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A Critical Evaluation of Remote Sensing Based Land Cover Mapping Methodologies

PhD Thesis

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Natural Resources Department, School of Applied Sciences

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A novel, disaggregated approach to land cover survey is developed on the basis of land cover attributes; the parameters typically used to delineate land cover classes. The recording of land cover attributes, via objective measurement techniques, is advocated as it eliminates the requirement for surveyors to delineate and classify land cover; a process proven to be subjective and error prone. Within the North York Moors National Park, a field methodology is developed to characterise five attributes: species composition, cover, height, structure and density.

The utility of land cover attributes to act as land cover 'building blocks' is demonstrated via classification of the field data to the Monitoring Landscape Change in the National Parks (MLCNP), National Land Use Database (NLUD) and Phase 1 Habitat Mapping (P1) schemes. Integration of the classified field data and a SPOT5 satellite image is demonstrated within per-pixel and object-orientated classification environments. Per-pixel classification produced overall accuracies of 81%, 80% and 76% at the field samples for the MLCNP, NLUD and P1 schemes, respectively. However, independent validation produced significantly lower accuracies. These decreases are demonstrated to be a function of sample fraction. Object-orientated classification, exemplified for the MLCNP schema at 3 segmentation scales, achieved accuracies approaching 75%.

The aggregation of attributes to classes underutilises the potential of the remotely sensed data to describe landscape variability. Consequently, classification and geostatistical techniques capable of land cover attribute parameterisation, across the study area, are reviewed and exemplified for a sub-pixel classification.

Land cover attributes provide a flexible source of field data which has been proven to support multiple land cover classification schemes and classification scales (sub-pixel, pixel and object). This multi-scaled/schemed approach enables the differential treatment of regions, within the remote sensing image, as a function of landscape characteristics and the users' requirements providing a flexible mapping solution.

Chapter Four: Field Survey Implementation

Chapter Five: The Classification of Remote Sensing Data

Chapter Eight: Conclusions and Implications

Appendices

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ANN	Artificial Neural Network	**MLCNP**	Monitoring Landscape Change in the National Parks
ANOVA	Analysis of Variance	**MMU**	Minimum Mapping Unit
API	Aerial Photograph Interpretation	**NCC**	Nature Conservancy Council
BGS	British Geological Survey	**NDVI**	Normalised Difference Vegetation Index
CORINE	Co-ordination of Information on the Environment	**NLUD**	National Land Use Database
DEM	Digital Elevation Model	**NSRI**	National Soils Research Institute
DN	Digital Number	**NVC**	National Vegetation Classification
DSM	Digital Surface Model	**NYMNP**	North York Moors National Park
DTM	Digital Terrain Model	**NYMNPA**	North York Moors National Park Authority
FCM	Fuzzy C-means Algorithm	**OASIS**	Optimising Access to SPOT Infrastructure for Science
GCP	Ground Control Point	**OLS**	Ordinary Least Squared
GIS	Geographical Information System	**ORI**	Orthorectified Image
GLUD	Generalised Land Use Database	**P1**	Phase 1 Habitat Survey
GPS	Global Positioning System	**PCA**	Principal Components Analysis
GWR	Geographically Weighted Regression	**PCM**	Possibilistic C-Means Algorithm
HRG	High Resolution Geometric	**PDOP**	Percent Dilution Of Position
IFSAR	Interferometric Synthetic Aperture Radar	**PSU**	Primary Sampling Units
JM	Jeffries-Matusita Distance	**RMSE**	Root Mean Square Error
LCM2000	Land Cover Map 2000	**SMA**	Spectral Mixing Analysis
LCMGB	Land Cover Map of Great Britain	**SMPID**	Sample Point Identification number
LGN	Dutch Land Use Database	**SPOT**	Le Système Pour l'Observation de la Terre Satellite
LIDAR	Light Detection And Ranging	**SSC**	Scaled Percentage Top Cover
LMM	Linear Mixture Modelling	**SSU**	Secondary Sampling Units
LUCAS	Land Use/Cover Area Frame Survey	**SVI**	Spectral Vegetation Indices
ML	Maximum Likelihood Algorithm	**TERUTI**	Utilisation Du Territoire

CHAPTER 1

Land Cover Mapping and the Research Project

This chapter provides an introduction to land cover mapping. Introductory sections will define the term land cover and consider key concepts in the derivation of land cover classification schemes.

A literature review highlights issues surrounding the applicability of current land cover mapping approaches to common monitoring and management tasks. It is in the context of these land cover mapping issues that the research project is outlined.

Finally, the chapter will consider current land cover methodologies and their implementation within the United Kingdom. This review is intended to set the context for mapping developments as proposed by the research project.

1.1 Introduction

Knowledge of the Earth's surface materials and their use is an integral part of landscape monitoring, modelling and management. Consequently, up to date land cover information at global, national and local scales is a requirement for sustainable management of the environment.

An important distinction must be made between land cover and land use. The term land cover, in its strictest sense, is reserved for the description of features/materials on the earth's surface. This is opposed to land use which describes the human activities on, or the economic function of, the earth's surface. This terminology difference is exemplified by a sports pitch the land cover of which is grass, the land use 'amenities and recreation'.

From these definitions it can be demonstrated that land cover is determined directly from observation of the earth's surface whereas land use requires interpretation of the socio-economic activities which take place on that surface (Fisher *et al*, 2005). Remote sensors do not record land use activity directly; the sensor response is based on the characteristics of the earth's surface. However, the interpreter uses contextual information, for example, patterns, tones, textures, shapes and site associations to derive information about land use activities (Anderson *et al*, 1976).

The relationship between land cover and land use is complex. A single land use can be composed of many land covers or a single land cover contribute to multiple, differing, land uses. This situation is further complicated by land covers which support multiple, temporally variable land uses and the definition of land use types which do not necessarily contain the same land covers in all situations (Fisher *et al*, 2005).

The distinction between land cover and land use can become distorted within 'land cover' classifications; a trend which has been prevalent for at least the last 25 years (Fisher *et al*, 2005). Fisher *et al* (2005) attribute this distortion to a shift in mapping paradigm from being demand or application led to data driven, a shift which is related to an increased prevalence of automated satellite image classification, a drive towards an all encompassing classification scheme and a need to satisfy diverse user requirements (Fisher *et al*, 2005). As a consequence of these factors classification schemes typically incorporate both land use and land cover elements (Anderson *et al*, 1976; Di Gregorio & Jansen, 2000).

1.2 Land cover mapping and vegetation classification concepts

Classification produces a simplified, abstract representation of the current field situation based on well-defined diagnostic criteria (Di Gregorio & Jansen, 2000). Land cover mapping therefore represents the subdivision of the landscape into discrete, contiguous classes according to the properties of the earth's surface.

In relation to vegetated land covers this implies that plant species can be classified into discrete communities where a community represents a region of vegetation which is relatively uniform in structure and species composition (Kűchler, 1967). Inherent in this classification is the definition of what constitutes a plant community and hence defines the boundaries between different communities. Kűchler (1967) states that plant communities have so many characteristics as to prohibit inclusion of them all in vegetation classification. The author therefore identifies six main criteria on which the boundaries between plant communities can be delineated:

- Physiognomic
- Ecological
- Physio-ecological
- Areal geographical-ecological
- Dynamic-floristic
- Physiognomic-floristic

Of these criteria floristic and physiognomic characteristics describe the plant community structure. Floristic characteristics relate directly to the species composition of the community. Conversely, physiognomic characteristics describe the life form, structure and seasonal periodicity of those species. Remaining criteria describe characteristics outside the plant community structure including vegetative evolution of the community and the geographical location of the site relative to physical, chemical, water and human factors which influence community composition.

The classification of vegetation on the basis of different characteristics, that is, physiognomic, floristic or ecological criteria, will result in the delineation of different plant communities; for example, classification on the basis of ‘height’ and ‘cover’ will result in significantly different vegetation classes when compared to classifying the same features using ‘leaf phenology’ and ‘leaf type’ (Di Gregorio & Jansen, 2000). This relationship underlines the importance of defining the criteria on which the classification scheme will be based.

The criteria underlying a classification scheme typically reflect a particular task and can be influenced by map emphasis, scale and classification technique. Each of these factors will be further influenced by the user/policy requirements of the agency or institution responsible for the data (Comber *et al*, 2003). A consequence of this variability in classification criteria is varying definitions for what might be considered a single land cover type. For example, Lund (2004) identifies over 720 definitions of what constitutes a forested/wooded area.

This complexity in definition is illustrated by consideration of the basic land covers of land and water. It would seem simple to delineate land and water that is "until one considers such problems as seasonally wet areas, tidal flats, or marshes with various kinds of plant cover" (Anderson *et al*, 1976). Arbitrary decisions are required to delineate these land covers hence the importance of classification criteria. To ensure that any classification is repeatable and consistent criteria governing class definition must be well defined (Anderson *et al*, 1976; Di Gregorio & Jansen, 2000).

1.2.1 Hierarchical versus non-hierarchical classification schemes

Classification systems can be broadly categorised as hierarchical or non-hierarchical. The fundamental difference between these systems is that a hierarchical structure enables the inclusion of different levels of information. This is achieved via the systematic sub-division of broad-level classes to more detailed sub-classes typically as a result of increased diagnostic criteria (Di Gregorio & Jansen, 2000).

1.2.2 *A-priori* and *a-posteriori* classification definitions

Classifications can be devised before (*a-priori*) or subsequent (*a-posteriori*) to the description of plant community or land cover characteristics. *A-priori* classification schemes consider the land cover of the study area as a whole and the subdivision of these land covers into meaningful parts (Kűchler, 1967). Mapping of the study area requires the subdivision of plant communities into these pre-defined land cover classes. *A-posteriori* classifications define land cover classes on the basis of plant species characterised in the study area. Classes are typically defined via the clustering of species associations on the basis of similarity measures (Di Gregorio & Jansen, 2000).

1.2.3 Minimum mapping unit

The minimum mapping unit (MMU) of a classification scheme is defined as the size of the minimum area which can be depicted as belonging to any class (Anderson *et al*, 1976). Minimum mapping unit is a function of the classification scheme and the mapping technique implemented.

1.3 Land cover mapping issues

A review of land cover mapping within the United Kingdom (section 1.8) has demonstrated that at the present time in the United Kingdom there are:

- A number of existing land cover mapping products.
- A certain amount of overlap between land cover mapping products.
- A duplication of effort in collecting land cover information.
- A number of land cover, land use and habitat classifications currently in use.
- A variety of data collection methodologies.

Consequently, the identification of appropriate and direct comparison of land cover data sets within the UK is extremely complex (Perkins & Parry, 1996).

It is proposed, in this research, that land cover products, both within and outside the UK, are currently underutilised. This proposal was supported by a literature review, outlined below, which has identified a number of issues regarding current land cover mapping approaches.

1.3.1 General non-targeted products

Land cover maps are produced to fulfil general uses; they are rarely targeted to the needs of the user. Consequently, the map may not be at a suitable scale, level of accuracy or the classification scheme appropriate for the intended use. Such a problem has been highlighted in the Dutch market where the lack of a “customer-tailored product” has been detailed as one reason for low take up of LGN, the land cover classification map of the Netherlands. Research in this area has detailed the need for user tailored products from the updated LGN-2, however, interest was only expressed for such products produced in a digital format (Boogaard, 1996).

1.3.2 Mapping emphasis

Where land cover maps are targeted to a specific application, the mapping emphasis can limit the transferability of the resultant land cover product to other studies.

Mapping emphasis is often found to reflect the application for which the land cover map was developed.

In a study of the Cascade and Sierra Nevada Mountains, Basham May *et al* (1997) concluded that mapping within the area was focussed on detailing the forest resource with little emphasis placed on the mapping of shrub and meadow communities. This lack of emphasis limited the applicability of the available mapping resources to a study of these communities.

1.3.3 Rigid land cover classes

Reed (1997) concluded that inappropriate class definitions, for some applications, were a fundamental problem with current land cover products. This issue is typically linked to a-priori classification schemes which assume that all possible classes required by the user have been defined. The advantage of an *a-priori* classification scheme is a standardised classification output irrespective of area. However, the description of all land cover classes, required by all users, is often prohibitive (Anderson *et al*, 1976; Di Gregorio & Jansen, 2000).

Although many of the United Kingdom land cover products investigated (section 1.8) have a hierarchical classification scheme which enables the mapping of vegetation at variable levels of detail, the class definitions and hierarchy structure are pre-defined and therefore rigid restricting the user to a standardised classification schema.

1.3.4 Temporal resolution

Temporal resolution is identified by Reed (1997) as a fundamental problem of current land cover products. This issue of currentness is emphasised in land covers which are highly variable or seasonal in their characteristics; in such environments land cover products will quickly become outdated, or inaccurate, as a function of land cover change, degradation or succession.

1.3.5 Map accuracy reporting

Land cover products, derived from any source, will inherently contain error. However, within current land cover products it is not uncommon for map accuracy to be inadequately documented (Dicks & Lo, 1990). Such a tendency, to inadequately document accuracy, can lead to the incorrect assumption that map products show 'absolute truth' and can lead to the inappropriate use of the map product.

1.3.6 Compatibility

Differences in classification scheme are largely a function of the different rationales behind the mapping procedures. Differences exist not only in the number of classes but also in the parameters used to define these classes. For example, the National Vegetation Classification (NVC) scheme is based solely on species floristics whereas class definitions in the Phase 1 habitat classification include environmental, species composition and vegetation physiognomy criteria (Jackson, 2000). Such differences in classification scheme make detailed comparisons between classification products complex as no simple relationship exists between the classification schemes.

Problems of comparison can also result from modifications to the classification procedure. This is exemplified by the national land cover mapping products, Land Cover Map of Great Britain (LCMGB) and Land Cover Map 2000 (LCM2000), which due to changes in the classification methodology and classification scheme are not directly comparable (Fuller *et al*, 2002). Modifications to the classification methodology between the LCMGB and LCM2000 surveys reflect technical advancements in classification technology and changes in the mapping emphasis as a consequence of policy and user pressures (Comber *et al*, 2003).

1.3.7 Consistency

The lack of a systematic application of classification criteria, within current classification schemes, leads to issues of spatial inconsistency. These inconsistencies are attributable to class definitions which are imprecise, ambiguous or require subjective decisions regarding the diagnostic elements of the class (Di Gregorio &

Jansen, 2000). Adams *et al* (1992) in a comparison of Phase 1 habitat maps produced in seven eastern England counties concluded that map comparisons were impractical as a consequence of differing definitions of habitat type and site quality; "in many cases the habitat classifications used differed from each other and from the classification system developed in the Phase 1 survey handbook" (Adams *et al*, 1992). Subjectivity in the Phase 1 classification was further demonstrated by Cherrill and McClean (1999) in a comparison of habitat maps derived by 6 surveyors for the same study area. The authors concluded that the maximum agreement between any pair of maps was only 38.8%; the area of land agreed on by all surveyors was only 7.9%. Consequently, quality assessment is required to validate the consistency with which ecological maps are produced via field survey (Cherrill & McClean, 1999).

1.3.8 Indeterminate boundaries

The identification of boundaries between land cover types is a function of the abruptness and magnitude of change in vegetation composition. The more abrupt the composition change the more distinct the boundary. However, a boundary that is abrupt but which delineates a small change in magnitude is not necessarily easily detectable (Johnson *et al*, 1992).

The distinctiveness of boundaries, controlled by abruptness and magnitude of change, can be related to landscape composition. Burrough and McDonnell (1998) describe these landscapes in terms of the field/entity model. The field model includes landscapes characterised by a continuum of gradually changing land cover types. Conversely, landscapes in the entity model are typified by abrupt changes in land cover at hard boundaries creating a landscape represented by discrete parcels. As these descriptions imply land cover boundaries in the entity model are significantly more distinct that those in the field model.

Semi-natural environments are characteristic of the field landscape model as within these areas land cover boundaries are less frequent, distinct and diffuse in nature (Jones & Wyatt, 1988). Boundaries which do exist may be a consequence of management practices (e.g. differential grazing rates, draining or burning) or a change in substrate (Williams, 1987). Naturally diffuse boundaries can be further complicated by the superposition of human boundaries onto the gradual change (Kent *et al*, 1997).

The diffuse nature of these boundaries strongly influences the accuracy with which land cover is classified. Typically, land cover classification schemes try to place boundaries where, in reality, a gradient exists (Wood & Foody, 1989). This can lead to inappropriate or ‘erroneous’ mapping results with the choice of species, data type, sample design and edge detection methods all influencing the spatial position of the boundary (Fortin & Edwards, 2001).

The problem in land cover map production therefore becomes whether these transitional areas should be mapped in detail or broken into arbitrary classes on the basis of threshold values (Gimingham, 1972). Foody and Trodd (1993) argue that these transitional zones should be mapped in detail as they can represent important indicators of land cover change/degradation.

A number of classification techniques exist for the mapping of indeterminate boundaries. Schneider (1996) concludes that at least three alternative methods exist for the modelling of undetermined boundaries: fuzzy models, probabilistic models and data modelling. However, such methods are typically not implemented as standard in national land cover mapping approaches.

1.4 Research project introduction

The preceding literature review has identified a number of factors responsible for an under utilisation of current land cover map products: inappropriate scales, standardised classification schemes, high levels of data aggregation and the provision of 'general use' rather than customer tailored products. Such issues are compounded by the incompatibility of many current land cover maps produced at both a national and local scale.

In order to tackle these issues it is proposed that there is a requirement for a land cover mapping procedure which:

- Allows greater flexibility in land cover class definition.
- Is less reliant upon 'expert' judgement for boundary placement particularly in environments typified by continuums of vegetation change.
- Considers the characteristics of the environment in which land cover classification is being conducted.
- Tackles the issues that changing map emphasis has upon map comparisons.

Following Friedl *et al* (2001) current ecological remote sensing techniques can be split into two branches, the mapping of discrete vegetation habitats (via supervised and unsupervised classification) and the mapping of land surface bio-physical properties, for example, leaf area index, biomass or percentage cover. Traditionally land cover mapping concentrates on the first of these branches; the mapping of vegetation classes. In developing a more versatile approach to land cover mapping this research proposes the integration of the two branches of ecological study with less emphasis being placed on landscape subdivision during field data collection and subsequent classification.

1.5 Research aim and objectives

1.5.1 Aim

To evaluate remote sensing, geographical information systems (GIS) and field survey procedures for the parameterisation of land cover attributes for non-defined land cover classification.

1.5.2 Objectives

In achieving this aim the objectives of the research were to:

- Review current land cover mapping procedure.
- Identify a field site and establish appropriate measurement parameters for that site.
- Develop an appropriate sample design.
- Acquire detailed field survey data within the study area.
- Assess the suitability of ancillary data sources for spatial characterisation of land cover attributes.
- Develop and assess the quality of standard land cover maps produced from the field data collected.
- Assess the potential of a land cover parameterisation approach.
- Discuss the applicability of the techniques developed to other land cover environments.

1.6 Research implementation

The research study area was required to encompass a range of land cover types and boundaries, characterised by the field and entity models, against which a land cover mapping methodology could be developed. Consideration of the typical landscapes of the United Kingdom concluded that the upland national parks include land covers typical of both landscape models as the semi-natural heather moorlands, typical of the field model, are contrasted by the valley agricultural areas, typical of the entity model.

For logistical reasons the North York Moors National Park (section 2.1) and a focused 210km^2 sub-region (section 2.3) were the selected study areas. The importance of land cover maps in the management and monitoring of the vegetation resource of the National Park was demonstrated by reference to the objectives of the National Park Management Plan (section 2.1.4).

The research project methodology was subdivided into two major elements; firstly, a field survey, which described the current status of the land cover and subsequently the development of a methodology to allow the integration of this field data with remote sensing and ancillary data sources.

1.7 Land cover map derivation

The remainder of this chapter discusses current land cover mapping methodologies and their implementation within the United Kingdom. This review is intended to set the context for mapping developments as proposed by the research project.

1.7.1 Ground survey

Ground survey requires high levels of skill to ensure that field observations are consistent and accurate. When this high level of accuracy is achieved very detailed information about the composition and variability of the land surface can be recorded (Wyatt, 2000). Achievement of this high degree of accuracy is balanced against the labour intensive nature and high costs associated with the technique. It is these labour and cost implications which typical constrain ground surveys to localised areas.

1.7.2 Remote sensing survey

Remote sensing can be defined as the capture of information about the earth's surface properties, using the electromagnetic spectrum, by a sensor not in physical contact with the earth's surface. Remote sensing techniques are advantageous in the production of thematic land cover maps as they provide a spatially continuous representation of the earth's surface at a variety of spatial, spectral and temporal resolutions (Foody, 2002).

Airborne survey

Mapping of land cover via aerial photograph interpretation (API) has been an established technique since the 1940s (Lillesand & Keifer, 1987). Development of the technique, in addition to ground surveys, was a consequence of the extensive areas over which data could be cost effectively collected. However, this is at the cost of reduced capacity for detailed vegetation discrimination (Wyatt, 2000).

Land cover information is typically extracted from aerial photographs in a manual interpretation procedure which can be labour intensive over extensive areas. The advantage of this manual interpretation procedure is the contextual information available, and therefore inferences which can be made by the surveyor, in deriving land cover class.

Satellite remote sensing

Manual interpretation of digital remote sensing products is possible as exemplified by the CORINE land cover survey (section 1.8.1). However, with technical advances land cover maps are increasingly derived via the automated classification of satellite images (chapter 5).

Land cover maps derived from satellite image classification, and indeed ground survey and aerial photograph interpretation, are not without error. The accuracy of land cover maps, derived via automated classification techniques, is typically assessed against a reference dataset derived from a more accurate source, typically, ground survey. Accuracy assessments are made within a confusion matrix (section 5.4.1), a cross-tabulation of the two datasets (Congalton & Green, 1998). Misclassification errors, the incorrect labelling of land cover classes, by automated remote sensing techniques arise from:

- *Classification scheme:* Automated classification techniques are dependent upon the assumption that land cover classes, as defined in the classification scheme, can be separated on the basis of their multi-spectral characteristics. Cover types which are similar in their botanical and structural characteristics have similar reflectance properties. In such circumstances misclassification results from the spectral confusion of the land covers. This type of misclassification is particularly evident in classification schemes based on the floristic characteristics of plant species (Sannier *et al*, 2005).
- *Classification procedure:* Errors can be introduced into the land cover map as a consequence of the classification procedure implemented. Within automated classification techniques errors can be related to a number of factors including, inappropriate classifier training and the violation of classifier assumptions. For example, habitats defined on the basis of ecological criteria may consist of multiple species, soil types and moisture conditions. Consequently, the habitat exhibits a

multi-modal distribution limiting the applicability of many statistical classification techniques (Belward *et al*, 1990).

Studies have suggested a target accuracy of between 80% and 85% from automated remote sensing techniques (Anderson *et al*, 1976; Mather, 1999a). This statement is however deceptive as classification accuracy is strongly related to the spatial and spectral resolution of the observations relative to the target land cover classes (Mather, 1999a). When using remote sensing derived thematic data it is important to consider that classes will be variable in the accuracy with which they are mapped.

1.7.3 Complementary techniques

Wyatt (2000) concludes that ground survey, airborne and satellite remote sensing techniques each have their strengths and weaknesses (table 1.1) and as such should be considered complementary rather than competitive techniques. This interrelationship between the survey methodologies is demonstrated by the inclusion of detailed vegetation information, typically from ground survey, within automated classification training and validation.

Table 1.1: A comparison of ground survey, API and satellite remote sensing techniques for the derivation of land cover maps

Ground Survey	Aerial Photograph Interpretation	Automated Satellite Classification
Advantages		
• Very detailed information on vegetation and its spatial variability • Can provide information on subsurface conditions • Not weather dependent	• Cost effective solution over extensive areas • Often possible to infer land use from the context in which the land cover occurs • Possible to detect patterns not visible on the ground • Typically more accurate than automated classification techniques • Sub-metre spatial resolution	• Multi-spectral and band ratios (vegetation indices) provide additional information about the surface • Wide area of coverage • Temporal resolution of data capture • Lower cost implications than ground survey or aerial photo capture • Variable spatial resolution
Disadvantages		
• Labour intensive • Significant cost implications • Attention required to ensure consistency • Not easily applied to extensive areas • Problematic in inaccessible areas and difficult terrain • Revisits to study landscape change can be impractical limiting the temporal resolution	• Less detailed information mapped in comparison to ground survey • Weather dependent (excluding radar systems) • Weather dependency and capture costs can limit temporal resolution	• Weather dependent (excluding radar systems) • Contextual information not easily obtained in automated classification • Land cover classes must be defined so that they are spectrally distinct • Ground data /aerial photography required to calibrate classification algorithms

Adapted from: Wyatt (2000)

1.8 Current national and local land cover mapping schemes within the United Kingdom

The field of land cover mapping has been researched extensively with a number of land cover classification schemes and methodologies having evolved in the United Kingdom (table 1.2). This evolution of a variety of land cover products reflects changing public perceptions and a need for mapping organisations to meet different objectives regarding land cover monitoring and management (Perkins & Parry, 1996).

The remainder of this section will outline the classification scheme and classification methodology, where appropriate, for a subsection of land cover products available within the United Kingdom. These classification schemes were selected as they represent a variety of land cover classification criteria, classification methodologies, new classification developments and are schema for which maps are currently available within the North York Moors National Park.

Table 1.2: Selected recent land cover mapping products in the United Kingdom

Product	Organisation	Date of Publication	Coverage
Land Cover Map of Great Britain (LCMGB)	Department of the Environment Department of Trade and Industry Centre for Ecology and Hydrology British National Space Centre Natural Environment Research Council	1990 (Satellite imagery: 1990 +/- 2 years)	National
Land Cover Map 2000 (LCM2000)	Department of the Environment Centre for Ecology and Hydrology Natural Environment Research Council Environment Agency Countryside Council of Wales National Assembly of Wales Scottish Executive, Scottish National Heritage	2000 (Satellite imagery: 1997 and 1998)	National
Co-ordination of information on the Environment (CORINE)	European Commission European Environment Agency Centre for Ecology and Hydrology (UK agency)	Variable (UK: Based on LCMGB and LCM2000)	Pan-European
Phase 1 Habitat Survey (P1)	Joint Nature Conservation Committee Local Authorities County Naturalist Trusts	Variable	National (Implemented locally)
National Vegetation Classification (NVC)	Joint Nature Conservation Committee University of Lancaster	Variable	
Monitoring Landscape Change in the National Parks (MLCNP)	Countryside Commission Cranfield University National Park Authorities	1991	National Parks
Land Cover of Scotland (LCS88)	Scottish Office Scottish Natural Heritage Macaulay Land Use Research Institute	1998	Scotland

1.8.1 CORINE

CORINE, 'CO-ordination of Information on the Environment', is a programme commissioned by the European Union to develop procedures to map the land cover of member states. These procedures represent a standardised approach, which has been developed to ensure consistency and compatibility in land cover mapping across Europe (Bossard *et al*, 2000).

The CORINE classification scheme considers land cover and land use, resulting in 44 separate classes (Fuller & Brown, 1996). These 44 classes are grouped into a 3-level hierarchy (appendix A). An additional 4th and 5th level can be added to the hierarchy by member states wishing to meet specific conditions and priorities in that country (EEA, 2002).

Implementation of the classification scheme results in the mapping of land cover/use area features at a scale of 1:100,000 using a minimum mapping unit of 25ha (Fuller & Brown, 1996).

The recommended mapping methodology for the CORINE survey is computer-assisted photo-interpretation of satellite images with simultaneous consultation of ancillary data. Initially photo-interpretation was implemented on a hard-copy satellite image geometrically and radiometrically corrected in digital image processing software prior to printing. However, with technology advances it is now recommended that photo-interpretation is implemented in a soft-copy environment (Bossard *et al*, 2000). It should be noted that member states may have implemented methodologies different to that proposed, where agreed by the European Environment Agency, to produce comparable classification results. Within the United Kingdom Fuller & Brown (1996) present an automated method to convert the Land Cover Map 1990 (LCMGB) dataset to CORINE land cover classes.

1.8.2 Land Cover Map 2000

Land Cover Map 2000 (LCM2000), part of the Countryside Survey (2000), represents an update to the Land Cover Map of Great Britain (LCMGB) produced in 1990.

LCM2000 is a thematic classification of multi-spectral, multi-temporal satellite images captured by the Landsat Enhanced Thematic Mapper (ETM), Landsat Thematic Mapper (TM) or Indian Research Satellite LISS sensor (listed in order of preference). Multi-temporal images were captured to coincide with the main growing period, mid-May to late July, and winter period, ideally at the time of first frosts (Fuller *et al*, 2002).

LCM2000 classes are devised to enable the distinguishing of broad habitats, as defined under the United Kingdom Biodiversity Action Plan (described by Jackson, 2000). These broad habitats best match the 27 classes in level two of the LCM2000 classification (appendix A). Target classes, level 1 of the classification hierarchy, are defined to amalgamate the level two classes into groupings which could be consistently identified by multi-spectral classification. It should be noted that class definitions do vary compared to those of broad habitats; as reflected in the class nomenclature (Fuller *et al*, 2002).The final, third, hierarchical classification level contains a number of spectral variants of the broad habitats defined to aid thematic classification (Fuller *et al*, 2002).

In contrast to LCMGB, which implemented a per-pixel classification technique, LCM2000 is based on the classification of image segments. Segments represent groups of image pixels, broadly equivalent to land cover parcels, derived via the CLEVER-Mapping procedure. The CLEVER-Mapping procedure can be summarised into two separate stages: firstly, the identification of boundary features using edge-detection methods; secondly, the identification of image segments using region growing algorithms initialised at seed points located to avoid boundary features (Smith & Fuller, 2002). The classification of image segments was based on a maximum likelihood algorithm trained on a sample of known land covers. Subsequent to classification, a knowledge-based correction procedure was applied to allocate alternative class labels, where appropriate, to segments classified with low confidence or out of their natural context (Fuller *et al*, 2002).

1.8.3 Monitoring Landscape Change in the National Parks

The aim of the Monitoring Landscape Change in the National Parks (MLCNP) project was to obtain the distribution, and change over time, of a wide range of landscape features within the National Parks of England and Wales. Changes in landscape features were measured between two dates; firstly, the 1970s and secondly, the 1980s (Taylor *et al*, 1991a).

The classification scheme utilised within the MLCNP survey was based on the Hunting Technical Services, Monitoring Landscape Change in England and Wales project (Taylor *et al*, 1991a). However, modifications to the classification were made to meet the specific objectives of the MLCNP survey (Taylor *et al*, 1991a). Within the final classification scheme landscape features were divided into three groups; firstly, linear features for example, hedgerows; secondly, small or isolated (point) features for example, individual trees; and land cover types (area features). Land cover is classified into 38 classes arranged into a classification hierarchy of 3 levels (appendix A).

MLCNP land cover maps were derived from a census of surface features via API. Photographs were typically 1: 20,000 or 1: 25,000 scale black and white stereo photographs captured during the 1970s and subsequent to 1985, respectively, to reflect the multi-temporal nature of the study (Taylor *et al*, 1991a).

The API methodology identified area features, greater than $20m^2$, in the 1980s aerial photography which when drawn directly onto 1: 10,000 scale Ordnance Survey map sheets were classified according to the pre-defined land cover classification scheme. To ensure consistency between survey dates only areas of change, as identified in a comparison of the photograph sets, were mapped from the 1970s photographs. Land cover boundaries identified in the manual interpretation process were subsequently digitised within a geographical information system (GIS).

The MLCNP procedure included a validation and accuracy assessment process based on ground survey data collected within each National Park between 1988 and 1990.

1.8.4 National Land Use Database

The National Land Use Database represents a classification scheme developed with the aim of establishing a consistent, nationwide scheme for the description of land use and land cover (Harrison, 2006).

A revised classification definition for the NLUD scheme, version 4.4, was published in 2006 (Harrison, 2006). This classification scheme differs from those previously outlined as it is a multi-dimensional approach which distinguishes between land cover and land use. Consequently, land cover and land use are treated as discrete elements of the landscape.

Class definitions, for both land cover and land use, are represented in a two tier hierarchy consisting of orders and sub-groups (appendix A). The land use nomenclature contains 13 orders (e.g. forestry or transport) and 41 sub-groups (e.g. managed forest or car parks). The land cover nomenclature comprises 10 orders (e.g. woodland or permanent made surfaces) and 32 sub-groups (e.g. conifer wood or other made surfaces). To ensure consistency classes are coded using an alphanumeric system of four characters. The initial character defines the class as either land cover or use, C versus U, respectively. After this prefix two numbers identify the order and the final number the sub-group. For example, C011 indicates field crops.

At the current time there is no plan to implement a national NLUD survey (NLUD, 2007). Studies have however demonstrated the potential to integrate the NLUD classification with the Ordnance Survey Mastermap product (Harrison, 2002; Infoterra, 2005).

A generalised version of the NLUD classification has been surveyed at a national scale via adaptation of the Ordnance Survey Mastermap product to include land cover labels. The simplified Generalised Land Use Database (GLUD), implemented during 2005, contained only nine land use categories. These categories primarily describe land cover except buildings which are split according to their economic function; residential or commercial (GLUD, 2007).

1.8.5 Phase 1 Habitat Surveys

The aim of the Phase 1 habitat survey (P1) is to "provide relatively rapidly, a record of semi-natural vegetation and wildlife habitats over large areas of countryside" (JNCC, 1993).

Land cover definitions in the P1 survey are principally based on the dominant and characteristic plant species of the habitat. However, for certain land covers, particularly where vegetation is not the dominant component of the habitat, this information is supplemented with soil, land-use and hydrological information. These characteristics define 90, colour coded, habitat types (appendix A).

P1 habitat mapping is principally based on ground survey although aerial photograph interpretation may support the survey in particular to aid boundary delineation. The mapping methodology requires field surveyors to identify every homogenous area, parcel, of vegetation within the study area. Parcels are subsequently assigned to a land cover class on the basis of the pre-defined classification criteria.

Land cover parcels are mapped on 1: 10,000 (recommended) or 1: 25,000 scale Ordnance Survey maps implementing a minimum mapping area of 0.1 hectares or 0.5 hectares, respectively (JNCC, 1993). Information on land covers smaller than the MMU are made as 'target' notes linked to map annotations.

1.9 Thesis structure

Chapter 2: The North York Moors National Park

The North York Moors National Park is the geographical setting of this research. In this chapter the landscape of the national park, and study area in particular, is outlined to provide context for the mapping approach developed.

Chapter 3: Field Survey Design

Following an introduction to field survey, which outlines the importance of field data collection, this chapter concentrates on the development of the field survey design. The chapter can be subdivided into two main sections; firstly, the land cover attributes and their measurement and secondly, the sample design.

Chapter 4: Field Survey Implementation

Field survey development culminated in a full survey being conducted during the summer months of 2004. Chapter 4 reviews the implementation of this ground survey in terms of the sampling rates achieved, field data collation and GPS processing.

Chapter 5: The Classification of Remote Sensing Data

The primary application of the field survey data is its integration with remote sensing data to provide continuous land cover information across the study area. Within this introductory chapter the proposed classification techniques for this characterisation are outlined. In particular the subdivision of the methodology into two independent classification approaches, construction and parameterisation, is introduced.

Chapter 6: Land Cover Map Construction: Results and Analysis

The results of the methodology developed for land cover map construction are presented. The primary aim of the approach is to determine if an array of land cover maps, which display the same characteristics as current UK mapping schemes, can be derived from a single field survey dataset of land cover attributes. Per-pixel classification techniques are tested as a means of ‘constructing’ land cover classes similar to those of the MLCNP, NLUD and P1 land cover schemes.

Chapter 7: Land Cover Attribute Parameterisation

This chapter discusses a disaggregated approach to characterise the land cover attributes, as opposed to land cover classes, across the study area. This approach is landscape specific and as such concentrates on the field landscape model characteristic of the upland land covers.

Chapter 8: A Versatile Land Cover Mapping Approach

This final chapter discusses the development of a versatile land cover mapping approach as illustrated in this research project. Issues in the development and application of such an approach, with particular reference to current land cover mapping approaches and the identified stakeholder requirements, are discussed and conclusions drawn on the applicability of the approach to wider environments.

CHAPTER 2

The North York Moors National Park

The research was implemented in the North York Moors National Park specifically a 210km^2 area in the north-west of the region. This study area was chosen because of the range of landscape types, land cover types and management regimes contained within the region.

Chapter 2 describes the study area including geology, soils, climate and typical land covers. Current management and mapping of land cover in the region, in relation to the applicability of the current land cover mapping approach, is outlined.

2.1 Introduction: The North York Moors National Park

The North York Moors National Park (NYMNP), one of twelve national parks within England and Wales (figure 2.1), is located in north-east England near the towns of Scarborough, Whitby and Helmsley (figure 2.2). The Moors were designated a national park in 1952 due to the variety of landscapes they contain. This includes some of the most extensive tracts of heather moor found in England and Wales (NYMNPA, 2002).

Figure 2.1: The location (and year of designation) of the twelve national parks of England and Wales.

Source: Council National Parks (2007)

Figure 2.2: Major towns and villages within the North York Moors National Park

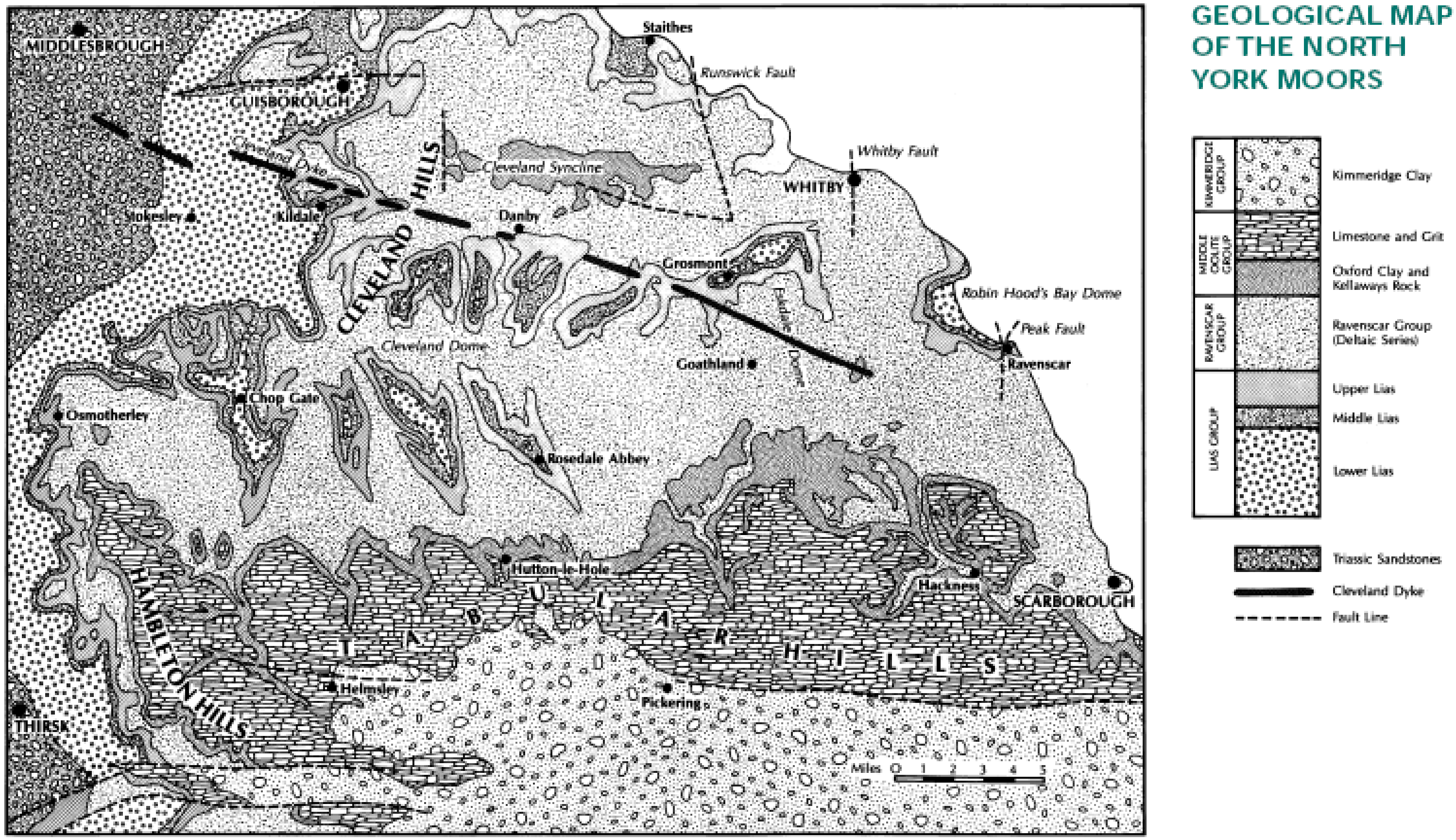
Source: NYMNPA (2002)

2.1.1 Physical description

The abrupt boundaries of the North York Moors in the east plus north and west, are formed by the coastal cliffs and Cleveland Hills, respectively. These boundaries are in contrast to a southern boundary of sloping agricultural land formed by a limestone belt which rises from the Vale of Pickering. Within these boundaries the park rises from sea level to an elevation of 454m on Urra Moor (NYMNPA, 2002).

The geology of the park (figure 2.3) was largely lain down during the Jurassic period with rocks being almost entirely sedimentary. These sedimentary rocks vary from limestones and sandstones to slates and mudstones depending on the conditions prevalent at the time of deposition. Three distinct deposition periods are evident. The Lias group, the oldest Jurassic rocks, are predominantly shale and underlie the entire area. Rocks from the middle Jurassic, the Ravenscar group, are extensive in the central moorland plateaus being characterised by sandstones and shales. The youngest Jurassic rocks are the Kimmeridge and Middle Dolite groups, typically limestone and gritstone in composition, deposited on the southern boundary of the park. This sedimentary rock sequence has been further modified by subsequent ice ages. Extensive deposits of boulder clay and sandy moraine hummocks result from the last retreating ice age (NYMNP Education Services, 1994; Sykes, 1993).

Variation in rock type across the park significantly influences vegetation patterns. The acidic sandstones support primarily heather moorland composed of blanket bog, dry and wet heath. This is in contrast to the limestone and calcareous grits, located at the southern park boundary, which support a greater plant diversity (Sykes, 1993).



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

Figure 2.3: Geological map of the North York Moors

Source: NYMNP Education Service (2007)

2.1.2 Climate

Precipitation

Prevailing winds in the north of England are moist and westerly. As these winds blow onshore much of the moisture is lost, as precipitation, over the Pennines and Lake District. A consequence of this loss of precipitation is the sheltering of the east coast and hence North York Moors which are characterised by relatively low rainfall in comparison to other upland areas. Figure 2.4 illustrates this west to east decrease in rainfall; annual totals fall from 1600mm in the Pennines and Lake District, located in the west of England, to approximately 700 or 800mm in the North York Moors. Although drier than the westerly upland areas, a trend of increasing rainfall with increasing elevation is evident in the North York Moors; values range from 600/700mm at the park boundary to 800mm on the central plateaus (figure 2.4). Some precipitation within the national park falls as snow during the winter months especially with increasing elevation.

Temperature

Average accumulated temperature, above zero degrees centigrade, between January and June is illustrated, for the north of England, in figure 2.5. This parameter is used to illustrate temperature variability due to its relationship with growing season (Jarvis *et al,* 1984). The North York Moors is characterised by a higher accumulated temperature, 1150 day-degrees, in comparison to western upland areas, for example, 950 day-degrees in the Pennines. This is a consequence of the lower elevation of the North York Moors and proximity of the region to the North Sea. Local variations in accumulated temperature are a function of elevation with temperatures tending to decrease, represented by lower average accumulated values, with increasing elevation (figure 2.5).

Climate and moorland vegetation composition

As a consequence of climatic variation, precipitation and temperature, across the north of England the upland habitats vary in extent, species composition and habitat structure. Thompson *et al* (1995) describe this variation in terms of a climatic and dry-wet gradient. The climatic gradient illustrates gross north-south and east-west differences in key upland species. The dry-wet gradient is characterised by a tendency for heath communities to dominate in the eastern, drier, uplands versus bog communities in the wetter western uplands.

The predominance of bog communities in the west and north of Great Britain, where they can form the climax community, is attributable to the higher precipitation values characteristic of these regions. If rainfall is sufficiently high there is the potential for active bog formation (Fielding *et al*, 1999). Eastern uplands typically contain drier heath communities although wet heath communities and groundwater controlled bog can occur as a consequence of local conditions. Bog communities in these eastern uplands tend to be less extensive and contain fewer species (Fielding *et al*, 1999).

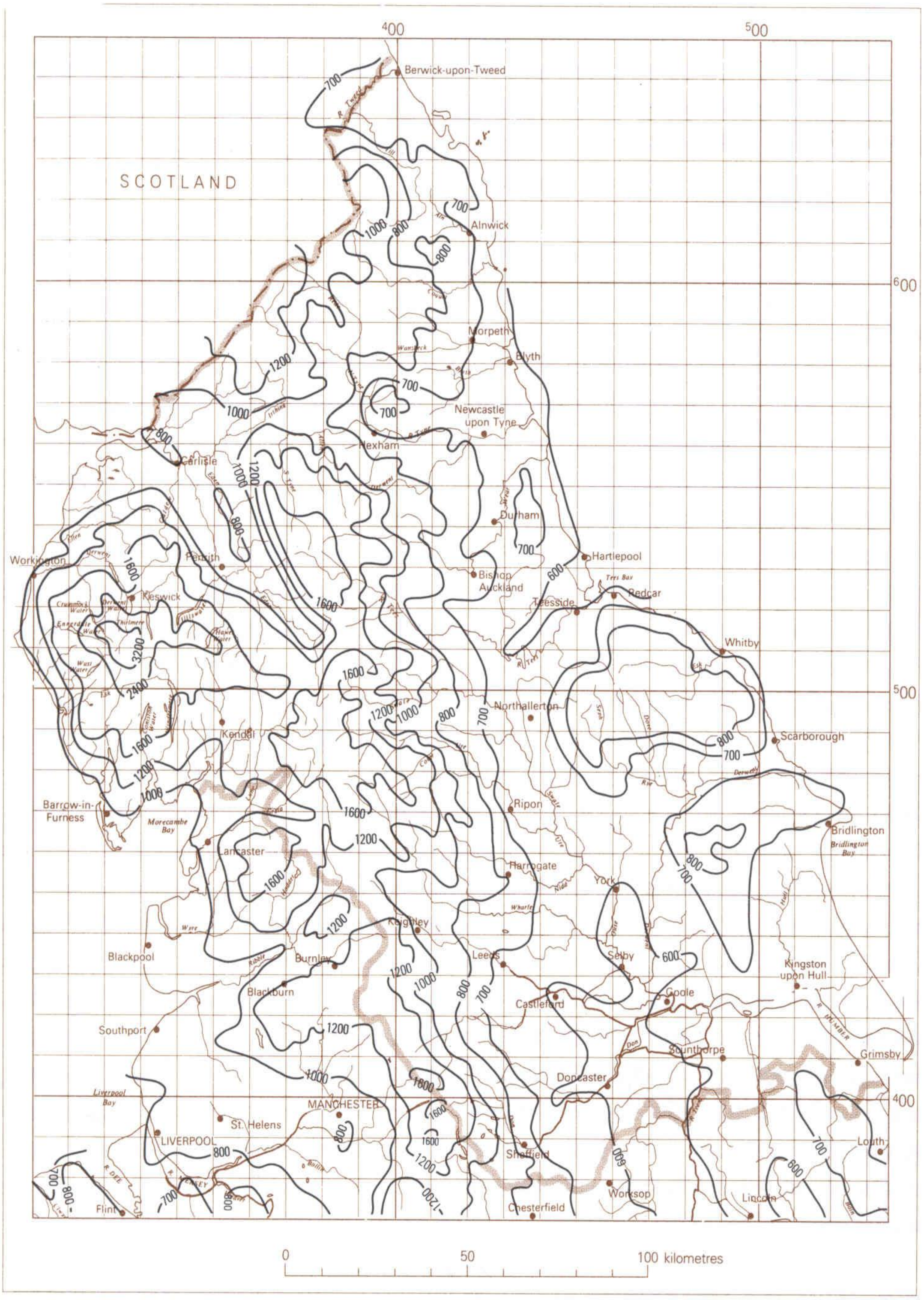


Figure 2.4: Average annual rainfall (mm) variability within Northern England.

Rainfall values are calculated between 1941 and 1970

Source: Jarvis et al (1984)

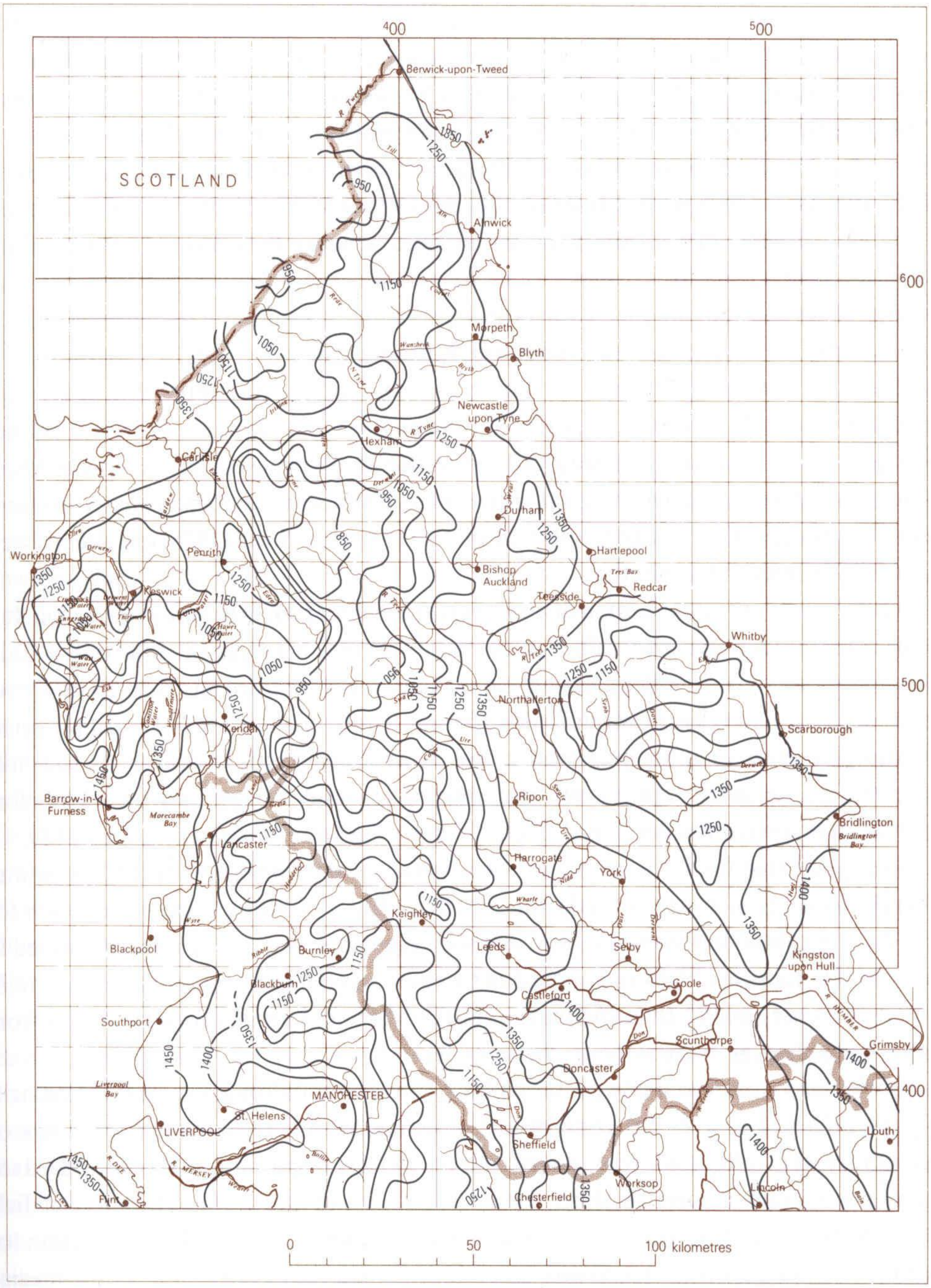


Figure 2.5: Average accumulated temperature above OºC (day-degrees) variability within northern England

Accumulated temperatures are calculated between January and June, 1959 to 1978

Source: Jarvis et al (1984)

2.1.3 Land cover

Although designated a national park, the North York Moors cannot be considered a wilderness. The park is a working landscape. Consequently, land cover and vegetation composition is influenced by anthropogenic management and conservation in addition to the climatic and geological factors previously discussed. Within the park several distinct land covers can be distinguished: moorland, grassland and woodland.

