blue)
373 (No. of Pixels)
0 (TM-4)
86.772118 2.173663
79 93
1 (TM-5)
96.697051 2.186694
89 103
2 (TM-3)
41.058981 1.291726
38 47

4.7	0.1	0.4	Covariance Matrix
0.1	4.8	0.8	
0.4	0.8	1.7	

3 (Class 4 : Bare/Low Vegetation) 3 (Cyan)
364 (No. of Pixels)
0 (TM-4)
99.112637 2.877854
90 107
1 (TM-5)
141.560440 5.329287
123 160
2 (TM-3)

65.008242 3.996891

53 76

8.3	6.7	7.2	Covariance Matrix
6.7	28.4	15.6	
7.2	15.6	16.0	

4 (Class 5 : Cereal) 4 (Yellow)

46 (No. of Pixels)

0 (TM-4)

112.956522 6.844159

100 124

1 (TM-5)

79.543478 3.751779

70 87

2 (TM-3)

43.130435 2.561325

38 49

46.8	-9.1	-9.0	Covariance Matrix
-9.1	14.1	6.6	
-9.0	6.6	6.6	

5 (Class 6 : Coniferous Woodland) 12 (Brown)

76 (No. of Pixels)

0 (TM-4)

83.750000 2.525206

78 92

1 (TM-5)

59.157895 7.002957

49 74

2 (TM-3)

30.881579 1.624538

29 38

6.4	6.8	2.4	Covariance Matrix
6.8	49.0	5.2	
2.4	5.2	2.6	

6 (Class 7 : Scrub/Broadleaved Woodland) 13 (Orange)

55 (No. of Pixels)

0 (TM-4)

115.545455 7.274558
100 127
1 (TM-5)
78.127273 3.421363
67 87
2 (TM-3)
34.090909 2.894904
30 41

52.9	12.6	-13.8	Covariance Matrix
12.6	11.7	1.1	
-13.8	1.1	8.4	

APPENDIX 6

QUALITATIVE CLASSIFICATION RESULTS :-

FROM CHAPTER SEVEN SECTION 7.3.4.2.1 FOR TM JULY 1984

Qualitative assessment of both minimum distance and maximum likelihood classifiers performance for all classes in the whole WSPTA extract are given below :-

Minimum Distance :-

1 MG1 - 30% of the range, not quite match NCC field map for this class

2 CG3di & CG3d - 40% of the range, quite a good match with EN 3di and 3d distributions

3 CG3a & CG3a/di - 30% of the range, some isolated classified areas off the range including roads and runways

4 Agri I grass (SSSI) - all green/yellow areas on FCC, picked out small areas within range

5 Agri II grass (SSSI) - all dull orange areas on FCC, completed SSSI I fields and classified complete fields of SSSI II status

6 Winter barley - distinct class fully classified

7 Winter wheat I - picked out all dark red wheat growth stage

8 Oil seed rape - distinct class (pink/orange on FCC) fully classified

9 Winter wheat II - picked out all dark dirty blue wheat growth stage

10 Bare/stubble - good correspondence with all the bare, stubble or mown areas

11 Urban - some good correspondence with urban areas and runways, but small bits of the range and areas in fields of winter wheat II also classified

12 Coniferous Woodland - some areas correctly classified, whilst other areas classified as winter wheat II

13 Deciduous or Mixed Woodland - this class was broadly classified correctly, however it was overclassified in areas that were winter wheat I i.e., the edges of fields etc.

14 Open cast quarry (chalk) - distinct class fully classified

Maximum Likelihood :-

1 MG1 - similar to the minimum distance result

2 CG3di & CG3d - similar to the minimum distance result

3 CG3a & CG3a/di - similar to the minimum distance result, but overclassified around the chalk tracks

4 Agri I grass (SSSI) - similar to the minimum distance result, but more of the NW pastoral region classified

5 Agri II grass (SSSI) - similar to the minimum distance result, but some confusion with crop areas

6 Winter barley - same as minimum distance

7 Winter wheat I - same as minimum distance

8 Oil seed rape - bright pink on FCC, smaller amount classified compared to minimum distance

9 Winter wheat II - similar to the minimum distance result

10 Bare/stubble - smaller amount classified compared to minimum distance

11 Urban - as well as urban areas it was vastly overclassified in wheat, bare/stubble and range areas, classifying from dark red/blue to light blue areas on the FCC