Moorland

The rearing of red grouse (*Lagopus lagopus*) is an important financial resource of the North York Moors and results in the intensive management of upland areas. Management of the moor is primarily based on a rotational burning regime devised to ensure all structural stages of heather growth (figure 2.6a), essential for grouse feeding, breeding and nesting, are present. Where moor management is intensive an almost total monoculture of ling or common heather (*Calluna vulgaris*) can be produced (figure 2.6b).

Variability in moorland management results in complex assemblies of ericaceous shrubs, grasses, herbs and ferns varying with aspect, slope, moisture and substrate. In addition to *Calluna vulgaris* two *Erica species* heathers occur in the North York Moors; *Erica tetralix* and *Erica cinerea*. Cross leaved heath (*Erica tetralix*) is found on wetter soils, bell heather (*Erica cinerea*) on drier sandy hummocks. Bilberry (*Vaccinium myrtillus*), a shrub found in association with the heathers, tends to occur on north facing slopes (figure 2.6c). A common, invasive, fern of the area is bracken (*Pteridium aquilinum*) which exploits the well-drained soils of the sloping valley sides forming a transition zone between the moorland and valley.

Where moisture conditions in the moorland become waterlogged the vegetation composition reflects wet heath associations (figure 2.6d). Vegetation species common in these wet heath communities are cross leaved heath (*Erica tetralix*), purple moor grass (*Molinia caerula*), cotton grass (*Eriophorum species*), rushes (*Juncus species*) and various moss species. The combination of species present in a wet heath is related to moisture conditions, nutrients and microclimate (Sykes, 1993).

Grassland

As elevation drops the landscape becomes characterised by grassland. These grasslands vary in type from acidic grasslands, typical of the moorland fringe, to recently planted ryegrass-reseeded silage fields. The acidic grasslands of the upper dales (figure 2.7a) are strongly influenced by sheep grazing which produces a sward of grass species, sedge species and low growing herbs. Where grazing is intensive sward composition can change to be dominated by matt grass (*Nardus stricta*) an unpalatable grass species. In addition to grazing intensity sward composition is influenced by moisture, with rushes and purple moorgrass (*Molinia caerula)* being indicative of poorer drainage.

Farming within the national park is dominated by pastoral farming although some arable farming is evident (figure 2.7b). Soil substrate, geology and drainage strongly influence farming practice.

A)

B)

C)

D)

Figure 2.6: Characteristic habitats of the upland moors

A) Calluna vulgaris mosaic as a consequence of the upland management regime.
B) Calluna vulgaris dominated moor.
C) Vegetation mosaics; bracken is evident on the steep slope while bilberry inter-grades with Calluna vulgaris in the foreground.
D) A 'wet' moor containing Erica tetralix, rush, grass and sedge species in addition to Calluna vulgaris.

A)

B)

Figure 2.7: Grasslands characteristic of the North York Moors National Park.

A) Acid grassland.

B) Grasslands typical of lowland valleys, pastoral grazing, rye-grass reseeding and arable farming are all evident.

Woodland

Both broadleaf and coniferous tree species are common in the North York Moors with stands reflecting both single and mixed species compositions. Woodland areas range in size from small natural broadleaf woodlands, primarily located in the valley bottoms, to extensive coniferous plantations, visible on the steep valley sides (figure 2.8).

Figure 2.8: Coniferous and broadleaf woodlands

2.1.4 Management and conservation of the landscape

A changing landscape

Although protected under various legislative policies the landscape of the national park is a working environment and therefore subject to change. In terms of land cover this change can reflect a modification to the spatial extent of a vegetation assembly or degradation of that assembly via changes in species composition, structure or fragmentation.

Across the whole national park changes in the spatial extent of moorland, defined as including heath (dry and wet), mires, acid grassland and bracken, are particularly evident with a loss of approximately 180km^2 of this land cover between 1950 and 1997 (table 2.1). The major driver in this moorland loss was a conversion to forestry which represented 124km^2 of the total 180km^2 change (table 2.1). Moorland loss over this time period was not constant with 90% of losses occurring between 1950 and 1974 (table 2.2). Reduced moorland conversion rates after this date reflect changes in afforestation and moorland conservation legislation (NYMNPA, 1998a).

Table 2.1: Changes in the spatial extent of moorland and associated land cover conversion between 1950 and 1997.

	Change in Moorland Area 1950 to 1997			
	Area (Miles^2)	Area (Km^2)	Proportion of 1950 Total (%)	Proportion of Park (%)
Moorland area in 1950	261.3	678.7	100%	47.7%
Moorland area in 1982	194.3	503.4	74.1%	35.1%
Moorland area in 1997	192.6	499.0	73.6%	34.7%
Land Cover Conversion				
To agriculture	20.8	55.7	8.2%	
To forestry	47.9	124.0	18.2%	
Total	**68.7**	**179.7**	**26.4%**	**12.5%**

Notes: No further information is not provided regarding the derivation of these data.

Source: NYMNPA (1998a)

Table 2.2: The rate of heather moorland loss, within the North York Moors National Park between 1950 and 1996

Year	Heather Moorland Extent (Km^2)	Loss (Km^2)
1950	680	-
1963	573	107
1974	517	56
1979	509	8
1983	503	6
1996	499	4

Source: NYMNPA (1998a)

Land cover change is strongly correlated with land management practices and legislation as evident by the rate of heather moorland conversion between 1950 and 1997. Recent literature has identified a series of current pressures on the landscape of the NYMNP which have the potential to influence future land cover management and therefore change (table 2.3).

Table 2.3: Current landscape pressures, within the North York Moors National Park, identified as potential drivers of future land cover change.

Landscape Pressures
National
• Open access legislation (Countryside Rights of Way Act 2001)
• Consequences of the foot and mouth outbreak
• Changing farming patterns due to agricultural policy and subsidy reviews
• Environmental threats (including acid rain)
Regional
• Growth in traffic and visitor pressure
• Electricity pylons
• Small scale wind farm development
• Telecommunication masts
• Over stocking and over grazing

Sources: NYMNPA (2002); White & Lovett (1999); North York Moors Association (2001)

Land ownership and management

Monitoring and management of these landscape pressures within the NYMNP is a primary function of the North York Moors National Park Authority (NYMNPA), an independent authority within local government, responsible for the management of the natural, built and cultural resources of the park. The main aims of the authority, as outlined in the 1995 Environment Act, are:

- To conserve and enhance the natural beauty, wildlife and cultural heritage of the National Park.
- To promote opportunities for the understanding and enjoyment of the special qualities of the National Park by the public. (NYMNPA, 1998b)

Although the NYMNPA are responsible for the monitoring and management of the land cover resource they do not own the land. National Park status does not change land ownership. Approximately 80% of the park is privately owned (table 2.4). The proportion of land, within each of the main land covers, managed in line with the conservation targets of the NYMNPA (table 2.5) illustrates that although in private ownership the majority of moorland and woodland areas are managed in accordance with the conservation objectives of the NYMNPA.

In addition to the main conservation aim the NYMNPA and its sub-committees are responsible for the implementation of local, national and governmental policy regarding conservation and recreational access in the park. Implementation of this legislation, within the context of the overall conservation aim, is achieved via the National Park Management Plan.

Table 2.4: Percentage landownership within the North York Moors National Park (1990)

Organisation	Proportion of the Park Owned (%)
Private	79.9
Forestry Commission	16.6
Ministry of Defence	0.5
Water companies	0.1
National Trust	1.2
National Park Authority	0.6
Other	1.1

Source: Countryside Commission (1993)

Table 2.5: The proportion of each land cover managed in accordance with the conservation objectives of the National Park Authority between 1992 and 2004

Land Cover	Total Area (Hectares)	Area managed in accordance with conversation objectives (Percentage of total area)			
		1992	1997	2003	2004
Farmland	57,292	8	24	34	31
Woodland	31,850	29	31	70	81
Moorland	49,900	60	96	91	95
Coast	936	-	-	-	37
Total park area	**143,600**	**31**	**50**	**61**	**64**

Source: NYMNPA (2004)

The current North York Moors Management Plan was published in 1998 (NYMNPA, 1998b). Following government guidelines this was reviewed after 5 years (2003) to ensure currency. Management objectives, contained in the plan, relevant to the current research are those which could potentially, or routinely are, monitored, enforced or achieved via land cover mapping. Objectives which meet these criteria are the:

- Monitoring of habitat mosaics, within moorland and farmland, to prevent further loss or degradation of semi-natural habitats.
- Monitoring of moorland quality, in terms of extent and habitat biodiversity. Factors indicative of quality loss or degradation are overgrazing, erosion and habitat fragmentation.
- Monitoring of the extent of bracken particularly encroachment of the species into moorland areas.
- Derivation of a map showing areas considered particularly important for conservation as required under section 3 of the Wildlife and Countryside Act 1985.

The importance of spatial datasets in support of the National Park Management Plan is highlighted as a management objective to "develop an integrated and co-ordinated system for the storage, exchange and management of data relating to the national park, using GIS where appropriate" (NYMNPA, 1998b).

2.2 Land cover mapping within the National Park

2.2.1 Current land cover approaches

As implied above land cover maps form an integral part in the management and monitoring of the vegetation resources of the national park specifically:

- Monitoring the influence of current management practices on the spatial extent, composition and condition of vegetation assemblies.
- Monitoring of land cover status in terms of achieving the conservation objectives as outlined in the Management Plan.

As part of these activities the NYMNPA have a mandatory responsibility for the maintenance of up to date land cover maps (5 yearly revisions) showing conservation areas, moor, heath, woodland, down, cliff and foreshore, as specified under section 3 of the Wildlife and Countryside Act (amendment) 1985 (NYMNPA, 1998b).

In addition to mapping as part of the Wildlife and Countryside Act (1985), the land cover of the region has been surveyed in a series of projects (table 2.6). These products were created using a variety of field survey and remote sensing techniques providing data at a variety of scales and therefore levels of detail about the vegetation.

Table 2.6: Land cover mapping schemes implemented within the NYMNP

Mapping scheme	Year	Organisation
Monitoring Landscape Change in the National Parks	1970s /1980s	Cranfield University
Land Cover Map of Great Britain	1990	Centre for Ecology and Hydrology
Upland Vegetation Survey	1995/1996	English Nature
Land Cover Map 2000	2000	Centre for Ecology and Hydrology
Phase 1 Habitat Surveys	2002	NYMNPA

2.2.2 Land cover mapping within the context of the research project

Issues regarding the applicability of current land cover maps to the management of the land cover resource within the National Park have been identified via discussions with stakeholders and a review of the currently available mapping products (table 2.6). Consequently, it can be concluded that:

- Mapping derived from the automated classification of satellite imagery (LCMGB and LCM2000) do not contain sufficient detail in the classification scheme or classification accuracy to permit detailed landscape management. This is exemplified by the classification of large moorland areas as "dwarf shrub heath". This broad classification does not allow monitoring of the moorland on the basis of species composition, species dominance or structural stage.
- Although the automated classification of remote sensing products cannot produce detailed vegetative information the temporal characteristics and cost efficiency of data capture are beneficial.
- Mapping via ground survey techniques (P1 and upland habitat surveys) provides detailed information on species composition, management regimes and various other environmental factors. However, such surveys are labour intensive and as a consequence have resource implications. This limits the temporal resolution of repeat surveys.
- The current land cover surveys, due to differing classification schemes, spatial resolutions and data collection techniques, are not directly comparable. This limits the applicability of the data to multi-temporal studies.

As highlighted in the preceding points a land cover mapping approach based on remote sensing techniques is advantageous due to the improved temporal resolution of repeat surveys. However, to be applicable to management of the National Park the resultant product should provide detailed information on the vegetation, flexibility in class definition and be based on a logistically viable field survey strategy so not to limit resurvey.

2.3 The research study area

2.3.1 Location

The research project, for logistical and methodological reasons, concentrated on the development of a land cover mapping approach within a focussed study area. Covering 210km^2 the study area was located in the northwest of the NYMNP including the towns of Castleton, Danby and Commondale (figure 2.9). The location of the study area was chosen, following consultation with the NYMNPA and Natural England, to ensure a range of land cover types and management regimes were included.

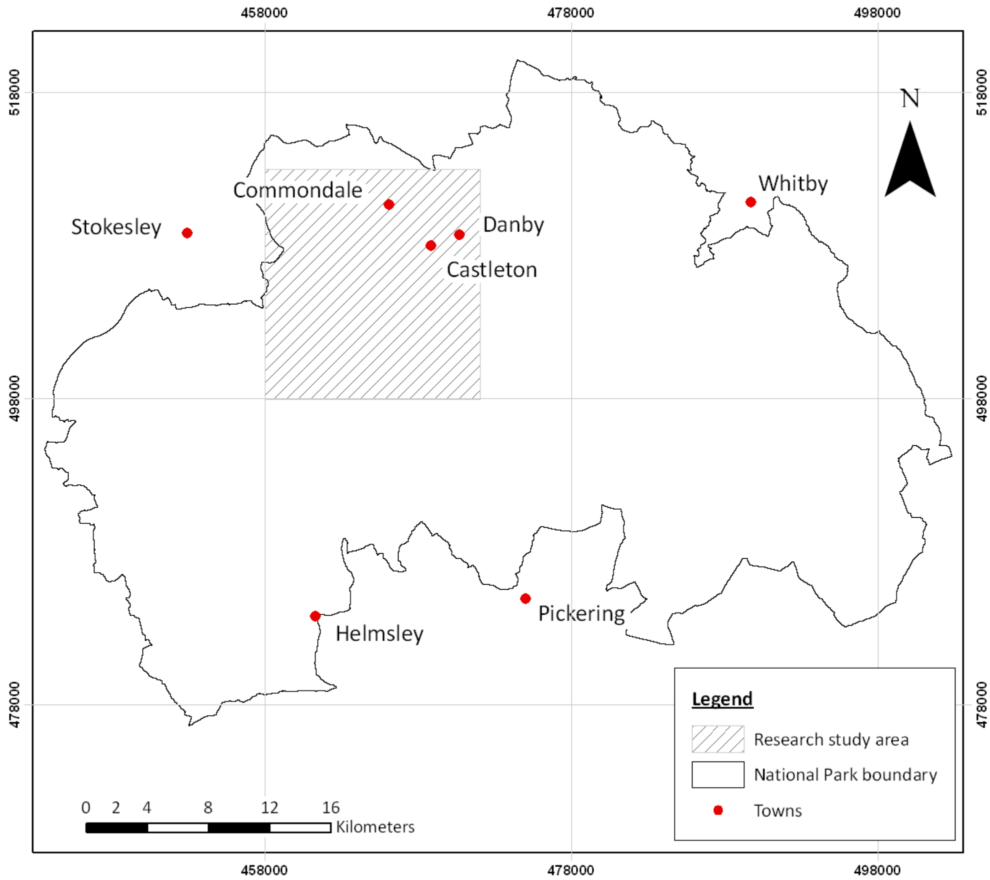


Figure 2.9: Study area location within the North York Moors National Park.

2.3.2 Rainfall

Average annual and monthly rainfall totals (mm) for four weather stations within or in close proximity to the study area (figure 2.10) illustrate that broad trends in rainfall are similar across the study area; high rainfall values in the spring and autumn months are contrasted by low rainfall during the summer and winter. Inspection of the daily rainfall values indicates that typically low rainfall values are interspersed with storm events during the summer months. Low rainfall values in the winter months are a consequence of precipitation falling as snow.

Average yearly accumulated rainfall values are similar for the Kildale (926mm) and Danby (930mm) weather stations located in the north of the study area. Monthly rainfall patterns show some variability between the stations. However, the broad trends are comparable. A higher average yearly rainfall value at the Farndale weather station (1089mm) is indicative of a north-south trend in rainfall across the study area. This is supported by the monthly rainfall values which, while displaying the same trends in rainfall as the Kildale and Danby stations, tend to be higher. This generalised north-south trend in rainfall can, it is proposed, be attributed to elevation changes with the higher moorland plateaus being located in the south of the study area. The proposed elevation, rainfall gradient is supported by the Carlton-in-Cleveland weather station which is situated at a much lower elevation. Significantly lower monthly and yearly rainfall totals at this station are attributable to the lower elevation of the station and sheltering of the area by the adjacent Cleveland Hills.

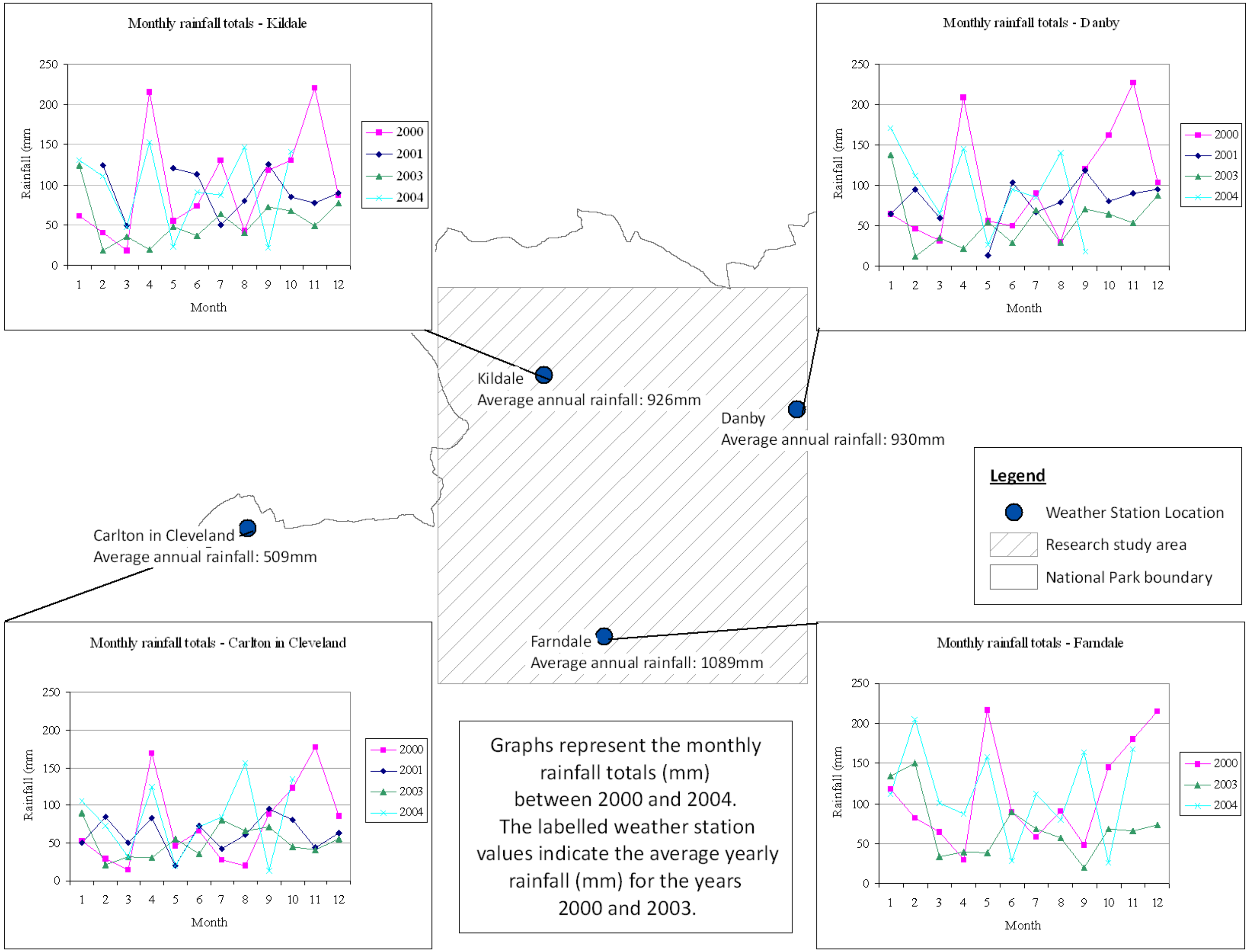


Figure 2.10: Rainfall totals (mm) at weather stations in close proximity to the study area.

Source: UK Meteorological Office (2004)

2.3.3 Physical description

Elevation

The study area is characterised by upland plateaus intersected by a series of steep sided valleys (figure 2.11). The upland plateaus in the south of the study area tend to be at higher elevations than those in the north and it is in this upland area that the maximum elevation of approximately 450m above sea level occurs on Urra Moor. Away from these upland plateaus the elevation drops quickly into steep sided valleys. The lowest elevation, of approximately 100m above sea level, occurs in the most westerly of these valleys.

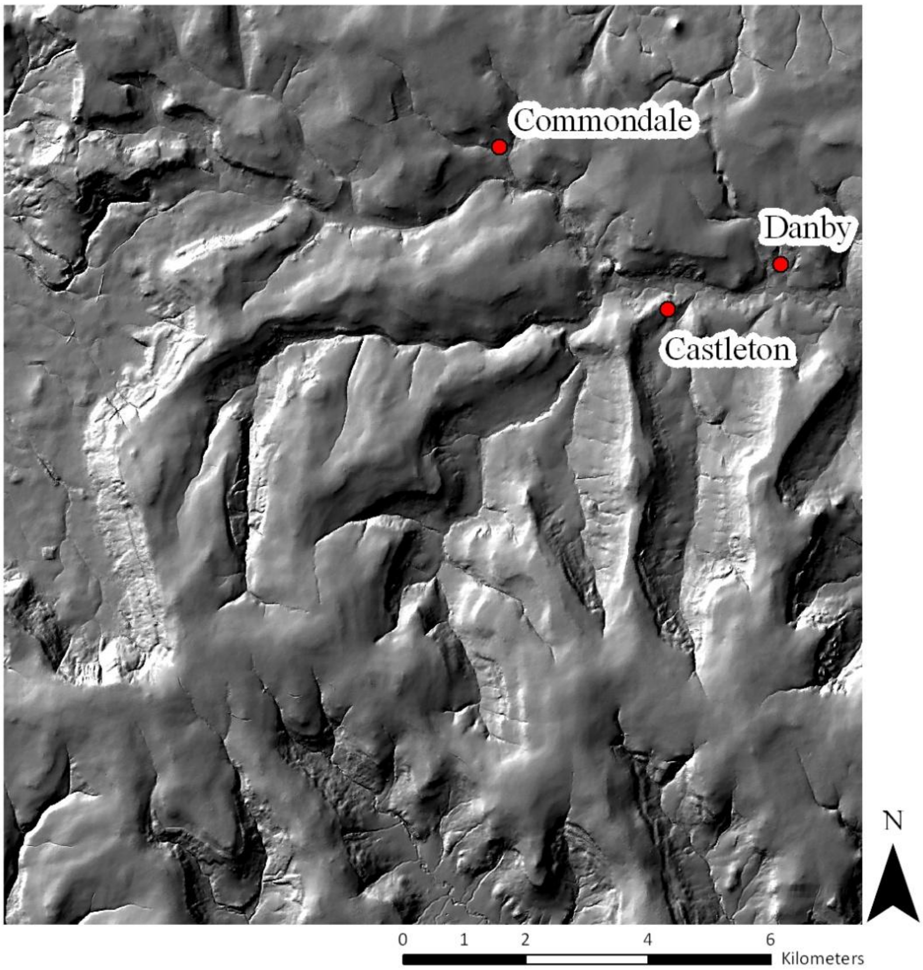


Figure 2.11: Hillshade representation of elevations within the study area

Source: NEXTMap DTM (Intermap Technologies)

Soils

The predominant soil series of the study area, broadly categorised as peats, clays and loams (figure 2.12), vary spatially according to underlying geology and elevation. Broad trends in the spatial distribution of soil are evident with peats isolated to the upland plateaus and clayey/loamy soils in the lowlands.

Peaty soils are defined as containing a humic, organic horizon. In the Winter Hill series, located on the highest upland plateaus to the south of the study area, this organic horizon is greater than 40cm in depth, the soil is therefore considered a raw, deep peat (Carroll & Bendelow, 1981). The Maw and Onecote series, which occur at slightly lower elevations than the Winter Hill series, are characterised by a peaty top soil of less than 40cm above a humus soil pan and thick clayey subsoil, respectively (Carroll & Bendelow, 1981). The Winter Hill, Maw and Onecote soil series are all slowly permeable, prone to seasonal water logging and characterised by high acidity levels. As a consequence of these poor soil conditions, and tendency for the soils to occur on open upland plateaus, the soils are typically found in association with moorland species, in particular heather (*Calluna vulgaris*) although species composition is variable depending on local conditions.

Lowlands in the study area contain both loamy and clayey soil series, some spatial separation of these series is evident; clayey soils are dominant on the sloping valley sides and eastern lowlands, loamy soils in the lowlands to the west of the study area and Danby valley. The clayey series are characterised by grassland. However, some arable production is possible with soil management practices (Carroll & Bendelow, 1981). Loamy soils are characterised by grassland land covers although arable practices are evident in the drier lowlands (Carroll & Bendelow, 1981).

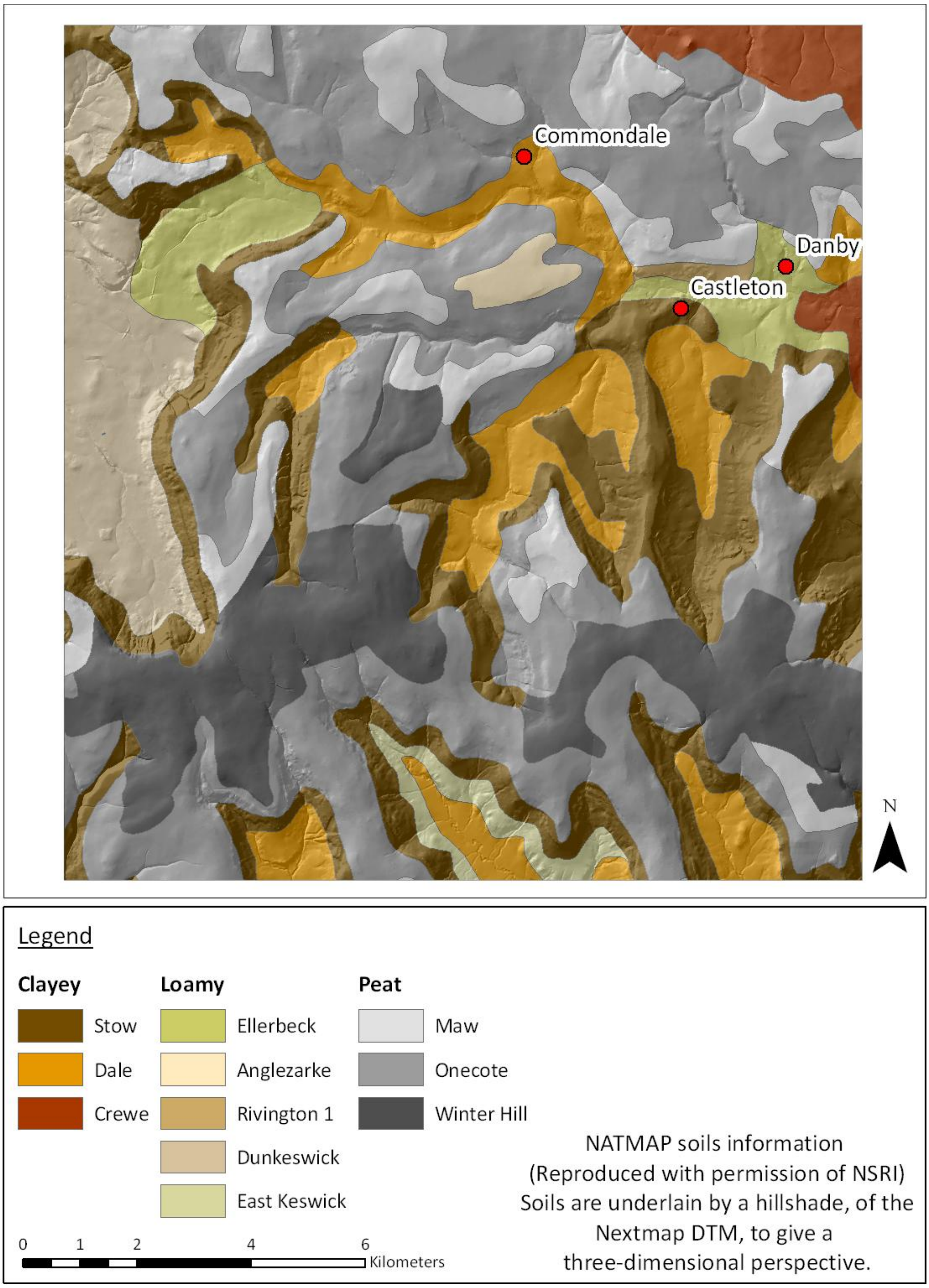


Figure 2.12: Main soil series of the study area

Source: NSRI, 2002

2.3.4 Land cover

The land cover of the study area demonstrates the general trends of the NYMNP (section 2.1.3). This land cover structure is illustrated (figure 2.13) by the land cover map derived by the Monitoring Landscape Change in the National Parks (MLCNP) project (Taylor *et al*, 1991d). As this land cover map dates from the 1980s small scale land cover changes can be expected. However, due to the relative stability of major land cover types the data presented are indicative of the spatial arrangement and approximate extent of the land cover types described.

Woodland

The MLCNP classification defines broadleaf and coniferous woodland according to the dominant species which should make up 80% of the canopy (Taylor *et al*, 1991b). Should neither species be dominant, that is, the canopy cover of both species is less than 80%, the woodland is considered mixed.

Coniferous woodland is the most abundant in the study area covering 4% of the total land area. These coniferous woodlands, primarily in the west of the study area, are characterised by extensive plantations located on steep valley sides. Broadleaf woodlands are smaller in extent and tend to be restricted to the valley bottoms where they occur in small patches or as elongated woodlands along river courses. Woodlands which contain a mix of coniferous and broadleaf species are not frequent in the study area covering less than 1% of the total land area.

Moorland

Following the MLCNP land cover classification the most predominant land cover of the study area is upland heath defined to include areas with greater than 80% canopy cover of heather or bilberry species. This class is the dominant class of the upland plateaus and is typically characterised by stands of *Calluna vulgaris* although a greater mix of species can occur as a function of management regime and moisture conditions (section 2.1.3).

Bracken, a major contributor to the land cover of the study area covering approximately 11% of the land area, is an invasive species typically considered a ‘problem’ plant. Encroachment of this species is considered a serious threat to habitat diversity and the economic viability of the moor, due to its association with sheep and grouse diseases (Sykes, 1993). Bracken is typically managed by treatment with a herbicide to deter the spread of the plant. The species occurs throughout the study area, excluding the exposed moor and very wet areas. However, it typically dominates the steep sloping valley sides fringing the moorland.

The remaining land cover of the moorland is composed of upland grass moor and peat bog which have a much smaller spatial extent each covering less than 1% of the study area. Although small in extent the peat bog habitat is an important habitat within the study area and North York Moors as a whole. Peat bog is typically found in wet conditions and is identified by the presence of sphagnum moss within the species composition.

The mosaic land covers of the MLCNP classification represent combinations of the moorland classes where neither of the classes is dominant. These mosaics often represent the transitional zones between intergrading moorland land covers. Within the study area the most common mosaic is between upland heath and bracken, this mosaic is typical of the moorland fringe where the upland heath merges into the bracken covered slopes.

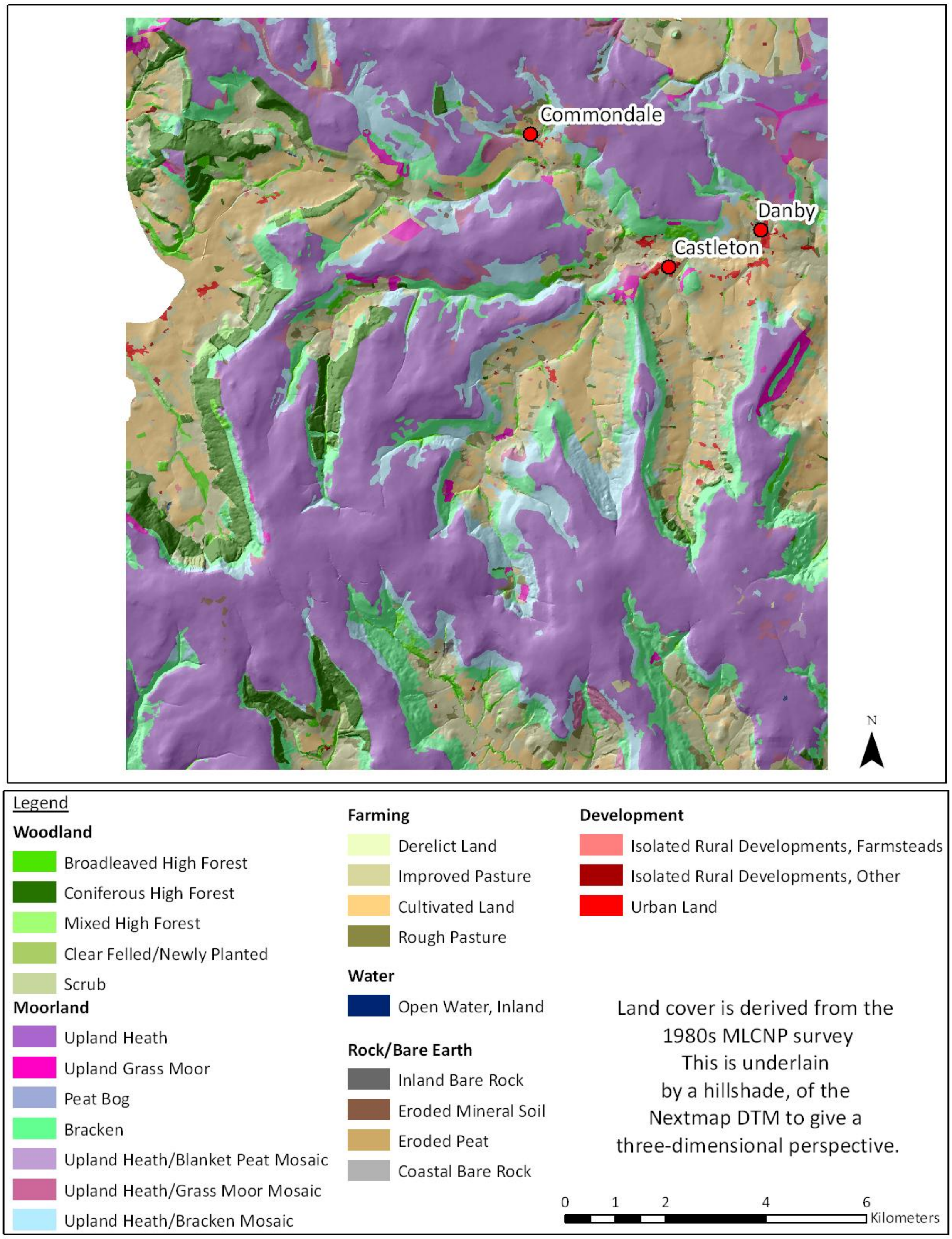


Figure 2.13: Land cover of the study area derived from the MLCNP land cover survey

Source: Taylor et al (1991d)

Farming

According to the MLCNP land cover classification lowland valleys were categorised into three primary land cover types, cultivation, improved and rough pasture.

Grasslands within this area are segregated, according to their management, being classified as either improved or rough pasture. Improved pasture is described as grassland intensively managed for grazing (sheep and cattle) or fodder production. Via these management techniques, drainage, reseeding and fertiliser or herbicide application, the grassland sward is significantly modified eradicating bracken, rush and sedge species (Taylor *et al*, 1991b). Rough pasture is defined to include those grasslands which while enclosed are not subject to sufficient management to modify the grassland sward. The sward is characterised by increased species composition including grasses and often invasive species such as bracken, thistles and rushes (Taylor *et al*, 1991b).

Improved pasture is more extensive in the study area covering approximately 12% of the study area, in comparison to 2% for rough pasture. Both land cover types are restricted to the lowland valley areas. However, rough pasture is largely found in association with woodlands or the moorland fringe.

Cultivated land is defined to include fields which are cropped or ploughed for future cropping. Crops typical of the study area include cereals, oil-seed rape, vegetables and fodder crops. Cultivated crops are relatively extensive in the lowlands of the study area covering approximately, the same land area as improved pasture (12%).

Development

Comprising urban areas and isolated developments very little developed land occurs in the study area covering less than one percent of the land area. Conurbations in the study area, for example, Westerdale, Danby and Kildale predominantly occur in the lowland valleys.

2.4 Chapter summary

The key points of this chapter are summarised as:

- The research was conducted in a 210km^2 area near the north-west boundary of the NYMNP.
- The study area was subjectively chosen to incorporate a range of landscape, land cover and management regimes.
- Land cover types of the study area can be broadly categorised according to two landscape models; the field and entity models (Burrough & McDonnell, 1998). The moorlands, characteristic of the uplands, are typified by land covers which inter-grade. Species composition varies as a consequence of local conditions and the moorland management regime. The lowlands are best described by the entity model due to the discrete land cover parcels which result from farming management practices. Land covers typical of the landscape are cultivated crops and improved pasture.
- The NYMNP is a working landscape and as such is characterised by changing land cover patterns.
- Land cover maps are required within the NYMNP to support management, monitoring and conservation tasks.
- Land cover maps are currently available for the NYMNP but these have issues of scale, currency and compatibility. A requirement for a versatile land cover mapping approach has therefore been demonstrated.

CHAPTER 3

Field Survey Design

Land cover attributes, as opposed to land cover class, were the basis of field survey in the current research. The justification for this attribute characterisation and definition of attributes on the basis of current land cover classification schemes is outlined. For each land cover attribute information is provided on the measurement methodology implemented during a pilot study and subsequent full field survey.

This chapter considers the development of the sample design from that implemented in the pilot study. Clustered, systematic aligned and systematic random designs are compared on the basis of sample proportions, potential sample bias and logistic viability. A semi-automated methodology for the grouping of sample points, to represent logistically viable survey days, on the basis of land cover, 3D travel distance and change in altitude is presented.

3.1 The requirements for a field survey

Field survey represents the collection of data, at or near the ground surface, in support of remote sensing and GIS analysis. In the context of remote sensing applications field survey data are typically applied to three tasks: to provide a reference dataset for remote sensing analytical techniques, for example, classifier training; to model multi-spectral, landscape relationships, for example, quantification of the relationship between plant biomass and multispectral response; and to verify the accuracy of remote sensing outputs (Campbell, 1996). Irrespective of application, field survey data should consist of three components: the measurements or attributes describing the ground conditions, the location at which these measurements were taken and a description of the observations in terms of the date and time at which they were collected (Campbell, 1996). The data collected at each survey location are a function of the application; field survey design is therefore task specific.

The aim of the current field survey was to quantify a series of attributes describing the current status of land cover within the study area. Subsequently these attributes form the basis of classifier training providing a link between land cover status and radiometric quantities of the remotely sensed data (Baban & Luke, 2000).

Lakhani (1981) states that for a field survey to be successful the survey objectives must be clearly defined: the field survey objectives, within the context of this research, were to:

- Define a series of attributes which form the basis of land cover characterisation.
- Design a sampling strategy as a means of identifying locations at which the land cover attributes should be measured.
- Quantify the land cover attributes at the predefined locations using measurement methodologies which are consistent, accurate and repeatable.

Finally, the field survey should be simultaneous with remote sensing image capture to ensure the reference data adequately represent the remote sensing information.

3.2 The pilot study

Lakhani (1981) recommends the inclusion of a preliminary, small scale, field or pilot study within the field survey design process as a means of identifying unexpected occurrences within the proposed data collection methodology. Such a preliminary study allows further modification of data collection methods, sample design and sampling allocation to ensure the final field survey is achievable, representative and repeatable.

A pilot field survey was implemented during August 2003 which specifically aimed to:

- Gain practical experience in identifying the common plant species of the study area.
- Resolve any sampling, parameter measurement or logistical issues surrounding the proposed field survey method.
- Complete a reconnaissance survey of the study area.

The pilot study surveyed three sites selected from a systematic random aligned sample design to ensure a representative range of vegetation types and management regimes. A site encompassed a square area of 0.36 km^2 and contained six regularly distributed samples points (section 3.4.4). The surveyed sites can be summarised as, a moorland site characterised by dry heath and intensive grouse management, secondly, a moorland site containing a greater mix of *Ericaceous*, grass, rush and sedge species and finally, a steeply sloping valley site containing both rough and improved grassland.

3.3 Land cover attributes

3.3.1 Land cover attribute derivation

Traditionally field survey for land cover map production is based on the recording of land cover classes as defined by the classification scheme of the mapping approach. This data may be collected at a single point or in a sample area based on the delineation of homogenous land cover parcels (section 3.4). Such an approach to field survey is not appropriate in the current research as the aim states that mapping should not be based on a pre-defined land cover classification. As a result a field survey approach which records land cover attributes, rather than land cover classes, was required.

While the research aim dictated that land cover attributes form the basis of field mapping a requirement of the methodology was that these attributes, with subsequent remote sensing and GIS processing, could be used to construct current land cover definitions. To ensure this requirement was met, land cover definitions, taken from widely used land cover mapping schema, formed the basis of land cover attribute definition. This was achieved by dissection of the land cover class definitions to identify attributes used in the delineation of boundaries between classes.

Four common land cover mapping schemes, P1 (JNCC, 1993), LCM2000 (Fuller *et al*, 2002), NLUD (Harrison, 2006) and CORINE (Bossard *et al*, 2000) were considered in addition to the Natural England Favourable Habitats Management Plan (Blackshall *et al*, 2001). Factors identified as frequently defining class boundaries within the land cover mapping schemes, classified as being floristic, physiological, environmental or structural to aid comparison, are summarised in table 3.1; full classification breakdowns are included in appendix B.

Table 3.1: Attributes common to each land cover classification scheme used in the delineation of land cover class boundaries

Category	Delineation Attributes
Floristic	Species presence or absence*
Structural	Canopy cover Class dimensions (area/length/width) Percentage cover* Plant density* Productivity Species height*
Physiological	Leaf type* Seasonal characteristics*
Environmental	Artificial surfaces (presence or absence)* Enclosure* Erosion Management (land use)* Peat depth* Soil pH, type and moisture level* Topography and elevation Water table height (seasonal inundation)

*Notes: * indicates parameters measured during the field survey*

To minimise field survey burden it was concluded that ancillary sources, where available and of sufficient accuracy, should be used to characterise land cover and landscape attributes. This is exemplified via the NEXTMap digital terrain model which was used to parameterise the topographic variables of elevation, slope and aspect. Consequently, a subset of attributes were measured at each sample point during the field survey as indicated in table 3.1.

The following sections consider the measurement methodologies employed for each land cover attribute. As outlined each of these measurement methodologies was developed following a literature review and subsequent testing during the pilot study.

3.3.2 Site characteristics

Site characteristics were recorded both photographically and via a text description. The ad-hoc approach to the landscape and management descriptions, implemented during the pilot study, was found to result in widely varying, inconsistent descriptions both in terms of the keywords used and level of detail recorded. To ensure consistent terminology between sites in the full field survey a series of keywords were devised, from the pilot study comments, from which the surveyor could select terms most relevant to describe the site. The keywords were subdivided into several landscape (topography, aspect, geology and soils, erosion, proximity to water) and management (management, evidence of management) categories for ease of use. Full keyword listings are included in the field survey protocol (appendix C).

3.3.3 Soil characteristics

Soil characteristics considered during the pilot study were pH, soil moisture and peat depth. These parameters were recorded once at each sample point.

pH

Pilot study pH measurements were restricted to grassland sites as this is, typically, the only land cover type classified on the basis of this parameter. A single soil sample, at each survey point, was analysed using a colorimetric field pH kit, accurate to a level of 0.5 units. Subsequent to the pilot survey the intended colorimetric pH methodology required adaptation as a consequence of the significantly greater number of samples in the full field survey.

The primary issue highlighted by the pilot study related to the depth at which the soil sample for pH analysis should be extracted. Further literature reviews recommended that soil was sampled at two depths within the profile (Grime *et al*, 1988) with both being independently pH tested. In such an approach the full field survey required approximately 480 soil pH samples; this was not logistically viable using the colorimetric pH measurement approach.

Consequently, the National Soil Map of England and Wales (NSRI, 2002) was identified as an alternative ancillary data source for the characterisation of broad pH classes. This ancillary data source was supplemented with an estimate of pH made at all samples using a simple soil pH meter. This simple pH measure was not as accurate as the colorimetric measurement as results were strongly influenced by soil moisture. However, the technique was rapid and measurements could be taken in-situ giving an indication of soil pH.

Soil moisture

The measurement of actual soil moisture was considered too time consuming for the requirements of the project therefore a descriptive estimation of soil moisture, based on underfoot wetness and vegetation species present, was tested during the pilot study. This approach was continued in the full field survey which classified sites according to three moisture classes:

- *Very wet*: The site is characterised by standing water at the surface
- *Wet*: The site is wet underfoot but does not contain standing water
- *Dry*: The site is dry underfoot

While this measure was very subjective and dependent upon the preceding weather conditions it was considered sufficient for the requirements of the current research project.

Peat depth

As peat depth is a component factor in both the P1 and LCM2000 classification schemes the measurement of this parameter, using a standard soil auger, was tested during the pilot study.

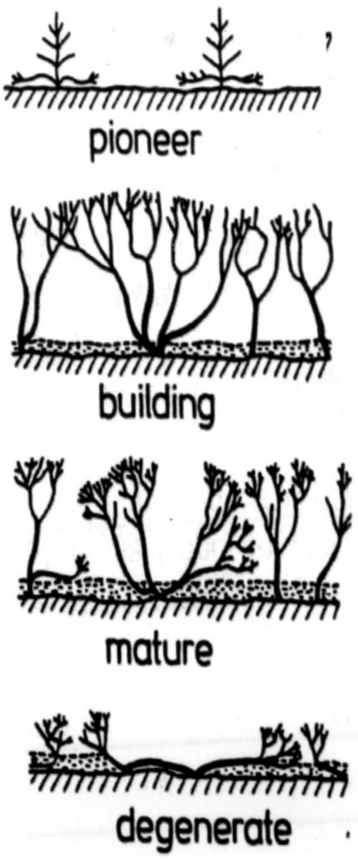
The pilot study results concluded that peat depth measurements were both time consuming to collect and influenced by the ability of the surveyor to accurately identify the peat horizon. Consequently, an alternative ancillary data source, the British Geological Survey peat drift map (BGS, 1966), was identified as a means of characterising areas where peat drift is greater than 50cm. This approach is similar to that implemented in LCM2000 (Fuller *et al,* 2002).

3.3.4 Heather species structural stages

Heather communities can be classified into four life cycle stages as a function of their structure and age: pioneer, building, mature and degenerate (Webb, 1986). These terms still persist in describing the stages of heather growth and have been further defined by Gimingham (1992), (figure 3.1).

As previously stated (section 2.1.3), a rotational burning regime is implemented in the moorland regions of the study area. This results in a mosaic of heather (*Calluna vulgaris*) patches at various structural stages. A mixture of structural stages is an important element in grouse and upland management (Blackshall *et al*, 2001). Consequently, field survey measurements of the heather species, *Calluna vulgaris, Erica tetralix* and *Erica cinerea* were categorised according to species and structural stage.

To ensure consistency with previous studies conducted, by Natural England and the NYMNPA, the definitions of Gimingham (1992) were applied to heather structure characterisation (figure 3.1). These definitions were supplemented with typical plant heights as characterised by previous studies within the NYMNP (Jerram *et al*, 1998), (table 3.2). Typical plant heights are specific to *Calluna vulgaris. Erica* species due to their less vigorous growth tend to be smaller than *Calluna vulgaris* plants of a similar age.



Pioneer phase:

This is the period of establishment, of either seedlings or sprouts from stem bases surviving after fire. In both cases the young plants are neatly pyramidal shaped, but seedlings are scattered whereas, stem base sprouts are clustered. Flowering usually begins in the second growing season after establishment, and from about this time growth is no longer concentrated in a leading shoot but takes place in a number of radiating branches. The pioneer phase will typically last until the plant is between 2 and 6 year years old.

Building phase:

Radiating growth gives rise to a dome-shaped bush in isolated individuals or to a closed canopy in dense stands. This is the most vigorous growth-phase, with abundant production of light green short shoots near the periphery of the branches and of flowers and seeds. Very little light penetrates the canopy. The plant is typically classified as building until an age of between 10 and 15 years.

Mature phase:

In time, extension growth becomes rather less vigorous while the woody parts of the branches continue to increase in girth. The short shoots are now rather darker in colour and more clustered while the canopy becomes more irregular and inclined to open up. In isolated plants a central gap may form in the canopy. Plants will typically remain in the mature stage until they are between 20 and 25 years of age.

Degenerate phase:

Gaps in the canopy increase as the older central frame-branches become moribund and die. Branches tend to collapse sideways, increasing the gaps, but any layering branches that have rooted in the moist humus may remain alive for long periods. Eventually the whole plant may die.

Figure 3.1: The structural stages of heather growth

Source: Gimingham (1992)

Table 3.2: Approximate plant heights, in the North York Moors National Park, for Calluna vulgaris in each structural stage

Structural Stage	Approximate Height (cm)
Pioneer	Less than 15
Building	15 to 30
Mature	30 to 40
Degenerate	Greater than 40

Source: Jerram et al (1998)

3.3.5 Species cover

Cover is a commonly used plant abundance measure defined as the "proportion of ground occupied by the perpendicular projection of the aerial parts of the species under consideration" (Kershaw, 1973). Following a literature review several techniques used to measure this vegetation parameter were identified. The most common of these, the frame and pin quadrats, were compared and tested during the pilot study to determine the most appropriate method for implementation in the full field survey.

Visual estimation within a frame quadrat

Based on the analysis of a sample area, marked out on the ground, the frame quadrat provides the basis for the visual estimation of the area occupied by the canopy of each species. Frame quadrats can, in theory, be any shape or size but are conventionally four sided. A square, rather than rectangular, quadrat is typically used where no evidence of spatial patterning exists (Gilbertson *et al*, 1985).

The dimensions of the frame quadrat are largely governed by the size, distribution and ground pattern of the vegetation being studied. Ideally the quadrat should contain sufficient plants and species to be representative of the site but minimised to a manageable size. In the case of grassland and dwarf shrub communities, typical of the study area, Gilbertson *et al* (1985) conclude that an optimum quadrat size is between 1m x 1m and 2m x 2m.

Percentage cover calculations using the frame quadrat are reliant upon the surveyor estimating the proportion of the frame covered by each species. The consistency with which these proportions can be estimated is increased by splitting the frame into segments. The 1m^2 frame, as suggested by Gilbertson *et al* (1985), is advantageous as it can easily be split into a ten by ten grid in which each segment represents 1% cover.

During the pilot study percentage top cover was independently estimated, after initial training, by two surveyors. This enabled the influence of observer upon percentage cover estimates to be assessed (appendix D). No significant differences were proven between surveyors' however, these results masked large differences, particularly at the quadrat level. Several factors were identified as being responsible for surveyor differences including: vegetation colour, structure, floristics, patchiness and cover proportion. In conclusion, the 1m^2 quadrat and visual assessment technique while rapid to implement was prone to subjectivity and bias. This conclusion follows that of previous studies. Grieg-Smith (1983) concluded that this observer bias can be as much as 25% of the mean.

Pin quadrat estimation

The pin quadrat, commonly considered the least biased of the percentage cover measurement techniques, is based on the assumption that observer error can be minimised by reducing the sample area to a point. At the scale of a point little or no judgement is required by the surveyor to assess vegetative cover (Elzinga *et al*, 1998). The sampling points of the pin quadrat can be "sampled in frames (which form the sampling unit), as single randomly located points (each point is the sampling unit), or as points located along a transect (either the points or the transect form the sampling unit)" (Elzinga *et al*, 1998). While a number of studies have concluded that independent random point samples are the most efficient arrangement (Goodall, 1952) a restrictively large number of points are required for a statistically valid survey.

As a random point design was restrictive the pilot study was based on a 10 pin frame. The pin frame employed was a single supporting rod design (figure 3.2). Pins in the frame were located at 10cm intervals and formed the basis of top cover and proportional cover calculations (figure 3.3). Results comparable to the frame quadrat were achieved by repetition of the pin frame 10 times, at 10cm intervals, in the 1m^2 quadrat creating a grid of 100 points. The reporting accuracy of this data was a single percent. However, the 100 points cannot be considered as independent and were not reported below the quadrat level.

The pin frame technique is based on the assumption that the vegetation is recorded at a point of no diameter. When implemented with pins of diameter greater than zero significant errors, in comparison to optical sighting measures, are introduced into cover estimates (Kershaw, 1973). While optical sights are, theoretically, more accurate measures at central pins and of proportional cover are particularly problematic with these devices. Consequently, the pilot study was based on pins. To minimise errors and standardise results the pin diameter was minimised as far as possible and the same pin diameter used at all sites.

The pilot study demonstrated the time consuming nature of the 100 pin frame technique. Consequently, adaptations, in particular a reduction in pin number were required to implement the technique. Statistical tests, comparing results obtained with 5 (50 points), as opposed to the proposed 10 frames (100 points), concluded that no significant differences in results were evident (appendix D).

The accuracy of pin frame measurements was found to be correlated with vegetation structure, in particular vegetation height and density, and the ease of species identification. Errors were introduced into data collection where plant leaves hit by the pin could not be attributed to a particular species.

The pilot study identified the potential for pin frames located at regular intervals within the quadrat to miss species which occurred at low cover proportions. Elzinga *et al* (1998) in a comparison of visual and pin frame estimates for a 50cm by 50cm plot demonstrated that the pin quadrat method failed to detect 19% of the species discovered visually. All of the species which remained undetected covered less than 2% of the plot area (Elzinga *et al*, 1998).

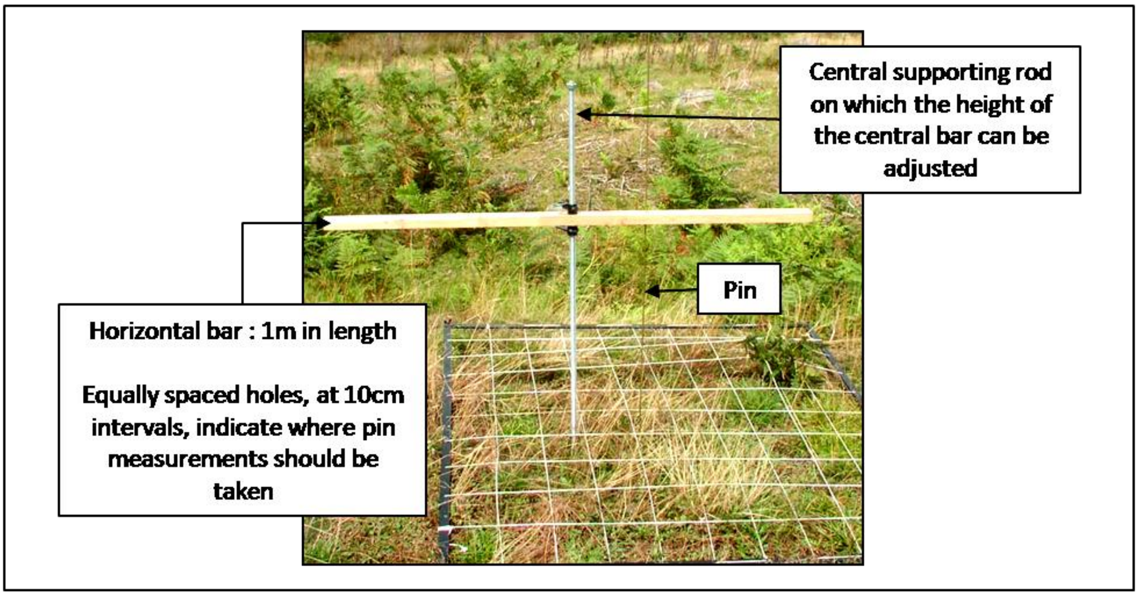


Figure 3.2: The pin frame quadrat

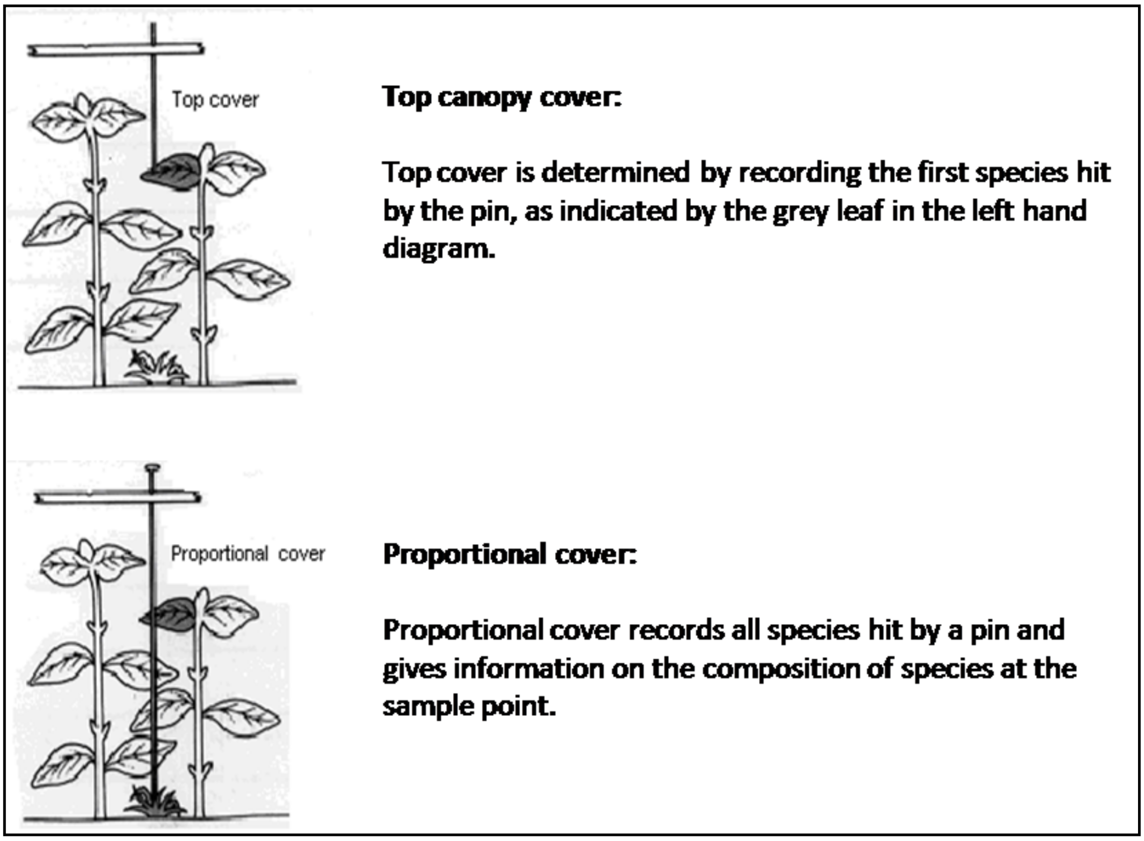


Figure 3.3: Top and proportion cover determination within the pin frame quadrat

Source: Chalmers and Parker (1989)

A comparison of the visual estimation and pin frame techniques

No significant difference in percentage cover values as recorded via the frame quadrat and pin frame were evident in the pilot study data (appendix D). However, data included in this analysis were limited and plotting of the data revealed greater disparities at the quadrat level (appendix D). Via the pilot study a number of advantages and disadvantages in relation to each cover measurement were identified (table 3.3).

Table 3.3: A summary of the advantages and disadvantages of percentage cover determination via visual and pin frame estimation

	Quadrat Visual Estimation	Pin Frame
Advantages	• Rapid	• Less subjective • Very good in short vegetation • Repeatable
Disadvantages	• Subjective • Prone to observer bias • Not repeatable • Can overlook rare species • Results influenced by species mixing.	• Can overlook rare species • Time consuming • Impractical in tall vegetation • Influenced by vegetation structure • Influenced by the pin diameter

The pin frame was the most repeatable, objective methodology. However, its implementation in the full ground survey was not considered viable as a consequence of the techniques' time consuming nature. The frame quadrat can be implemented rapidly in all vegetation communities, however, the data collected are subjective and prone to observer bias. Consequently, a hybrid technique (described below) was developed to measure percentage cover during the full field survey.

Full field survey: percentage cover

A compromise, between rapid implementation and objective results, was achieved via an adaptation of the visual estimation technique to record species presence/absence. In this modified methodology each quadrat cell was systematically searched and the presence of any species in the top cover noted. As in the pilot study the quadrat frame was $1m^2$ and contained 100 cells each of 10cm by 10cm.

An issue highlighted by the pilot study was the consistency and accuracy with which full species identification could be achieved. A review concluded that inaccurately identified species, due to their complex physiognomic and floristic characteristics, were more readily identified at the genus or family level. To ensure minimisation of taxonomic errors percentage cover estimates were modified to include varying levels of vegetation identification at the family, genus and species (table 3.4). The agglomeration of species to the genus/family was species specific to ensure those species easily identified and potentially spectrally distinct at the resolution of the available remote sensing imagery were recorded.

Table 3.4: Levels of vegetation identification applied when recording percentage top cover

Family/Groups	Genus	Species
Grasses	Bedstraws – *Galium sp.*	All shrub sp. [2]
Rushes	Thistles – *Cirsium sp.*	
Sedges	Buttercups – *Ranunculus sp.*	
Mosses – “Feather”	Chickweeds – *Stellaria sp.*	
Mosses – *Polytrichum*	Dandelions – *Taraxacum sp.*	
Mosses – Sphagnum	Clovers – *Trifolium sp.*	
Mosses – Other		
Lichen – *Cladonia*	Other Flowering plants[1]	
Lichen - Other		

Notes:

[1] If any flowering plant could not be identified to the genus level the group ‘other flowering plants’ was applied.

[2]Ericaceous species and Calluna vulgaris were also split into structural groups (section 3.3.4)

3.3.6 Species present

Requiring only that all species present in the quadrat are recorded, presence/absence data provide information on species composition irrespective of their contribution to top cover.

In the pilot study two alternative means of recording presence/absence were tested. Firstly, a nested quadrat approach was implemented at grassland sites to enable methodical searching of the quadrat. Secondly, at moorland sites, all proportional species, species which did not contribute to top cover, were recorded with no formal methodical strategy being implemented.

- *Nested quadrat*

Following Hodgson *et al* (1995), the nested quadrat technique splits the $1m^2$ quadrat into cells of: 10 x 10 cm, 20 x 20 cm, 30 x 30 cm, 40 x 40 cm, 50 x 50 cm and 100 x 100cm with the species present in each successively larger cell being recorded. This technique was found to be an efficient method to search the quadrat for species and record species composition.

- *Proportional species*

Implemented simultaneously with the visual estimation of percentage cover this technique required notation of all species, in addition to those contributing to top cover, within the quadrat. As no protocol was devised to ensure that the quadrat was searched systematically species were often overlooked by one or more surveyors.

Field survey measurement of target species presence/absence

During the pilot study the nested abundance technique was found to provide consistent results, promoted by methodical quadrat searching. This methodology was therefore implemented in all quadrats within the full ground survey.

The nested quadrat methodology implemented in the pilot study required the surveyor to record the presence/absence of vegetation at the full species level. As in the determination of percentage cover (section 3.3.5) this level of species identification could not be achieved consistently or accurately. This issue was resolved in percentage cover measurements by the agglomeration of species to the genus or family. While this agglomeration improves the accuracy, repeatability and efficiency of cover measurements concerns were identified regarding a loss of species specific information important in the determination of habitat type, habitat conditions and management practices.

Species composition, presence/absence, measurements were therefore modified to supplement percentage cover data by recording the presence/absence of target species only (table 3.5). Species were defined as 'target' species if they were:

- Characteristic of a habitat.
- Indicative of environmental conditions, for example, soil acidity status.
- Invasive.
- Characteristic of a particular land cover management regime.
- Readily identifiable to ensure accurate recording.

Where species identification was complex target 'species' were agglomerated to the scale of the genus. For example, complexity in the subdivision of sphagnum moss species was resolved by recording only that the species belonged to the sphagnum genus.

Table 3.5: Target species recorded if present within the quadrat during the full ground survey.

Common Name	Latin Name	Comments
Shrubs		
Heathers[1]	*Erica tetralix* *Erica cinerea* *Calluna vulgaris*	
Bilberry	*Vaccinium myrtillus*	
Cowberry	*Vaccinium vitis-idaea*	
Crowberry	*Empetrum nigrum*	
Gorse	*Ulex europaeus*	
Bracken	*Pteridium aquilinum*	
Grasses		
Rye Grass Yorkshire Fog Red Fescue	*Lolium perenne* *Holcus lanatus* *Festuca rubra*	Indicative of agricultural improvements
Wavy Hair Grass Matt Grass	*Deschampsia flexuosa* *Nardus stricta*	Indicative of acidic soil conditions
CocksFoot Crested Dogstail False Oat Grass	*Dactylis glomerata* *Cynosurus cristatus* *Arrhenatherum elatius*	Indicative of neutral soil conditions
Tor-Grass Crested Hair-grass	*Brachypodium pinnatum* *Koeleria macrantha*	Indicative of calcareous soil conditions
Purple Moor Grass	*Molinia caerulea*	Can indicate overgrazing
Common Bent	*Agrostis capillaris*	
Sedges		
Hairstail Cotton Grass Common Cotton Grass	*Eriophorum vaginatum* *Eriophorum angustifolium*	Indicative of wet heath
Deer Grass	*Trichophorum cespitosum*	
Rushes		
Heath Rush	*Juncus squarrosus*	
Flowering Plants		
Sheep's Sorrell Heath Bedstraw	*Rumex acetosella* *Galium saxatile*	Indicative of acidic soil conditions
Daisy	*Bellis perennis*	Indicative improved grassland
Rosebay Willow Herb	*Chamerion angustifolium*	Indicative tall herb community
Nettles	*Urtica sp.*	Indicative nutrient enrichment
Dandelions Buttercups Clovers	*Taraxacum sp.* *Ranunculus sp.* *Trifolium sp.*	Indicative improved grassland
Common Sorrell	*Rumex acetosa*	
Tormentil	*Potentilla erecta*	Indicative unimproved grassland
Mosses and Lichens		
Moss – Feather	*Hylocomium sp.* *Plerozium sp.* *Hyprium sp.*	
Moss – Sphagnum	*Sphagnum sp.*	
Moss – Polytrichum	*Polytrichum sp.*	
Lichen	*Cladonia sp.*	

Notes:

[1] Heather species (Erica sp. and Calluna sp.) would also be split according to structural stage.

3.3.7 Species height

Vegetation standing height is an indicator of both community structure and land cover management regime. During the pilot study multiple measurements of this parameter were collected. Actual standing vegetation height was measured at pins 1, 4, 7 and 10 in each pin frame and average species height was estimated for all species occurring in the frame quadrat. In both cases the heights were recorded to the nearest 5 cm.

A comparison of the estimated, average species heights to the actual measurements taken in the pin frame concluded that the measurement techniques yielded similar results, with 89% of all the estimated values falling within one increment (5 cm) of the average measured value. Similar results between the measurement techniques can be attributed to the coarse measurement interval (5 cm) and uniformity of vegetation stands encountered.

While no significant difference can be proven between the techniques, a review of pilot study species height measurements concluded that actual rather than estimated measurements should be recorded during the full field survey. This conclusion was based on the assumption that the estimation of height would include errors as a consequence of the subjective selection of 'average' sized plants. A further methodological adaptation reduced the measurement interval to +/- 2 cm to improve height measurement resolution.

As the full field survey implemented the frame rather than pin quadrat, height measurements were randomised within the quadrat. In an iterative process, a cell was selected at random from the quadrat and the standing height of all vegetation classes, following the percentage cover classification (table 3.4), located at the centre of the cell recorded. A disadvantage of this randomised methodology was the potential exclusion of heather heights from the field data. As height is an important factor in the discrimination of the heather structural stages, the methodology included an additional element to ensure heights were recorded for every heather species (*Calluna species* or *Erica species*) present in the quadrat (appendix C).

3.3.8 Heather species, plant density

Rooted density, the number of rooted plants per unit area (Elzinga *et al*, 1998), was recorded as an indicator of plant abundance. This parameter is most accurately measured when individual plants can be readily identified and therefore has limited applicability for many grass and sedge species (Kershaw, 1973). Consequently, the pilot study recorded the rooted density, per m^2, for the heather species, ling (*Calluna vulgaris)*, cross-leaved heath (*Erica tetralix)* and bell heather (*Erica cinerea)* only.

Density measures are often excluded from ecological studies due to difficulties in accurately identifying and counting individual plants within the quadrat. This was reflected in the pilot study which highlighted issues in identifying the heather plant rootstock, its location relative to the quadrat boundary and the time consuming nature of counting the, potentially, large number of pioneer stage plants within a quadrat.

Due to the strength of this parameter as an indicator of community structure it was concluded that the methodology should be adapted to accommodate the specified measurement issues. Adaptations considered included line transect, canopy gap and plot-less density estimator techniques. However, a change of survey structure, away from the frame quadrat, was rejected. Methodological adaptations developed a density estimation measure which recorded the number of plants contributing to total percentage cover irrespective of whether they were actually rooted in the quadrat. To ensure minimisation of bias within this estimate, related to subjective quadrat boundary decisions, and to ensure consistency across samples, an alternative in/out boundary rule was implemented (appendix C).

3.4 Sample design

3.4.1 Why sample?

The most accurate determination of a parameter is via a census; the characterisation of that parameter at all locations. Such an approach is rarely viable due to cost, time and resource implications. Sampling therefore provides a means of characterising a subset of the population from which inferences about the entire population can be drawn (Dixon & Leach, 1978). To ensure that the sample is representative and inferences regarding the population are appropriate the sample should be designed to minimise both sampling error, the error that results from taking a sample as opposed to a census, and sample bias, the over representation of some part of the population at the expense of the remainder of the population; this is achieved via sample randomisation (Dixon & Leach, 1978).

A further important element in ensuring a representative sample design is the sample fraction, the proportion of the population for which observations are made. This sample fraction is typically dependent upon the required survey precision, characteristics of the study area and financial and human resources available (Bettio *et al*, 2002). Ideally the sample fraction should be minimised, reducing resource implications, while still ensuring data which is representative of the population and hence can give a reliable answer with the required degree of precision.

Sampling approaches used in the characterisation of population statistics are typically defined according to the way in which the sampling units are identified. In terms of land cover survey, the list and area frame sampling approaches are particularly relevant.

3.4.2 List frame sampling

This sampling scheme is based on an exhaustive list of population elements. For example, in agricultural land cover survey this list would contain all farms in the area. A sample is derived via the extraction of farms from the list, at which land cover should be surveyed. These sample farms may be extracted at random or in a systematic pattern, that is, every n^{th} farm.

The accurate implementation of this survey design is dependent upon the construction of an exhaustive and comprehensive list of population elements. This reliance on a list of population elements is the main limitation of this type of survey as the sampling frame is rarely current at the time of sampling (Gallego, 1995). Creation and updating of such a list is time consuming with potential errors resulting from, for example, farm mergers, boundary changes and the definition of what constitutes a 'farm' (Gallego, 1995).

This sampling approach was not adopted for the current research project due to the time consuming nature of stakeholder identification. Secondly, a methodology for the recording of detailed vegetation parameters within such an approach was not implicit, that is, the relationship between quadrat location and the identified stakeholder was not readily defined.

3.4.3 Area frame sampling

Area frame sampling approaches provide an alternative to the list frame for land cover survey. In such an approach the sampling frame (population) is tied to a geographical area. Sample elements, or units, within this frame can take the form of areas, often termed segments, or points.

Area frames from segments.

A segment based division of the area frame consists of the division of the frame into segments of regular or irregular shapes. Segments can be a variety of shapes provided that they are exclusive, that is, they do not overlap, and are exhaustive, that is, they constitute the entire frame (Gallego, 1995).

Segments with physical boundaries

Segments with physical boundaries are irregular in shape and based on the definition of regions, contained by physical boundaries, within the sampling frame. Common bases for segment division, particularly in agricultural surveys, are field boundaries.

An advantage of this sample design is the ease with which sample segments, which coincide with land cover parcels, can be identified in the field. While construction of the sampling frame is time consuming, where such data do not already exist, once constructed the database can be used in subsequent surveys with minimal updates required (Gallego, 1995).

The successful implementation of this sampling approach is reliant upon the landscape containing sufficient, readily identifiable, physical boundaries from which segments can be defined. This has been illustrated in the United States where landscapes are typified by fields and roads which form a regular grid pattern. Although applied in Europe the implementation of the survey was considerably more complex due to the irregular field patterns and therefore identification of segments of similar size (Sannier *et al*, 2007).

In the context of the current research project, while segments based on physical boundaries could be identified in the lowland regions of the study area identification within upland regions would be inappropriate. Within this semi-natural landscape a lack of physical boundaries and continuum of vegetation change limits the delineation of representative sample segments.

Segments without physical boundaries

An alternative approach has been developed in which the sample segments take the form of a simple geometric pattern. A commonly implemented geometric pattern is a series of square areas, for example, national grid squares, which are overlaid on the region of interest (figure 3.4). Such an approach is advantageous as it is easily implemented irrespective of landscape features (Gallego, 1995).

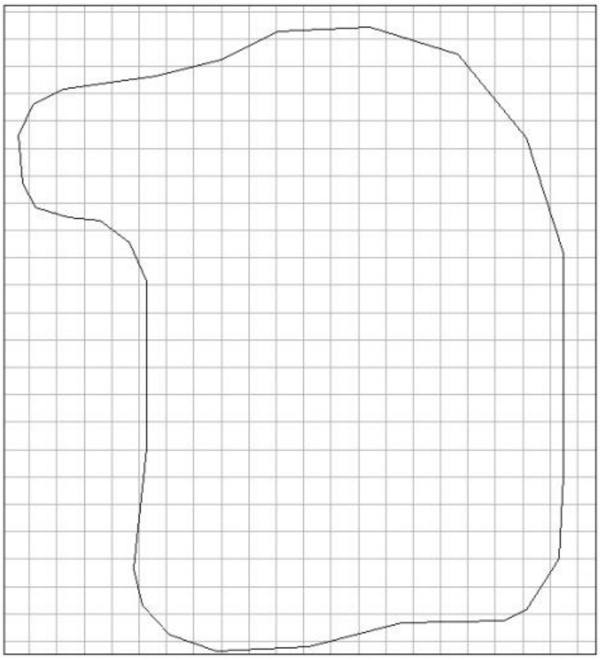


Figure 3.4: A sampling frame based on square segments

When implementing a sampling frame, a methodology must be implemented to select those squares in which land cover will be surveyed, that is, the sample. Several approaches are available for the sampling of segments including: simple random, systematic and stratified designs.

- *Simple random sampling*

A simple random design (figure 3.5) is implemented via the independent selection of sample squares while ensuring that each segment has the same probability of being selected. The design is quick and easily implemented by assigning each sample square a number. The generation of a series of random numbers then dictates which sample squares are surveyed. Typically, this random selection is performed without replacement, that is, once selected an individual is removed from the population. While this slightly increases the probability of remaining sample squares being selected this is not significant unless the sample fraction is high. The method is advantageous as it prevents the reduction of sample variation by the multiple selection of a single sample square (Dixon & Leach, 1978).

The random selection of samples can result in segments which are spatially isolated to a particular region or form distinct clusters. In terms of land cover this can result in samples which are not representative of the entire study area or in the case of adjacent segments, data redundancy (Gallego, 1995).

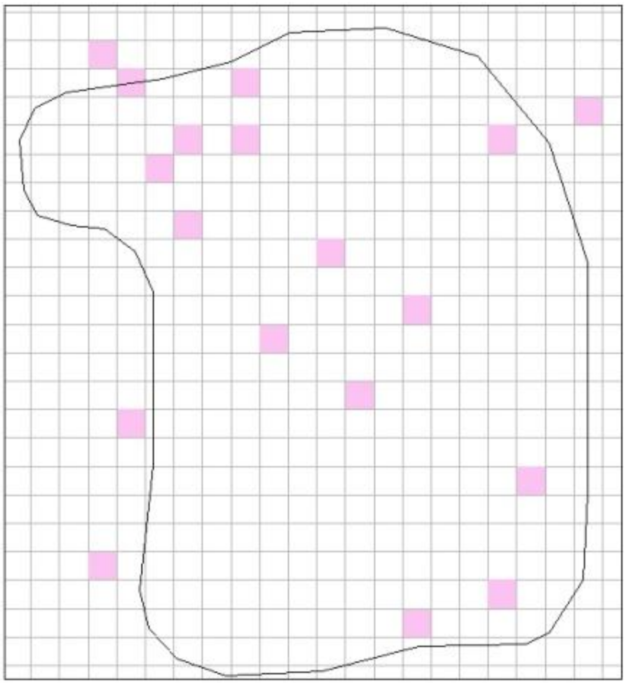


Figure 3.5: Simple random sampling based on square segments

- *Systematic sample designs*

Systematic sample designs provide one means of ensuring a 'good' geographical distribution of sample squares within the region of interest thereby reducing the limitations of the simple random design. Systematic designs are based on the subdivision of the sampling frame into blocks. Blocks are designed to contain multiple sample squares and hence the block dimension must be a multiple of the sample square size. Additionally, blocks should be exclusive and cover the entire sampling frame.

To ensure a good geographical distribution a fixed number of sample squares are selected, at random, from each block. This selection may be in an aligned or un-aligned design (figure 3.6).

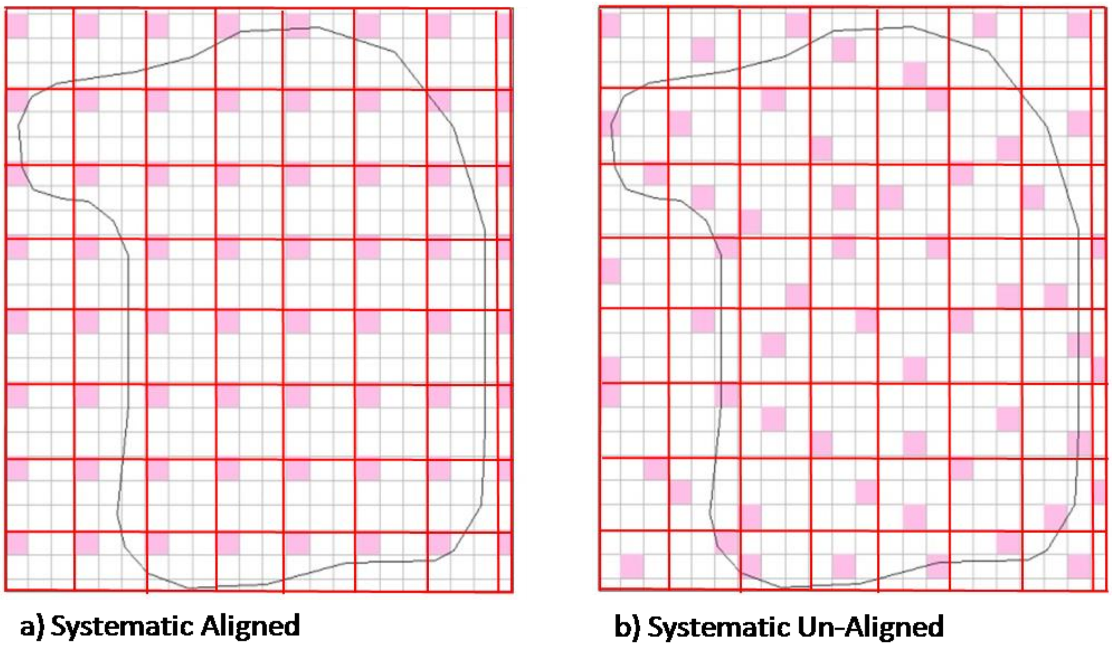


Figure 3.6: Aligned (a) and unaligned (b) systematic area frame sample designs.

An aligned systematic design is constructed via the extraction of the same sample square(s) from each block. The sample square(s) from the first block is selected at random, this pattern is repeated in all subsequent blocks.

Implementation of an aligned design can be unsound if the sampling interval coincides with some periodicity in the data being sampled (Kent and Corker, 1992). While this risk is negligible in land cover surveys (Gallego, 1995) the design may miss isolated land cover types. For example, the design illustrated in figure 3.7 does not sample a strip of land cover, identified in yellow, isolated to the central portion of the region.

An alternative to the aligned design, the unaligned design is based on the random selection of sample square(s) from each block. As a result each sample square has the same probability of being selected within that block and the resultant sample square(s) will vary with each block.

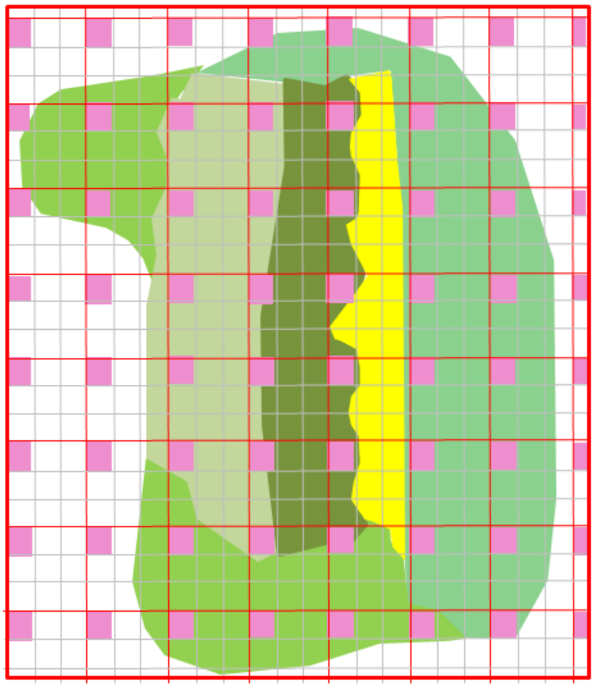


Figure 3.7: The exclusion of Isolated land covers (identified in yellow) within a systematic aligned design

In both the aligned and un-aligned designs single or multiple samples can be selected in each block depending upon the required sample fraction. The inclusion of more than one sample square per block is termed replication.

- *Stratification*

Stratification can be defined as the splitting of the area frame into multiple regions, strata, on the basis of characteristics of those regions. Strata can be any size, should differ from each other on the basis of defined characteristics, must not overlap and when combined should constitute the whole population.

Sampling within each stratum is based on the previously outlined sampling designs. In its simplest form sampling fractions are the same in each stratum. However, sample fractions can be varied across strata to reflect variability in the population. A common parameter on which sampling fractions are derived is the spatial extent of the strata (Dixon & Leach, 1978).

Summary

Implementation of an area frame sample design identifies sample segments which cover a specified spatial extent. Land cover is typically surveyed within these segments via the delineation of homogenous areas, tracts, based on a predefined classification of land cover types.

As this demarcation of tract boundaries implies a classification of the land cover/landscape this method was not considered compatible with the research aim that field data be collected in relation to a non-defined classification scheme. Secondly, a methodology for the recording of detailed quadrat based, vegetation parameters within such an approach was not implicit, that is, the relationship between quadrat location and the identified sample segment was not readily defined.

Area frames from points

A point frame is, in theory, a series of dimensionless points. The number of points within the frame can therefore be considered infinite (Gallego, 1995). In practice points within the frame are typically given an area, this is particularly important in land cover survey to allow appropriate classification of vegetation at the point. Sample designs implemented within the point frame approach are similar to those of the segment frames, that is, random, systematic and stratified.

Point based sample designs have been successfully employed in the LUCAS (Bertin *et al*, 2003) and TERUTI (Gay and Porchier, 2000) surveys. Both the LUCAS and TERUTI surveys are based on a clustered point design which relies on a two stage sampling approach. The initial stage defines the primary sampling unit, sample point cluster locations. The second stage identifies the point samples at which data are recorded within the cluster.

Point based sample approaches are advantageous as they are easy to implement and minimise the inference of tract or segment characteristics by reducing measurements to a dimensionless or minimised area (Bettio *et al* 2002). Such an approach was appropriate for the current research project as the definition of a survey point allowed the characterisation of the predetermined land cover attributes at a given location. In the current research the point was not dimensionless but represented an area covered by four quadrats in which the measurements were collected.

3.4.4 Sampling within the pilot study

Sample design

The sample design implemented in the pilot study was a two tier clustered sample scheme, constructed of primary and secondary sampling units, adapted from the LUCAS survey (Bertin *et al*, 2003).

The primary sampling units (PSU) represented a square area (600m x 600m) within a randomly located grid. Each PSU was located using a systematic random, aligned, triple replicate sampling design (figure 3.9). The secondary sampling units (SSU) consisted of 6 sample points located, to provide a regular distribution, within each PSU. Each SSU can be considered to cover a circular area approximately 4m in diameter as data were collected from four 1m x 1m quadrats orientated to the compass cardinals (figure 3.8). Data was recorded in four quadrats, as opposed to a single quadrat placed at the sample point to ensure that error due to localised variability was reduced (Wood *et al*, 2003).

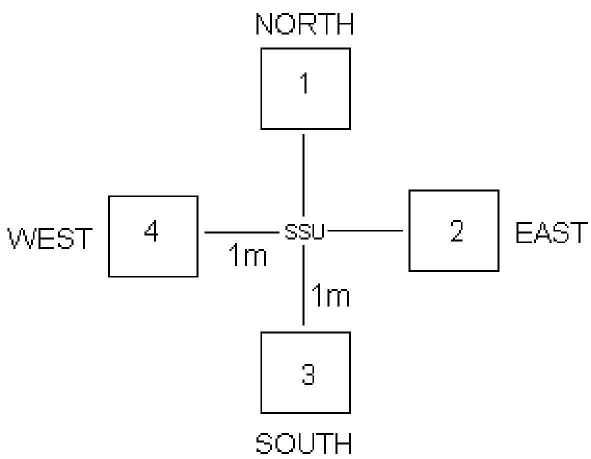


Figure 3.8: The orientation of quadrats at each secondary sampling unit.

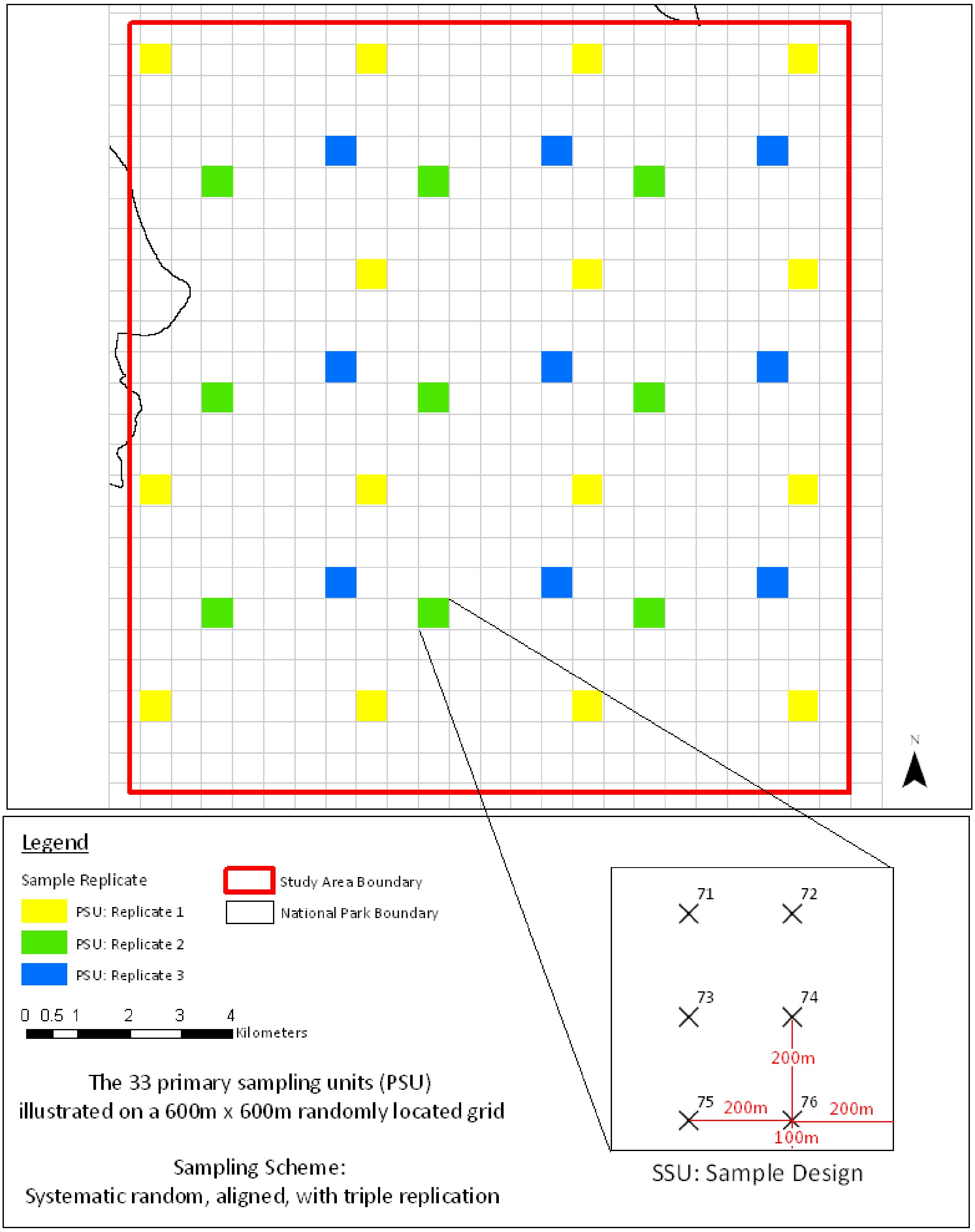


Figure 3.9: The relationship between primary and secondary sample units, as implemented in the pilot study

The two-tier sampling scheme was designed to enable data collection at two scales; the PSU and SSU. At the PSU both hard and soft land cover boundaries dissecting the sample segment were plotted against aerial photography (UK Perspectives) to characterise the landscape composition while at the SSU detailed vegetation composition measurements were made.

In practice the delineation of hard boundaries within the PSU was much more feasible than soft boundaries Soft boundaries were often overlooked or inaccurately plotted due to landscape changes between the dates of aerial photography capture and field survey.

Sample point cluster implications

Although the clustering of SSU, within the PSU, was found to be logistically efficient concerns were raised regarding the applicability of this design to subsequent processing techniques. A related literature review highlighted several issues:

- *Level of precision*

In general, if clustered more sample points are required to achieve an equal level of precision compared to the same number of points in an un-clustered design (Dixon & Leech, 1978).

- *Large extrapolation regions*

The clustering of sample points results in holes, of large spatial extent, in the coverage of training data across the study area. Should interpolation or geostatistical techniques be subsequently applied to these data, larger interpolation errors would be expected between clusters, where interpolation distances between points are greater, than within the cluster. Dungan and Coughlan (1999) in a comparison of regression, cokriging and conditional simulation to conifer canopy mapping concluded that results, in particular those obtained via cokriging, were strongly influenced by a small sampling fraction and clumped distribution of ground measurements.

- *Screening effect*

Particularly significant in geostatistics, the clustering of sample points can lead to a screening effect. Screening is the process by which samples at the back of a cluster are obstructed by those at the front closest to the interpolation query location. This process results in sample points adjacent to the interpolation query location, but in a cluster, being given a lower importance than individual sample points located further away (Webster & Oliver, 2001).

- *Aggregation to the PSU*

Incompatibility between the clustered sample design and analytical techniques can be resolved via aggregation of the SSU data to the PSU. As the PSUs are randomly located there is no requirement for internal homogeneity therefore, SSUs within a PSU can exhibit extreme variability in vegetation composition. SSU aggregation is therefore not recommended. Results derived from such an aggregation would be extremely limited in resolution.

3.4.5 Sample design comparisons

The literature review highlighted the apparent importance of a sample design based on evenly spaced, as opposed to clustered, sample points. Prior to the modification of the field survey sample design, the clustered design was compared to two evenly spaced designs; a systematic aligned and unaligned grid. Comparisons were made to ensure the final design was logistically viable and representative of the entire population.

Systematic aligned grid

This sample design is based on the repetition of sample points, at a given interval, from a randomised start location. Determination of the optimum grid interval was an iterative process based on achieving a logistically viable number of samples. Following the pilot study it was concluded that 6 sample points could feasibly be surveyed per day therefore, approximately 240 samples could be surveyed within an eight week field survey period. This number of sample points was best achieved with a grid interval of 950 metres (table 3.6).

Table 3.6: The relationship between systematic grid interval and the total number of sample points occurring within the study area

Sample Interval (metres)	Number of sample points
750	380
800	342
900	272
950	240
1000	210

Systematic unaligned grid

This design was based on the independent selection of a randomly located sample point within each 950 x 950m sample square of the study area. The sample frame size of 950m was chosen to ensure a total number of samples comparable to the systematic aligned sampling scheme.

Clusters

The systematic sampling schemes were devised to maximise the number of sample points logistically viable within an 8 week field survey period. To ensure that the clustered design also met this criterion and was directly comparable to the other sample designs the number of PSUs was increased from 33, as implemented in the pilot study, to 42 via the addition of a fourth sampling replicate.

Land cover

As stated previously a major concern regarding a regular grid of sample points was that the interval of the grid intersected a spatially periodic trend in land cover (Kent & Corker, 1992). To ensure the sample designs representatively sampled each land cover a comparison was made of the number of sample points falling in each land cover class, where land cover information was extracted from the 1980s MLCNP survey (Taylor *et al*, 1991d).

Comparison of the number of samples falling in each land cover class (table 3.7) indicated the over sampling of upland heath by each of the sample designs. However, this comparison was deceptive as no account was taken of the geographical extent of each land cover class (table 3.8). It would be expected that more samples occur in land cover types with a greater geographical extent.

For each sample design the proportion of samples falling within each land cover class, relative to the spatial extent of that class, was calculated via a root mean square analysis (equation 3.1).

$$RMS = \sqrt{\frac{\sum(\%sa - \%sp)^2}{n}}$$

Equation 3.1

where:

%sa *is the spatial extent of the land cover class expressed as a proportion of the total study area. %sp is the proportion of sample points, for the specified design, occurring in the land cover class. n is the number of land cover classes.*

In a representative sample it would be expected that the geographical extent of each land cover class, expressed as a proportion of the study area, would be similar to the proportion of sample points falling in that class. A low root mean square (RMS) value was therefore indicative of a representative sample design (table 3.9).

Table 3.7: The number of samples, for the systematic aligned, unaligned and clustered sample designs which occurred within each MLCNP land cover type.

Land cover		Sample Design		
		Cluster	Aligned	Unaligned
Broadleaved High Forest	(C1)	6	1	2
Coniferous High Forest	(C2)	14	11	10
Mixed High Forest	(C3)	1	1	1
Scrub	(C4)	3	1	1
Clear Felled/Newly Planted	(C5)	1	2	0
Upland Heath	(D1)	135	99	108
Upland Grass Moor	(D2a)	2	3	3
Bracken	(D3)	23	29	30
Upland Heath/Grass Moor Mosaic	(D6a)	7	8	6
Upland Heath/Bracken Mosaic	(D6b)	8	17	8
Upland Heath/Blanket Peat Mosaic	(D6c)	0	0	0
Eroded Peat	(D7a)	0	0	0
Eroded Mineral Soil	(D7b)	0	1	0
Cultivated Land	(E1)	20	25	31
Improved Pasture	(E2a)	29	35	29
Rough Pasture	(E2b)	3	2	1
Open Water, Inland	(F2)	0	0	0
Peat Bog	(F3a)	0	0	0
Inland Bare Rock	(G2a)	0	0	0
Coastal Bare Rock	(G2b)	0	0	0
Urban Land	(H1a)	0	0	1
Derelict Land	(H2b)	0	0	0
Isolated Rural Developments, Farmsteads	(H3a)	0	0	0
Isolated Rural Developments, Other	(H3b)	0	0	0

Table 3.8: The spatial extent of each MLCNP land cover class within the study area

Land Cover		Total Area (Km^2)	Total Area (%)
Broadleaved High Forest	(C1)	4.31	2.07
Coniferous High Forest	(C2)	10.02	4.81
Mixed High Forest	(C3)	1.06	0.51
Scrub	(C4)	0.93	0.45
Clear Felled/Newly Planted	(C5)	0.54	0.26
Upland Heath	(D1)	90.59	43.50
Upland Grass Moor	(D2a)	2.08	1.00
Bracken	(D3)	22.38	10.75
Upland Heath/Grass Moor Mosaic	(D6a)	4.17	2.00
Upland Heath/Bracken Mosaic	(D6b)	14.89	7.15
Upland Heath/Blanket Peat Mosaic	(D6c)	0.10	0.05
Eroded Peat	(D7a)	0.01	0.00
Eroded Mineral Soil	(D7b)	0.25	0.12
Cultivated Land	(E1)	25.14	12.07
Improved Pasture	(E2a)	26.69	12.82
Rough Pasture	(E2b)	3.33	1.60
Open Water, Inland	(F2)	0.02	0.01
Peat Bog	(F3a)	0.19	0.09
Inland Bare Rock	(G2a)	0.06	0.03
Coastal Bare Rock	(G2b)	0.01	0.00
Urban Land	(H1a)	0.70	0.34
Derelict Land	(H2b)	0.07	0.04
Isolated Rural Developments, Farmsteads	(H3a)	0.47	0.23
Isolated Rural Developments, Other	(H3b)	0.23	0.11

The sampling scheme with the lowest RMS value (table 3.9) was the aligned systematic grid indicating that this scheme was the most representative in terms of land cover sampled. Concerns regarding the sampling interval of this design intersecting a periodic trend in land cover were therefore not evident. The clustered design was the most unrepresentative with an RMS two times greater than that of the aligned design; this is largely a result of over sampling within the upland heath class.

Table 3.9: RMS values comparing land cover class area to sample proportion

	Sample Design		
	Cluster	Aligned	Unaligned
RMS	2.42	0.95	1.13

Travel distance and logistic viability

The pilot study concluded that the clustered sample design was logistically efficient due to the reduced travel distances between sample points contained in a cluster. An implication of employing both the aligned and unaligned grid designs was increased travel distances between sample points. Although travel distances would be much increased using the 'un-clustered' designs it was hypothesised that due to the spread of access routes across the study area the designs remained logistically viable. This hypothesis was analysed by a comparison of the straight-line, 2D distance between sample points and potential access routes.

Analyses were conducted using a GIS and were based on access routes digitised from the 1:25,000 Ordnance Survey mapping of the area. Access routes considered included all road classifications, public rights of way and any additional farm or upland tracks.

Initially sample points were considered independently, with the distance between each sample point and closest linear feature, of each type, being calculated. Analysis of these distances (table 3.10) illustrated only minor differences between each of the sample designs with no sample design having consistently lower distances between access routes and sample points. The frequency distribution of the sample point distances demonstrated that the sample designs were again similar with no design having a consistently increased data skew or spread.

Table 3.10: A comparison of the average, minimum and maximum distance (Km) between sample points in each design

Distance (Km)	Sample Design		
	Clusters	Aligned (950m)	Unaligned (950m)
Roads			
Average	0.79	0.8	0.79
Minimum	0	0	0
Maximum	3.53	3.74	3.31
Sum	199.03	192.99	184.77
Rights of Way			
Average	0.3	0.32	0.3
Minimum	0	0	0
Maximum	1.09	1.38	1.16
Sum	75.22	75.71	70.86
Path/Tracks			
Average	0.24	0.24	0.26
Minimum	0	0	0
Maximum	0.94	1.09	1.18
Sum	59.84	56.88	60.11
All Routes			
Average	0.14	0.15	0.15
Minimum	0	0	0
Maximum	0.87	0.75	0.82
Sum	35.93	35.4	36.09

An advantage of the clustered sample design was the inherent grouping of sample points into logical survey groups and the reduced within cluster travel distances. To fully assess the logistic viability of the systematic aligned design the preceding analysis was modified to consider sample point groupings where each group of 6 points represented a survey day.