12 Coniferous Woodland - similar to the minimum distance result

13 Deciduous or Mixed Woodland - as well as broadleaved woodland areas it was vastly overclassified in urban and coniferous areas, classifying from dark brown/red to bright orange areas on the FCC

14 Open cast quarry (chalk) - same as minimum distance

APPENDIX 7

UNSUPERVISED CLASSIFICATION RESULTS :-

FROM CHAPTER SEVEN SECTION 7.4.1.1

Unsupervised Classification of the Wylye Extract, July 1984 TM (Bands 4, 5 and 3)

An unsupervised classification was first performed to give an indication of the number of spectral classes present in the imagery. Fourteen classes were chosen for the analysis and the resultant classes are described in terms of informational cover classes :-

Table A7.1 : Unsupervised Classification of the Wylye Extract, July 1984 TM (Bands 4, 5 and 3)

Class *	Colour on FCC	Informational class
1R	dark red/black	water, coniferous and mixed woodland and wheat
2G	pink	spring cereals, rape and some mixed woodland
3B	light green	stubble or mown
4C	orange/green	small part of range and schedule III land, some of SSSI fields and river meadows
5Y	dark blue	winter cereals
6M	orange	SSSIs fields fully or partially
7Lr	green	exclusive to and most of the range
8Lg	light blue	bare no vegetation
9Lb	bright red	cereal growth stage
10Lc	yellow/green	SSSIs fields partially and river valley meadows
11Ly	blue/black	small amount of winter cereal growth stage
12Lm	bright blue	winter cereal growth stage
13Br	bright purple	cereal growth stage
14O	light yellow/green	very small amounts of SSSIs permanent pasture

* for explanation of the annotated colour symbols see Table 7.7, where R equals red, G equals green etc.

FROM CHAPTER SEVEN SECTION 7.4.2.1 TM May 1985

Unsupervised classification of Wylye Extract, May 1985 TM (Bands 4, 5 and 3)

An unsupervised classification was first performed to give an indication of the number of spectral classes present in the imagery. Fourteen classes were chosen with an adequate number of peak value pixels to represent the natural clusters for the analysis and are described below in Table A7.2:-

Table A7.2 : Unsupervised Classification of Wylye Extract, May 1985 TM (Bands 4, 5 and 3)

Class	Colour on FCC	Informational class
1R	blue/grey	mainly rangeland, parts of SSSI fields and some urban
2G	mottled purple to white	mainly cereal areas, emergent growth with soil background
3B	bright reds/ oranges	mainly winter cereals, vigorous green growth, some river meadows
4C	dirty orange/ green	majority of SSSI fields full and partial and periphery part of range
5Y	green/black	all broadleaved and mixed woodland, some coniferous
6M	dirty black/ purple	cereal growth stage I, completed some fields that were classified as class 2, as well as some woodland
7Lr	brown/red	cereal growth stage II, completed fields that were classified as class 6
8Lg	blue/white	cereal growth stage III, more soil background influence
9Lb	black	water and some coniferous woodland
10Lc	pink/orange	crop I (spring oil seed rape)
11Ly	white	bare soil
12Lm	light blue	small amount of range, mostly bare/low vegetation class
13Br	bright pink/ orange	crop II (spring oil seed rape)
14O	grey	low vegetation or stubble

FROM CHAPTER SEVEN SECTION 7.4.3.1 SPOT June 1986

Unsupervised Classification of Wylye Extract, June 1986 SPOT (Bands 3, 2 and 1)

An unsupervised classification was first performed to give an indication of the number of spectral classes present in the imagery. Eleven classes were chosen with an adequate number of peak value pixels to represent the natural clusters for the analysis (Table A7.3).