While sample point groupings were inherent in the clustered design the systematic aligned sample design could be grouped into several arrangements. During initial analysis the aligned grid was split into regular or standard groupings with no consideration of access routes, elevation changes or other landscape factors (figure 3.10). The straight-line distance analysis was repeated (table 3.11) based on these standardised group centres.

Table 3.11: A comparison of the average, minimum and maximum distance (Km) between group centres, in the cluster and systematic aligned sample designs, and access routes of varying type

Distance (Km)	Sample Design	
	Clusters	Aligned (950m): Standard Sample Groupings
Roads		
Average	0.78	0.72
Minimum	0	0.01
Maximum	3.35	3.19
Sum	32.95	28.64
Rights of Way		
Average	0.28	0.3
Minimum	0	0.01
Maximum	0.94	1.02
Sum	12.45	11.87
Path/Tracks		
Average	0.22	0.2
Minimum	0	0
Maximum	0.94	0.69
Sum	10.41	8.17
All Routes		
Average	0.14	0.14
Minimum	0	0
Maximum	0.93	0.6
Sum	5.92	5.62

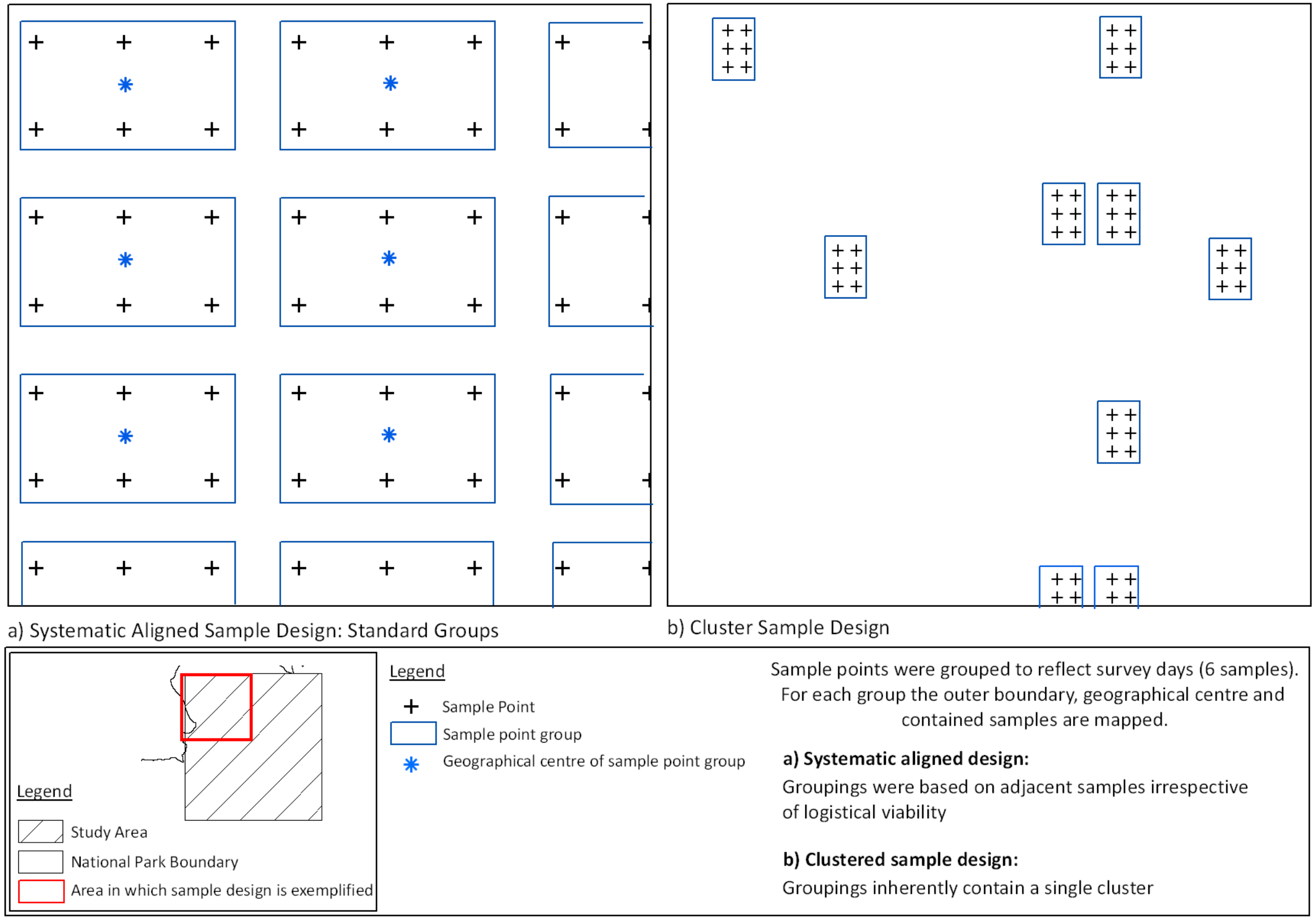


Figure 3.10: Grouping of sample points in the clustered and systematic aligned sampled designs to reflect survey days

Interpretation of the resultant distances (table 3.11) concluded that the sample designs were again very similar in their distance to access routes although, there was a tendency for distances to be lower in the systematic aligned sample design. While the results from table 3.11 appeared to indicate little difference between the sample designs these results did not consider the distance that must be travelled in and around the group to survey each of the 6 sample points. On average approximately 1km would have to be travelled from the cluster group centre to visit all sample points, this is opposed to 4.75km in the case of the standard groupings in the aligned design.

The greater travel distances in the systematic aligned sample design were potentially a function of the standardised sample point groupings. Consequently, the analysis was repeated using sample point groupings modified, on the basis of the proximity of sample points to access routes, to reflect more logistically viable survey days (figure 3.11).

A comparison of the alternative sample point grouping strategies for the systematic aligned grid (table 3.12) illustrated that simply grouping the sample points around common access routes, in particular roads and public rights of way, led to a small overall reduction in the straight-line distance between access routes and group centres. This reduction was however potentially mitigated by the elongation of sample point groupings and potential increase in distance travelled within groups.

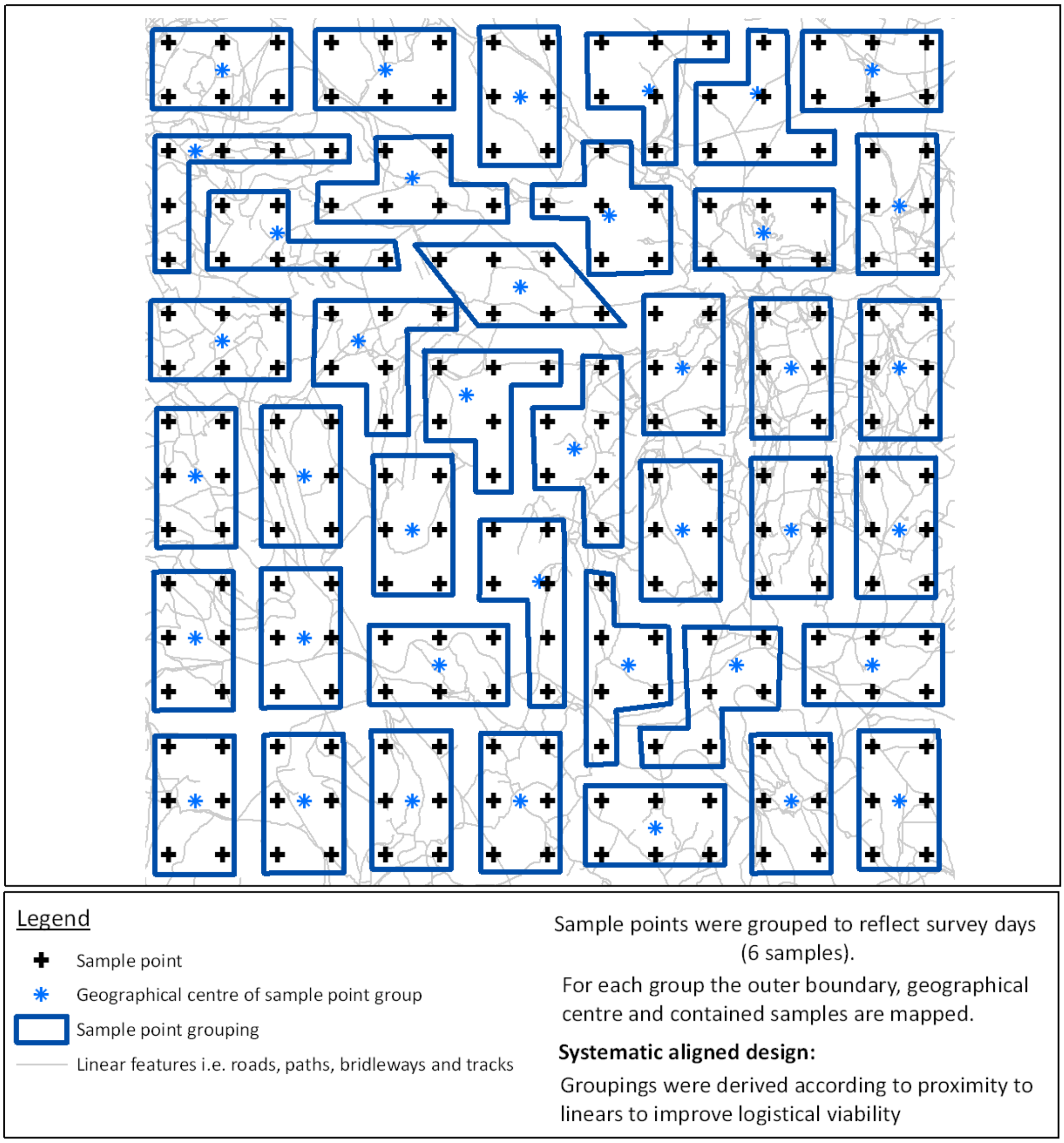


Figure 3.11: Sample point groupings, for the systematic grid, derived via proximity to access routes.

Table 3.12: Distances (Km) between access route and group centres within the systematic aligned sample design. Comparisons are made between standardised and access route derived (logistical) sample point groupings.

Distance (Km)	Sample Design	
	Aligned (950m): Standard Sample Groupings	Aligned (950m): Logistical Sample Groupings
Roads		
Average	0.72	0.75
Minimum	0.01	0
Maximum	3.19	3.11
Sum	28.64	30.18
Rights of Way		
Average	0.3	0.27
Minimum	0.01	0.04
Maximum	1.02	0.86
Sum	11.87	10.69
Path/Tracks		
Average	0.2	0.2
Minimum	0	0
Maximum	0.69	0.59
Sum	8.17	8.18
All Routes		
Average	0.14	0.13
Minimum	0	0
Maximum	0.6	0.52
Sum	5.62	5.39

Based on the 2D distance analysis outlined the average distance that would have to be walked between roads and group centres and therefore travel times, for the aligned sample design, were estimated to be:

- Average distance to group centre from road: 0.75km
- Average distance travelled around the group: 4.75km
- Walking speed at 5km/hour + 50%: 1hr 40min

Walking times were based on Naismiths rule, 5km per hour, with 50% added to account for difficult terrain (Fritz & Carver, 2004).

Based on these assumptions, approximately 1.75 hours per day would be allocated to walking, although this could reach a maximum of 2.5 hours. Within the pilot study, surveying of sample points took approximately 1 hour per sample point although, subsequent modifications to the field survey protocol decreased this value. On the basis of these assumptions it was concluded that the aligned sample design was logistically feasible.

Sample design comparison: Conclusions

Clusters

Based on previous research by Armstrong (1998), Dixon and Leech (1978), Dunglan and Coughlan (1999) and Webster and Oliver (2001) several issues can be highlighted regarding the applicability of data collected in this format to subsequent remote sensing and GIS analytical techniques. Additionally, sampling rate analysis established a tendency for the sampling strategy to over sample in the most extensive land cover classes of the study area.

Advantages of this design were primarily logistical with the compact nature of the sample point groups allowing efficient field survey.

Unaligned systematic grid

Although comparable to the systematic grid design in terms of the land cover classes sampled and distance between access routes and sample points, this sample design was excluded as a consequence of complexity in deriving suitable sample point groupings.

The random nature of sample points in this design was not only problematic in deriving sample groups but could also be detrimental to subsequent analysis due to the tendency for sample points to form clusters. In such cases the disadvantages of the clustered design applied.

Aligned systematic grid

The literature review implied that the systematic grid design was the most suitable for subsequent analytical techniques (Armstrong, 1998; Dunglan & Coughlan, 1999; Webster & Oliver, 2001). However, concerns regarding the representativeness and logistic viability of the design were highlighted (Kent & Corker, 1992).

Examinations of sampling rates within each land cover class proved that the aligned systematic grid was in fact the most representative sample design and therefore in this respect the preferential sampling technique.

Simple analysis of 2D straight-line distance supported the hypothesis that the distribution of access routes across the study area was sufficient to make the required walking times feasible. Further modifications to the sample point groupings, on the basis of access, 3D distance, elevation and terrain, would, it is proposed, further improve this logistic viability.

Consequently, it was concluded that the aligned systematic grid was the most applicable for implementation within the full ground survey. To ensure that the number of sample points surveyed was maximised a systematic aligned grid with an interval of 950m was implemented.

3.4.6 Sample point clustering, survey days

Problem definition

As discussed previously, implementation of the systematic aligned sample design required the grouping of sample points into logistically efficient survey days. In the preceding analysis groupings were derived via a standard allocation of 6 neighbouring samples or secondly on the proximity to common access routes. It was proposed that such groupings did not represent the most logistically efficient solution as they did not consider more complex factors including land cover, 3D distance travelled or changes in elevation.

Sample point grouping

A primary consideration when deriving sample point groupings, in terms of their logistic viability, related to the ease with which the surveyor could travel to and between sample points. Factors which would influence the ease of travel were:

- *Land cover*

Due to the regular grid construction of the sample design sample points did not fall adjacent to access routes within the study area. Where the surveyor was required to deviate from access routes, the land cover type being crossed must be considered. Land cover will influence the ease with which the landscape can be traversed.

- *Elevation*

Large changes in elevation influence both the distance the surveyor must travel between sample points and the ease with which the landscape can be traversed. Consequently, elevation changes within sample point groupings should be minimised.

- *Access route type*

Access to a group of sample points would be from one of the access routes which dissect the landscape. The type of route from which groups will be reached should be considered as this will influence the ease of access to the site.

In theory a number of potential access routes exist to reach each sample point. A methodology was therefore developed whereby a series of potential paths, between access routes and sample points, were derived. For each sample point, potential paths were analysed on the basis of the factors above to determine the most efficient route to the sample location. Subsequent sample point groups were based on samples which shared a common access route.

Path scoring and ideal path definition

The derivation of potential paths and path scoring was implemented within a GIS using a bespoke application. Methodology steps in the application can be summarised as follows:

- *Access route division*

Initially access routes were split into a series of points from which potential paths could originate. Points could be defined on the basis of a specified interval or a required number of points placed equidistant along the access route.

- *Potential path definition*

For each sample, potential paths were created as a series of linear features between the sample and all access route points, created in the previous step. To minimise the number of potential paths only those access route points within a user specified distance of the sample point were considered.

- *Path scoring*

Path scoring was an iterative process, requiring user input, to assign the suitability scores of each factor influencing path selection. Factors included in the scoring process were:

    - Access route from which the path originates.
    - Land cover types crossed between the access and sample points.
    - 3D length of and change in elevation along the potential path.

Each factor was assigned a series of user defined suitability values on the basis of the range of potential path attributes. If any path attribute was considered an absolute barrier to consideration a no-data value could be assigned to ensure exclusion of the path from all subsequent analysis. Examples of absolute barriers included paths which cross open water or woodland.

Following suitability score assignment, the final path score was calculated on the basis of a multi-criteria weighted function (equation 3.2).

$$final\ score = \frac{(w\ \times LC) + (w\ \times R) + (w\ \times E) + (w\ \times L)}{\sum w}$$ **Equation 3.2**

where:

w is a weight
LC – Land cover score, R – route score, E – elevation score, L – 3D length score

- *Optimum access route assignment*

Following the final suitability score calculation each sample point was assigned a value indicating the access route from which the highest scoring path originated. This value indicated, based on the specified factor weighting values, the most appropriate access route from which to approach any given sample point.

It should be noted that this process was iterative therefore several iterations were required to identify the most appropriate suitability values for each factor.

Survey day clustering

The original methodology proposed the grouping of sample points on the basis of the optimum access route, as derived in the preceding analysis. Automated GIS techniques tested to perform this grouping were clustering, buffering, allocation and classification. However, extensive testing concluded that none of these techniques were capable of grouping the sample points on the basis of the information provided.

The inability of these techniques to perform this grouping highlights the complexity of the grouping process. Manual grouping automatically considers complex contextual factors, not easy modelled within the techniques tested, including:

- *Circular routes*

When planning daily field survey itineraries, particularly those on foot, circular rather than out and back routes often presented more logistically viable solutions. Such complexity could not be built into the existing model, within the scope of the current research project.

- *Movement between samples*

An assumption of the above analysis was that all sample points would be visited from an access route. While this was true of the first sample points, subsequent sample points did not require the surveyor to return to an access route. Such subjectivity, regarding between sample distances could not be built into the above method within the scope of the current research project.

- *Access and ownership issues*

A further assumption of the analysis was that no constraints existed regarding sample point access. As a result samples were grouped irrespective of land ownership boundaries.

It was proposed that such concepts would be best incorporated into the current model by network analysis, however, these further developments were outside the scope of the project. Final sample point groupings were therefore based on a semi-automated approach including visual interpretation of the optimum access route analysis and Ordnance Survey mapping in addition to information regarding sample point specific access permissions.

3.5 Chapter summary

The key points of this chapter are:

- The research aim required the recording of land cover attributes as opposed to land cover class.
- Land cover attributes were derived from current land cover class definitions to permit the reconstruction of such classification schemes.
- The full field survey recorded seven attributes which influence the delineation of land cover types:
    - Site characteristics.
    - Soil characteristics.
    - Species cover (including heather species structural stage).
    - Species composition (target species presence/absence).
    - Species height.
    - Heather species density (including heather species structural stage).
- Attributes were recorded at the scale of a sample point which consisted of four quadrats aligned to the compass cardinals.
- Clustered, systematic aligned and systematic unaligned sample designs were compared on the basis of land cover type, logistic viability and applicability to further remote sensing techniques. It was concluded that the systematic aligned design was the most appropriate design.
- The grouping of samples in the systematic aligned design to represent survey days (six samples) was based on a semi-automated method. This method included optimum access routes, as derived from a bespoke multi-criteria overlay analysis, Ordnance Survey mapping and access permission information.

Field Survey Implementation

Field survey development culminated in a full survey being conducted during the summer months of 2004. Chapter 4 reviews the implementation of this ground survey in terms of the sampling rates achieved in each land cover, field data collation and GPS processing.

Sampling rates achieved during the field survey are compared to the survey design with the impact of inaccessible points being discussed. GPS processing, for the determination of survey sample location, was limited to code phase processing as outlined in the chapter. The influence of this level of post-processing, in comparison to full carrier phase correction, on sample point location accuracy is considered.

4.1 Introduction

The full field survey was undertaken, by two surveyors, during July and August 2004. The timing of the field survey, relative to the characteristic management cycle of the upland heath, was an important consideration to ensure access to sample points. Implementation of the survey during July and August ensured fieldwork was not coincident with the grouse breeding season or heather burning. However, overlap with the grouse shooting season did impose temporary access limitations. These temporary access limitations were resolved by re-visiting areas, where possible, and consultation with landowners and estate managers.

Data collection within the full field survey followed a standardised format as prescribed in the field survey protocol (appendix C). Data collection efficiency, consistency and standardisation were further promoted by the automated collection of field data within a bespoke field survey application program (appendix E).

4.2 Survey implementation: linear features

As the sampling methodology was based on a point design it was possible for an intended sample point to intersect a linear feature, where a linear feature was defined as a hard boundary less than 3m in width (Bertin *et al*, 2003). In addition to restricting the implementation of the intended quadrat layout the pilot study illustrated that linear features had a direct influence on surrounding vegetation composition. Sample points which intersected linear features were therefore shifted spatially, following standard rules (described below), to ensure a full quadrat layout was achieved and to remove any linear feature influence on vegetation composition.

As the influence exerted by a linear feature on vegetation composition was related to the height of the feature, movement of the sample point was based upon this parameter. Consequently, sample points which intersected linear feature were moved perpendicular to that feature to a distance which was three times the height of the feature or a minimum of three meters should the feature have no height i.e. tracks or roads.

Errors in locating sample points, both in the field and on the remote sensing imagery, result from GPS and georeferencing errors, respectively. Due to these errors it was ensured that sample points were internally homogenous and representative of the surrounding vegetation. Consequently, the sample point quadrats could not straddle abrupt changes in land cover. Such abrupt changes were considered boundaries and treated as linear features with no height.

In addition to linear features, sample points were moved if they intersected any object superimposed on the land cover which restricted the layout of the quadrats, for example, grouse butts or silage bales.

Features which caused sample points to be moved are listed in table 4.1.

Table 4.1: Features which caused sample points to be moved.

Feature	Examples
Linear	
Access routes	Tracks, Paths, Roads, Bridleways
Field boundaries	Hedges, Walls, Fences
Waterways	Streams, Rivers
Drainage channels	Grips, Ditches
Trees	Strip woodland, Woodland edges
Non-Linear	
Water features	Ponds/lakes
Management features	Grouse butts, Silage bales

4.3 Field survey statistics

4.3.1 Surveyed sample points

The proportion of sample points surveyed, of the intended 240 in the original sample design, is illustrated in table 4.2. Delays in the survey resulted in 19 sample points remaining completely un-surveyed. To restrict un-surveyed sample points to a single area, therefore ensuring a consistent block of vegetation data, sample points at the southern boundary of the study area were excluded. The movement of the southern boundary reduced the original 240 sample points to 225, of these only two remained un-surveyed (table 4.3).

Table 4.2: The proportion of samples surveyed during the field survey

	Number of Sample points	Proportion of Samples (%)
Surveyed	221	92
Not surveyed	19	8
Total	**240**	**100**

Table 4.3: The breakdown of samples excluded from the field survey

	Number of Sample Points
Outside National Park	5
Not surveyed	2
Excluded due to contracted study area	12
Total	**19**

For analysis purposes sample points were classified into six classes according to the measurements taken:

- *Full quadrat*: a full set of measurements were collected as outlined in the field survey protocol.
- *Limited (inaccessible) information*: only limited information in the form of a generalised site and vegetation description was available as the intended sample point could not be reached.
- *Woodland*: the sample point occurred in woodland.
- *Developed*: the sample point occurred on an artificial surface primarily associated with urban development.
- *Not surveyed*: the sample point remained un-surveyed.
- *Outside National Park*: sample points which fell outside the boundary of the National Park and were consequently not included in the survey.

Table 4.4 illustrates the proportion of sample points occurring within the contracted study area, classified according to these definitions. Of primary importance to the research project were the detailed measurements taken at the full quadrat sample points. These comprehensive measurements contain detailed information on vegetation composition. Table 4.4 confirms that full quadrat measurements were available for 156 of the 225 sample points representing 69% of the total sample.

Table 4.4: The breakdown, according to measurement type, of the sample points occurring within the contracted study area.

	Number of Sample Points	Proportion of Total (%)
Full quadrat measurements	156	69
Inaccessible (of which woodland)	60 (17)	27 (8)
Developed	2	1
Not surveyed	2	1
Outside National Park	5	2
Total	**225**	

4.3.2 Spatial arrangement of sample points

The spatial arrangement of samples containing full quadrat measurements was considered as the spatial distribution of the measurements influenced the applicability and precision of the proposed data analysis techniques. To ensure consistent results, ideally, the detailed measurements should be well distributed across the study area and representative of all land cover types present.

Figure 4.1 illustrates the spatial distribution of each sample type within the contracted study area. From visual inspection of the figure it was concluded that full quadrat measurements tended to occur in contiguous blocks and were reasonably well distributed across the study area, excluding the northwest corner. Comparison with the landform of the study area (figure 4.2) revealed that contiguous blocks of full quadrat measurements tended to correlate with the moorland plateaus. Conversely, inaccessible sample points were concentrated on steep slopes or in the valley bottoms.

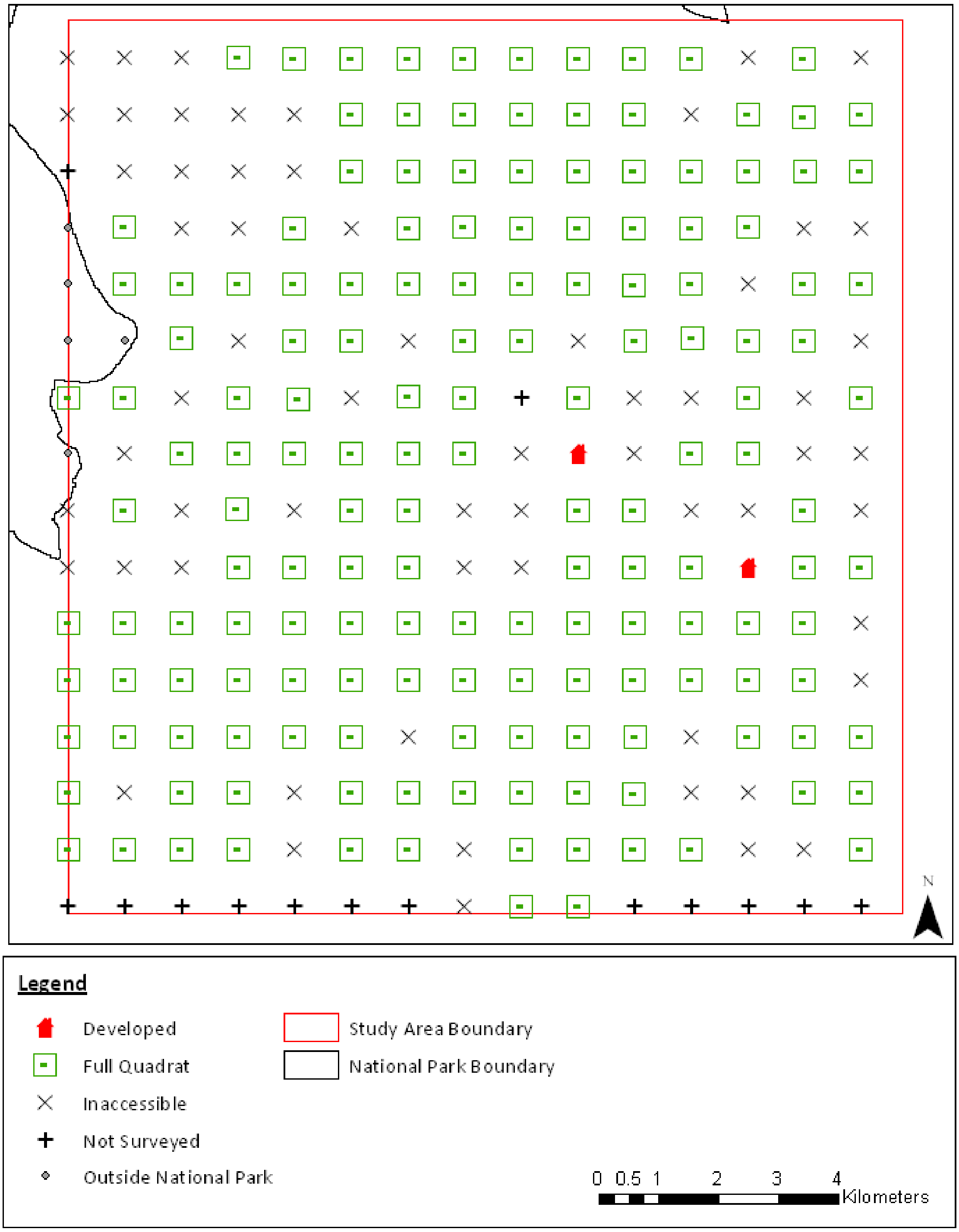


Figure 4.1: The spatial arrangement of sample points in the study area, classified according to the type of measurements.

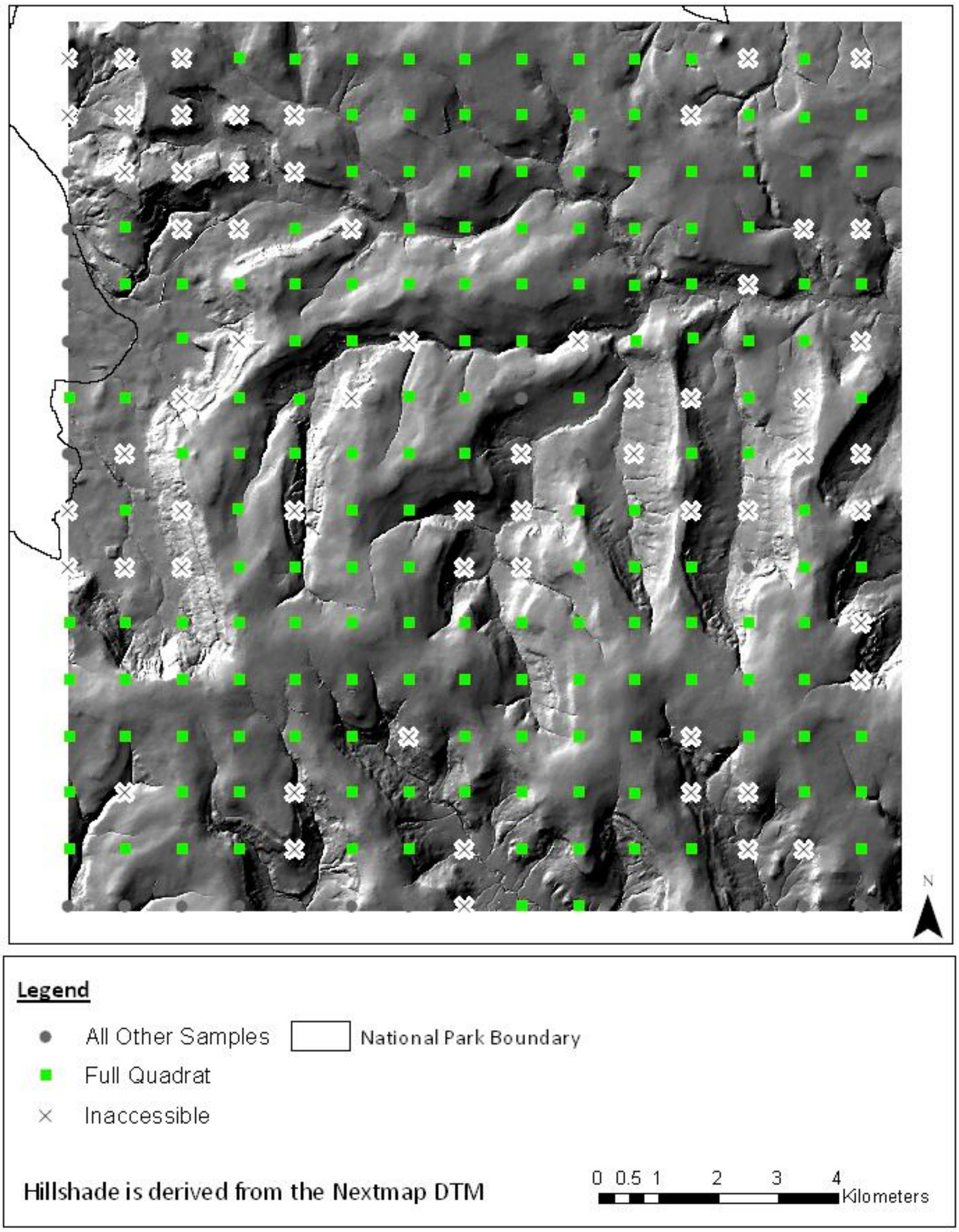


Figure 4.2: The spatial arrangement of full quadrat and inaccessible sample points, compared to the landform of the study area

4.3.3 Land cover sampling rates

Figure 4.3 overlays the classified sample points on the generalised land cover of the study area. The land cover map was extracted from the 1980s MLCNP survey (Taylor *et al*, 1991d). Although this land cover information was historical, the relative stability of the major land cover categories within the study area allowed the extraction of general trends.

Figure 4.4 summarises figure 4.3 by illustrating the proportion of full quadrat measurements falling in each land cover class. Initial analysis of this figure indicated that the full quadrat measurements over sampled the upland heath land cover class. However, as discussed in chapter 3, sampling rates must be considered within the context of the spatial extent of each land cover class (table 3.8).

As 44% of the study area was composed of upland heath, ideally a similar percentage of full quadrat measurements should occur in this land cover class. As 58% of quadrat samples fell within this class (figure 4.4) upland heath was considered to be over represented in the field survey data set. If the original sample design was considered, 44% of sample points fell in upland heath; the class was therefore not over represented in the original design. It was proposed that the cause of the higher sampling proportion within upland heath was the consistency with which sample points falling in this land cover category could be surveyed.

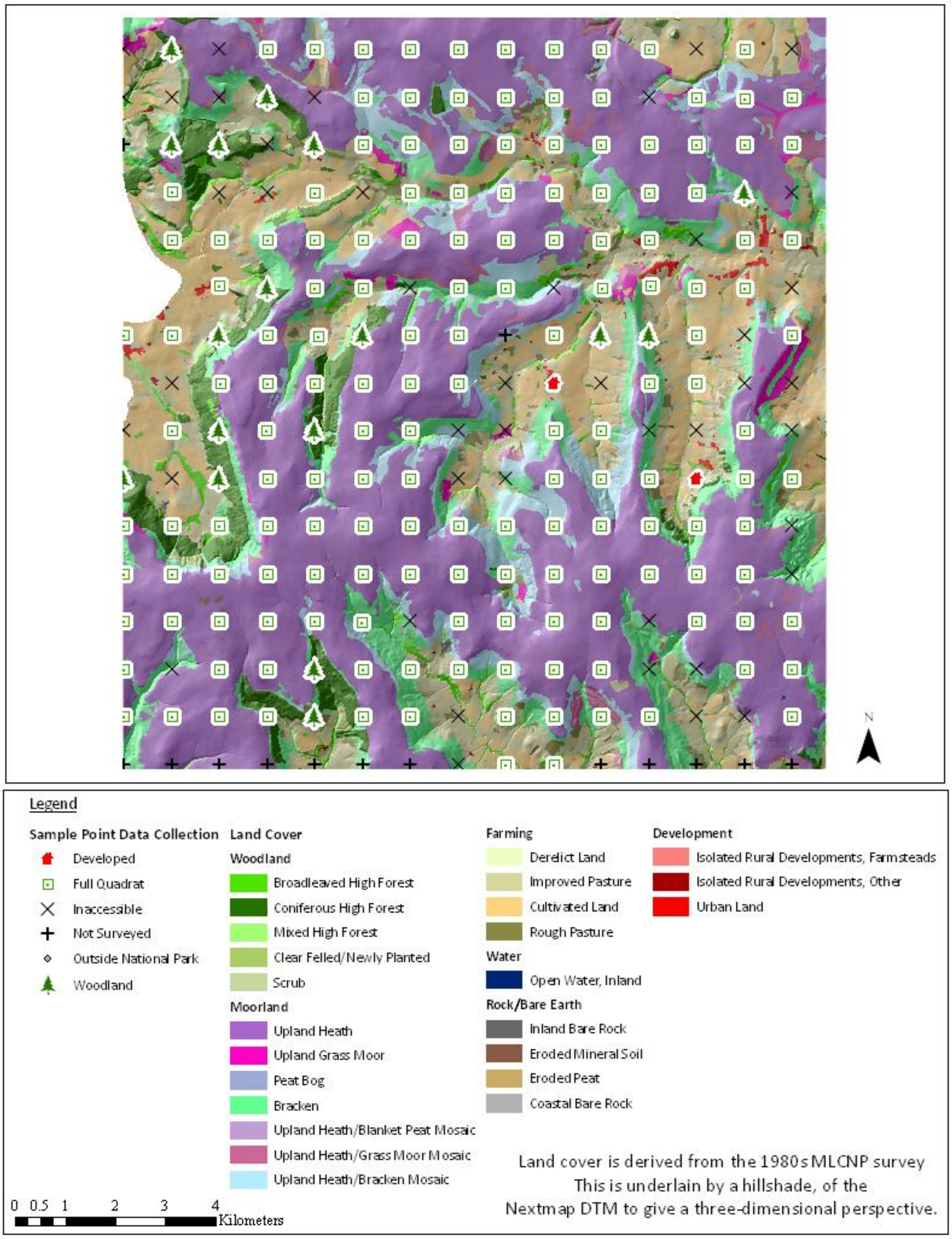


Figure 4.3: A comparison of sample points, classified according to measurement type, and the generalised land cover of the study area.

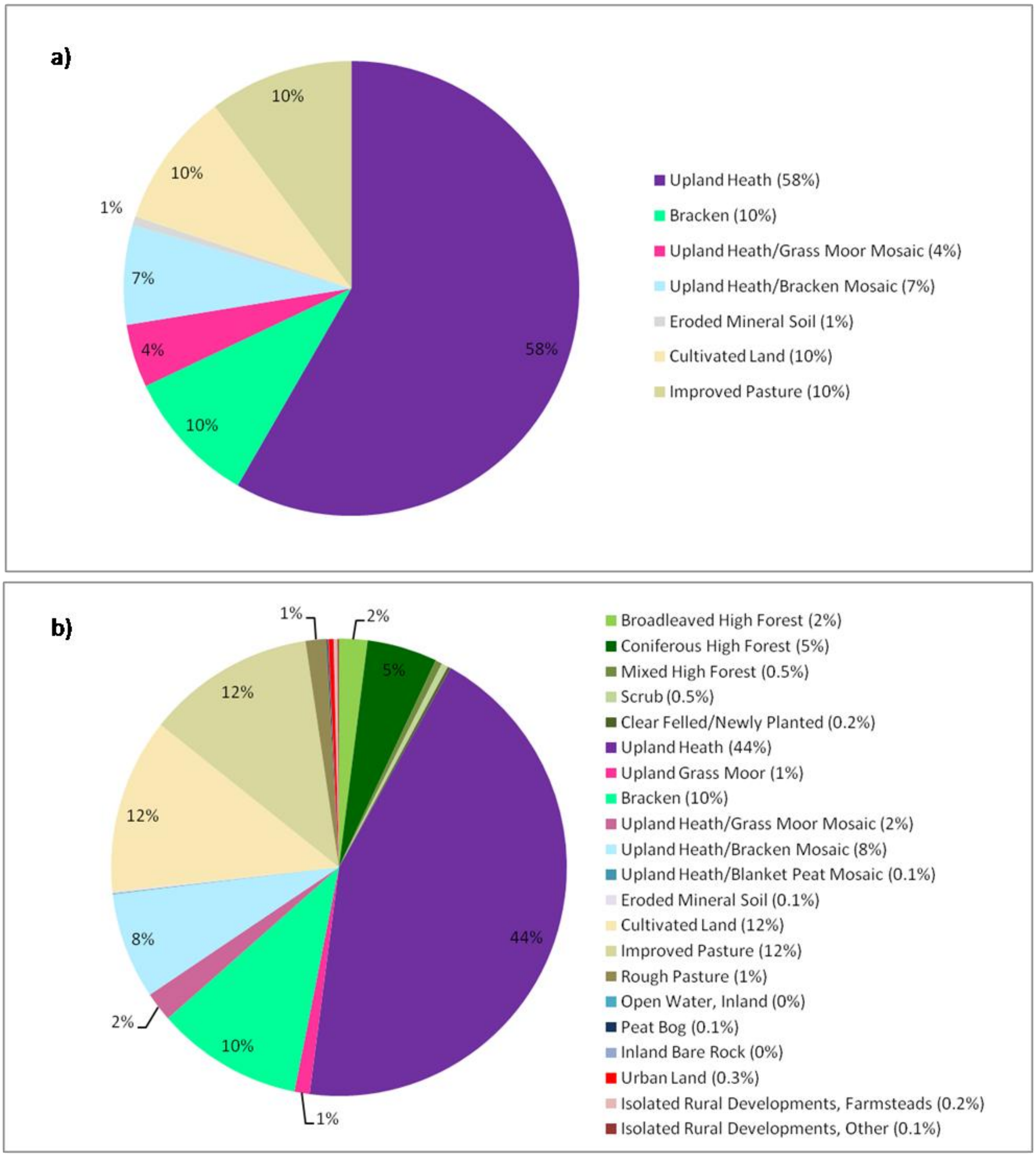


Figure 4.4: a) The proportion of full quadrat sample points, within the reduced study area, classified according to land cover category; b) The proportion of each land cover category within the contracted study area.

Land cover classes not represented in the field survey data, i.e. upland heath/blanket peat mosaic and peat bog are those with a small spatial extent in the study area. Due to the random sample design land cover types with a small spatial extent have a low probability of being sampled hence the exclusion of these land cover classes from the sampling scheme.

4.3.4 Inaccessible samples.

Land cover types under-represented by the full quadrat samples, i.e. bracken and cultivated land (figure 4.4) were identified as the major cause of inaccessible sample points (figure 4.5).

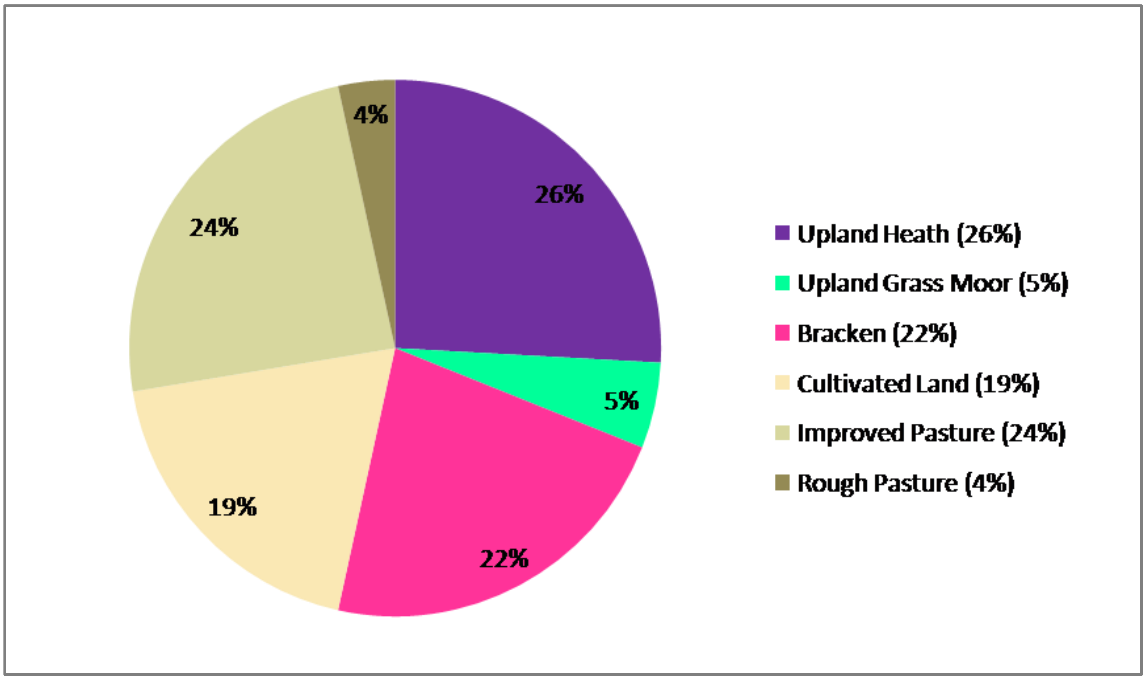


Figure 4.5: The proportion of inaccessible sample points, within the reduced study area, classified according to land cover class.

Within the agricultural land cover class inaccessible sample points could be attributed to a variety of factors including:

- Planted crops.
- Livestock; calving was a particular issue at the time of the field survey.
- Owner identification and access permission issues.

- Management practices, for example, herbicides application or land clearance.

While the field survey protocol suggested that any inaccessible sample point be revisited this was not found to be feasible due to time limitations.

In addition to agricultural land, bracken was also identified as a major cause of inaccessible sample points (figure 4.5). The height and density of bracken plants and a tendency for the land cover to be located on very steep slopes prevented access.

4.4 Field data collation

4.4.1 Percentage cover

The collection of percent cover during the field survey used a technique based on a hybrid of the pin quadrat and visual estimation (section 3.3.5). Derivation of percent top cover using this technique could result in total values, for individual quadrats, exceeding 100%. This was a consequence of the recording of more than one species as contributing to top cover in each quadrat cell. The implications of a top cover percentage exceeding 100% are application specific. However, for techniques such as sub-pixel classification this format is not appropriate; top cover per quadrat should sum to 100%. To resolve this issue the top cover values recorded in the field survey were scaled (equation 4.1).

$$\mathbf{SSC}(\%) = Species\ cover\ (\%) \times \left(\frac{1 - (Total\ Quadrat\ Cover\ (\%) -\ 100)}{Total\ Quadrat\ Cover\ (\%)}\right) \qquad \textbf{Equation 4.1}$$

where;

SSC (%) is the scaled percentage top cover for a particular species

4.5 GPS processing

4.5.1 GPS data collection

The field survey protocol was devised to ensure the collection of sufficient GPS data to allow further (post) processing of the recorded sample point locations, subsequent to the survey, to improve positional accuracy.

This post-processing or differential correction calculation is based on the determination of GPS data error via comparison of the GPS derived and pre-determined location of a reference receiver (base station). Using these calculated error values corrections are applied to the GPS measurements collected in the field (rover file). Improvements in accuracy from this process vary according to the type of differential correction (code or carrier) and the amount of data collected in the reference and rover (field) GPS units.

Sample point locations were recorded using the TerraSync software available on the Trimble GeoXT GPS device. Each sample point was recorded as a point feature identifiable via a unique sample point identification number (SMPID). Following the field survey protocol, GPS positions and carrier phase data were logged for at least 10 minutes at each sample point.

The reference or base station data were supplied by the GPS archive BIGF[1]. Base files were available for the Scarborough base station (British National Grid reference: 505643, 485304) for all field survey days. The base station files were supplied in two formats, depending on field survey date, in which the recording interval varied between 15 and 30 seconds.

Differential correction can be categorised into two techniques, code and carrier phase correction. Code processing gathers data via the C/A (coarse acquisition) code receiver, or pseudo-random code, for use as the basis of GPS location calculations. Carrier processing is a more complex technique which collects data via the carrier signal. This

[1] Natural Environment Research Council (NERC) British Isles GPS archive Facility (BIGF), www.bigf.ac.uk

carrier signal operates at a much higher frequency than the pseudo-random code and can be used to make more accurate position estimates (Trimble, 2004).

Requirements, which must be met, when recording GPS data for use in code and carrier phase correction are that, a minimum of 4 satellites are used to establish the GPS position, PDOP (percent dilution of position) should not exceed 6 and finally the signal-noise ratio and satellite elevation should be greater than 4 and 15°, respectively. In addition for carrier phase correction a minimum of 10 minutes carrier data is required and the distance between the reference and rover receivers should not exceed 50km (Trimble, 2004).

4.5.2 Differential correction

The intention of the field survey protocol was to differentially correct the sample point locations using carrier phase processing. Initial attempts to apply this level of correction to the data were unsuccessful or, where correction was successful, limited in the proportion of positions per point corrected.

Low correction percentages

The correction of a small proportion of GPS rover measurements was a consequence of the difference in data collection rates between the rover and base files. While the rover files recorded GPS locations at a 1 second interval the base station collected data at a 15 or 30 second interval, depending on the file type. As only rover GPS records which coincided with base station records could be corrected the resultant correction rates were 6% (15 second base station interval) and 3% (30 second base station interval).

Uncorrected files

Issues identified as causing carrier phase processing failure were:

- *Distance to reference station*

Although the Scarborough station was the closest active RINEX base station to the study area this station was working at its operational limits (50 km) in terms of the distance between the rover and reference file. This was illustrated by the straight-line distance calculated between the reference station and all points within the study area (figure 4.6). Locations in the northwest corner of the study area did not meet the 50 km requirement; carrier phase correction was not recommended for sample points falling in this area due to the increased error associated in GPS correction beyond this distance threshold (Trimble, 2004).

- *RINEX file header misreporting*

Following the completion of the GPS processing an error was identified by BIGF in the header files of all LEICA RS500 receivers, including the Scarborough station, which resulted in the misreporting of available observations. The error was centred on the C1 observable which was misreported as P1. Consequently, the reference file headers read P1, P2, L1, L2, S1, S2 instead of C1, P2, L1, L2, S1, S2. Using manual techniques the file headers were reconstructed for a subset of files and carrier phase correction tested. Following modification, carrier correction of a subset of the rover files, which could previously not be corrected, was feasible. However, these corrected files suffered from low correction proportions as a function of base station recording interval.

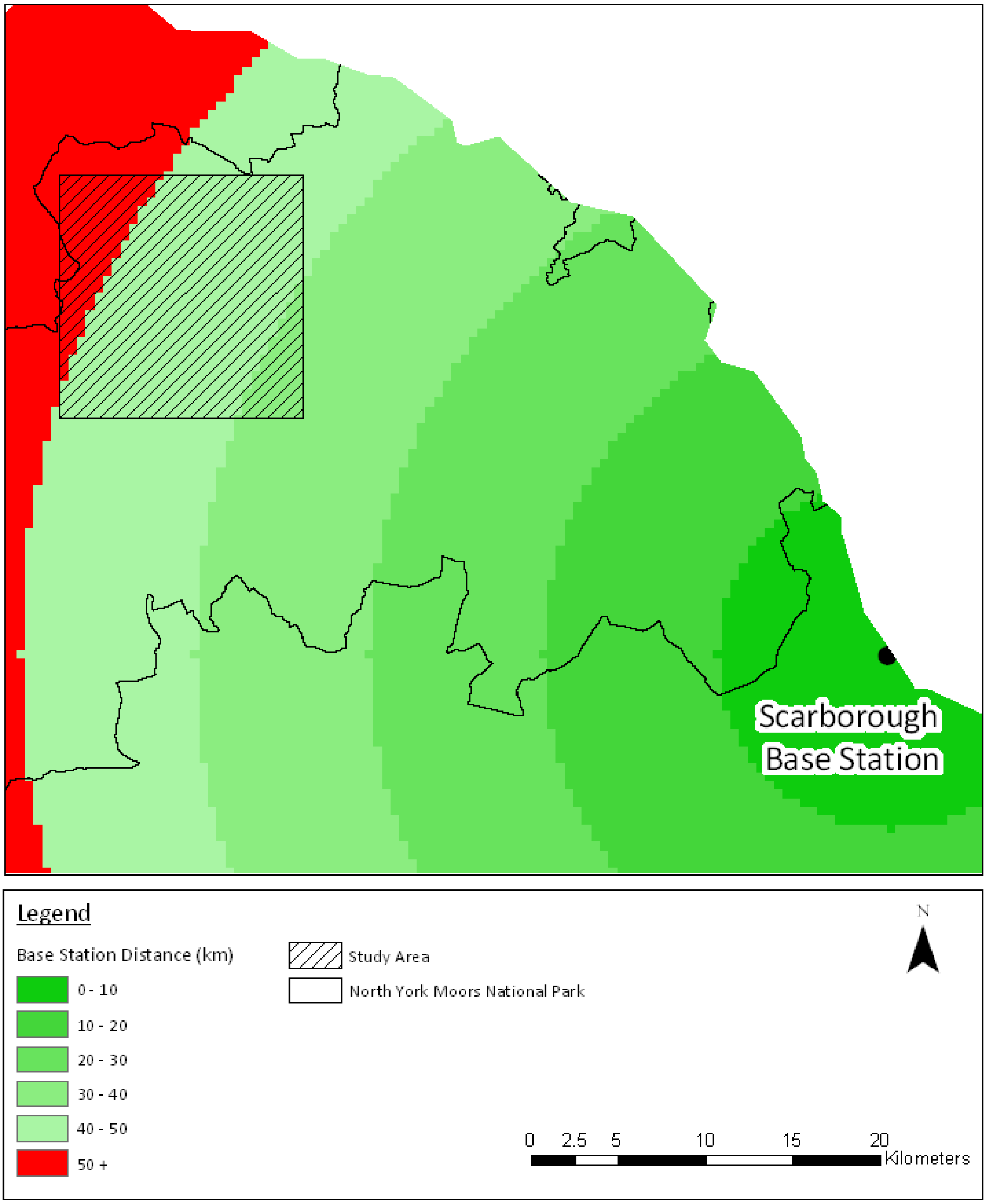


Figure 4.6: The straight line distance between the Scarborough active RINEX base station and the study area.

- *The D1 observable*

According to the Trimble literature a requirement of carrier phase correction, within the Pathfinder Office software, is the D1 observable or L1 Doppler data. This information was not collected as standard by the Ordnance Survey active RINEX network prior to 29/06/2005 except at 6 General Lighthouse Authority (GLA) stations. This did not include the Scarborough reference station. As this D1 observable is not available in any of the reference files there is a disparity as to why carrier phase correction was feasible for files within the 50km threshold. While no solution has been identified several causes can be hypothesised following communication with Trimble. Firstly, the D1 data could be automatically replaced by 'dummy' data in the active RINEX file or secondly, the software could be using triple-differencing techniques to provide the solution. The impact of either of these techniques on the final accuracy of the carrier phase solution is unknown.

Due to the issues outlined, it was found impossible to consistently apply carrier phase correction across all GPS data collected in the field. Consequently, code phase correction was considered.

4.5.3 Code phase correction implications

To test the implications of applying code correction to the field data an experiment was developed whereby the locations of a subsection of sample points were compared after carrier, code and no correction.

Sample points included in this analysis were selected manually to ensure they were within the 50km carrier phase correction threshold (table 4.5). Carrier phase correction percentages ranged from 3% to 6% as the datasets included both the 30 second and 15 second interval reference files.

Table 4.5: Sample points included in the carrier versus code correction comparison

SMPID	Raw X Coordinate	Raw Y Coordinate	Code X Coordinate	Code Y Coordinate	Carrier X Coordinate	Carrier Y Coordinate
Sample 27	468469.65	499063.32	468469.30	499062.01	468469.37	499061.87
Sample 50	461818.62	500962.57	461819.09	500962.34	461819.47	500961.83
Sample 55	466569.07	500961.81	466568.79	500961.54	466568.99	500961.62
Sample 56	467526.92	500961.02	467523.94	500959.55	467523.94	500959.48
Sample 65	461818.58	501912.48	461818.47	501912.17	461818.41	501912.35
Sample 66	462761.65	501912.44	462767.11	501913.65	462767.33	501913.07
Sample 67	463718.46	501913.77	463716.24	501911.73	463716.38	501911.59
Sample 70	466569.32	501912.21	466568.86	501911.68	466568.87	501911.09
Sample 71	467518.90	501913.40	467519.02	501913.03	467519.17	501912.77
Sample 82	463719.40	502862.95	463718.91	502862.04	463718.81	502861.60
Sample 85	466569.47	502862.78	466569.25	502862.09	466569.20	502862.25
Sample 86	467516.52	502863.98	467516.41	502862.93	467516.25	502862.85
Sample 105	471318.99	503812.19	471320.28	503813.03	471320.21	503813.42
Sample 127	463720.27	505713.81	463718.52	505712.68	463718.61	505712.45
Sample 128	464669.41	505712.72	464668.81	505712.09	464668.81	505712.08
Sample 142	463719.28	506668.40	463716.70	506667.65	463717.11	506667.63
Sample 143	464667.43	506660.74	464666.58	506660.29	464666.56	506659.80

Notes:

All GPS locations are reported in Ordnance Survey National Grid coordinates.

Raw coordinates represent the original GPS location prior to differential correction. Code and carrier coordinates represent the GPS locations after code and carrier processing, respectively.

Each of the differential corrections, carrier and code, were processed independently in the Pathfinder Office software.

A comparison of the coordinate pairs, resulting from the different correction methods, was based on the calculation of the root mean square difference (RMSE) (equations 4.2 and 4.3). Comparisons made were between carrier and raw, code and raw and carrier and code (table 4.6).

$$RMS_x = \sqrt{\frac{\sum(x_1 - x_2)^2}{n}} \qquad RMS_y = \sqrt{\frac{\sum(y_1 - y_2)^2}{n}}$$ **Equation 4.2**

And

$$RMSE = \sqrt{RMS_x^2 + RMS_y^2}$$ **Equation 4.3**

Where:

n = number of sample points

$x(y)_1$ and $x(y)_2$ are the x (y) coordinates being compared

Table 4.6: RMSE differences between three alternative differential correction techniques calculated for a subset of sample points

Comparison	Raw versus Carrier	Raw versus Code	Carrier versus Code
RMS X	1.834	1.831	0.173
RMS Y	1.097	0.958	0.322
RMSE	2.137	2.066	0.366

If the alternative processing techniques resulted in identical national grid locations then the RMSE would be zero therefore, a low RMSE is indicative that sample point locations for the different techniques are similar. From the comparative results (table 4.6) it can be concluded that:

- Differential correction, code or carrier, caused a large improvement in sample point positional accuracy.
- The improvement in accuracy between code and carrier correction was orders of magnitude lower than the raw to corrected comparisons.

- The process of differential correction, carrier or code, was an important element in improving the accuracy of the sample point locations.
- Due to the lower correction percentages and distance between the rover and reference files (approximately 40km), in the case of this study, the influence of carrier correction over code correction was minimal.
- As, on average, the code correction was within 40cm of the carrier, the results suggested that sub metre accuracy was being achieved with the code correction.

4.5.4 Sample point area versus GPS accuracy.

The results of the carrier versus code comparison suggest sub metre accuracy is being achieved within the code phase correction. While the samples are thought of as points they in fact have a circular area (diameter 4m) represented by the four quadrats (figure 3.8). The sub metre accuracy of the code processed sample point locations therefore falls within the 'area' represented by the sample point. Consequently, it was concluded that this level of processing would have little impact upon the accuracy of further remote sensing techniques.

4.6 Field survey discussion: measurement issues

The remainder of this chapter discusses the general execution of the field survey protocol by outlining measurement issues which may impact on further data processing. Of importance are:

- *Density*

Caution should be exercised when interpreting heather plant density values as this parameter was found, as expected (section 3.3.8), to be prone to measurement errors. A tendency for heather plants to form dense mats and inter-mix with other species made the recording of this parameter subjective.

- *Eriophorum vaginatum and Eriophorum angustifolium*

The field survey protocol specified that these cotton grass species should be separated during species composition measurements. During the field survey this segregation was found to be impractical as the flowering heads, which allow easy identification of the species, were not present. Flowering of the cotton grass species occurs from April-May in the case of *Eriophorum vaginatum* and May-June for *Eriophorum angustifolium.* Both of these flowering periods were prior to the survey period.

- *Grass, rush and sedge identification*

There was concern that the grass, rush and sedge families were not accurately and consistently identified during the field survey. In particular, it was concluded that grasses were over estimated at the expense of the sedges. Rushes were believed to have been more successfully segregated due to their distinctive characteristics and concentration in predominantly wetter soil conditions.

- *Heather species, structural classification*

The structural classification of heather species can be subjective particularly for those plants close to a structural boundary. In an attempt to ensure consistency both surveyors discussed the most appropriate structural classification. However, distinction of the *Erica tetralix* and *Erica cinerea* structure groups and building/mature boundary of *Calluna vulgaris* were found to be particularly complex.

4.7 Chapter summary

The key points of this chapter are:

- The full field survey was conducted by two surveyors during July and August, 2004.
- The full characterisation of land cover attributes, as outlined in the field survey protocol, that is, full quadrat measurements were achieved at 69% of the samples surveyed.
- A tendency for full quadrat measurements to be achieved consistently at moorland sites led to the over sampling of these land covers. Conversely, inaccessible samples tended to occur on steeply sloping and agricultural land leading to an under-representation of the bracken and agro-pastoral land covers in the field data.
- Carrier correction of sample point locations was not feasible due to the distance between the study area and nearest Ordnance Survey reference station. A comparison of code and carrier correction concluded that, due to the reference station being located at its operational limits, code correction does not result in a significant decrease in positional accuracy. Code correction was therefore applied to all sample point locations.
- A series of issues concerning data collection within the field survey have been identified. Of particular relevance to further processing were inconsistencies in the separation of firstly, the grass, rush and sedge families and secondly, the structural stages of the heather species in particular *Erica tetralix* and *Erica cinerea*.

CHAPTER 5

The Classification of Remote Sensing Data

A literature review discusses remote sensing techniques commonly utilised in the automated classification of satellite images for land cover map derivation. Following this review, the applicability of the techniques outlined to the research aim is discussed.

The integration of the land cover attributes, as collected via the field survey, and remote sensing imagery is achieved via two distinct methodological approaches: land cover map construction and land cover attribute parameterisation. These methodologies are defined and their fundamental differences outlined.

Finally, the land cover construction methodology is outlined. This methodology aims to construct multiple land cover maps from a single field survey. This is achieved via classification of the field samples, on the basis of the land cover attributes recorded, and their subsequent inclusion within per-pixel and object-orientated classification methodologies. The methodologies implemented to construct the MLCNP, NLUD and P1 land cover maps within the study area are outlined.

5.1 The role of remote sensing and ancillary data

The research project aims to investigate the use of remote sensing imagery, in combination with image processing techniques, for the characterisation of land cover attributes, in particular species composition and top cover, across the entire study area. The characterisation of the land cover attributes using remote sensing data requires data in addition to the satellite imagery. The first of these is commonly referred to as training data. Training data forms the basis for relationship development between the land cover and satellite image characteristics. Within the current research, the training data were derived via field survey (chapters 3 and 4).

Secondly, ancillary datasets supplement the remote sensing data with the aim of refining and hence improving the accuracy of land cover attribute mapping. Ancillary datasets might be derived from a series of sources, including other remotely sensed data. The ability of ancillary datasets to aid land cover characterisation is a function of their relevance and relationship to the parameter being considered; there must be a relationship between the land cover attribute and ancillary dataset.

5.1.1 Remote sensing data: SPOT 5 (Le Système Pour l'Observation de la Terre)

The HRG (High Resolution Geometric) instrument of the SPOT 5 satellite records information in 6 spectral bands each of which is situated in a different portion of the electromagnetic spectrum. The spatial resolution of these data is 5m in the panchromatic band, 10m in the visible and near-infrared bands and 20m in the short-wave infrared. Full technical specifications of the satellite are included in appendix F.

A SPOT 5 image, captured on the 14th August 2004, covering 85% of the study area was made available to the research project via a European Commission program (OASIS).

Data preparation

The SPOT imagery supplied was pre-processed to the level 1B. This implied that the satellite image had been radiometrically calibrated and systematic effects, in terms of georeferencing, removed. Because the research did not include multi-temporal techniques, it was concluded that further radiometric correction, i.e. reflectance derivation, was not required. However, as the geometric accuracy of the satellite image was unknown, refinement of the image georeferencing was required. Due to significant elevation changes in the study area and a requirement for accurate locating of field sample points, orthocorrection as opposed to geometric correction was applied to the image.

To support orthocorrection ground control points (GCPs) were derived from Ordnance Survey 1:10,000 mapping. Elevation reference data were derived from two sources: the NEXTMap and Landmap (Landmap, 2007) digital elevation models.

The NEXTMap digital elevation model (DEM) (section 5.1.2) was the most detailed of the elevation models with a resolution of 5m. However, coverage was limited to a subset of the SPOT image. To enable orthocorrection of the entire SPOT image the NEXTMap DEM was supplemented with the satellite derived Landmap DEM. To enable combination of the datasets, the Landmap DEM was resampled from its original 25m to 5m resolution.

Initial orthocorrection of the SPOT imagery within the Leica Photogrammetry Suite resulted in a systematic shift of the image due to an incompatibility with the 1B processing level of the imagery. Consequently, orthocorrection was conducted in the PCI OrthoEngine software implementing Toutins correction model. A comparison of the orthocorrected images resulting from nearest neighbour and cubic convolution re-sampling indicated that re-sampling method did not significantly influence pixel values. Due to the geometric preservation of boundaries within the cubic convolution algorithm (Mather, 1999b) this image was selected for inclusion in the research project. A consequence of including this re-sampled image, which contains modified pixel values, was a potential, influence upon subsequent classification algorithms.

To ensure a systematic shift was not replicated in PCI OrthoEngine the accuracy of the derived orthocorrected image was verified against a series of independent verification GCPs, also derived from Ordnance Survey 1:10,000 scale mapping. Comparison of the Ordnance Survey and orthoimage coordinates at distinctive landscape features allowed the calculation of the average difference, root mean square error (RMSE) and proportion of image points falling within one pixel distance of the mapped location. These measures were calculated for all image points and secondly for only those points falling within the study area (table 5.1).

The resultant values (table 5.1) indicated that the orthocorrected image was within one pixel (10m) of the mapped location. Evaluation of the derived error measurements indicated that the orthocorrected image was more accurate in the study area. This was expected due to the more accurate DEM and concentration of GCPs in this area.

Table 5.1: Independent verification of orthoimage accuracy via a comparison of Ordnance Survey mapped locations and image locations for distinctive features

2004 image – multi-spectral	Entire Image	Study Area
Average difference	5.78m	5.37m
RMSE	6.75m	6.47m
Proportion of points within 1 pixel	93%	89%

Further analysis considering the directional difference between image and map points concluded that no systematic shift in the image was evident. In conclusion the orthoimage illustrated no systematic error and was corrected to better than one pixel.

5.1.2 Ancillary data: digital elevation models

Digital elevation models (DEMs) represent the elevation of the earth's surface, typically in a digital format, as an array of points. Strictly, the term DEM refers to 'bare' earth models. However, the term is frequently used to encompass all digital elevation data (Fisher & Tate, 2006). A digital surface model (DSM), the red line in figure 5.1, is a representation of the earth's surface inclusive of cultural structures, such as buildings, and vegetation. Conversely, a digital terrain model (DTM) or digital elevation model in the strictest sense, the black line in figure 5.1, is a topographic model of the earth's bare surface. In a DTM all cultural and discernible vegetation features are digitally removed.

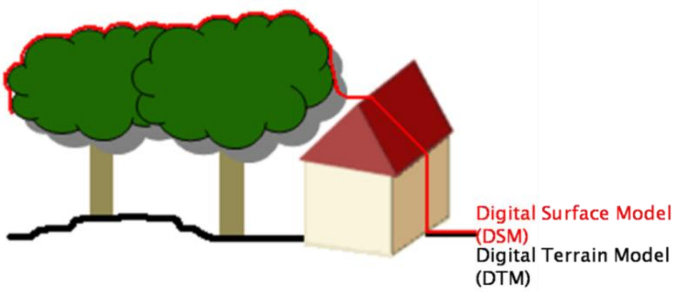


Figure 5.1: An illustration of the digital surface (DSM) and terrain (DTM) model concepts.

Adapted from: Dowman et al (2005)

NEXTMap IFSAR

Elevation data available to the research project was extracted from the national NEXTMap survey. This survey, conducted by Intermap Technologies during 2002, produced DEM data via airborne interferometic synthetic aperture radar (IFSAR). IFSAR is based on radar remote sensing in which electromagnetic pulses, in the microwave portion of the spectrum (X-Band: 9.5675 GHz), are transmitted towards the earth's surface. The two primary products derived from the IFSAR processing chain are the orthorectified radar image (ORI) and DSM. The third NEXTMap product, the DTM, is derived from the DSM through the removal of cultural and vegetation surface features in a semi-automated process using the TerrainFit® algorithm, a hierarchical, pyramidal surface fitting approach (Coleman, 2001). Full technical specifications are included in appendix F.

The NEXTMap DTM and DSM are produced at 5 metre postings (and 5m pixels), where the post represents the elevation (z) at that x, y location. The quoted accuracies for these products are included in table 5.2.

Table 5.2: The technical specifications of the NEXTMap DSM and DTM

Product	Horizontal Accuracy	Vertical Accuracy	Posting
DSM	2.5m RMSE	0.5m/1m* RMSE	5m
DTM	2.5m RMSE	1m/1.5m* RMSE	5m

**South East England and East Anglia available at 50cm vertical (DSM) and 1m vertical (DTM) resolution.*
Source: Intermap Technologies (2003)

The elevation recorded in each 5m pixel represents the combined signal of all scatterers, first surface contacts, within the sample area. Consequently, surface elevation within a pixel results from an averaging of multiple scatterers, potentially of differing heights, and interaction between these features.

DEMs as an ancillary data source

DEMs and their derivatives, slope and aspect, form important ancillary datasets in land cover characterisation due to their strong influence on vegetation species establishment. Examples of these relationships include the characteristic 'upland' and 'lowland' vegetation assemblies or predominance of bracken on steep slopes (section 2.1.3). In addition to these land cover, DEM relationships the availability of a DSM and DTM in the study enables the potential inclusion of surface feature height as an ancillary data source.

Feature height is defined as the DSM:DTM difference, that is, the height of cultural and vegetation features removed from the surface model. It was proposed that this parameter could potentially provide a valuable ancillary data source for the:

- Discrimination of primary land cover types, in particular woodland and urban areas.
- Determination of the heather species structural stages.

The applicability of DEMs to vegetation characterisation, as an ancillary data source, is a function of the accuracy of the elevation measurements. To enable accurate and consistent land cover class distinction, DSM measurements must be accurate and the TerrainFit® algorithm efficient in the removal of all cultural features to a 'true' bare earth. To establish this, an analysis was conducted to assess the accuracy of the DTM, via a comparison with reference elevation surface data and secondly, the reliability of the DSM:DTM difference as an indicator of relative surface feature heights (appendix F).

On the basis of this analysis it was demonstrated that the average error of the DTM surface, within the study area, was 1.8m. However, this value masked increased error as a function of slope and land cover with errors increasing to a maximum of 4.94m and 5.6m in woodland and on steep slopes, respectively (appendix F). Comparison of the DSM:DTM difference highlighted a particular issue, outside the datasets core specification, regarding DTM high elevations, that is, elevations where the DTM was higher than the DSM. Equally, the inconsistent removal of features from the DSM, in creating the DTM, was demonstrated.

As a consequence of these inconsistencies, which can be related to IFSAR data capture and landscape characteristics, the DSM:DTM difference was not recommended as a viable ancillary data source (appendix F). Despite errors in the DSM:DTM difference it was concluded that the DTM was sufficiently accurate to quantify the relationship between land cover and elevation or slope (appendix F).

5.2 An introduction to classification

Classification is the process by which features are allocated to classes on the basis of a set of pre-defined, diagnostic, criteria. Classes typically consider a particular task or way of viewing the landscape, for example, land cover, land use or land suitability. This task is reflected in "the structure, the semantics, the spatial definition and the characterisation of the entities" (Bock *et al*, 2005).

Within land cover classification habitat classes can be defined on the basis of floristic, physiognomic or ecological characteristics (section 1.2). Within remote sensing these definitions are related to the reflective properties of the surface within each spectral waveband. Essential to the reflective properties of the vegetated surface are the "photosynthetically active biomass, the dead biomass, soil-cover and water" (Bock *et al*, 2005). However, in addition to these physical and chemical properties, the spectral response of the surface will be influenced by the viewing and illumination angles, spectral and spatial resolution of the sensor (Mather, 1999b).

Conceptually, a remote sensing image can be considered a multi-dimensional dataset where a multi-dimensional dataset is composed of remote sensing and ancillary data components. Classification, within this context, is defined as the partitioning of this multi-dimensional data into a series of classes which are meaningful in terms of the surface cover, and mapping task, at the time of image capture (McCloy, 2006). Ideally, the spectral values of the multi-dimensional data, within each class, are defined so that they include only features of that class, the classes are discrete. Typically, land cover classes are not mutually exclusive and hence classification is primarily concerned with techniques and methods that aim to set the boundaries between classes within the multi-dimensional data. These boundaries should be defined so as to minimise error during the allocation of features to classes.

5.2.1 Classification terminology

Supervised versus unsupervised classification techniques

Supervised methods of classification require the user to train the classifier via definition of the constituent classes. Typically, this is via the selection of 'training' sites, examples of each class, from which the class statistics and definitions within the multi-dimensional space can be derived. The suitability of the supervised classification will depend upon how adequately these statistics describe the classes. Training data must therefore contain sufficient pixels and class examples to be representative.

In contrast unsupervised classifications are less dependent upon user input. Typically, unsupervised classifiers derive classes directly from the input, i.e. multi-dimensional remote sensing data. The derivation of class statistics is typically an iterative procedure based upon clustering techniques as exemplified by the ISODATA algorithm (see below).

The applicability of the unsupervised and supervised classification techniques is typically task specific. However, the classification accuracy obtained via unsupervised methods is typically lower than achieved by supervised methods (Tso & Mather, 2001).

Pixels, sub-pixels and objects

Conventionally classification has been based on the independent allocation of each image pixel to an appropriate class. Classification of individual pixels is advantageous in terms of simplicity. However, the applicability of this type of classification is dependent upon the spatial resolution of a pixel relative to the target classes and landscape characteristics. Where a pixel represents a large spatial extent it has a greater tendency, depending upon the scale of the classification scheme, to contain multiple classes. The spectral signature for this pixel therefore represents a mixture of, for example, land covers. In response to this, a series of classifiers which consider the composition of land covers contributing to the spectral response of a single pixel have been developed; such techniques are termed sub-pixel classifiers (chapter 7). At the other extreme of the classification scale are objects. Objects represent groups of adjacent pixels which are considered to be homogenous and classified as a single entity. Image object examples include fields or wooded areas, however, it should be noted that the definition of an image object is wholly dependent upon the target classes and scale of classification.

Hard versus fuzzy classification

The relationship between an entity and class definition can be defined as one-to-one (hard classification) or one-to-many (soft classification). Within a hard classification each entity, pixel or object, is assigned to a single class, typically the class with the highest similarity to that entity. Such a classification assumes that the entity contains only a single land cover and therefore each entity is forced to belong to a single class. Alternatively, fuzzy classifiers (soft classification) determine the grade of membership of the entity to each class. Membership corresponds to the level of similarity between the entity and class description. Membership grades are, typically, calculated as the distance between the entity value and class mean within the multi-dimensional data. Common distance measures include Euclidean and Mahalanobis distance. Fuzzy classification can be applied to the pixel, often termed sub-pixel classification, or object.

Ancillary data

Several studies have demonstrated improved classification accuracies following the inclusion of ancillary data, in addition to the remote sensing image (De Bruin & Gorte, 2000; Maselli *et al*, 1995; Watson & Wilcock, 2001). Conceptually, ancillary data are included to aid in the discrimination of classes, particularly those classes which have poor multi-spectral separability. Ancillary data can be drawn from derivatives of the remote sensing image, for example, texture or vegetation indices; from the entities, for example, the topological relationship between entities in object classifications; or from secondary data sources, for example, DEM derived elevation, slope and aspect. Ancillary data can be continuous or thematic, however, the format of the data may influence the classification algorithm applied.

Classification algorithms

As discussed in the preceding sections various classification strategies exist with regard to the classification of multi-dimensional remote sensing data. Within this context there is a range of classification algorithms available to derive the output classification. Classification algorithms implemented within the current research will be described in detail in subsequent sections but to provide context the principal types of classification algorithm will be outlined.

Statistical, supervised, classification algorithms

Three commonly implemented statistical classifiers are the parallelepiped, minimum distance to means and maximum likelihood algorithms (figure 5.2).

The parallelepiped classification algorithm is a quick and easy technique based on the definition of a parallelepiped (multi-dimensional rectangle), calculated from the extreme entity values for each class. The decision rule, on which entities are classified, determines if the entity falls in any of the class parallelepipeds. Although quick and easy the parallelepiped classifier is prone to errors associated with overlapping parallelepipeds, parallelepipeds which do not accurately describe the shape of the class samples, and entities which fall close to parallelepiped boundaries remaining unclassified.

The decision rule adopted by the minimum distance classifier is to label entities according to their distance from class centres. Distances within the feature space can be derived using either the Euclidean or Mahalanobis equations (described further by Tso & Mather, 2001; McCloy, 2006). Using these distance measures, as distance decreases, similarity increases, that is, the entity approaches the class mean. This classification algorithm is conceptually simple and computationally efficient. However, in its simplest form it is infrequently employed in remote sensing studies (Campbell, 1996; Tso & Mather, 2001).

Neither the parallelepiped nor minimum distance to means classifiers, in their basic forms, consider within class variation or the implications of classes which exhibit overlapping distributions. Such factors are introduced in the maximum likelihood (ML) classifier which, based on estimates of the class mean and variance, estimates the probability of a correct classification to each class. The entity is, within a hard classification, then assigned to the class for which the probability is highest. Probability calculations within the algorithm are based on the Bayesian probability formulae (equation 5.1).

$$P(x, w) = P(w|x)P(x) = P(x|w)P(w)$$ **Equation 5.1**

where:

x and w are events, P(x, w) is the probability of the co-existence of the events x and w, P(x) and P(w) are the prior probabilities of events x and w and P(w|x) is the conditional probability of event x given event w.

Source: Tso & Mather (2001)

A full description of the derivation of Bayesian probability and its implementation within a maximum likelihood classification is given in Tso & Mather (2001); McCloy (2006) and Mather (1999b).

Bayesian probability results in the description of each class by an enclosing ellipsoid the location, orientation and dimensions of which are a function of the means, variances and covariance of the features defining each class within the training data. Conceptually, the Bayesian probability is best considered as a series of concentric ellipses centred on the mean of the class. These ellipses represent contours of equal probability, with the probability of membership to the class declining with distance from the mean. If the entity to be classified in figure 5.2 (c), is considered, a minimum distance classifier would classify the entity as belonging to class B, the closest class. However, the probability of membership is higher for class A hence the entity would be classified as belonging to this class in a ML classifier.

The derivation of Bayesian probability within the ML algorithm is based on the assumption that the frequency distribution of class membership is approximated by a multivariate normal distribution. This assumption is rarely met by remote sensing data. However, studies have shown that the algorithm is not sensitive to small departures from the assumption provided that the frequency distribution of the data is unimodal (Campbell, 1996; Mather, 1999b).

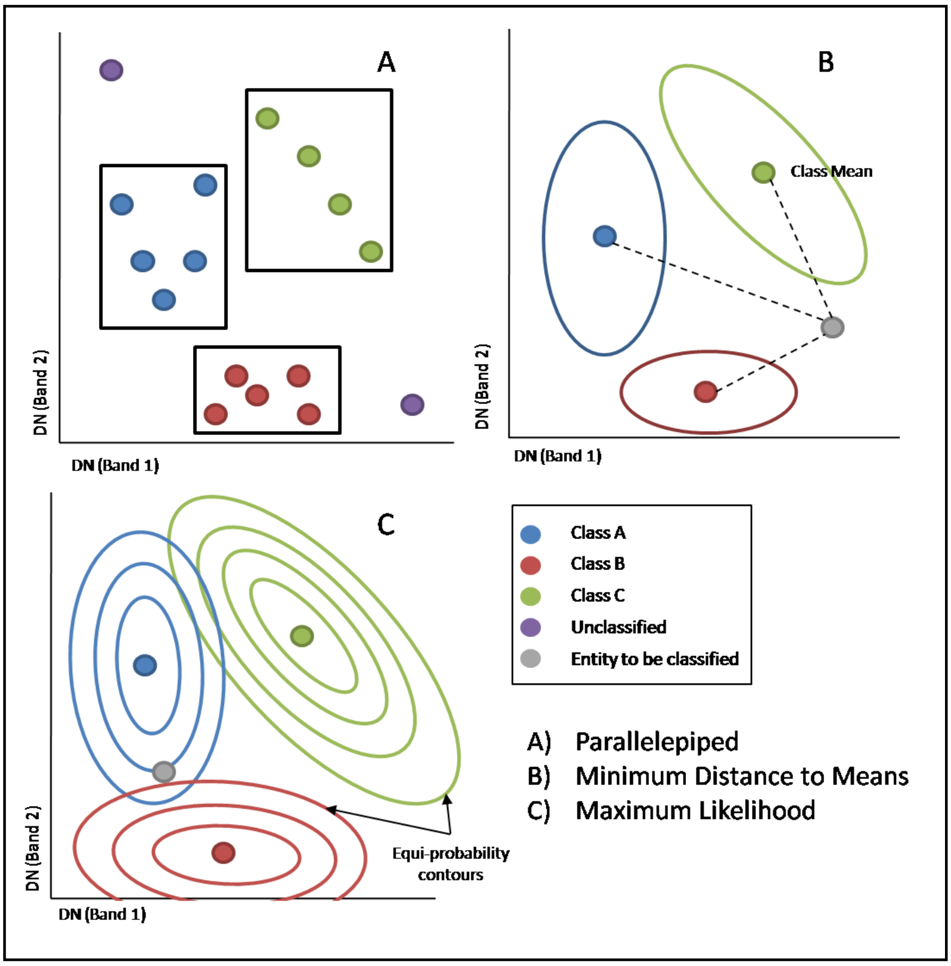


Figure 5.2: The decision rules implemented in the parallelepiped, minimum distance to means and maximum likelihood statistical classifiers

Adapted from: Mather (1999b)

Unsupervised classification algorithms: ISODATA

The ISODATA algorithm is a basic migrating means clustering algorithm widely implemented as a means of automatic image classification (Tso & Mather, 2001). The algorithm is based upon iterative migration of a set of cluster means using a closest distance to mean calculation. Iterations continue until the clusters remain static between successive iterations, or changes are below a specified threshold value defined according to the number of pixels moving between clusters or a measure of cluster compactness. Distances are typically calculated as the Euclidean distance, however, studies have also implemented the Mahalanobis distance calculation, to reflect data variance and covariance, as a means of improving cluster definition (Tso & Mather, 2001).

In contrast to supervised classifications, which require training data input, the only user input into the ISODATA algorithm is the specification of a maximum number of clusters or classes (N). This value represents the maximum number of clusters which will be created by the algorithm. However, similar clusters can be merged resulting in a lower number of classes. To enable implementation of the algorithm, a mean value must be specified for each of the N clusters in the first classification iteration. Typically, initial cluster means are evenly distributed within the feature space. Following the assignment of all entities to a cluster, on the basis of minimising the distance between the entity and cluster mean, the cluster mean is recalculated based on the entities allocated to the class. Studies have concluded that arbitrary definition of the initial cluster means does not impact upon classification accuracy as long as sufficient iterations are allowed (Leica Geosystems, 2005).

The iterative nature of this ISODATA algorithm is advantageous as it ensures that the resultant clusters are not geographically biased by the location of entities within the data file. However, to ensure sufficient iterations, the clustering process can be time-consuming.

Fuzzy classifiers

The term fuzzy classification is used to encompass a range of classification algorithms including fuzzy, linear mixture modelling, distance and probability (ML) based algorithms. What is common to each of these algorithms is the determination of a membership grade for each entity to each class as opposed to a single class assignment. As an advanced classification technique these algorithms are further considered in chapter 7.

Artificial neural networks (ANN)

ANNs are "computer programs designed to simulate human learning through establishment and reinforcement of linkages between input data and output data" (Campbell, 1996). Typically an ANN is made up of a series of processing layers (figure 5.3), termed neurons. All neurons of a given layer are connected to all neurons of the subsequent layer via linkages termed synapses. Processing within the ANN is via functions within the neurons and weights applied to their linking synapses. Functions are typically summations, however, more complex mathematical operations may be applied (Mather, 1999b).

The ANN classifier has to train its synapses to ensure that the appropriate output is achieved for a given set of input data. This is achieved with a set of training sites for which the input data, pixel or entity values, and class assignment are known. This process of training will typically be iterative until the classification error is within acceptable levels. Should error levels remain high then the architecture of the ANN, including the neuron functions, number of neurons, hidden layers or synapses must be modified. This training can be a supervised or unsupervised method (Mather, 1999b).

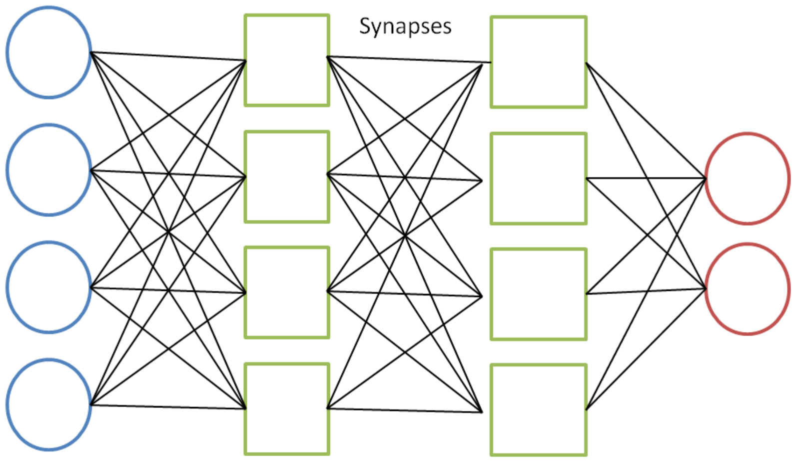


Figure 5.3: The typical architecture of an artificial neural network.

Adapted from: Campbell (1996)

An advantage of the ANN is that it does not make any assumptions regarding the statistical distribution of the input data. However, the architecture is complex in its initial definition and requires a large amount of training data to ensure accurate results. These disadvantages often preclude ANN from land cover classification (Campbell, 1996).

Hierarchical classifiers

Hierarchical classifiers, also termed decision trees, assume that an entity can be classified using a sequence of decisions. The concept behind this approach is that, distinct, physical characteristics can be used to distinguish classes at different stages of the hierarchy. Typically, a hierarchy will progress from broad to detailed distinctions, as exemplified in figure 5.4. The classification process is implemented by a set of rules, often in the form of thresholds, which determine the path that the classifier follows and ultimately the allocation of a class. Rules can be based on remote sensing, or ancillary, continuous or thematic datasets. Hence this classification procedure is very flexible.

The efficiency and accuracy of this type of classification is strongly affected by the structure of the decision tree and the rules implemented. Tree design can be developed in a supervised or unsupervised manner (Mather, 1999b). Development via semi-automated and automated approaches has largely arisen from the time consuming nature of manual tree construction in which the distinctive characteristics of each class must be defined.

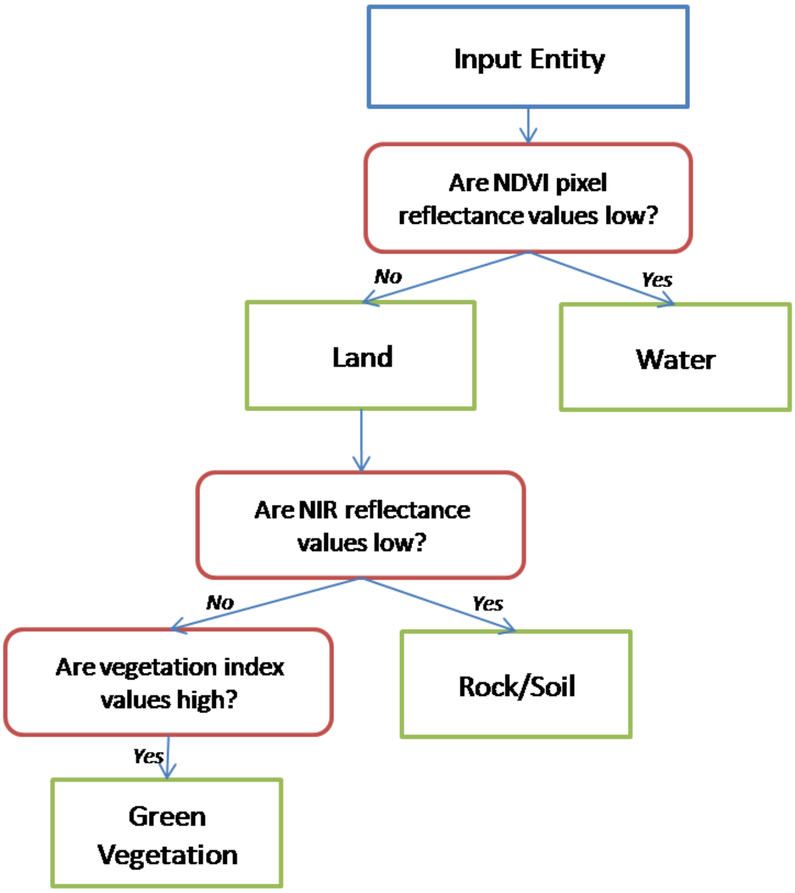


Figure 5.4: An example of a hierarchal decision tree classifier

Appropriate classification strategy

The preceding sections exemplify the wide range of techniques available for the classification of remote sensing data. Which combination of these techniques, supervised or unsupervised, classification algorithm, the inclusion of ancillary data and classification scale (pixel or object), is most appropriate is a function of the:

- Classification aim and hence required output.
- Criteria used in class definition.
- Spatial and spectral resolution of the remote sensing data, especially in relation to the classification criteria.
- Characteristics of the landscape or classes in terms of their interaction at class boundaries. Boundaries characterised by ecotones are typically best represented at the pixel or sub-pixel level whereas distinct land cover units are best represented by an object-based classifier.

5.3 Classification within the context of this research

An objective of this research is to investigate the utility of the classification techniques outlined to the mapping of the land cover attributes collected during the field survey. This is based on the classification of multi-dimensional remote sensing data including a 2004 SPOT 5 image and ancillary data derived from the SPOT image (NDVI) and secondary sources (elevation, slope, soils). Training of the classification is facilitated by the data collected during the field survey, as outlined in chapters 3 and 4.

To enable flexibility in land cover mapping, data collected during the field survey was not collected in relation to a specific land cover classification scheme. Representation of these land cover attributes, in relation to land cover mapping, can be achieved via two distinct approaches: land cover map construction, the focus of this chapter, and parameterisation of the land cover attributes across the entire study area (chapter 7).

The fundamental difference between these methods is the level of data aggregation during implementation of the remote sensing and GIS techniques. Land cover map construction necessitates the aggregation of the field data into existing land cover classification schemes prior to classification. This represents a loss of information in terms of the field data collected. Conversely, parameterisation of the land cover attributes across the study area, via remote sensing techniques, retains the disaggregated nature of the field data.

5.4 Land cover map construction: methodology

The construction methodology aimed to create multiple land cover maps from a single field survey. Advantages of such a methodological approach are:

- Minimisation of fieldwork effort in comparison to multiple resurveys.
- Flexibility in land cover definition subsequent to field survey ensuring compatibility with user requirements and existing products.
- Elimination of the requirement for semantic relationships to be developed between the mapped land cover and target classification scheme.
- An ability to assess the independent accuracy of each mapping product.

The methodology was divided into the following sections:

- The construction of land cover classes, as specified by the classification scheme definitions, from the land cover attributes collected.
- Inclusion of the derived land cover classes within classification techniques capable of producing land cover maps of the study area.
- Assessment of the accuracy of the resultant land cover classifications.

To determine the applicability of the methodologies developed to the construction of multiple land cover classification schemes, the Monitoring Landscape Change in the National Parks (MLCNP), National Land Use Database (NLUD) and Phase 1 Habitat Survey (P1) land cover classifications were selected for the analysis. These schemes were chosen to represent a broad range of land cover classification techniques and characteristics (table 5.3).

Land cover map construction was implemented within a per-pixel classification procedure. This scale of classification was selected for development of the classification methodology due to its ease of operation and applicability in characteristically different landscape types. An additional assessment was made of the applicability of object-orientated classifiers to land cover class construction and classification.

Table 5.3: Comparison of the main characteristics of the MLCNP, NLUD and P1 classification schemes

	Monitoring Landscape Change in the National Parks (MLCNP)	National Land Use Database (NLUD)	Phase 1 Habitat Classification (P1)
Data collection	Aerial photograph interpretation	Ordnance Survey Mastermap modifications	Field survey
Number of classes in the lowest level of the hierarchy	38	32	90
Mapping scale	1:10, 000	-	1: 10,000
Application environment	National Park	National land cover/use mapping	Habitat survey
Minimum mapping unit	400 m^2	-	0.1ha

5.4.1 Per-pixel classification methodology

The basic methodology implemented to construct the MLCNP, NLUD and P1 classifications from land cover attributes is summarised in figure 5.5.

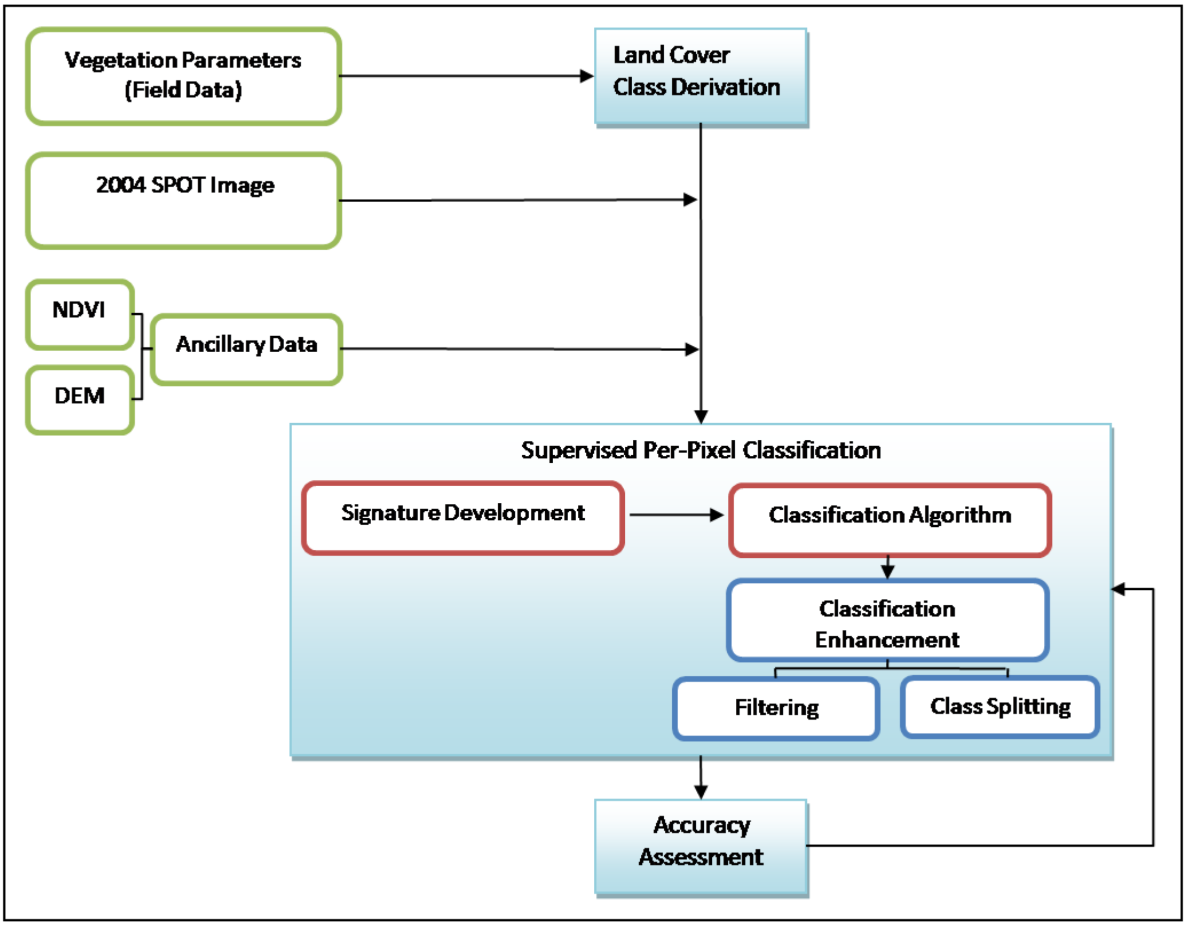


Figure 5.5: Per-pixel methodology implemented to construct the MLCNP, NLUD and P1 land cover maps.

Land cover class derivation

Prior to classifier training the land cover attributes, as recorded at each sample in the field survey, were aggregated to represent land cover classes, as defined in the MLCNP, NLUD and P1 classifications, respectively. This aggregation resulted in the classification of the sample sites. However, instead of being applied in-situ at the time of data collection the classification was applied subsequent to the field data measurements. This aggregation was possible due to the design of the field survey which ensured compatibility between the land cover attributes measured and standard classification schemes (section 3.3.1).

To enable the classification of a large number of samples, in an objective manner, an automated approach to field data classification was developed. The approach, implemented within Microsoft Excel, derived a land cover class on the basis of the presence/absence of target species, top cover and ancillary parameters, such as elevation, at each sample. Sample points which met specific thresholds in relation to these criteria, as extracted from the MLCNP, NLUD and P1 class definitions, were selected and classified as belonging to the appropriate land cover type.

Classification

Maximum likelihood algorithm

To ensure ease of implementation within the developed land cover mapping technique it was concluded that the classification algorithm employed should be easily applied, require limited training, be widely available and routinely applied in land cover map derivation. To meet these requirements a per-pixel, maximum likelihood (ML) algorithm was chosen. The classification algorithm and associated decision rules are outlined in section 5.2.1.

Signature development

Land cover class signatures, for implementation within the ML algorithm, were developed on the basis of the classified field data.

Although the field data represent single points, approximately equivalent in size to a pixel, signature development on a per-pixel basis was found to result in insufficient pixels to allow covariance matrix inversion, as required by the classification algorithm and signature assessment techniques. Consequently, signatures were developed on the basis of a region of homogenous, adjacent pixels centred on the sample point location. Homogeneity within the region was defined using the Euclidean distance between pixel values. To ensure land cover class training pixels represented homogenous areas pixels were required to be below an Euclidean distance threshold of ten and adjacent to the sample point pixel.

The within-class variability, of the developed land cover class signatures, was assessed via multi-spectral plots. Samples found to be spectrally different were excluded if sufficient evidence was available to conclude that the sample was not characteristic of the land cover type. Samples excluded from the analysis included those in close proximity to linear features, influenced by clouds or haze in the imagery or samples at which significant land cover change between field survey and image capture was evident.

Ideally, classifications should be based upon classes which are spectrally distinct. However, some overlap of class signatures is typically expected within land cover applications. A statistical assessment of class separability, the distance between signature pairs, was made using the Jeffries-Matusita (JM) distance (equation 5.2).

$$D_{JM} = 2(1 - e^{-B})$$

where:

Equation 5.2

$$B = 0.125(\bar{x}_1 - \bar{x}_2)^T \left\{\frac{(\Sigma_1 - \Sigma_2)}{2}\right\}^{-1} (\bar{x}_1 - \bar{x}_2) + 0.5ln\left\{\frac{2|(\Sigma_1 - \Sigma_2)|}{\sqrt{|\Sigma_1|}\sqrt{|\Sigma_2|}}\right\}$$

where:

$\bar{x}_1$ *and* $\bar{x}_2$ *, the means of classes 1 and 2, respectively.*
Σ_1 *and* Σ_2 *, the covariance matrices for classes 1 and 2, respectively.*

Source: McCloy, 2006

JM distance is characterised by a saturating behaviour at high degrees of separation. Therefore a maximum value of 1.414, often scaled to 1414, is characteristic of classes which are totally separable in the multi-spectral bands being analysed.

Additional classification techniques

Included within the development of the land cover construction methodology was the testing of several additional classification techniques. These classification techniques were selected due to the potential of the methods to improve classification accuracies as indicated from the literature review.

Ancillary data

Following consideration of the relationships between land cover class and the available ancillary data sources the influence of image derived vegetation indices and DEM derivatives (table 5.4) upon classification accuracy were assessed.

Table 5.4: Ancillary data included in the land cover construction maximum likelihood classifications

Data	Source
Image Derivatives	
Normalised Difference Vegetation Index (NDVI)	2004 SPOT image
Secondary Ancillary Data	
Elevation	NEXTMap 5m DTM
Slope	NEXTMap 5m DTM

Vegetation indices transform bands, extracted from the multi-spectral image, to an index which is typically correlated with the amount and physical properties of the surface vegetation. These indices are based on the characteristic of vegetation having high reflectance and low reflectance values in the near-infrared and red wavebands, respectively. The normalised difference vegetation index (NDVI) is one of the most common vegetation indices. This index (equation 5.3) is strongly correlated with the amount of photosynthetically active vegetation in an entity (Mather, 1999b). Ranging between zero and one, low NDVI values are associated with an un-vegetated surface i.e. water and vice versa.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$ **Equation 5.3**

where:

NIR and Red are the reflectance of the near-infrared and red wavebands, respectively

It should be noted that due to the relationship between NDVI and vegetation productivity, that is, photosynthetically active vegetation, the index is seasonally variable. In fact studies have utilised the temporal characteristics of the indices to strengthen land cover class distinctions (Defries & Townshend, 1994; Lucas *et al*, 2007).

The relationship between land cover class and slope/elevation has been previously outlined (section 2.1.3). Jones & Wyatt (1988) have demonstrated the ability of these topography relationships to improve land cover class delineation. Within the current classification, slope and elevation parameters were input as continuous variables, that is, the data were not categorised according to the degree of slope or elevation.