Table A7.3: Unsupervised Classification of Wylye Extract, June 1986 SPOT (Bands 3, 2 and 1)

Class	Colour on FCC	Informational class
1R	dark red to pink to grey	majority of the rangeland, parts of SSSI fields, various cereal growth stages and broadleaved/mixed woodland
2G	light pink	portions or whole SSSI fields and more mature cereal areas
3B	black/reds to black/greens	mainly woodland coniferous and mixed also roads/hedgerows and copses, some within field crop variation and small amount of the range
4C	light to dark grey	low vegetation/bare fields and chalk tracks
5M	light green/grey	sections of roads and within field cereal variation
6Lr	blue/white	predominantly bare, small vegetation component
7Lg	light pink/white	predominantly bare, some significant green emergent vegetation growth
8Lb	white	bare
9Lc	grey	low vegetation/bare fields
10Ly	pink/orange	water
11Lm	bright pink	mature cereal

FROM CHAPTER SEVEN SECTION 7.5.1 TM JULY 1984

Unsupervised Larkhill Range Classification

Unsupervised classification was undertaken to give an idea of the number of spectral classes present and to see how they related to WSPTA. Seven significant peak number of classes were found. The statistics and how they relate to the ground cover types are given by Table A7.4.

Table A7.4 : Unsupervised Class Statistics Larkhill Range, July 1984 TM (Bands 4, 5 and 3)

Class	Colour on FCC	Band means 4	5	3	Informational class
1R	green/blue to grey	90	80	36	80% of the rangeland
2G	light green/grey	90	100	42	10% of the rangeland
3B	orange	110	80	33	5% of the range mainly on periphery and schedule III land
4C	light grey/blue	90	120	51	low vegetation/bare fields on schedule III land and chalk tracks
5Y	black/blue	50	60	36	some coniferous areas, mainly areas of burnt range
6M	purple	65	75	36	areas linked to burnt areas (mixels)
7Lr	black	35	35	30	burnt areas

APPENDIX 8

GROUND REFERENCE DATA :-

WYLYE STUDY AREA

Permanent Chalk and SSSI containing Grassland

Table A8.1 Ground Data used in the Wylye Study Area Analysis

COUNTY/SELECTION AREA : WILTSHIRE

Site Name	Grid Ref	Site Area (Ha)	Habitat Type : Grass	Notes
Corton down	SU928387	19.9	basic/calc, lowland	
Parsonage down	SU050412	188.6	basic/calc, lowland	rich Wessex downland, archaeological interest
Scratchbury & Cotley hills	ST915437	53.5	basic/calc, lowland	out standing insect fauna
Starveall & Stony down	ST992404	19.0	basic/calc, lowland	rich Wessex grassland
Steeple Langford down	SU037387	21.1	basic/calc, lowland	Wessex type grass
Stockton Wood & down	ST958366	61.5	basic/calc, lowland	orchid rich area
Tytherington down	ST912385	6.1	basic/calc, lowland	
Well bottom down	ST957417	16.3	basic/calc, lowland	
Wylye & Church dean downs	SU003360	72.8	basic/calc, lowland	vital site for Wessex grassland
Yarnbury castle	SU037403	9.1	basic/calc, lowland	archeological interest

APPENDIX 9

LIST OF NOTATIONS :-

TM	Thematic Mapper
ATM	Airborne Thematic Mapper
SPOT-HRV	Systeme Probatoire d'Observation de la Terre - High Resolution Visible
S.SPOT	Simulated SPOT
MSS	MultiSpectral Scanner
EN	English Nature
SPTA	Salisbury Plain Training Area
WSPTA	Western Salisbury Plain Training Area
ESPTA	Eastern Salisbury Plain Training Area
NVC	National Vegetation Classification scheme
MG	Mesotrophic Grassland
CG	Calcarious Grassland
ITE	Institute of Terrestrial Ecology
SAR	Synthetic Aperture Radar
AVHRR	Advanced Very High Resolution Radiometer
USGS	United States Geological Survey
DIPS	Digital Image Processing System
CCT	Computer Compatible Tapes
RAE	Royal Aircraft Establishment
FCC	False Colour Composite
SFCC	Standard False Colour Composite
TCC	True Colour Composite
NRSC	National Remote Sensing Centre
GCP	Ground Control Point
BGN	British National Grid
RMS	Root Mean Square
PCA	Principle Component Analysis
OIF	Optical Index Factor
GLAI	Green Leaf Area Index
BRDF	Bidirectional Distribution Function
NDVI	Normalised Difference Vegetation Index
TD	Transformed Divergence
IR	Infra-Red
BV	Brightness Value
DN	Digital Number
KB	Knowledge Base
CPU	Computer Processing Unit
GIS	Geographical Information System
SECHO	Supervised Extraction & Classification of Homogeneous Objects
DEM	Digital Elevation Model
LUT	Look-Up Tables
ANOVA	Analysis of Variance