Class sub-division

An issue with classifications based on a pre-defined set of classes is definitions which do not account for within class variability. For example, coniferous woodland stands will exhibit marked variability in their multi-spectral properties as a function of tree species, stand age, canopy cover and productivity. This within class variability may be further increased as a function of the relationship between the sensor, target and sun position which influences the illumination angle and amount of shadow. Such within class variability, which can exceed between-class variation, has the potential to limit the applicability of a classification algorithm (Lucas *et al*, 2007). Consequently, highly variable classes should be sub-divided into spectrally similar components.

Class variability has the potential to be further emphasised in broad land cover classes, which contain a greater variability of habitats, varying species mixes and mosaics of vegetation. This is exemplified by the upland habitat “upland dry heath” which is common to each of the classifications. Although the exact class specifications vary with classification (table 5.5) this class typically contains heather stands of varying age, varying species composition and land cover mosaics. Consequently, in each classification this class was split into spectrally similar components using an unsupervised classification technique.

Unsupervised classification techniques are advantageous as they require limited user input and therefore provide an objective means of sub-dividing the class on the basis of its multi-spectral variability. For each land cover classification the “upland dry heath” training pixels were input into the ISODATA algorithm (section 5.2.1). The maximum number of clusters was estimated from knowledge of the upland environment. However, consecutive classifications tested the influence of cluster number upon classification accuracy (table 5.5). Cluster signatures derived from the ISODATA algorithm were implemented within the ML algorithm to ensure compatibility with the remaining land cover classes.

Table 5.5: Classes subdivided to determine the impact of within class variability upon classification accuracy. Iterative classifications tested the influence of the maximum number of clusters specified.

Classification Scheme	Class	ISODATA Clusters
MLCNP	Upland Heath (D1)	5, 8, 10
NLUD	Heathland (CO41)	5, 10
P1	Dry Dwarf Shrub Heath (D1.1)	5, 8, 10

A-priori probability specification

ML classifications in the preceding methodological sections assumed that each land cover class had the same probability of occurrence. An adaptation to the ML algorithm allows modification of this assumption and modelling of the prior probability, that is, the probability of occurrence, via the allocation of class weights. A higher weight for a given class implies that there is a higher probability of an entity belonging to that class (Mather, 1999b).

The spatial extent of each class was tested as a proxy measure for the probability of occurrence of that class following Mehner *et al* (2004). Such an approach has the potential to improve classification accuracy where misclassification errors result from classes which although spectrally similar have greatly varying spatial coverage.

Classification filtering

Within a per-pixel classification, as implemented in the current methodology, each pixel is classified independently. This technique can result in classifications which have a “peppered” appearance caused by spurious single or small groups of pixels in otherwise homogenous areas. Filtering is one technique by which these spurious pixels can be removed to reduce local variability and consequently, the visual and statistical impact of misclassified pixels. Classification outputs were therefore passed through a majority filter of varying kernel size (3x3, 5x5).

Accuracy assessment

Accuracy assessment was an important element in the development of this method as it enabled the determination of the accuracy achieved in this approach to land cover map production. Accuracy assessment was based on standard techniques to ensure standardisation, rigorous testing and compatibility with other studies. The most common accuracy measure used in the assessment of hard, per-pixel, classifications is the confusion matrix.

Confusion matrices

The confusion matrix is a cross-tabulation which enables quantification of the agreement/disagreement between datasets. Typically, during accuracy assessment, one dataset in the matrix is considered as being correct; the reference data. To ensure robust accuracy assessments this reference dataset should be independent of classifier training.

Construction of a confusion matrix is based on a comparison of the reference (columns) and classified class (rows) at a series of samples. Statistics commonly derived from this matrix are measures of the user, producer and overall accuracies (figure 5.6).

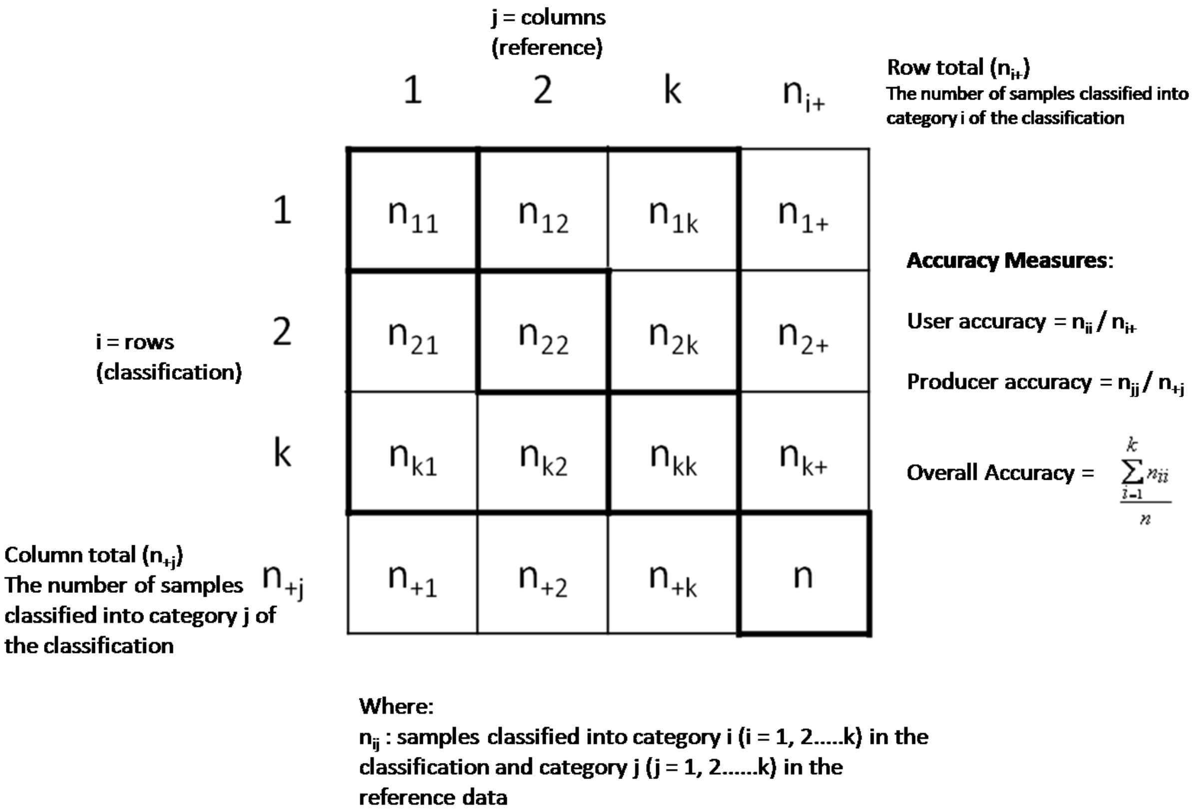


Figure 5.6: The mathematical representation of a confusion matrix

Source: Congalton and Green (1998)

The overall accuracy of the classification represents the proportion of classification elements, pixels, correctly classified. Class specific accuracies are reflected in the user and producer accuracy measures. The difference between these accuracy measures is the base against which the accuracy is assessed, the area of the class in the reference map versus the classified image in the producer and user accuracies, respectively. Consequently, the user accuracy is indicative of the reliability of the classification as a predictive tool for the specified class while the producer accuracy indicates the proportion of the class correctly classified.

An additional statistic commonly utilised within accuracy assessment is the KHAT statistic. This statistic, which results from a Kappa analysis, provides a statistical method for determining if one error matrix is statistically different to another (Congalton & Green, 1998). Full descriptions of the equations implemented in determination of the KHAT statistic are included in appendix G.

Calculation of the KHAT statistic, for a single confusion matrix, provides a measure of the agreement between the classification and reference data. Testing of significance for this KHAT value determines whether agreement between the classified and reference data is significantly greater than zero, i.e. the classification result is significantly better than a random assignment of classes. Significance testing of two KHAT statistics allows for the comparison of matrices to determine if either matrix represents a significant increase in accuracy.

Reference data

As stated previously, accuracy assessment should be based on a reference dataset which is independent of the data used in classifier training. Within this research, the reference data would ideally consist of a subset of the field data samples. If these data were considered, 186 samples occurred within the 2004 SPOT 5 image and included surveyed, inaccessible and woodland samples. This number of samples, especially when inaccessible samples are disregarded, did not represent sufficient samples to enable splitting of the field data into training and reference data sets.

As time limitations precluded further ground survey, validation of the classifications, on the basis of field data samples, was only feasible if the same samples were used within classifier training and validation. To enable independent validation a further set of land cover reference samples were derived via aerial photograph interpretation (API) of the UK Perspectives photography (appendix F).

Aerial photograph interpretation (API)

Reference land cover was derived, via API, at a further five sampling frames. To ensure compatibility these additional samples were created as replicates of the original field survey sampling frame, a systematic aligned grid of points with a spacing of 950m. Each replicate was initiated from a randomised location within the first 950m x 950m block.

The inclusion of API derived data, as a reference dataset, is based on the assumption that land cover classification via this technique is more accurate than the automated classification of a satellite image. This assumption is made due to the improved spatial resolution of the aerial photographs and inclusion of additional contextual information during visual analysis. To enable validation of this assumption and determination of the API accuracy achieved, the API procedure was repeated at the field survey samples with no reference to the field data. A comparison of the resultant API and reference land cover class, that is, land cover class derived from the classification of the field data, allowed an assessment of the API accuracy achieved.

5.4.2 Object-orientated methodology

This aim of this methodology was to exemplify the application of the object-orientated classification approach, using the Definiens Professional software suite, to land cover classification.

Object-orientated or parcel classification techniques differ from traditional methods in that the basic processing units are image objects, or segments, as opposed to image pixels. In this context an object can be defined as a group of pixels which, when combined, represent a definitive spatial region within the image. The extent of this spatial region, area of interest, is dependent upon the scale of the intended classification. Increasingly, this object-orientated approach is being applied to land cover classification as the concept of objects is easily related to discrete land cover/use classes (Alpin *et al*, 2000; Janssen *et al*, 1990; Lobo, 1997; Lucas *et al*, 2007).

The advantage of object-orientated techniques to land cover mapping also stems from the additional information, in comparison to per-pixel approaches, available to describe objects. Features used to describe objects are their physical properties, that is, reflectance characteristics, shape and texture, and relationships to surrounding objects. Relationships between objects are described in terms of topological parameters, for example, left, right, a given distance, or semantics, for example, urban woodland is typically surrounded by urban objects.

The object-orientated classification was tested on a subset of the study area. Definition of a subset was necessary to ensure computational processing stability within the Definiens Professional software. The subset area (figure 5.7) was chosen subjectively to ensure a range of environments and land cover types were included. Within this subset, a land cover classification, based on the land cover definitions of the MLCNP classification scheme, was conducted. The methodology implemented, within the object-orientated classification approach, is summarised in figure 5.8.

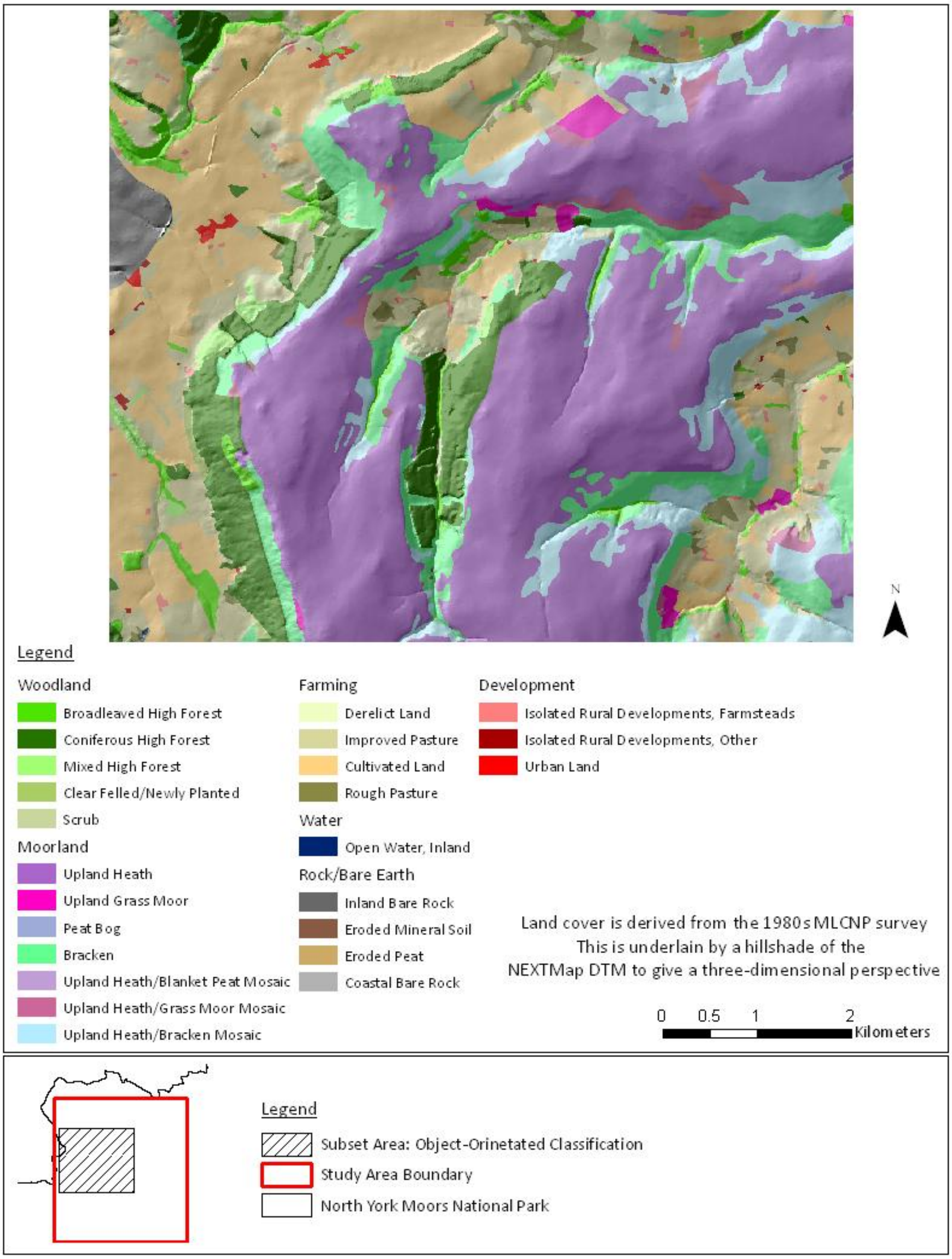


Figure 5.7: Land cover characteristics of the subset area defined for object-orientated classifier testing.

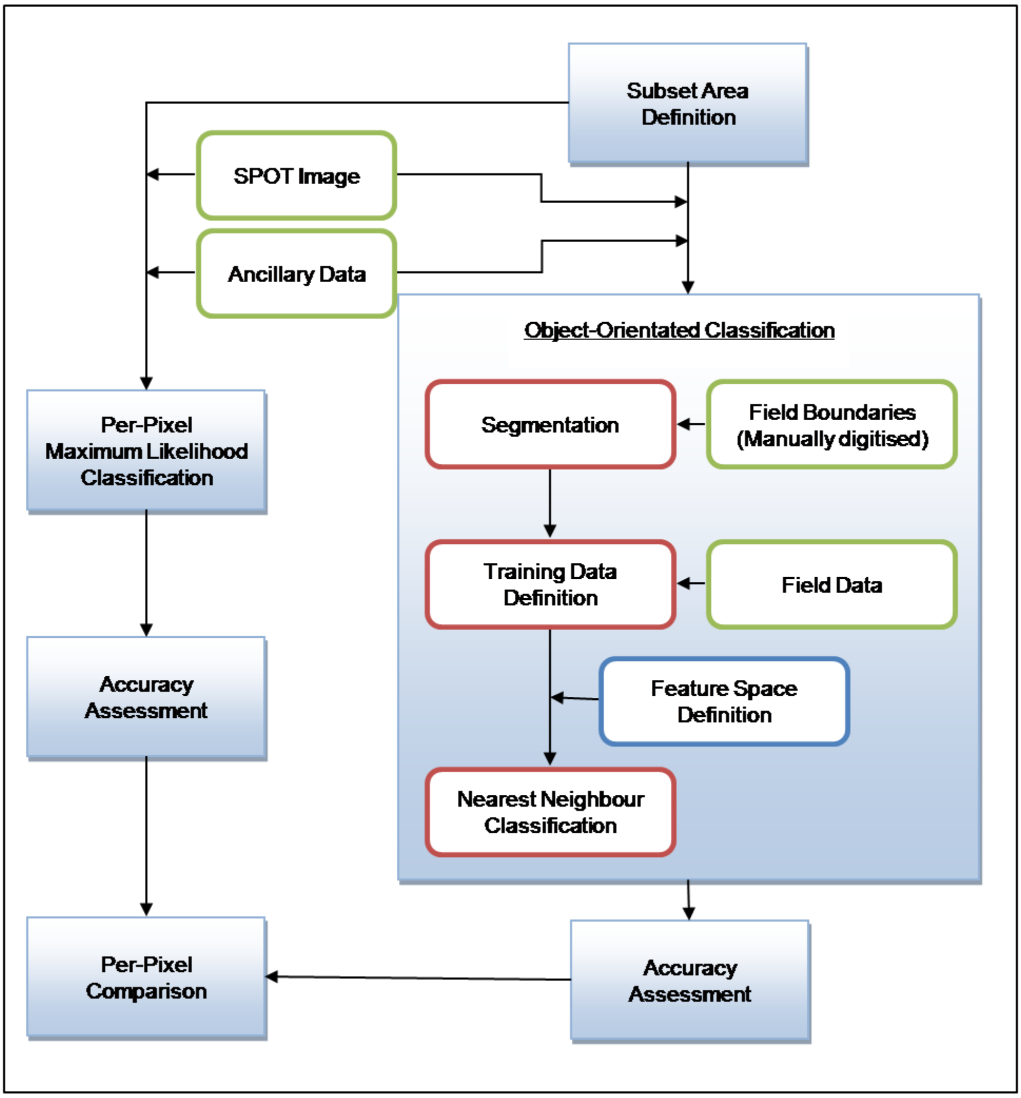


Figure 5.8: Object-orientated methodology used to exemplify the reconstruction of the MLCNP classification.

Segmentation

Segmentation, the delineation of image objects, is the initial step within object-orientated classification. Previous research has led to the characterisation of segmentation techniques into two broad categories, knowledge and data driven (Definiens, 2006). In knowledge driven techniques the user has typically predetermined the objects in the image which are extracted via derivation of an appropriate model. In data driven techniques objects are extracted using statistical methods, applied to the entire image, on the basis of certain homogeneity characteristics (Blaschke *et al*, 2000). Objects from these techniques are typically referred to as image object primitives as they have no real-world meaning (Definiens, 2006).

As would be expected different segmentation algorithms, and segmentation parameters, will result in differing image objects. As stated previously, image objects are the building blocks on which the classification is based and as such the most appropriate segmentation is strongly related to the aim of the classification. Determination of the scale at which image objects contain the most relevant information is typically an iterative process.

Varying image object scales, across an image or due to variation within class definitions, are handled in the Definiens Professional software by the concept of an image object hierarchy. Image objects derived at a particular scale are described as being at the same level. The addition of multiple levels, or segmentation scales, results in the construction of an image object hierarchy. Within this image object hierarchy every image object in a lower level is linked to an image object of its super level. Conceptually, sub objects are the further subdivision of super objects. This image hierarchy enables the description of classes at varying scales and additionally enables class descriptions to consider sub objects. For example, an urban area would constitute a mix of buildings and impervious surface sub objects.

Three segmentation algorithms are available within Definiens Professional: multi-resolution, quad-tree and chessboard (figure 5.9).

Within land cover classification objects should describe parcels which represent a single land cover class. Land cover parcels should be internally homogenous therefore spectral variability is greater between parcels than it is within parcels. As land cover parcels are neither regular in shape or size they are best delineated by the multi-resolution segmentation algorithm which can characterise parcel boundaries on the basis of internal multi-spectral homogeneity. This approach follows studies by Lingenfelder *et al* (2001); Lucas *et al* (2007) and Whiteside & Ahmad (2005).

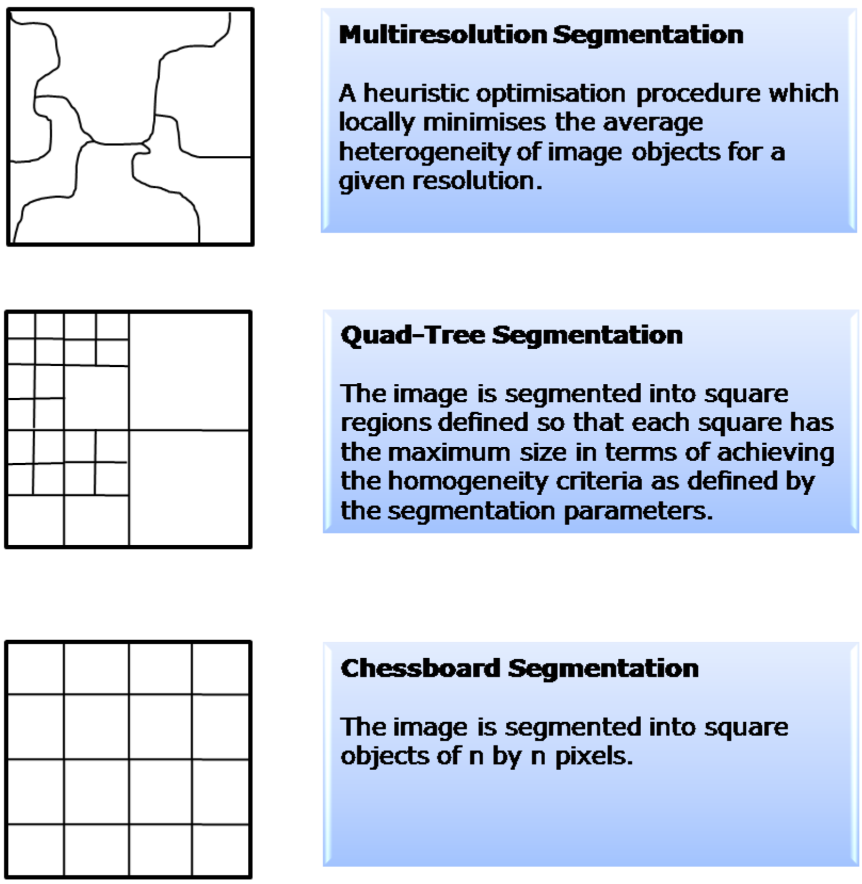


Figure 5.9: Segmentation algorithms available within the Definiens Professional software.

Adapted from: Definiens (2006)

The multi-resolution segmentation algorithm is a region-merging technique in which smaller objects (initially pixels) are amalgamated into bigger objects. This clustering process aims to minimise the average heterogeneity of image objects. If the smallest object growth exceeds a heterogeneity threshold, as defined by the scale parameter, the process will halt. The scale parameter is an abstract term which determines the maximum allowable heterogeneity of the image objects and therefore directly influences image object size. Heterogeneity to which the scale parameter refers is derived from two criteria; colour and shape.

Colour refers to the spectral (DN) heterogeneity, measured as the standard deviation of the image pixels. If more than one image layer is included in the segmentation the standard deviation values are summed according to the weight, importance given, to each layer. Although colour is typically the most important parameter in image object definition, studies have illustrated that shape often improves object definition by minimising the presence of highly fractured image objects (Definiens, 2006). The shape criterion is composed of two parameters: compactness, determined from the perimeter length and number of constituent pixels in an object, and smoothness, a ratio of the actual perimeter length to the perimeter of the smallest possible bounding shape.

Further segmentation parameters can be introduced via the addition of a thematic attribute layer. Class boundaries within this thematic layer form a segmentation restriction which image objects cannot straddle. Such an approach was utilised in the current methodology via the introduction of a thematic layer containing lowland field boundaries digitised via API. It should be noted that segmentation below the scale of the field boundary was permitted so as to accommodate within field spectral changes. Such within field variability may result from field subdivision, the presence of invasive vegetation, woodland stands or the influence of varying management techniques.

To enable comparison of image object scale upon classification accuracy, image objects resulting from three segmentations were considered:

- *Segmentation 1*: This segmentation was conducted on the basis of the multi-spectral, 2004 SPOT 5, data layers only. Iterative testing of segmentation parameters and visual analysis concluded that the most appropriate parameters were: scale 25, colour 0.9 and shape 0.1 (compactness 0.5 and smoothness 0.5). Image objects derived using these parameters best approximated the field parcel boundaries of lowland areas.
- *Segmentation 2:* Segmentation two was conducted using the same parameters as segmentation one. The difference results from the introduction of a thematic layer to the classification. This thematic layer represented the field boundaries as digitised via API.
- *Segmentation 3*: Segmentation three was a sub-object level of segmentation two. In this segmentation the colour and shape parameters remained unchanged while the scale parameter was reduced to 15 resulting in smaller image objects. In the lowlands the consequence of this reduction was the creation of image objects which subdivided fields into spectrally homogenous sub-regions. The impact in upland areas was not as obvious due to the lack of abrupt land cover changes and hence distinct land cover objects.

Classification

Classification within Definiens Professional is based on fuzzy logic i.e. objects are defined as having a membership grade. Classification outputs include a fuzzy classification, which outlines the probability of the image object belonging to each class, and a hard classification, in which image objects are assigned to the class with the highest probability of occurrence.

Classification decision rules are implemented via class descriptions, single or multiple conditions, which result in a fuzzy class assignment. When combining conditions a variety of operators are available which influence how the conditions are evaluated in relation to each other and therefore the derived membership function. Conditions are constructed via expressions which can express memberships, similarities to other classes or nearest neighbour functions.

Fundamental to this classification process is the definition of the feature space against which image object conditions and class descriptions will be compared. Features can be broadly categorised as being object or class related. Object related features are obtained from the objects themselves and relate to the physical properties of the entity. Parameters available to describe objects include, the values derived from satellite or ancillary data, shape indices, texture measures and super/sub object components. Class related features take into consideration the classification result of previous objects when classifying the current image object.

As implied in the preceding section, classification algorithms can be applied to single or multiple classes. As such each class can be described using a different set of features, expressions or conditions. Class descriptions should be constructed so as to improve the classification by optimising class separability. Related to the concept of differing class descriptions is the classification hierarchy.

The classification hierarchy is the frame in which class descriptions and the relations between them are constructed. Class relationships are described via the concepts of inheritance and groupings. Inheritance defines parent and child classes and the conditions which are passed from parent to child. This is exemplified by a parent class of woodland which contains two child classes of deciduous and coniferous woodland. Each of the child classes inherits the properties of the woodland class, however, each child class contains differing conditions to classify the woodland as deciduous or coniferous. The purpose of inherited definitions is to reduce redundancy, repetition and complexity in class descriptions. Groupings describe the semantic relationships between classes enabling the grouping of classes which, while containing differing class descriptions have a similar semantic meaning. An example of a semantic grouping would be the grouping of suburban vegetation and impervious surfaces into an urban parent class.

Inheritance and groupings in addition to class specific descriptions, which include a greater range of features than per-pixel classification, are the fundamental concepts behind object-orientated classification which aims to employ class descriptions which implement logic similar to that involved in visual interpretation (Definiens, 2003).

Typically, the definition of the classification hierarchy and class descriptions, in terms of the most appropriate features and critical values that best describe classes, are derived iteratively. Derivation of these hierarchies is potentially time consuming and highly subjective. To minimise these issues it was concluded that initial investigations should be based on a classification approach which could be standardised across all land cover classes. Classifications were therefore based on the standardised nearest neighbour classification algorithm.

Standardised nearest neighbour classification

This algorithm assigns image objects to a given class based on the class of the nearest feature space image object within a representative sample set. For example, if an image objects' closest sample object belongs to class A, the object will be assigned to that class.

The standardised distance between the image object and sample object, within the feature space, is calculated according to equation 5.4. Distances are standardised by the standard deviation of all feature values to enable varying feature ranges to be combined. A standardised distance value of one indicates that the distance equals the standard deviation of the feature values.

$$d = \sqrt{\sum_f \left(\frac{v_s - v_o}{\sigma}\right)^2}$$

Equation 5.4

where:

d Distance between the sample object (s) and image object (o)
v_s *Feature space value of sample object for feature f*
v_o *Feature space value of image object for feature f*
σ *Standard deviation of feature value for feature f*

Source: Definiens (2003)

Fuzzy membership grades are derived from the standardised distance (d) via an exponential membership function (figure 5.10). Where class membership is below a specified threshold, 0.1 by default, the image object will remain unclassified.

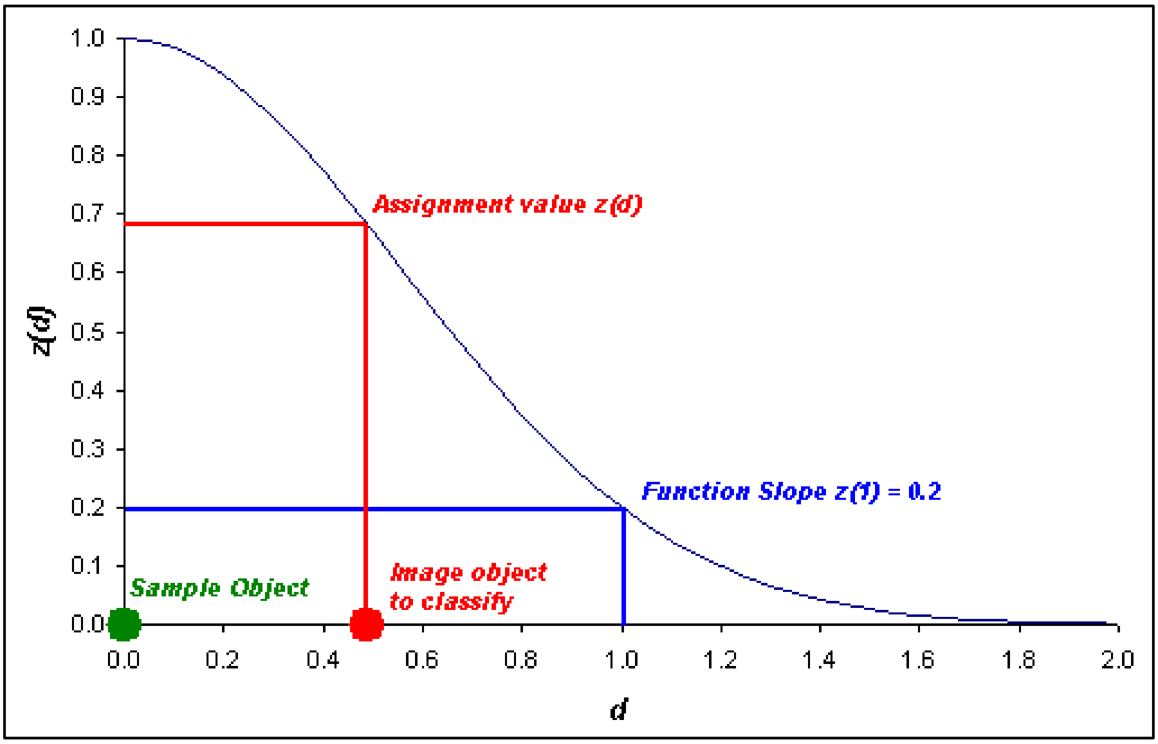


Figure 5.10: The nearest neighbour membership function.

Source: Definiens (2003)

A requirement of the standardised nearest neighbour algorithm is the definition of the classification feature space. To enable the influence of feature space definition upon classifier accuracy to be assessed, iterative classifications were performed using varying feature space definitions (table 5.6).

Table 5.6: Feature space definitions implemented within the standardised nearest neighbour algorithm

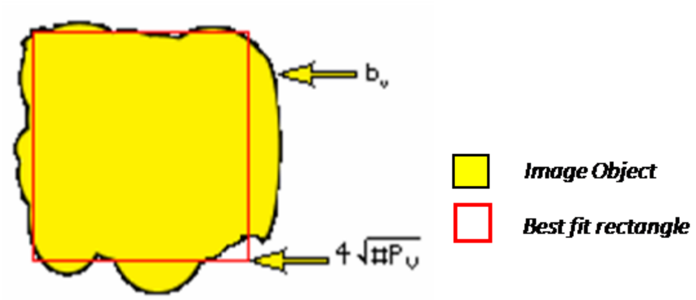
Classification	Feature Space Elements: Multi-Spectral Image (SPOT 2004)	Ancillary Data	Shape Indices
A	Standard Deviation		
B	Mean		
C	Mean	Slope (mean)	
D	Mean	Elevation (mean)	
E	Mean	Slope + Elevation (mean)	
F	Mean		Rectangular Fit
G	Mean		Shape Index

As each object has the potential to encompass one or more pixels, definition of the feature space, for continuous and thematic layers, must include some measure of the pixel range. Possible measures include the mean and standard deviation of all object pixels. Initial comparison of the standard deviation and mean DN values concluded that the analysis should be based on the mean pixel value within the object (section 6.4.1). In addition to varying multi-spectral classifications, the influence of ancillary data and shape indices upon class definition were assessed. Details of the ancillary data are included in the per-pixel methodology (section 5.4.1).

Shape indices were included in the analysis to evaluate the potential of including object based attributes within class definitions. Initial classifications were based on the image object parameters of shape index and rectangular fit (figure 5.11). It was hypothesised that these indices would distinguish the typically, rectangular, smooth fields of the lowlands from the irregular upland heath mosaics and patches.

Shape Index

The shape index is a function of the border length (b) of the image object divided by four times the square root of the image object area (A). This index is a measure of the smoothness of image object borders.



Rectangular Fit

The rectangular fit indices compares the area of a rectangle, calculated to best fit the image object, to the area of image object falling outside the rectangle.

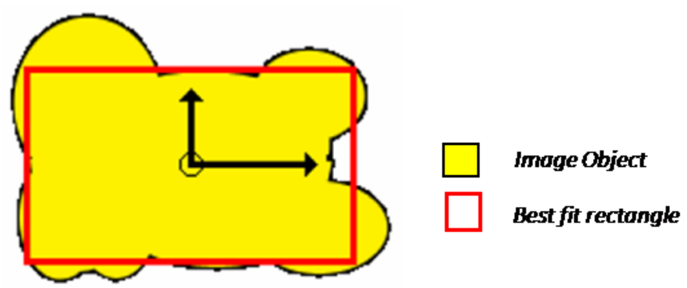


Figure 5.11: Derivation of the shape index and rectangular fit for image objects

Source: Definiens (2006)

Training data

Implementation of a standardised nearest neighbour algorithm required training objects in which the land cover was known. To ensure sufficient training data within the subset area a combination of field and API sample points (replicate A) were included. These training data represented a point sample design. However, object-orientated classifications require training polygons which represent homogenous land cover regions. A disparity therefore existed between the training data and classification algorithm.

Resolution of this disparity was only possible by the assignment of the land cover recorded at the sample point to the spatially coincident image object. The assumption of this method was that the image object, as it is spectrally homogenous, represented a single land cover identified by the point sample. As image objects are related to the scale and segmentation parameters specified during multi-resolution segmentation this assignment processes was repeated at each segmentation scale.

Only those classes present in the training data could be included in the classification. As a result urban areas remained unclassified. Consideration of the subset area concluded that no major urban areas were present hence this did not introduce a major source of misclassification.

Classification validation

Classifications were validated using independent, API derived (replicates B and C), sample points as the basis for confusion matrix construction (section 5.4.1).

In addition to confusion matrix analysis, the stability of the object-orientated classifications was assessed via a comparison of the first and second membership functions for each object. Within this comparison, the greater the difference between the membership functions the more unambiguous the assignment of the object to the final class. Similar membership functions indicate that the object could belong to more than one class as a result of potential class overlap; hence the classification is not stable.

Per-pixel comparison

A per-pixel classification was conducted within the subset area for comparison against the object-orientated classification. To ensure compatibility the ML algorithm implemented the same classification scheme and was trained on the same samples.

5.5 Chapter summary

The key points of this chapter are:

- Mapping of the land cover attributes, as recorded by the field survey, across the entire study area was segregated into two distinct methodologies:
    - Land cover map construction
    - Characterisation of the land cover attributes
- Land cover map construction represents a classification of the land cover attributes to land cover classes. Land cover classes can be defined by the user or extracted from pre-defined schema.
- A consequence of land cover map construction is a loss of detailed vegetative information.
- A methodology has been outlined to determine the accuracy with which the MLCNP, NLUD and P1 classifications can be constructed from the current field survey data.
- This methodology is based on a per-pixel ML algorithm. Various adaptations to the algorithm, as a means of improving classification accuracy were outlined.
- The application of an object-orientated methodology was outlined as a means of testing this alternative classification approach.

CHAPTER 6

Land Cover Map Construction: Results and Analysis

Chapter 6 describes results from the testing of a classification methodology developed to enable the construction of several land cover maps from a single field survey dataset.

A semi-automated approach to the classification of the field samples, to represent MLCNP, NLUD and P1 land cover classes, on the basis of the recorded land cover attributes is outlined. Classification issues regarding threshold definition and context are discussed.

A maximum likelihood, per-pixel, algorithm was tested as a means of constructing the MLCNP, NLUD and P1 land cover maps. In addition to multi-spectral classification the influence of ancillary data and image processing techniques upon resultant classification accuracies were assessed. Significant differences in classification accuracy were identified across all classification outputs, that is, the MLCNP, NLUD and P1 land cover maps. Consequently, the influence of sample design and sample fraction upon resultant classification accuracies was evaluated.

Finally the chapter reviews the object-orientated classification technique as a means of land cover map construction. MLCNP land cover maps derived at three segmentation scales, via a standardised nearest neighbour algorithm, were compared to assess the influence of segmentation scale upon classification accuracy.

6.1 Introduction

Building upon the previous chapter the aim of this part of the research was to develop and test a classification methodology able to construct several land cover maps from data collected during a single field survey. Specifically, per-pixel classification methodologies were tested to determine whether the land cover attributes could be combined with remote sensing and ancillary data to construct land cover maps based on the MLCNP, NLUD and P1 classification schemes.

6.2 Training data

6.2.1 Land cover class derivation

Prior to inclusion in the classification the field data had to be processed to represent land cover classes as opposed to land cover attributes. Following conventional land cover mapping approaches each sample was required to represent a single, unique land cover class. Samples encompassing multiple land covers were classified as a mosaic, where such a definition existed within the classification scheme, or as a single class based on the dominant land cover.

An automated approach to field data classification, as opposed to a manual approach, was advocated in the methodology to ensure objectivity and consistency. The foundation of such an approach was the definition of rules and thresholds which enabled the field data to be categorised on the basis of the available land cover attribute data. The development of such a methodology was tested to determine the consistency with which rules and thresholds governing land cover class delineation could be defined.

A review of class definitions within the MLCNP (Taylor *et al*, 1991a), NLUD (Harrison, 2006) and P1 (JNCC, 1993) classification schemes concluded that variability between the schemes could not be encompassed in a single rule set. Indicator species, cover thresholds and ancillary parameters were therefore defined independently for each classification scheme.

The development of a rule set, to enable land cover class definition on the basis of land cover attributes, encountered the following issues:

- *Threshold definition:* In an automated approach, species composition must be compared to pre-defined class definitions to determine the most similar and hence appropriate land cover class. The definition of class characteristics is dependent upon land cover class descriptions which reference the expected vegetation species and spatial coverage of these species. The MLCNP, NLUD and P1 classification schemes are not consistent in their definition of such species and cover thresholds. This is exemplified by the P1 classification in which, dry dwarf shrub (D1.1) is defined as "vegetation with greater than 25% cover of ericoids/small gorse species in relatively dry situations" (JNCC, 1993). This threshold of 25% cover, in addition to the typical species list, formed the basis of field data classification. Conversely, for the bracken land cover class (C1) the class definition, "areas dominated by *Pteridium aquilinum* or scattered patches of the species" (JNCC, 1993), includes no reference to the proportion at which the species is considered dominant.

- *Context*: Land cover definitions include contextual information, in addition to species composition, to delineate land cover boundaries. For example, improved grassland (CO21) within the NLUD classification, encompasses "areas of intensively managed grassland that show evidence of enclosure for stock control purposes and/or for fodder/hay, and evidence of improvement by use of fertilisers, pesticides, drainage or re-seeding, usually being dominated by a single grass species. Species such as rush, thistles and bracken are normally eradicated" (Harrison, 2006). The land cover attributes, included within the field data, contain no direct reference to enclosure or the management characteristics of the land cover parcel. Context issues in part result from a disparity between the point sample of the field survey and polygons characteristic of the MLCNP, P1 and NLUD land cover classification schemes. When delineating homogenous areas in the field, contextual information is automatically included by the surveyor. At the scale of a point sample, contextual information can only be implied from appropriate surrogates, for example, vegetation species present are indicative of management regime. The inclusion of further contextual information, regarding for example, enclosure, would require the surveyor to consider the land cover parcel containing the point sample. This introduces classification-specific concepts regarding for example parcel delineation, to field data collection.

Issues of threshold and surrogate definition precluded a fully automated approach to field data classification. In a hybrid, semi-automated approach, field data classifications were implemented on the basis of pre-defined percentage top cover thresholds or, where these data were not available, iterative testing of user defined thresholds. Verification of the resultant classification was conducted manually on the basis of sample point photographs, field notes and aerial photograph interpretation (API).

The accuracy, with which the vegetation parameters were classified in this hybrid approach was unknown, as an accurate measure of land cover class, at each sample concurrent with the field survey, was not available for comparison. It was predicted that the accuracy of land cover attribute classification was similar to that achieved during ground survey, if not better, due to the objective rules implemented.

6.2.2 Aerial photograph interpretation

An independent API exercise was implemented to supplement existing field data. The MLCNP, NLUD and P1 land cover classes were derived for an additional five sample frame replicates (section 5.4.1).

The accuracy of the land cover classification achieved during API, was assessed by repetition of the API procedure at the field survey samples, with no reference to the field data. This interpretation was conducted by a field surveyor. However, due to a time period of 3 years between the field survey and API procedure knowledge of the sample sites was not considered to significantly influence the analysis. Comparison of the resultant API and reference land cover class, that is, class derived via semi-automated classification of the land cover attributes, enabled the accuracy of the API to be estimated (table 6.1). Within this comparison it was assumed that the land cover class derived from the field data represented the most accurate classification.

Table 6.1: Overall classification accuracies of the MLCNP, NLUD and P1 land cover classification derived via API

Classification Scheme	Overall Accuracy (%)
MLCNP	84
NLUD	88
P1	73

MLCNP

Bird *et al* (2000) demonstrated that the overall classification accuracy achieved for API within the NYMNP was 71% when compared to ground survey at the full class level (table 6.2). The current API (*overall accuracy 84%*) is slightly more accurate than the results obtained in the MLCNP project (*overall accuracy 71%*). This small increase in accuracy was attributed to the lower number of land cover classes which existed in the study area (*11 classes*), in comparison to the park as a whole (*34 classes*), which improved land cover identification and the probability of a correct classification.

Table 6.2: Overall accuracy of API and ground survey for the MLCNP survey of the North York Moors National Park

MLCNP Comparison (All MLCNP classes)	**Overall Accuracy (%)**
Ground Survey (Between Surveyors)	75.1
API to Ground Survey	71
API to API (Between Surveyors)	81 – 87

Source: Bird *et al* (2000)

Amalgamation of the current MLCNP classification to the major class level, that is, upland heath (D), arable/pasture (E) and wetland (F) resulted in an increase in the overall accuracy of the API to 99%. This high classification result indicated that API misclassification was primarily a function of the mislabelling of composite classes within the major land covers. Such a result might have been expected as the major land covers occur in differing landscapes and are characterised by distinct vegetation species; characteristics easily separated via API. This was confirmed via inspection of the confusion matrices (table 6.3 (a)).

The major class upland heath (D) was characterised by confusion between the mosaic land covers (D6a and D6b) and their constituent classes: upland heath (D1), upland grass moor (D2a) and bracken (D3). This confusion, between mosaic and pure classes, reflects previous studies by Bird *et al* (2000) and Taylor *et al* (1991b). Errors in the delineation of a mosaic versus pure class were a consequence of sample misregistration, land cover change between the dates of classification and interpretation error.

Within the agro-pastoral class (E), misclassification occurred between the arable (E1) and the improved (E2a) and rough (E2b) pasture land covers. Confusion of these land covers was attributed to changes in land management practices, between the times of aerial photograph capture and field survey and interpretation errors resulting from the similar vegetation composition of the classes.

NLUD

The NLUD classification generated the highest overall accuracy achieved during API (table 6.1). It was proposed that this high accuracy, in relation to the other classification schemes, was a function of land cover classes being defined on criteria easily identified via API and the broad class definitions implemented in the classification. Broader land covers are typically distinct in their vegetative and landscape characteristics minimising the potential for between class confusion and increasing the probability of a correct class assignment. This was exemplified by the upland heath land cover (CO41) which encompassed the upland heath (D1), upland grass moor (D2a) and upland mosaics (D6a/D6b) of the MLCNP classification.

Despite the broad class definitions, disagreement was evident in the NLUD confusion matrix (table 6.3 (b)). As per the MLCNP classification, this disagreement was typically within the main land cover classes. For example, the confusion between improved (CO21) and rough pasture (CO22) was again evident in this classification. Confusion within the upland classes was minimised, primarily due to amalgamation of the uplands into two classes: upland heath (C041) and bracken (CO42). Misclassification between these land covers was a function of errors in delineation of the bracken/ heath edge, a boundary which typically intergrades and which varies temporally.

P1

The P1 classification had the lowest overall accuracy (table 6.1) and the greatest proportion of classes with zero producer and user accuracies (table 6.3 (c)). Low classification accuracies were attributed to the increased number of land cover types, the delineation of which was a function of detailed species composition, management practices and landscape characteristics not readily identifiable from API. Detailed class definitions are a consequence of the P1 classification being designed for ground survey as opposed to API. Increased misclassification, as a function of class subdivision, was evident in the agro-pastoral classes; the subdivision of pasture into un-improved (B1.1), semi-improved (B1.2), improved (B4) and marshy (B5) categories increased the probability of disagreement as evident by confusion between these categories (table 6.3).

API: sources of disagreement

Disagreement between the API derived and reference land cover of the MLCNP, NLUD and P1 classifications, was attributable to a common set of factors:

- *Temporal change*

The aerial photography (2000) was not captured coincidentally with the ground survey (2004). Disagreement was therefore attributed to changes in land management practices, land cover class and species composition between the specified dates.

- *Ground data errors*

The reference land cover classes derived from the land cover attributes (field data) had the potential to contain misclassification error. This error introduced false agreement/disagreement into the confusion matrix.

- *Class determination*

A characteristic of each of the classification schemes was increased disagreement between the composite classes of major land cover categories. Such a result would be expected due to increased similarity of land covers within, as opposed to between, the major classes. Increased disagreement was particularly evident where class definitions were based on criteria which were temporally variable, for example, arable management, or not readily identifiable from API, for example, target species, species composition and plant status.

- *Class boundary delineation*

Disagreement, both within and between major classes, was a function of the correct identification and delineation of the boundary between land cover parcels. This error was a major contributor to disagreement within the upland environments and was documented as being a function of the environments' characteristically continuous, intergrading land covers.

Table 6.3: Confusion matrices comparing classifications derived via API (classification) and ground survey (reference), for the (a) MLCNP, (b) NLUD and (c) P1 classifications

a) MLCNP

API	MLCNP Reference (Field Data)														
	C1	C2	C4	D1	D2a	D3	D6a	D6b	E1	E2a	E2b	F3	H1a	Total	*User Accuracy (%)*
C1															
C2															
C4															
D1				84	2		5							91	***92***
D2a				1	4		2					1		8	***50***
D3						7					1			8	***88***
D6a				1			5							6	***83***
D6b				1		1		3						5	***60***
E1										6				6	***0***
E2a										21	1			22	***96***
E2b										3	2			5	***40***
F3														0	
H1a															
Total				87	6	8	12	3		30	4	1		151	*Overall Accuracy (%)*
Producer Accuracy (%)				***97***	***67***	***88***	***42***	***100***		***70***	***50***	***0***			***84***

b) NLUD

API	NLUD Reference (Field Data)										
	CO11	CO21	CO22	CO31	CO33	CO34	CO41	CO42	CO63	CO94	Total	User Accuracy (%)
CO11		1									1	***0***
CO21		28	3								31	***90***
CO22		1	3				2				6	***50***
CO31												
CO33												
CO34												
CO41			2				91	2	1		96	***95***
CO42			1				4	2			7	***29***
CO63											0	***0***
CO94												
Total		30	9				97	4	1		141	Overall Accuracy (%)
Producer Accuracy (%)		***93***	***33***				***94***	***50***	***0***			88

c) P1

API	P1 Reference (Field Data)															
	A1.1.1	A1.2.2	A2.1	B1.1	B2.2	B4	B5	C1.1	C1.2	D1.1	D2	D5	E2.1	J1.1	J3.6	Total	User Accuracy (%)
A1.1.1																	
A1.2.2																	
A2.1																	
B1.1				4	1				1	3		1				10	***40***
B2.2					9	8	1							*4*		22	***41***
B4					3	3								*3*		9	***33***
B5																0	***0***
C1.1								8								8	***100***
C1.2																	***0***
D1.1				1					1	80	1		1			84	***95***
D2				1						2	4					7	***57***
D5				2				1		5	1					9	***0***
E2.1																	
J1.1														1		1	***100***
J3.6																	
Total				8	13	11	1	9	2	90	6	1	2	8		151	Overall Accuracy (%)
Producer Accuracy (%)				***50***	***69***	***27***	***0***	***89***	***0***	***89***	***67***	***0***	***0***	***13***			73

Notes: Boxes with grey outlines within the confusion matrix indicate land covers which were not characterised by quadrat measurements in the field survey on which the comparison was based.

6.3 Per-pixel ML classification

6.3.1 Spectral classification

The multi-spectral bands of the 2004 SPOT 5 image were classified using a ML algorithm. This classification was trained solely on the land cover classes identified at the field data samples. These samples incorporated those at which full quadrat measurements had been achieved and inaccessible samples at which the land cover was accurately known. This resulted in the classifier being trained on 153, 172 and 177 samples in the MLCNP, NLUD and P1 classifications, respectively. If each sample is considered to cover a circular area of 4m diameter ($12.6m^2$) and the contracted study area is defined to cover $196km^2$ the sample fraction, in each classification, represents less than 1% of the total study area. This was considered a very small sample fraction, as will be discussed in subsequent analysis. Finally, to ensure unimodal training signatures in each classification the land cover class relating to arable crops, E1, CO11 and J11 in the MLCNP, NLUD and P1 classifications, respectively, were split into two spectrally distinct classes according to whether the field contained a crop. The resultant land cover maps, for each classification scheme, are illustrated in figure 6.1.

A visual inspection of the classification results demonstrated that:

- Each classification had captured the broad, upland/lowland patterns of land cover typical of the study area.
- The pixel based classification resulted in a 'peppered' appearance to the land cover map. This was attributable to the classification of each pixel independently within the ML algorithm. Consequently, contextual information regarding the class assigned to adjacent pixels was not considered. This can result in single, mislabelled, pixels within otherwise homogenous stands.
- Each classification included obvious areas of misclassification. This was exemplified by the annotated MLCNP classification example (figure 6.2).

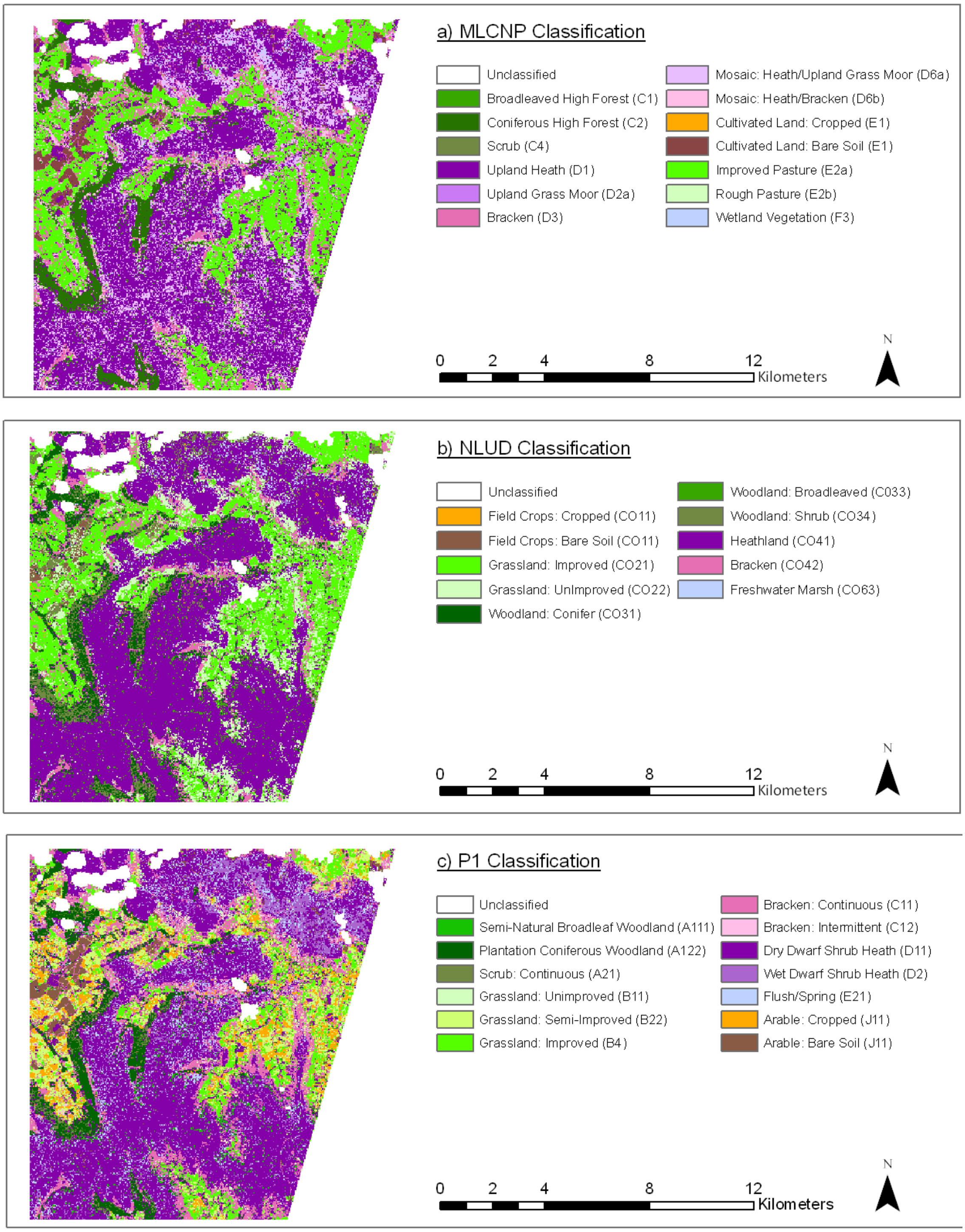


Figure 6.1: Multi-spectral, per-pixel, maximum likelihood classification outputs for the a) MLCNP, b) NLUD and c) P1 classification schemes

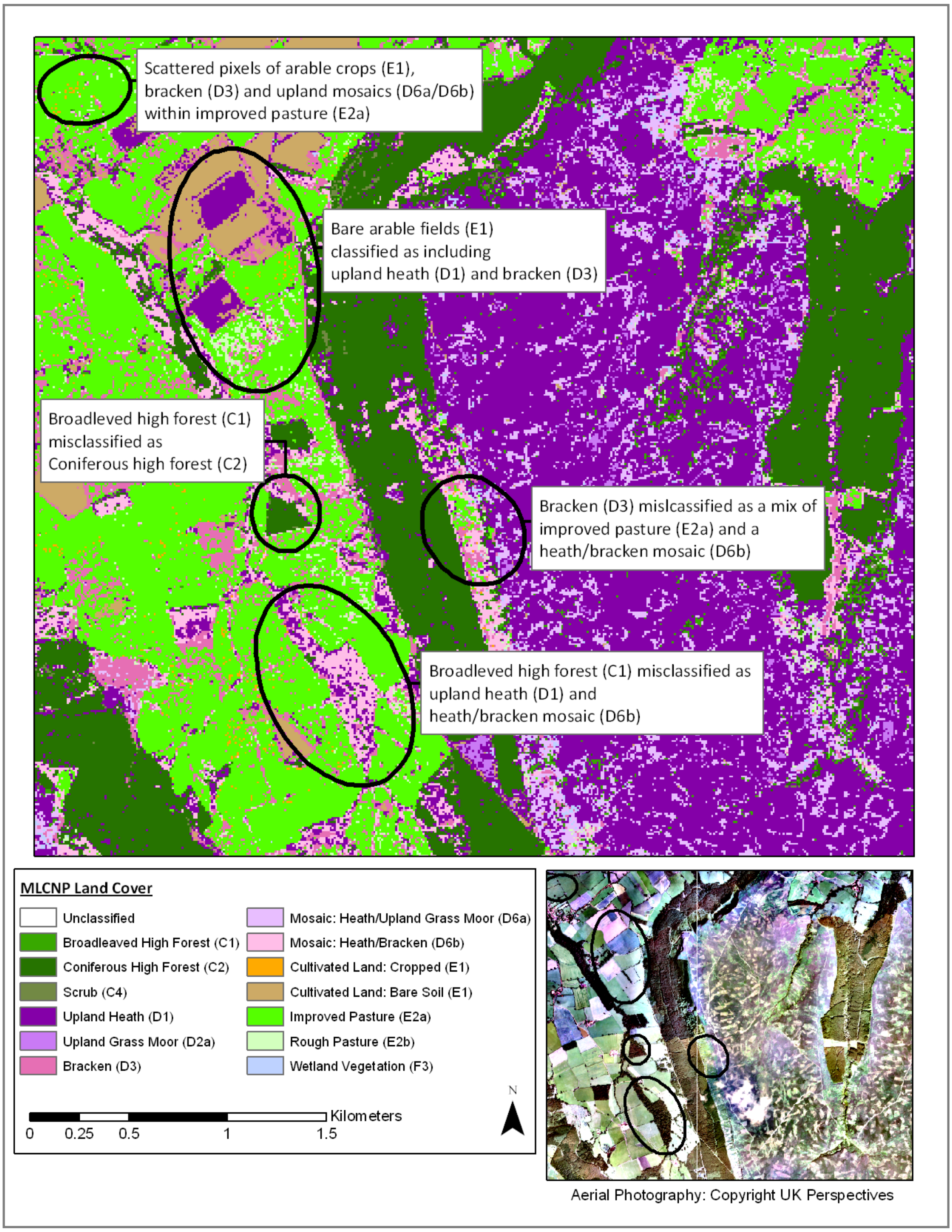


Figure 6.2: Annotated example of misclassification, near Ingleby Greenhow Wood, within the MLCNP land cover map

Notes: Land cover is derived from a ML classification of the multi-spectral 2004 SPOT 5 image

The accuracy of the ML classifications was assessed using confusion matrices derived from the field data samples (table 6.4). On the basis of the derived overall accuracies it can be concluded that the ML classifier performed well with the accuracy of each classification approaching the 80% threshold typically established within land cover classification (Mather, 1999a). However, the large distribution of user and producer accuracies, within each classification (table 6.4), indicated that the quality of land cover characterisation was variable as a function of land cover type. Inspection of the confusion matrices indicated that:

- Upland heath in the MLCNP (D1), NLUD (CO41) and P1 (D1.1) was spectrally confused with a number of classes, both within and between the major land cover types. In each classification scheme upland heath was characterised by a range of habitats encompassing variability in age, structure and species composition. This variability resulted in broad multi-spectral signatures and hence similarity with a number of land cover types. For example, misclassification between upland heath (D1/D1.1) and arable fields (E1/J1.1) in the MLCNP and P1 classifications was attributed to the spectral similarity of bare fields and recently burnt moorland areas.
- The inclusion of mosaic land covers within the MLCNP land cover classification resulted in multi-spectral confusion between the mosaics (D6a/D6b) and their constituent land covers: upland heath (D1), upland grass moor (D2a) and bracken (D3). This multi-spectral similarity was reflected in the low JM distances of the signature pairs (table 6.5) which were predominantly below the average JM distance for the classification.
- Within the P1 classification confusion between the continuous (C1.1) and scattered (C1.2) bracken land covers was attributable to their similar vegetative compositions. The JM distance between these land covers was 1195, in comparison to an average of 1364 for the classification, indicating the multi-spectral similarity of the classes.

Table 6.4: Confusion matrices, derived from the field data samples (training data), for the (a) MLCNP, (b) NLUD and (c) P1 classifications

a) MLCNP

MLCNP Classification	MLCNP Reference (Field Data)													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3a**	**Total**	***User Accuracy (%)***
C1	3			1									***4***	***75***
C2		6		1									***7***	***86***
C4			2										***2***	***100***
D1				60						1			***61***	***98***
D2a				2	3								***5***	***60***
D3				1		7	1			2			***11***	***64***
D6a				11			7						***18***	***39***
D6b				1		2		3			1		***7***	***43***
E1				2					7				***9***	***78***
E2a										25			***25***	***100***
E2b				1						1	3		***5***	***60***
F3a				3								3	***6***	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***72***	***100***	***78***	***88***	***100***	***100***	***86***	***75***	***100***		***81***

b) NLUD

NLUD Classification	NLUD Reference (Field Data)										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	**User Accuracy (%)**
CO11	6	1								7	***86***
CO21	1	25	4					1		31	***81***
CO22	1	4	5			1	2			13	***38***
CO31				9			2			11	***82***
CO33					3		3			6	***50***
CO34	1	2				4	4			11	***36***
CO41			2				79	1		82	***96***
CO42		1	1				2	10		14	***71***
CO63							3		3	6	***50***
Total	9	33	12	9	3	5	95	12	3	181	**Overall Accuracy (%)**
Producer Accuracy (%)	***67***	***76***	***42***	***100***	***100***	***80***	***83***	***83***	***100***		***80***

c) P1

P1 Classification	P1 Reference (Field Data)														
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**E2.1**	**J1.1**	**Total**	**User Accuracy (%)**
A1.1.1	3									1				4	75
A1.2.2		8								1				9	89
A2.1			3										1	4	75
B1.1			1	4										5	80
B2.2					8	3								12	67
B4					5	9								14	64
B5														0	0
C1.1		1			1		1	9		4			1	17	53
C1.2					1			1	3					5	60
D1.1						1		1		68			1	71	96
D2										4	5			9	56
E2.1										8		4		12	33
J1.1			1		4					1			14	20	70
Total	3	9	5	4	19	13	1	11	3	87	5	4	17	182	**Overall Accuracy (%)**
Producer Accuracy (%)	***100***	***89***	***60***	***100***	***42***	***69***	***0***	***82***	***100***	***78***	***100***	***100***	***82***		***76***

Table 6.5: JM distance values between mosaic and constituent land covers from the MLCNP classification

Classification Statistics			JM Distance
Average			1383
Minimum			958
Mosaic		**Constituent Element**	**JM Distance**
Heath/upland grass moor (D6a)	:	Upland heath (D1)	958
Heath/upland grass moor (D6a)	:	Upland grass moor (D2a)	1411
Heath/bracken (D6b)	:	Upland heath (D1)	1370
Heath/bracken (D6b)	:	Bracken (D3)	1215

Notes: JM distance values were derived from the multi-spectral 2004 SPOT 5 image based on the field data.

- Within the lowland regions of the study area, multi-spectral confusion was evident between improved pasture (B4, CO21) and semi-improved (B2.2) or unimproved (CO22) pasture within the P1 and NLUD classifications, respectively. This multi-spectral similarity was a consequence of the similar vegetative compositions of the land covers. Similar misclassification was, however, not reflected in the MLCNP classification between improved (E2a) and unimproved (E2b) pasture. It was proposed that this was a consequence of the training of unimproved pasture (E2b) on only three samples, insufficient samples to encompass the variability of the land cover and as such its potential similarity to improved pasture (E2a).

The high accuracies stated for the classifications (table 6.4) were not reflected in a visual interpretation of the resultant land cover maps which identified sources of misclassification throughout the image (figure 6.2). To verify the visual interpretation the accuracy of each land cover classification was assessed at a series of independent validation samples. This validation dataset contained approximately 224 sample points at which the reference land cover class was derived by API. The confusion matrix statistics for these validation samples are summarised in table 6.6. Full confusion matrices are included in appendix H.

Table 6.6: Summary of accuracy measures, calculated at the API derived validation samples

	Overall (%)	User		Producer	
		Range (%)	Classes exceeding 80% (Total Number of Classes)	Range (%)	Classes exceeding 80% (Total Number of Classes)
MLCNP	52	0 - 83	1 (12)	0 - 80	1 (12)
NLUD	59	0 - 73	0 (8)	0 - 87	2 (8)
P1	45	0 - 74	3 (13)	0 - 89	1 (13)

Accuracy measures derived at the validation points confirmed a reduction in classification accuracy in comparison to using the field data samples. A Kappa analysis (table 6.7) indicated that for each classification this decrease in accuracy was significant.

Table 6.7: Kappa statistic comparison of the overall accuracy achieved at field data versus validation samples for each land cover classification

	Overall Accuracy (%)		
	Field Data Samples (FD)	Validation Points (API)	Kappa: Z Statistic
MLCNP	81	52	4.63
NLUD	80	59	6.53
P1	76	45	6.13

Notes: Comparisons highlighted in red indicate a significant difference between the training and validation sample confusion matrices at the 95% confidence level.

Decreasing accuracy at the validation samples was also reflected in the user and producer accuracies. However, the extent of these accuracy decreases were class specific. Significant decreases in producer accuracy were evident for those classes trained on a limited number of samples. For example, within the MLCNP classification, upland grass moor (D2a), heath/bracken mosaic (D6b) and unimproved pasture (E2b), each trained on less than four samples, had producer accuracies of 0% at the validation samples in comparison to 100%, 100% and 75%, respectively, at the field data samples.

Coniferous woodland, common to each classification scheme, although characterised by a decrease in producer accuracies at the validation samples retained accuracies greater than 80%. Accurate mapping of this land cover was attributed to the distinct characteristics of the class. A JM distance comparison between coniferous woodland and remaining MLCNP classes (table 6.8) exemplifies the distinctiveness of the class as indicated by JM values approaching the maximum separability value of 1414.

Table 6.8: JM distance values comparing coniferous woodland (C2) to remaining MLCNP land cover classes

MLCNP Class		JM Distance
Broadleaf Woodland	**(C1)**	1382
Scrub	**(C4)**	1271
Upland Heath	**(D1)**	1374
Upland Grass Moor	**(D2a)**	1414
Bracken	**(D3)**	1409
Bracken, Grass Mosaic	**(D6a)**	1407
Heath, Bracken Mosaic	**(D6b)**	1403
Arable – Crop	**(E1)**	1414
Arable – Bare Ground	**(E1)**	1414
Improved Pasture	**(E2a)**	1414
Rough Pasture	**(E2b)**	1411
Wetland Vegetation	**(F3)**	1414

Notes: JM distances are calculated for the four multi-spectral 2004 SPOT 5 wavebands.

As the field data samples were based on a random sample it would, typically, be expected that the accuracy derived at these samples reflected the accuracy of the classification across the entire study area. However, results of the preceding analysis were indicative that accuracy was variable across the study area. The influence of sampling fraction, reference/validation errors and sampling frame upon the training/validation accuracy difference were further investigated and are reported in section 6.3.4.

In defining the 'true' overall accuracy of the MLCNP, NLUD and P1, multi-spectral classifications it is suggested that the accuracy falls between that of the field data and validation samples; the validation samples representing the worst case scenario, that is, a random sample wholly independent of the field data samples.

6.3.2 The role of ancillary data

Ancillary data derived from primary, related to the satellite image, or secondary sources has the potential to improve the separability of land cover classes and hence classification accuracy (De Bruin & Gorte, 2000; Maselli *et al*, 1995; Watson & Wilcock, 2001). This study focussed on slope, elevation and NDVI (section 5.4.1).

The DEM and its derivatives

Improved classification, based on the addition of ancillary data, is dependent upon a relationship existing between the ancillary data and land cover type. Land cover can be related to both slope and elevation, for example, bracken characteristically dominates steep slopes (section 2.1.3). Figures 6.3 and 6.4 plot, for each MLCNP land cover, the mean slope/elevation and variability of this measure about the mean, as derived at the field data samples from the NEXTMap DTM.

The multi-spectral MLCNP classification confusion matrix (table 6.4 (a)) demonstrated that bracken containing land covers (D3 and D6b) were spectrally confused with each other, in addition to the upland land covers (D1 and D2a) and improved pasture (E2a). On the basis of the slope/land cover relationship (figure 6.3) it was proposed that slope

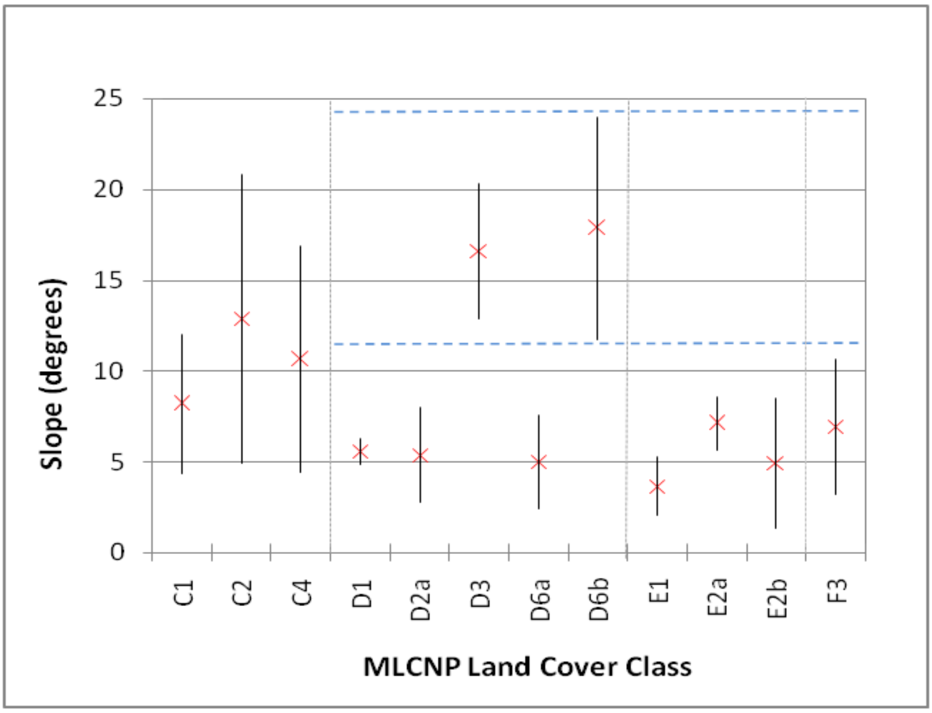


Figure 6.3: MLCNP land cover class versus the average slope and 95% confidence intervals, as derived from the field data samples

Notes: Blue dashed lines are added to aid interpretation of confidence interval overlap.

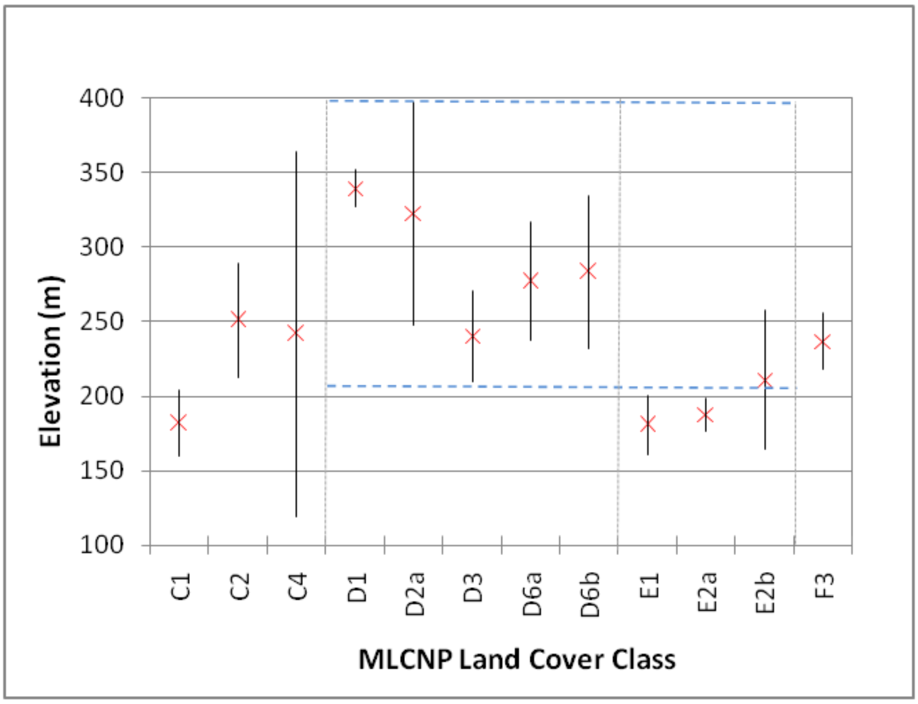


Figure 6.4: MLCNP land cover class versus the average elevation and 95% confidence intervals, as derived from the field data samples

Notes: Blue dashed lines are added to aid interpretation of confidence interval overlap.

had the potential to improve the separability of bracken classes from upland heath (D1), upland grass moor (D2a) and improved pasture (E2a) as indicated by the different slope distributions of each land cover class, that is, non-overlapping confidence intervals. On the basis of the elevation/land cover relationship (figure 6.4) it was hypothesised that elevation would enable the refinement of typically lowland versus upland classes; in particular the observed spectral confusion between agro-pastoral classes (E1 and E2a) and upland heath (D1)/bracken (D3) (table 6.4 (a)).

The inclusion of elevation and slope, in addition to the multi-spectral 2004 SPOT 5 image in the ML classification, resulted in overall classification accuracy improvements in the MLCNP, NLUD and P1 classification schemes. However, on the basis of a kappa statistic analysis not all of these accuracy increases could be considered significant (table 6.9). Full confusion matrices are included in appendix H.

Table 6.9: Overall classification accuracies (%), derived from the field data sample confusion matrix, for multi-spectral and multi-spectral plus slope/elevation classifications

Ancillary Data	Overall Accuracy (%)		
	MLCNP	NLUD	P1
	(Kappa: Z Statistic)		
None	81	80	76
Elevation	91 (2.42)	85 (1.29)	79 (0.59)
Slope	87 (1.43)	86 (1.61)	82 (1.41)
Elevation & Slope	95 (3.88)	89 (2.37)	87 (2.60)

Notes: Values highlighted, in red, indicate a significant difference, at the 95% confidence interval, between the multi-spectral and multi-spectral plus ancillary data classification accuracies. The Kappa statistic is included as the bracketed value.

As predicted, on the basis of the elevation and slope relationships, the accuracy of the MLCNP classification increased. However, the increase in accuracy as a consequence of the inclusion of slope, could not be considered statistically significant.

Variability in user and producer accuracies for each MLCNP land cover class, as a consequence of including ancillary data in the multi-spectral classification are summarised in table 6.10. It should be noted that the confusion matrices from which these user and producer accuracies were extracted (appendix H) contained a relatively small number of samples. Consequently, large changes in accuracy may result from changes to a small number of samples. A number of broad observations can however be documented:

- Bracken (D3) has been shown to characteristically occur on steep slopes of greater than 10° (figure 6.3). An increase in the producer accuracy would therefore be expected for this land cover as a consequence of including slope within the multi-spectral classification. This was not observed. This inconsistency was attributed to spectral confusion between bracken (D3) and the heath/bracken mosaic (D6b). In addition to being spectrally similar, as a consequence of their similar species compositions, these land covers are characteristic of similar slopes. Within the multi-spectral classification the JM distance between bracken (D3) and its mosaic (D6b) was 1215, this increased to only 1266 with the addition of slope into the classification algorithm. This increase was not sufficient to enable accurate separation of the land covers.
- Demarcation of characteristically upland versus lowland land covers on the basis of elevation, as suggested by the relationship in figure 6.4, was only partially achieved. Increases in producer and user accuracies for both rough pasture (E2b) and improved pasture (E2a) were a consequence of reduced misclassification between these land covers and the upland land covers: upland heath (D1) and bracken (D3), respectively. However, these accuracy increases were confined to a single sample. Additionally, confusion between all upland and lowland classes was not removed.

Table 6.10: User and producer classification accuracies (%), derived from the field sample confusion matrices, for multi-spectral and multi-spectral plus slope/elevation classifications

MLCNP Class		Ancillary Data: Accuracies (%)							
		None		Elevation		Slope		Elevation & Slope	
		User	Producer	User	Producer	User	Producer	User	Producer
Broadleaf Woodland	**(C1)**	75	100	100	100	100	100	100	100
Coniferous Woodland	**(C2)**	86	100	86	100	100	100	100	100
Scrub	**(C4)**	100	100	100	100	100	100	100	100
Upland Heath	**(D1)**	98	72	99	87	99	80	99	95
Upland Grass Moor	**(D2a)**	60	100	60	100	100	100	100	100
Bracken	**(D3)**	64	78	78	78	78	78	88	78
Heath, Grass Mosaic	**(D6a)**	39	88	57	100	40	100	67	100
Heath, Bracken Mosaic	**(D6b)**	43	100	60	100	60	100	60	100
Arable – Crop	**(E1)**	78	100	100	100	70	100	100	100
Improved Pasture	**(E2a)**	100	86	100	93	100	93	100	93
Rough Pasture	**(E2b)**	60	75	80	100	100	100	100	100
Wetland Vegetation	**(F3)**	50	100	100	100	75	100	100	100

In comparison to the MLCNP classification, accuracy improvements as a function of ancillary data were not as evident in the P1 classification. A potential cause was a weaker relationship between the ancillary parameters and land cover type; a possible consequence of increased class complexity within this classification scheme.

The elevation/ land cover relationship for the P1 classification, derived at the field data samples (figure 6.5), was more complex. However, broad class distinctions, similar to those found in the MLCNP classification, were evident. On the basis of the relationship plotted, elevation data would aid in the separation of, semi-improved/improved pasture (B2.2/B4) and upland dry/wet heath (D1.1/D2). However, within the multi-spectral classification (table 6.4 (c)), confusion between these land covers did not represent a major contribution to classification error. Major sources of misclassification errors resulted from the spectral similarity of semi-improved pasture (B2.2), improved pasture (B4) and arable fields (J1.1). Overlapping confidence intervals within the elevation/land cover relationship (figure 6.5) demonstrated that these land covers occurred at similar elevations hence the inability of the ancillary data to resolve this multi-spectral confusion and significantly improve the classification.

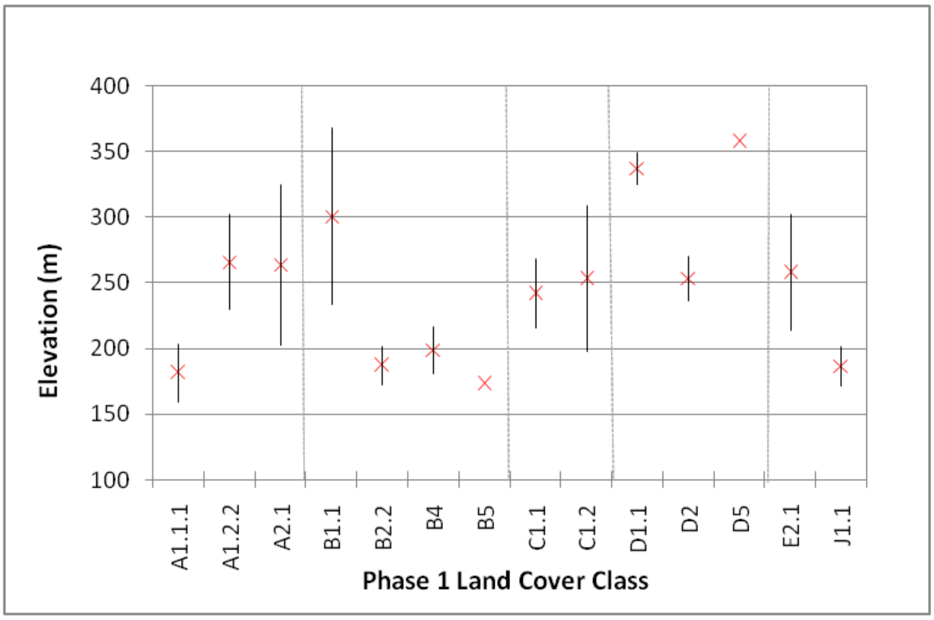


Figure 6.5: P1 land cover class versus the average elevation and 95% confidence intervals, as derived from the field samples

The preceding analysis was based on confusion matrix statistics derived from the field data samples. To verify that these conclusions were applicable across the study area, confusion matrices were also derived at the independent, validation samples (appendix H). From these validation accuracies (table 6.11) it was demonstrated that:

- Overall accuracies at the validation samples were significantly lower than the equivalent accuracy at the training samples.
- Overall accuracies, at the validation samples, retained a tendency to increase with the inclusion of ancillary data (table 6.11), however, none of these accuracy increases were statistically significant.

Table 6.11: Overall classification accuracies (%), derived from the validation sample confusion matrices, for multi-spectral and multi-spectral plus slope/elevation classifications

Ancillary Data	Overall Accuracy (%)		
	MLCNP	NLUD	P1
None	52	56	45
Elevation	57	58	49
Slope	56	59	51
Elevation & Slope	61	60	52

Notes: No significant differences exist between the multi-spectral and multi-spectral plus ancillary data classification accuracies at the 95% confidence level.

The MLCNP validation sample confusion matrices derived from the multi-spectral (table 6.12) and multi-spectral plus slope/elevation classifications (table 6.13), illustrated that:

- The confusion matrices for both classifications, excluding and including ancillary data, contained a significant amount of disagreement.
- The inclusion of slope and elevation within the classification algorithm did improve class separability on the basis of the relationships previously outlined. For example, confusion between bracken (D3) and arable/pasture classes (E1/E2a/E2b) was

reduced; as reflected by a user accuracy increase from 20% to 29% (table 6.12 and 6.13). However, a low user accuracy (29%) and low producer accuracy (57%) indicated that the class remained highly confused.

- Disagreement contained in the classifications was not consistent; the inclusion of ancillary data introduced 'new' sources of misclassification. This was exemplified by confusion between rough pasture (E2b) and upland heath (D1), introduced within the ancillary data classification. However, the separability of these classes would be expected to improve on the basis of the elevation/land cover relationship outlined (figure 6.4).

- Increased disagreement and variable accuracy improvements, via the inclusion of ancillary data, were observed at the validation samples of each classification scheme. It was proposed this variable accuracy was a consequence of the inability of the training data to fully describe the ancillary/land cover relationship; this may be a function of the minimal training data available.

Table 6.12: Confusion matrix, derived at the validation samples, for the MLCNP multi-spectral classification

MLCNP Classification	MLCNP Reference													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1			1									2	***50***
C2		4		1	2		1						8	***50***
C4		1											1	***0***
D1	1			51	10		3	1	2	1			69	***74***
D2a				2									2	***0***
D3	2			3		4	1	3	3	3	1		20	***20***
D6a				10	8		4				1	1	24	***17***
D6b	3			1	2	1				3	2		12	***0***
E1										1			1	***0***
E2a				1						25	4		30	***83***
E2b						1							1	***0***
F3						1							1	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***80***	***0***	***73***	***0***	***57***	***44***	***0***	***0***	***76***	***0***	***0***		***52***

Table 6.13: Confusion matrix, derived at the validation samples, for the MLCNP multi-spectral plus slope and elevation classification.

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1													0	***0***
C2	1	3					1						5	***60***
C4		1											1	***0***
D1	3	1		62	19	2	4	2	2		2	1	98	***63***
D2a													0	***0***
D3				2	1	4	1	2	2	1	1		14	***29***
D6a				4	1		3				1		9	***33***
D6b	1												1	***0***
E1									1				1	***100***
E2a	2			2	1	1				31	4		41	***76***
E2b										1			1	***0***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***60***	***0***	***89***	***0***	***57***	***33***	***0***	***20***	***94***	***0***	***0***		***61***

Normalised Difference Vegetation Indices (NDVI)

A further ancillary dataset included within the multi-spectral classification was NDVI. NDVI, derived via combination of the red and infra-red SPOT wavebands (section 5.4.1), is strongly correlated with the amount of photosynthetically active vegetation present in a pixel (Mather, 1999). Consequently, it is expected that land covers of varying vegetation types and characterised by differing management regimes have distinct NDVI characteristics.

From the relationship between NDVI and land cover, for the MLCNP classification (figure 6.6), it can be demonstrated that:

- NDVI values are consistently low across the study area.
- The arable land cover class (E1) is characterised by highly variable NDVI values. This is attributable to the variability of bare fields, associated with a low NDVI, and crops at varying growth stages. Misclassification error, as a function of this high within-class variability, was minimised by splitting of the arable class into vegetated and non-vegetated fields.
- The management regime of improved pasture (E2a), typically, results in a bright green sward. As a consequence improved pasture would be expected to be different in its NDVI characteristics to unimproved pasture (E2b) despite the similar vegetative composition of the land cover types. This management regime difference was reflected in the mean NDVI, which was higher for improved pasture (E2a). However, NDVI variability resulted in overlapping confidence intervals for improved (E2a) and rough (E2b) pasture. Similarity between the pasture classes was related to the date of image capture relative to the management regimes of the grassland, and variability introduced by error in delineation of the classes within the training data.
- Based on the field data samples variability in NDVI as a function of land cover type was evident. NDVI therefore has the potential to aid in the discrimination of spectrally similar land cover classes.

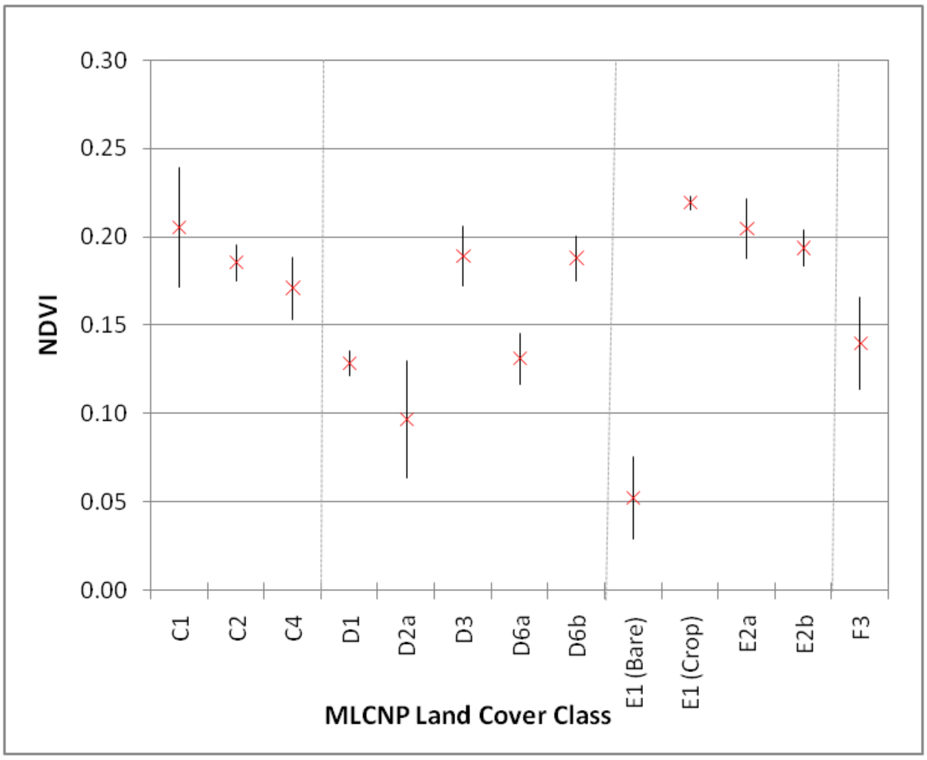


Figure 6.6: The average NDVI and 95% confidence interval, as derived from the field samples for each MLCNP land cover class

The inclusion of NDVI, within the multi-spectral ML classification algorithm, resulted in overall classification accuracy improvements for the MLCNP, NLUD and P1 classification schemes (table 6.14).

Table 6.14: Overall classification accuracy (%), derived from the field samples, for multi-spectral and multi-spectral plus NDVI classifications

Ancillary Data	Overall Accuracy (%)		
	MLCNP	NLUD	P1
	(Kappa: Z Statistic)		
None	81	80	76
NDVI	91 (2.27)	83 (0.81)	80 (0.57)

Notes: Values highlighted, in red, indicate a significant difference, at the 95% confidence interval, when compared to the classification excluding ancillary data. The Kappa statistic is included in as the bracketed value.

Comparison of the MLCNP spectral confusion matrix (table 6.4 (a)) to that derived from the classification including NDVI (table 6.15) illustrated that the significant improvement in classification accuracy was a consequence of reduced disagreement between and within the major land cover types. Improved separability between major land cover types was exemplified by an increased JM distance between broadleaf woodland (C1) and upland heath (D1) which increased from 1343, in the multispectral classification, to 1398 in the multi-spectral, NDVI classification.

The stated NDVI/ land cover relationships should, theoretically, be consistent across all three classification schemes. However, significant increases in accuracy were not observed in either the NLUD or P1 classification schemes.

table overleaf...

Table 6.15: Confusion matrix, derived at the field samples, resulting from the inclusion of NDVI within the multi-spectral, MLCNP, classification

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				78			4			1			83	***94***
D2a				1	3								4	***75***
D3				1		9				2			12	***75***
D6a				2			4						6	***67***
D6b								3					3	***100***
E1				1					5				6	***83***
E2a									2	26	1		29	***90***
E2b											3		3	***100***
F3												3	3	***100***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***94***	***100***	***100***	***50***	***100***	***71***	***90***	***75***	***100***		***91***

Plotting of the NDVI/land cover relationship for the P1 classification (figure 6.7) illustrated similar mean NDVI variability, as a function of land cover, to the MLCNP classification. Comparison of the P1 confusion matrices derived from the multi-spectral and multi-spectral/NDVI classifications, respectively (tables 6.4(c) and 6.16), demonstrated that the influence of NDVI was highly variable. This variability was exemplified by upland dry heath (D1.1) for which omission errors, relating to woodland (A1.2.2) were removed via the inclusion of NDVI; commission errors, however, remained. The NDVI relationship was therefore not consistent in separating woodland (A1.2.2) and upland dry heath (D1.1).

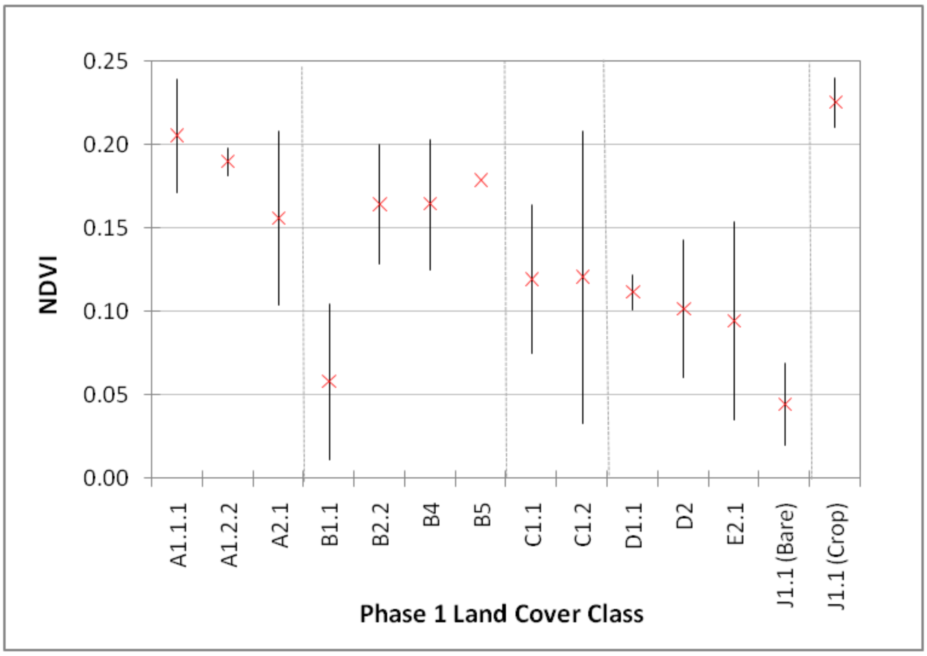


Figure 6.7: The average NDVI and 95% confidence interval, as derived from the field samples, for each P1 land cover class

Table 6.16: Confusion matrix, derived at the field samples, resulting from the inclusion of NDVI within the multi-spectral, P1 classification

Classification	P1 Reference														
	A111	A122	A21	B11	B22	B4	B5	C11	C12	D11	D2	E21	J11	Total	User Accuracy (%)
A111	3													3	***100***
A122		8												8	***100***
A21			3											3	***100***
B11				3										3	***100***
B22					8			1					1	10	***80***
B4					5	11							1	17	***65***
B5														0	***0***
C11				1	2	1	1	10	2	3			1	21	***48***
C12									1					1	***100***
D11		1	1							82	3	2	2	91	***90***
D2										1	2			3	***67***
E21												2		2	***100***
J11			1		4	1				1			12	19	***63***
Total	3	9	5	4	19	13	1	11	3	87	5	4	17	181	**Overall Accuracy (%)**
Producer Accuracy (%)	***100***	***89***	***60***	***75***	***42***	***85***	***0***	***91***	***33***	***94***	***40***	***50***	***71***		**80**

The validity of the NDVI relationship across the entire study area was verified by derivation of confusion matrix statistics at the validation samples (appendix H). At these samples overall accuracy increases as a consequence of including NDVI were not significant (table 6.17). Additionally all classification accuracies, derived at the validation samples, were significantly lower than the equivalent classification accuracy at the field samples. These trends followed those observed in the slope/elevation classifications.

Table 6.17: Overall classification accuracies at the validation points with the inclusion of NDVI

Ancillary Data	Overall Accuracy (%)		
	MLCNP	NLUD	P1
None	52	56	45
NDVI	61	57	55

Ancillary data: concluding comments

Training of the ancillary classifications was based on a small sample fraction limiting the trends which could be extracted regarding the success of ancillary data inclusion. However, within these limitations it can be demonstrated that:

- Although not statistically significant in all cases increases in accuracy were demonstrated for classifications, at the field and validation samples, as a consequence of including ancillary data.
- The ancillary data tested was not able to resolve all multi-spectral similarity. For example, elevation and slope were not able to improve the separability of bracken (D3) and its mosaic (D6b) as they were characteristic of the same environments.
- Ancillary data improvements were classification specific, as a consequence of multi-spectral similarity contained in the classification, and class specific as a function of slope/elevation/NDVI characteristics.

- Variability in the ancillary data (*elevation/slope/NDVI*) land cover relationship and hence classification error was observed as a consequence of the small sample fraction and training data quality.

6.3.3 Classification improvement techniques

Based upon the literature review provided in section 5.4.1 the potential of image filtering, class subdivision and *a-priori* class probabilities as techniques capable of improving per-pixel ML classification outputs has been highlighted. The techniques were tested on a subsection of the current classifications to determine their applicability to the mapping approach.

As a consequence of the highly variable classification accuracies achieved in the preceding analysis and limited sample fractions it was concluded that results from the classification improvement techniques were limited in their scope. Consequently, only results from the MLCNP classification, chosen subjectively to exemplify the applicability of these techniques, are outlined.

Filtering

Majority filters of varying kernel sizes (3x3, 5x5) were applied to the MLCNP classification resulting from the inclusion of the 2004 SPOT 5 multi-spectral image and field data samples in the ML algorithm.

A majority filter was utilised to remove isolated groups of pixels from otherwise homogenous areas, hence reducing local variability. The application of these filters reduced the 'peppered' appearance of the per-pixel classifier (figure 6.8) resulting in a more visually appealing classification image. The larger filter kernels (5x5) reduced local variability by a greater amount resulting in larger homogenous areas.

Comparison of the confusion matrix statistics, summarised in table 6.18, derived for the non-filtered and filtered images indicated that filtering and kernel size had no significant influence on overall classification accuracy. Full confusion matrices are included in appendix H.

Table 6.18: Overall accuracies at the training samples as a consequence of image filtering

Filter Kernel Size	Overall Accuracy (%)		Kappa: Z Statistic
	No Filter	Filtered	
3 x 3	81	82	0.23
5 x 5	81	82	0.16

Notes: Images included in the filters were derived from the ML algorithm implementing the multi-spectral SPOT 2004 image trained on the field data samples.

Although overall accuracies were relatively unaffected by the application of majority filters, inspection of the matrices indicated that class specific effects were evident. Specifically, it was noted that producer accuracies increased for land covers typified by discrete parcels, that is, the pasture land covers (E2a/E2b) and decreased for the continuous mosaic (D6a). It should be noted that these observations were based on a small sample fraction and as such are purely indicative. However, such class specific trends follow those of previous studies (Williams, 1988) and might be expected as internal homogeneity of pixel blocks would be expected in the pasture land covers.

It is evident in both the unfiltered and filtered images (figure 6.8) that the MLCNP classification contains significant classification errors irrespective of filter application. As classification errors are high conclusions regarding the utility of majority filtering were restricted.

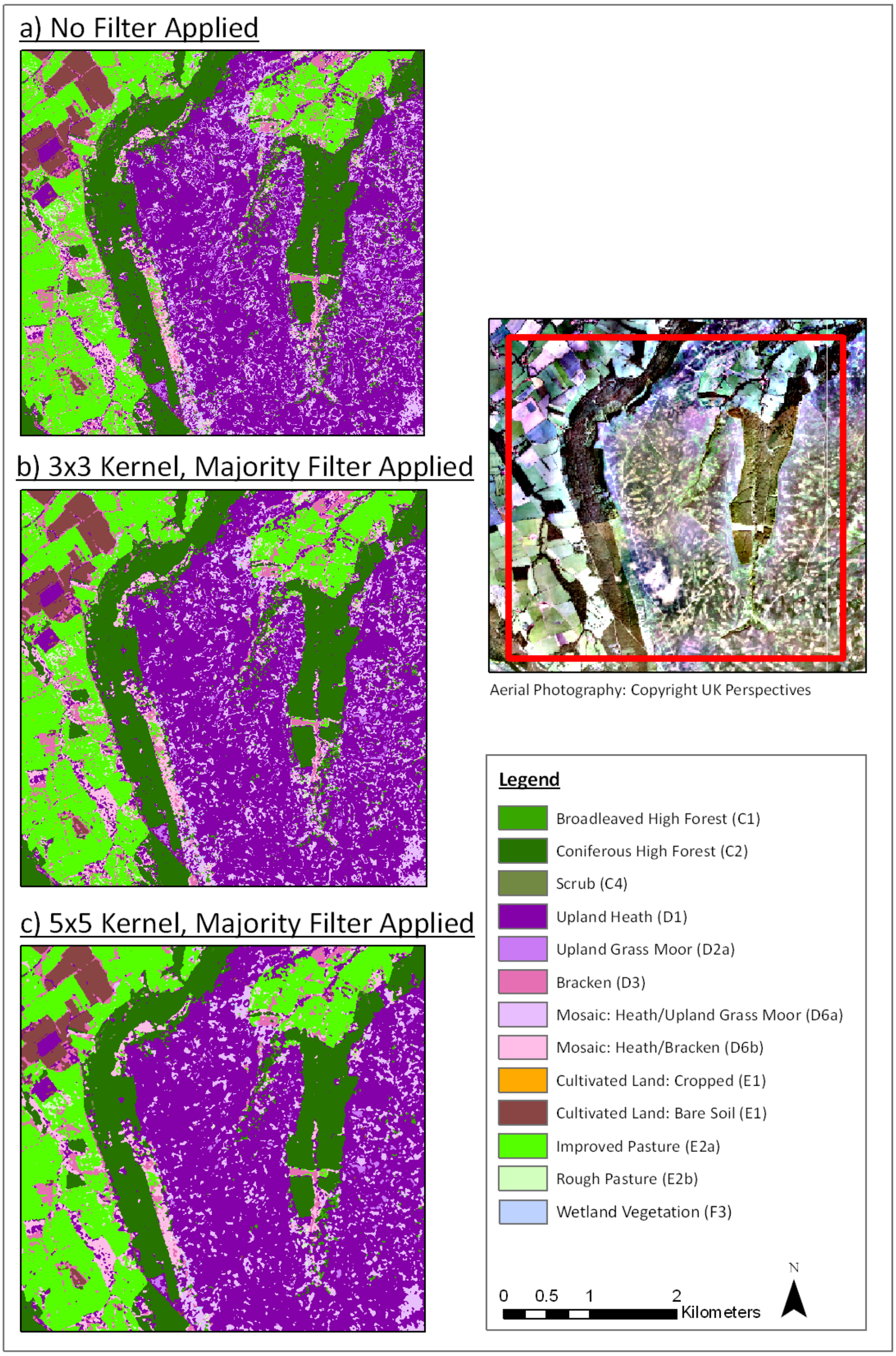


Figure 6.8: The reduction of local variability in the MLCNP classification, near Ingleby Greenhow Wood, as a consequence of increasing filter kernel sizes, (b) 3x3, (c) 5x5

Notes: ML algorithm classified the multi-spectral 2004 SPOT 5 image and was trained on the field data samples.

Class subdivision

The successful implementation of the ML algorithm is dependent upon the description of unimodal, spectrally distinct class signatures (Mather, 1999b). Where land cover classes are characterised by variable habitats class signatures have the potential to be multi-modal and, due to their broad characteristics, spectrally similar to remaining land covers. Due to the range of habitats included in the upland heath (D1) land cover it was proposed that this land cover type should be split into multiple spectrally defined classes (section 5.4.1).

Subdivision of the upland heath land cover (D1) was implemented using the ISODATA algorithm (section 5.2.1). Following definition of spectrally distinct habitats, or data clusters, within the upland heath (D1) field data samples the data were classified within the ML algorithm (section 5.4.1). Subsequent to classification confusion matrices were derived at the field data and independent validation samples (appendix H).

Comparison of the overall accuracies of the resultant classifications (table 6.19) demonstrated that:

- The subdivision of upland heath (D1) resulted in increased classification accuracies at the training samples. This increase was significant in the 10 cluster classification.
- This significant increase in accuracy was not reflected at the validation samples.

Inspection of the training sample confusion matrices (appendix H) illustrated that producer accuracy changes were isolated to the upland heath (D1) and upland heath mosaic (D6a). Accuracy increases in these land covers were primarily a consequence of reduced confusion between upland heath (D1) and the upland mosaics (D6a/D6b), bracken (D3) and upland grass moor (D2a) although some reduction with other major land cover types was also evident.

It is proposed that accuracy increases were not reflected at the validation samples as a consequence of the small training/validation sample fractions and validation errors (section 6.3.4).

Table 6.19: Overall classification accuracies achieved following subdivision of the upland heath (D1) land cover, using an ISODATA algorithm, and subsequent inclusion in the multi-spectral, field data trained MLCNP classification

Upland Heath (D1) Cluster Number	Training Samples Overall Accuracies (%)			Validation Samples Overall Accuracies (%)		
	Standard Classification	Classification with Class Subdivision	Kappa: Z Statistic	Standard Classification	Classification with Class Subdivision	Kappa: Z Statistic
5 Clusters	81	88	1.45	52	54	0.06
8 Clusters	81	89	1.95	52	55	0.01
10 Clusters	81	91	2.34	52	54	0.23

Note: Classification accuracies achieved without subdivision of the upland heath (D1) land cover are included for comparison. Values in red indicate a significant difference, at the 95% confidence interval, between the classification accuracy achieved with/without class subdivision.

A-priori probability

The ML algorithm can be adapted to consider *a-priori* probabilities, the probability that a class occurs within the study area (Mather, 1999). Within the multi-spectral MLCNP classification a-priori weights were inferred from the proportion of the land cover class occurring within the study area as derived from the 1980s MLCNP land cover map (Taylor *et al*, 1991d).

A visual comparison of the ML classification outputs derived from equal *a-priori* and *a-priori* weights inferred from class area (figure 6.9) demonstrated that:

- Misclassification in lowland regions remained relatively unchanged. For example, bare fields (E1) in the north east of the image remain classified as upland heath (D1).
- The introduction of a-priori weights resulted in a dominance of upland heath (D1) within the upland regions of the image.

The definition of a-priori weights increased overall classification accuracy, derived at the training samples, from 81% to 91% representing a significant increase. Comparison of the confusion matrices (table 6.4 (a) and table 6.20) illustrated that:

- Decreasing upland heath (D1) confusion resulted in a significant producer accuracy increase from 72% to 98%.
- The user accuracy of upland heath (D1) decreased from 98% to 90%. This accuracy reduction reflected a greater proportion of the image being classified as upland heath (D1) where the reference data determined the land cover to be an upland mosaic (D6a) or wetland (F3).

While an increase in overall classification accuracy was observed at the validation samples, from 52% to 58% (appendix H), this increase was not significant.

From these data it was concluded that while the accuracy of the classification increased there was a tendency for upland heath (D1) to be overestimated in the image at the expense of less extensive but spectrally similar land covers.

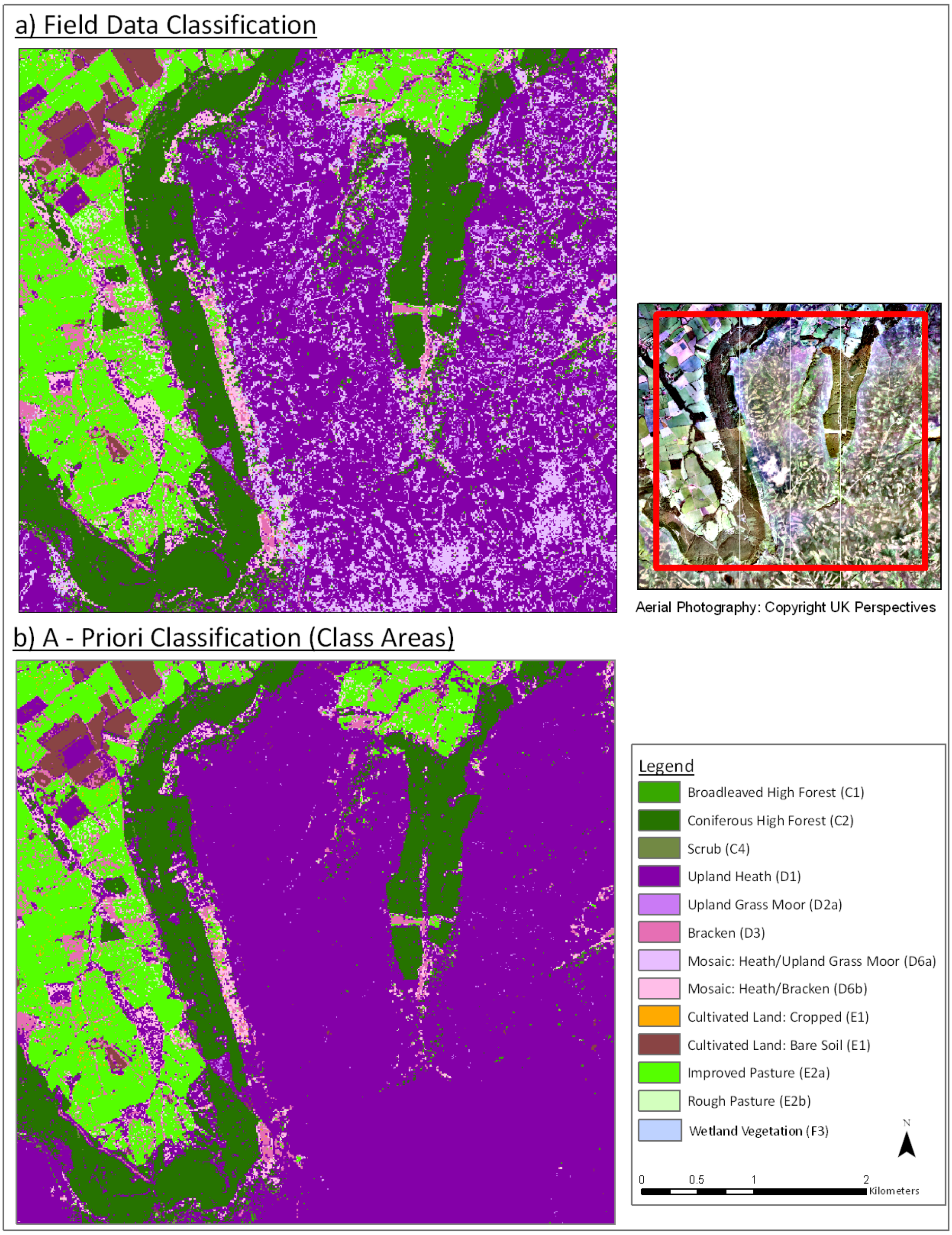


Figure 6.9: Comparison of ML, multi-spectral MLCNP classifications implementing a) equal a-priori weights and b) *a-priori* weights inferred from the land cover class spatial extent

Table 6.20: Confusion matrix, derived at the field data samples, for the MLCNP multi-spectral classification including *a-priori* weights

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				81			6			1		2	90	***90***
D2a				1	3								4	***75***
D3				1		8	1			1			11	***73***
D6a							1						1	***100***
D6b						1		3			1		5	***60***
E1									7				7	***100***
E2a										27			27	***100***
E2b											3		3	***100***
F3												1	1	***100***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***98***	***100***	***89***	***13***	***100***	***100***	***93***	***75***	***33***		***91***

Additional techniques: concluding comments

Via the MLCNP classification it was possible to demonstrate the potential applicability of filtering, class subdivision and *a-priori* probabilities to improve classification accuracies. However, it should be noted that all comparisons were based on a limited number of training/validation samples and data known to contain misclassification errors. A consequence of the small sample fraction is a limited proportion of samples changing classes between confusion matrices. Trends/conclusions drawn on this small sample fraction were considered purely indicative.

6.3.4 Sample design and data quality

Introduction

In each of the spectral and ancillary classifications a significant difference was observed between overall accuracies calculated at the field and validation samples. Theoretically, as both the field (training) and validation data are independent and based on a random sample design such a significant difference would not be expected. This significant accuracy variation could be the consequence of:

- *Sampling error introduced by the systematic sampling frame*

Several authors (Kent & Corker, 1992; Congalton, 1988) have highlighted the potential of a systematic sampling frame to introduce errors, as a function of sampling bias, into the classification algorithm.

- *Unrepresentative training data*

Training data which includes only a small sample fraction may be unrepresentative of land cover classes across the study area. A land cover class poorly described in the training data has the potential to contain large misclassification errors away from the training data sites (Mather, 1999; Pal & Mather, 2003; Van Niel *et al*, 2005).

- *Training data accuracy*

Inaccuracy within the training data, as a consequence of classifying the land cover attributes, had the potential to introduce error into the signatures on which the algorithm was trained thus degrading the quality of the resultant classification.

- *Unrepresentative validation data*

Validation data which contains only a small sample fraction will inadequately describe the accuracy of the classification across the study area (Congalton, 1988, 1991; Curran & Williamson, 1986; Hammond & Verbyla, 1996; Foody, 2002).

- *Validation data accuracy*

Inaccuracy within the validation data would introduce false disagreement within the confusion matrix reducing the derived accuracy statistics (Dicks & Lo, 1990). Within the current classification validation data were derived via API which has been demonstrated to contain classification errors (section 6.2.2).

To determine the relative contribution of these factors, the influence of API, sample design and sampling fraction upon classification accuracy were tested via adaptation of the ML classification methodology. Each adaptation required additional sample points for classifier training and validation. The reference land cover at these samples, four additional sample frame replicates, was derived via API (section 5.4.1). Due to this reliance upon API the P1 classification, as a consequence of its low API accuracy, was excluded from this analysis.

The influence of API

To assess the impact of API error upon land cover classification, specifically the MLCNP and NLUD classifications, ML classifiers were trained on the basis of API derived reference data; the validation samples. The resultant API trained classifications were validated using the field data samples; samples independent of the classifier training. Full confusion matrices are included in appendix H.

The resultant overall accuracy values (table 6.21), in comparison to the field data trained classifiers, indicated that:

- Classifiers trained on API derived samples demonstrated a significant difference in accuracy statistics derived at the training (API) versus validation (field data) samples.
- Training of the ML classifier on the basis of API derived samples, as opposed to field data, resulted in lower overall classification accuracies at the training samples. For all classifications, excluding the multi-spectral NLUD classification, this decrease in accuracy was significant at the 95% confidence interval, in terms of the Kappa statistic.
- Overall accuracies at the validation samples were similar for both the API and field data trained classifiers.

Table 6.21: Overall classification accuracies for the MLCNP and NLUD land cover classifications derived via a maximum likelihood classifier trained on field data (FD) versus API derived samples

Classification Data	Field Data Trained Overall Accuracies (%)			API Trained Overall Accuracies (%)		
	Training Samples (Field Data)	Validation Points (API)	Kappa: Z Statistic	Training Samples (API)	Validation Points (Field Data)	Kappa: Z Statistic
MLCNP						
Multi-spectral	81	52	6.13	68	50	4.07
Multi-spectral, Slope, Elevation	95	61	9.37	77	54	5.68
NLUD						
Multi-spectral	80	59	4.42	71	61	2.45
Multi-spectral, Slope, Elevation	89	63	6.07	74	61	3.09

Notes: Red values indicate a significant difference in overall accuracy, at the 95% confidence level, between the training and validation samples.

The overall accuracy decrease, for the multi-spectral MLCNP classification, of 81% to 68% when trained on the basis of field data versus API derived samples, represented a significant loss in accuracy at the training samples. Comparison of the confusion matrices (table 6.4 (a) and 6.22) illustrated that the accuracy decrease was a consequence of increased disagreement both within and between the major land cover types. Increased disagreement was particularly evident for those classes highlighted as containing high API inaccuracies, for example, improved/unimproved pasture (E2a/E2b) which exhibited decreases in producer accuracies of 86% to 82% and 75% to 50%, respectively.

The decrease in producer accuracy of upland grass moor (D2a), from 100% (table 6.4 (a)) to 55% (table 6.22), demonstrated the influence of training sample proportion on classification accuracy. In the field data trained classifier only 3 samples were included in this class; this small sample size reduced within class variability and consequently spectral confusion with remaining land cover classes. The API classification was trained on 22 upland grass moor (D2a) samples; this larger sample size which inevitably increased the spectral variability of the class also increased the spectral overlap with remaining land cover classes. A comparison of the JM distances for upland grass moor (D2a) and upland heath (D1) reflected this increased spectral similarity, decreasing from 1311 to 601 in the field data and API trained classifiers, respectively. It should be noted that the spectral similarity of these land covers was potentially further emphasised in the API trained classifier, as a result of the confusion between upland heath (D1) and upland grass moor (D2a) during API (section 6.2.2).

Decreasing classification accuracies, as a consequence of API derived training data, illustrated that API error influenced classification accuracy. In API derived validation samples these errors manifested themselves as inappropriate agreement or disagreement within the validation confusion matrix. However, the API trained classifications demonstrated a significant difference in accuracies derived at the training versus validation samples. Consequently, it is proposed that API error was not the only factor responsible for the observed training/validation accuracy differences.

Table 6.22: Confusion matrix, calculated for the training samples, for the MLCNP classifier trained on API derived samples.

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	7			1							1		9	***78***
C2		5											5	***100***
C4													0	***0***
D1				42	2								44	***95***
D2a				6	12							1	19	***63***
D3						6		1		2	1		10	***60***
D6a				15	3		7		1		1		27	***26***
D6b				1	2	1		3					7	***43***
E1				1	1		2		4	1			9	***44***
E2a					1					27	1		29	***93***
E2b				4	1					3	4		12	***33***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***0***	***60***	***55***	***86***	***78***	***75***	***80***	***82***	***50***	***0***		***68***

Sample design implications

Testing of the sample design subsequent to field survey concluded that the systematic sample design was not biased in terms of the land cover types sampled (section 3.4.5). To confirm this conclusion, and determine if the systematic sampling frame was influencing the classifier, the MLCNP and NLUD ML classifications were repeated using a random sampling frame.

A random sampling frame was simulated by extracting approximately 160 random samples from the systematic sample replicates, that is, the field data and four API derived replicates. The exclusion of samples, on the basis of unclassified API samples and cloud cover, resulted in 158 and 146 samples within the MLCNP and NLUD classifications, respectively. In both classifications this sample number was comparable to the number of field data samples; bias was therefore not introduced as a consequence of sample size.

The overall accuracy of the classification outputs were calculated at the training samples and a set of independent, validation points; an API derived replicate of the systematic sample design not implemented in classifier training (table 6.23). Full confusion matrices are included in appendix H.

Table 6.23: Overall classification accuracies for MLCNP and NLUD classifications, derived from a maximum likelihood classifier trained on a systematic versus random sampling frame

Classification Data	Systematic Sampling Frame Overall Accuracies (%)			Random Sampling Frame Overall Accuracies (%)		
	Training Samples (Field Data)	Validation Points (API)	Kappa: Z Statistic	Training Samples (Field Data + API)	Validation Points (API)	Kappa: Z Statistic
MLCNP						
Multi-spectral	81	52	6.13	70	51	3.85
Multi-spectral, Slope, Elevation	95	61	9.37	80	51	6.39
NLUD						
Multi-spectral	80	59	4.42	76	63	2.56
Multi-spectral, Slope, Elevation	89	63	6.07	81	62	3.84

Notes: Red values indicate a significant difference in overall accuracy, at the 95% confidence level, between the training and validation samples.

Comparison of the overall accuracies achieved from the random versus systematic sampling frames demonstrated that:

- Classifiers trained on the random sampling frame exhibited a significant difference in overall accuracies calculated at the training versus validation samples.
- Classification accuracies tended to be lower for the classifier trained on a random, as opposed to a systematic sampling frame. This difference was not significant, except for the multi-spectral plus slope/elevation, MLCNP, classification.

The tendency for classifications, based on the random sampling frame, to have a lower overall accuracy at the training samples was attributed to the inclusion of API derived samples in the training of the classifier. As demonstrated in the preceding analysis, the inclusion of API samples resulted in classifications of lower accuracy when compared to training on field data alone.

Significant differences between the training and validation samples were still evident in the classifications derived from the random sampling frame. Therefore, it was proposed that the systematic sampling frame did not influence classifier training and was not responsible for the observed training/validation accuracy differences.

Training data: sample fraction

The inclusion of API derived samples within classifier training has been demonstrated to influence classifier accuracy. However, a significant difference between the overall accuracy derived at the training and validation samples was still evident. It was hypothesised that sample size was a primary factor influencing this training/validation difference.

Sample fraction directly influences the number of samples available to train the ML classifier. An assumption of this algorithm is that the training samples are representative of land cover variability across the study area. When trained on a low sample fraction such an assumption is expected to be violated. Consequently, the class probability density function is not sufficiently precise to describe the class feature space (Van Niel *et al*, 2005). This has been proven to affect the ML classification algorithm (Pal & Mather, 2003).

Campbell (1996) suggests that classifiers should be trained on approximately 100 samples per class. Such a value is however, likely to be too simplistic. A common rule of thumb applied in classification is that the number of samples per class should be between 10 and 30 times the number of wavebands (p) contained in the remote sensing image (Jensen, 1986; Mather, 1999b; Pal & Mather, 2003). This stated minimum sample size is only valid where the members of the sample are independent. As adjacent pixels are typically spatially correlated (Mather, 1999b) the number of pixels contained in a training sample tends to overestimate the number of fully independent samples. Campbell (1981) demonstrated that the variance-covariance matrix was significantly influenced by blocks of adjacent pixels. Campbell (1981) proposed the extraction of random samples from the training area as opposed to contiguous pixel blocks.

The 10 – 30p rule (Jensen, 1986; Mather, 1999; Pal & Mather, 2003) has been criticised for overestimation of the required sample fraction. Van Niel *et al* (2005) state that sample fraction is in fact a function of the characteristics of the remote sensing data, site and required classification accuracy. Sites typified by low within and high between class variability will require less training samples than those with high within and low between class variability. Equally, if the number of spectral wavebands and classification accuracy remains constant more samples will be required to describe vegetation at the species than broader plant structure categories (Van Niel *et al*, 2005). In a classification of four agricultural land covers (rice, sorghum, maize and soya bean), each of which was easily separated in a multi-temporal feature space, Van Niel *et al* (2005) conclude that 95% of the accuracy attained using the 30p rule could be achieved with between 2p and 4p samples. This represented less than 15% of the recommended samples fraction. As implied by Van Niel et al (2005) sample fraction is a function of the discrimination problem. Curran & Williamson (1986) demonstrated that sample fraction, per class, was also a function of land cover type; heterogeneous land covers requiring more samples than homogenous stands.

As the landscape of the study area is complex and characterised by low between and high within class variability the higher sampling fraction of 10p to 30p was proposed to be most appropriate. This represents a sample fraction of between 40 and 120 samples per class in the multispectral classifications increasing to between 60 and 180 samples per class in the classifications including ancillary data. As demonstrated by the sample numbers in table 6.24, this recommendation was not met for all except one (Upland Heath, D1) of the MLCNP classes, a trend which was repeated in the NLUD classification.

Achieving the recommended sampling fraction was problematic within the current point sample design. A significant number of point samples were required, especially where classifier training was to be based on a single pixel, to approach the recommended samples sizes.

Table 6.24: The number of samples occurring in each MLCNP class within the field data

MLCNP Class		Number Of Samples
Broadleaf Woodland	**(C1)**	3
Coniferous Woodland	**(C2)**	6
Scrub	**(C4)**	2
Upland Heath	**(D1)**	83
Upland Grass Moor	**(D2a)**	3
Bracken	**(D3)**	9
Bracken, Grass Mosaic	**(D6a)**	8
Heath, Bracken Mosaic	**(D6b)**	3
Arable	**(E1)**	7
Improved Pasture	**(E2a)**	27
Rough Pasture	**(E2b)**	4
Wetland Vegetation	**(F3)**	3

The influence of sample fraction upon classification accuracy was tested by systematically increasing the number of classifier training samples. The reference land cover class at the additional samples, replicates of the systematic sampling frame, was derived via API.

The accuracy of classifications resulting from each sample fraction was assessed using confusion matrices derived at the field data samples and a set of independent, API derived validation points (appendix H). Accuracy assessment at the training samples included only the field data samples, as opposed to the field data and API samples on which the sample fraction classifiers were trained, to ensure compatibility between classifications and the exclusion of the API samples known to be of a lower accuracy. A potential consequence of excluding the API derived training samples was the overestimation of classification accuracy.

The overall accuracies (table 6.25) achieved for the MLCNP and NLUD classifications trained on increasing sample sizes demonstrated that:

- An approximate doubling of the sampling fraction (fraction 2) resulted in a significant drop in overall accuracy at the field data samples in the MLCNP classification; this was less evident in the NLUD classification.
- Overall accuracies at the field data samples of both classifications illustrated a decreasing trend with increasing sample fraction. In comparison overall accuracies at the validation points remained relatively stable.
- The difference between the overall accuracies, derived at the field and validation samples, decreased with increasing sample size.
- MLCNP classification accuracies, comparing the field and validation samples, were statistically similar when the sample fraction was greater than three.

Additional training samples had the potential to increase multi-spectral variability within the land cover class, and consequently spectral overlap between classes, as variability in the land cover was better described. This increased overlap was evident in the average JM distance values of the field data and sample fraction 2 MLCNP classifications which decreased with increasing sample size (table 6.26).

Table 6.27 contains the JM distance values comparing upland heath (D1) to each of the remaining MLCNP land cover classes within the field data and sample fraction 2 classifications. Increased multi-spectral similarity, as a function of an increased sample fraction, and hence a lower JM distance was evident between upland heath (D1) and upland grass moor (D2a), the bracken/grass mosaic (D6b) and rough pasture (E2b). Conversely, higher JM distance values between upland heath (D1) and bracken (D3), the heath/grass mosaic (D6a) and coniferous woodland (C2) indicated that the influence of sample fraction on multi-spectral separability was class specific.

Table 6.25: Comparison of overall classification accuracies achieved at the field data and validation samples for multi-spectral classifiers trained on increasing sample fractions

Sampling Fraction (Number of Samples)		Overall Accuracy (%) Field Data Samples	Overall Accuracy (%) Validation Points (API)	Kappa: Z Statistic
MLCNP				
Field data	*(153)*	81	52	6.1
Fraction 2	*(319)*	68	54	2.6
Fraction 3	*(416)*	65	55	1.9
Fraction 4	*(625)*	59	55	0.8
Fraction 5	*(773)*	54	53	0.2
NLUD				
Field data	*(172)*	80	59	4.4
Fraction 2	*(335)*	79	61	3.7
Fraction 3	*(481)*	77	64	2.8
Fraction 4	*(645)*	77	62	3.0
Fraction 5	*(777)*	75	62	2.5

Notes: Red values indicate a significant difference in overall accuracy, at the 95% confidence level, between the training and validation samples.

Table 6.26: Average and minimum JM distance values derived for multi-spectral signatures developed from the field data and sample fraction 2 MLCNP training data

MLCNP Sample Fraction	JM Distance Average	JM Distance Minimum
Field Data	1383	958
Sample Fraction 2	1319	614

Notes: JM distances were calculated for the four 2004 SPOT 5 wavebands.

Table 6.27: JM distance values, derived for multi-spectral signatures developed from the field data and sample fraction 2 MLCNP training data, comparing upland heath (D1) to the remaining land cover types

MLCNP Class		JM Distance	
		Field Data	Sample Fraction 2
Broadleaf Woodland	**(C1)**	1343	1218
Coniferous Woodland	**(C2)**	1374	1385
Scrub	**(C4)**	1396	1373
Upland Grass Moor	**(D2a)**	1311	738
Bracken	**(D3)**	1381	1396
Bracken, Grass Mosaic	**(D6a)**	958	614
Heath, Bracken Mosaic	**(D6b)**	1370	1385
Arable – Crop	**(E1)**	1414	1414
Arable – Bare Ground	**(E1)**	1386	1378
Improved Pasture	**(E2a)**	1411	1412
Rough Pasture	**(E2b)**	1402	1257
Wetland Vegetation	**(F3)**	1307	1307

Notes: JM distances were calculated for the four 2004 SPOT 5 wavebands.

The preceding discussion attributes increased within-class variability, and hence class multi-spectral similarity, to the incorporation of land cover variation as a function of training sample size. However, the source of these samples, that is, API, influenced multi-spectral signature definition. Errors are inherent in API (section 6.2.2) and have been demonstrated to influence classifier accuracy (section 6.3.4). The accuracy of classifications based upon the inclusion of an increasing number of samples from this source would be expected to decrease.

The significant drop in overall accuracy, at the training samples, with a doubling of the sample fraction (fraction 2) in the MLCNP classification was not evident in the NLUD classification. A significant drop in accuracy was potentially attributable to two factors. Firstly, sample fraction 2 represented a doubling of the training data consequently increasing within-class variability. This impact was potentially reduced in the NLUD classification by broader class definitions which, on the basis of the field data, encompassed greater land cover variability. Secondly, the introduction of API derived samples increased multi-spectral overlap as a function of API errors. The impact of this error was minimised in the NLUD classification due to its improved API accuracy (section 6.2.2). Within the MLCNP classification accuracy decreased as a function of increasing sample size beyond fraction 2. It is proposed that this was a function of less land cover variability being described via the addition of more samples and the introduction of similar misclassification errors. The relative contributions of API error and sample size to the increase in within-class spectral variability could not be identified.

With increasing sample fractions the significance of the difference between the field and validation data was reduced, as indicated by a decrease in the Kappa statistic. The basic hypothesis of this analysis would attribute this to improved land cover class descriptions as a function of increasing sample size hence the classifier was better able to represent classes across the study area. In such a scenario, increases would be expected in the overall classification accuracy at the validation points. A weak trend of increasing accuracy was evident in the NLUD classification but not the MLCNP classification. A visual examination of the MLCNP and NLUD classification outputs (figures 6.10 and 6.11), indicated improved land cover representation with increasing sample size. Classification improvement may not be reflected in the overall accuracy at the validation samples as a consequence of API errors or unrepresentative validation data.

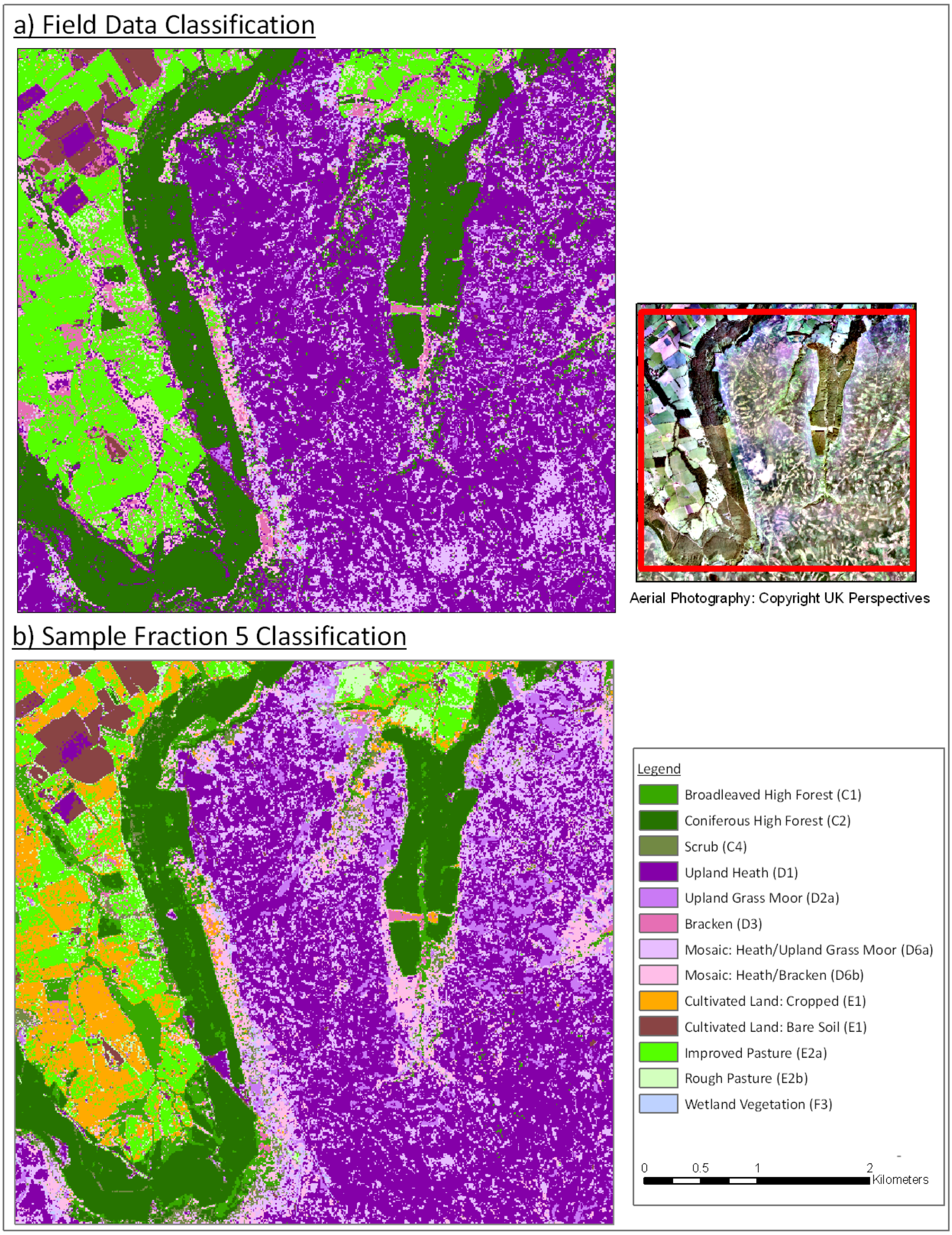


Figure 6.10: Extract of the MLCNP classifications, near Ingleby Greenhow Wood, comparing (a) field training data versus (b) sample fraction 5 training data

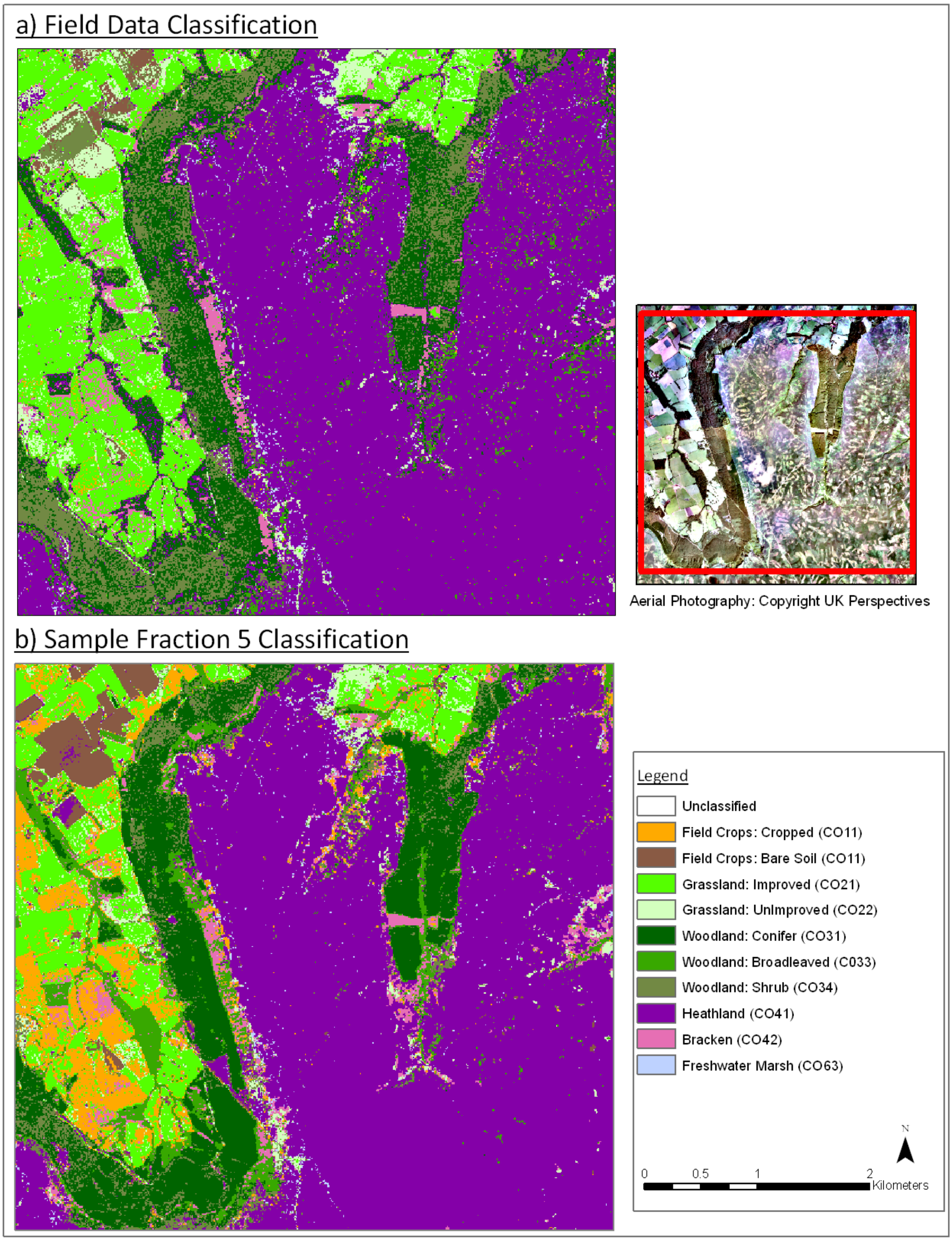


Figure 6.11: Extract of the NLUD classifications, near Ingleby Greenhow Wood, comparing (a) field training data versus (b) sample fraction 5 training data

Validation data: Sample fraction

The sample on which accuracy assessment is based should be probabilistic in design (Congalton, 1988; Hammond & Verbuya, 1996; Stehman & Czaplewski, 1998). It is not statistically justified to infer accuracy of the entire region from a subjective selection of reference samples (Stehman & Czaplewski, 1998). Equally, the validation data should contain sufficient samples to be representative of the population (Congalton, 1988; Stehman & Czaplewski, 1998).

Derivation of an appropriate sample fraction for accuracy assessment is typically via statistical methods or model-based inferential frameworks (Foody, 2002). Statistical methods infer the required sample proportion from the predicted classification accuracy and some amount of allowable error (Congalton, 1991). Congalton (1991) concludes that such approaches are too simplistic as a confusion matrix must contain sufficient samples to adequately represent the confusion between classes. Instead Congalton (1991) advocates a general rule of thumb of 50 samples for each land cover class contained within the confusion matrix. However, this value should be increased where the classification covers large areas or consists of a high number of land cover categories (Congalton, 1991). This sample fraction was not met in the current validation sample, as exemplified by the MLCNP classification (table 6.28).

Table 6.28: The number of samples occurring in each MLCNP class within the API derived validation data

MLCNP Class		Number Of Samples
Broadleaf Woodland	**(C1)**	7
Coniferous Woodland	**(C2)**	5
Scrub	**(C4)**	0
Upland Heath	**(D1)**	76
Upland Grass Moor	**(D2a)**	22
Bracken	**(D3)**	7
Bracken, Grass Mosaic	**(D6a)**	9
Heath, Bracken Mosaic	**(D6b)**	4
Arable	**(E1)**	5
Improved Pasture	**(E2a)**	33
Rough Pasture	**(E2b)**	8
Wetland Vegetation	**(F3)**	1

To determine the influence of validation sample fraction upon classification accuracy an analysis was devised whereby the training and validation sample fractions were both increased. The analysis was based on land cover reference data derived at four sampling frame replicates, one from the field data (FD) and three API replicates (A – C) (section 5.4.1). The four replicates were split into equal proportions, two replicates each, for training of a per-pixel ML classification algorithm and independent validation of the resultant MLCNP and NLUD classifications. To determine if sample replicate influenced the resultant accuracy statistics, classifications were repeated for all possible replicate combinations (table 6.29). Confusion matrix accuracy statistics are summarised in table 6.30. Full confusion matrices are included in appendix H.

Table 6.29: Sample replicate combinations implemented for classifier training and validation

Classification Identification	Sample Replicates	
	Training	Validation
i	FD : A	B : C
ii	FD : B	A : C
iii	FD : C	A : B
iv	A : B	FD : C
v	A : C	FD : B
vi	B : C	FD : A

Table 6.30: Comparison of overall classification accuracies achieved at the training and validation samples for each classification

Classification	Overall Accuracy (%)		Kappa: Z Statistic
	Training Samples	Validation Samples	
MLCNP			
i	66	57	2.39
ii	67	52	3.95
iii	60	56	1.09
iv	65	51	3.66
v	62	52	3.13
vi	57	55	0.9
NLUD			
i	79	66	4.5
ii	74	66	2.04
iii	74	68	2.07
iv	79	68	3.18
v	76	71	2.13
vi	76	71	1.3

Notes: Red values indicate a significant difference in overall accuracy, at the 95% confidence level, between the training and validation samples.

Statistically similar training/validation accuracies were achieved, for the MLCNP classification, in combinations iii and vi (table 6.30). Classifications iii and vi were characterised by low overall accuracies at the training samples; the cause of the training/validation accuracy similarity. Common to both classifications was the inclusion of the API derived replicate C within classifier training. This common training data source, and low classification accuracy, indicated that replicate C contained a greater amount of API error.

As each classification was trained on two replicates, and therefore a similar number of samples, the resultant classification accuracies, irrespective of training data, would be expected to be statistically similar. To determine if API replicates and, in particular, the training of classifiers solely on API derived samples influenced classification accuracy, a pair wise comparison of all classifications was made within a kappa analysis (appendix H).

The pair wise kappa analysis (appendix H) confirmed the influence of replicate C upon MLCNP classification accuracy. Classification vi, trained wholly on API derived samples including replicate C, was significantly less accurate than classifications i and ii, the most accurate classifications, the training of which excluded replicate C and included the field data samples. It was therefore concluded that for the MLCNP classification, classifiers trained solely on API derived samples demonstrated a tendency towards lower classification accuracies. Where this API derived data contained replicate C the errors introduced were sufficient to result in significantly lower classification accuracies. This trend was not reflected in the NLUD classification in which the API derived training samples did not demonstrate a significant influence upon classification accuracies. This differing characteristic was postulated to be a consequence of the higher API accuracy associated with the NLUD classification (section 6.2.2).

Classifications implemented within the current analysis were equivalent to sample fraction 2, in the preceding analysis, in terms of the number of sample points. The accuracy of the NLUD classification, for sample fraction 2, was determined to be 61% at the validation points. This overall accuracy was lower than, although not significantly so, the overall accuracy calculated at the validation points for each of the current NLUD classifications. Consequently, the validation sample fraction had the potential to influence the training/validation accuracy difference.

In the current classification a significant difference in the training/validation accuracy remained evident (table 6.30). This may have been a function of the sample fraction with a doubling of samples, on which the classifier was trained, being insufficient to fully characterise land cover classes. However, the inclusion of API samples in the classifier training and validation was demonstrated to influence this difference.

6.3.5 Conclusions: per-pixel classification

Training data

As a consequence of the demonstrated influence of API error upon classification accuracy the collection of training data via ground survey is advocated in situations typified by high spatial and temporal heterogeneity. This ground survey should be coincidental to remote sensing image capture. The collection of land cover attributes and subsequent classification within a ML algorithm has been demonstrated to be an appropriate land cover mapping methodology. However, this approach is reliant upon the land cover attributes describing the constituent elements of the classification scheme to be constructed.

Sample fraction

This research has demonstrated the reliance of remote sensing classification techniques upon sample fraction. The assumption of classification algorithms that training samples are representative of land cover variability across the study area is fundamental to their implementation and resultant classification accuracy (Jensen, 1986; Mather, 1999).

An inappropriate sample fraction resulted in a significant decrease in classification accuracy at independent validation samples. Systematic increments of the training sample fraction resulted in the convergence of overall accuracies derived at the training and validation samples, for the MLCNP classification scheme, at sample fraction three and above. Equivalent convergence did not occur in the NLUD classification scheme. This lack of convergence may be a function of sample size, sample fraction 5 may not contain sufficient samples to accurately describe the land cover class. However, convergence in both classifications was influenced by classification errors introduced as a function of API derived samples, the small sample fraction included in validation confusion matrices and the potential underestimation of the validation sample accuracy as a consequence of API error.

Definition of an appropriate training sample fraction is complex. According to several authors (Jensen, 1986; Mather, 1999, Pal & Mather, 2003) sample fraction should be 10 to 30 times the number of multispectral wavebands per land cover class. This would imply sample fractions exceeding 1000 sample points. Such a sample fraction follows those of previous land cover mapping approaches (i.e. Buchanan *et al*, 2005). However, Van Niel *et al* (2005) state that such a strict sample fraction definition is too cautious. The authors relate sample fraction to data dimensionality, site characteristics and the required classification accuracy.

Conclusions regarding an appropriate sample fraction, on the basis of the sample fraction analysis implemented, were not feasible due to the influence of API derived samples and validation sample fraction. Equally, an appropriate sample fraction is likely to be classification specific varying as a function of the complexity of the land cover definition hierarchy.

Multi-spectral confusion and ancillary data

Multi-spectral similarity between land cover classes was inevitable for two reasons. Firstly, the timing of image capture was determined by sample site access and not related to the seasonal characteristics of the major land covers in terms of their multi-spectral separability. Secondly, the classification schemes implemented were based on the species composition, management and use characteristics of each land cover as opposed to their spectral properties (Belward *et al*, 1990). One means of reducing land cover similarity was the inclusion of ancillary data in the classification algorithm.

Clear relationships between land cover and elevation/slope have been demonstrated. However, classification improvements as a consequence of including these data were highly variable. Variable accuracy improvements between the MLCNP, NLUD and P1 classification schemes related to the pre-existing multi-spectral confusion within the classification. Ancillary data were ineffective where misclassification was concentrated between classes of similar landscape characteristics.

The land cover/ancillary relationships established in the current research were potentially influenced by the small sampling fraction which inadequately characterised the land cover/ancillary relationship. Several authors have related the training sample fraction to multi-spectral data dimensionality (Jensen, 1986; Mather, 1999; Pal & Mather, 2003) hence the inclusion of ancillary data layers, within the classification algorithm, implies a requirement for an increased number of training samples.

As a consequence of the sample fraction ancillary data results were considered indicative. However, a trend of improved classification accuracy as a consequence of including ancillary data within the multi-spectral classification was observed. This supports the conclusions of other studies (De Bruin & Gorte, 2000; Maselli *et al*, 1995; Watson & Wilcock, 2001).

Recommendations for further work

To enable further development of this classification technique a number of issues need further investigation and development:

Land cover attribute classification

To reduce analysis effort a fully automated means of land cover attribute classification is required. Development of this technique requires assessment of the accuracy with which classification rules, target species and species cover thresholds, can be defined and applied to the collated field and ancillary data. The current research was limited in assessment of these criteria as no record was made of land cover class at each sample. It is proposed that a field survey is required whereby land cover attributes and reference land cover class are collected coincidentally.

Sample fraction and field survey design

Future implementation of this classification methodology is reliant upon an improved sample fraction. However, an increased sample fraction has implications in terms of the field survey effort required. With increased sample sizes there would be a requirement to improve survey efficiency.

A critical review is required to determine:

- The sample fraction required to ensure representative classifier training and validation.
- Appropriate sample designs, in terms of land cover sample proportions and logistic viability.
- If improved survey efficiency can result from a reduction in the number, format and type of field survey measurements taken. This may include analysis of whether four quadrats are required at each sample location.

ML classification algorithm and ancillary data

In the light of an improved field survey sample proportion, the classification should be repeated and verified to determine the true effectiveness of the ML algorithm in characterising multiple land cover maps.

Algorithm validation should include further testing of ancillary data sources. Further datasets, in addition to those included in the current analysis should be considered. For example, further research should consider the inclusion of multi-temporal NDVI images an ancillary dataset effective in delineating classes as a function of seasonal change and management regime (Defries & Townshend, 1994; Lucas *et al*, 2007). Classification improvements, as a function of the inclusion of this multi-temporal data, must be evaluated against the extra resources required and practicality of multi-temporal image capture in a predominantly cloud covered environment.

Implementation of the ML algorithm has highlighted the 'peppered' nature of the classification. This was particularly evident in the agro-pastoral and wooded land covers characterised by relatively homogenous parcels. Marginal improvements in classification accuracy and visual appearance can be achieved via image filtering techniques. However, the characteristically hard boundaries and internal homogeneity of these land covers is potentially best represented in an object-orientated classification approach.

6.4 Object-orientated analysis

The object-orientated classification was implemented within a subset of the study area, chosen to ensure a range of land cover types was included (section 5.4.2). This classification was based on the MLCNP land cover classification definitions.

6.4.1 Feature space definition

As outlined in the methodology (section 5.4.2), implementation of the standardised nearest neighbour classifier, requires definition of the classification feature space. Where feature space layers consist of pixels there is also a requirement to define how the constituent pixels of an object will be combined to produce an object specific value.

The influence of classifying the 2004 SPOT 5 multi-spectral image on the basis of a mean pixel value versus standard deviation of pixel values per object was tested at segmentation scale 1 (section 5.4.2). From visual interpretation of the resultant classifications (figure 6.12), it was apparent that the typical land cover patterns of the subset area, while evident in the mean multi-spectral classification, were not accurately delineated by the standard deviation classification. This was reflected in the independent overall accuracy of the mean and standard deviation classifications which were 73% and 44%, respectively; this represents a significant decrease in accuracy (appendix I).

An estimate of the mean characteristics of each land cover type in terms of the mean and standard deviation of pixel values within the image objects were plotted (figure 6.13) for a sample of image objects. On the basis of these plots it can be demonstrated that:

- The standard deviation of pixel values, within image objects, showed greater variability within land cover classes than the mean of pixel values, as indicated by the wider confidence intervals.

- The standard deviation of pixel values, within image objects, demonstrated little between class variability. Distinctive land covers were not characterised by varying standard deviation characteristics evident by the similar class means and overlapping confidence intervals.
- Similar variability in pixel values, within image objects, could be expected for all land cover types.

Such trends were evident throughout the SPOT5 multi-spectral bands. It was therefore concluded that the standard deviation of pixel values within image objects was not sufficiently distinct between land cover types to enable accurate classification.

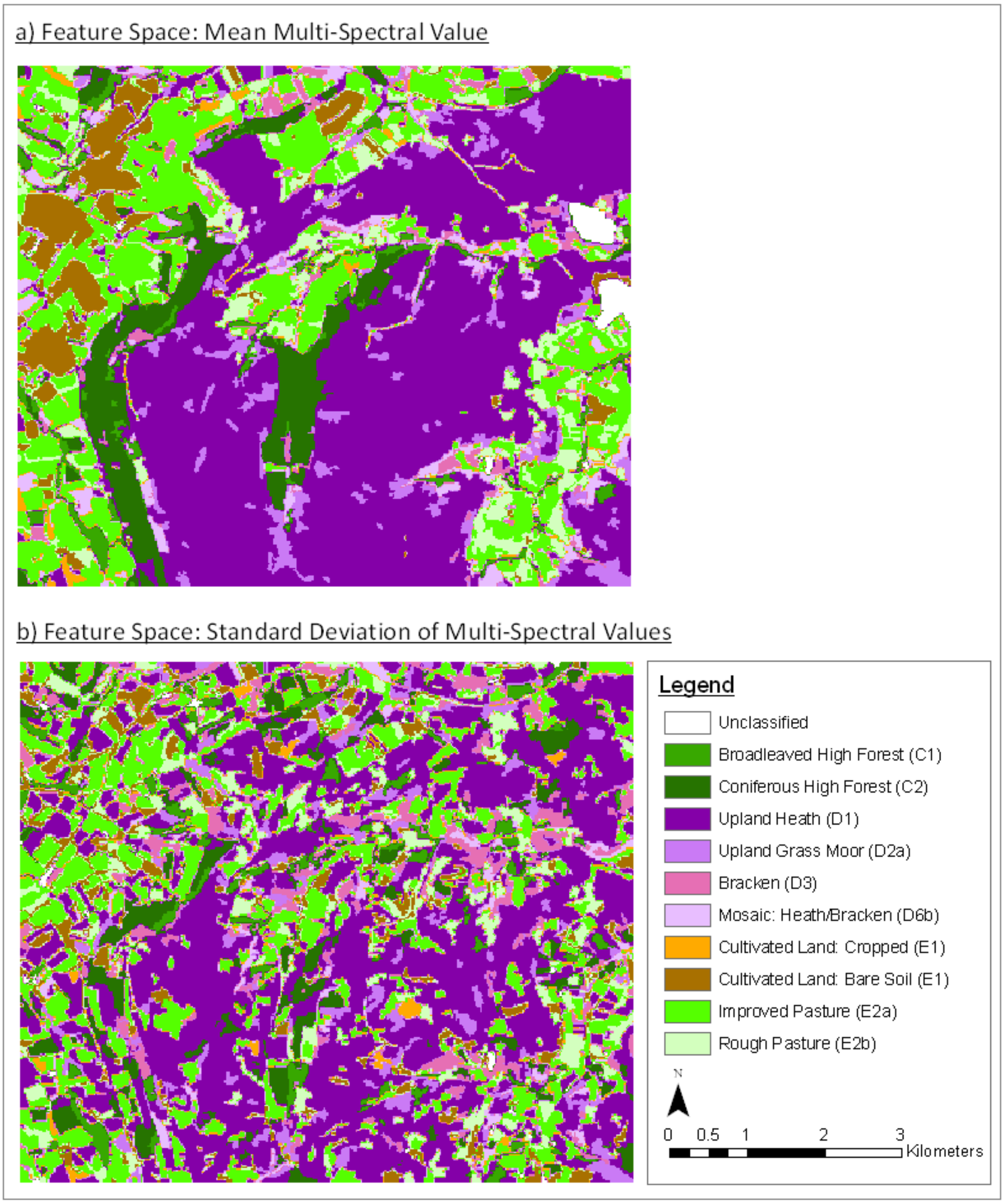
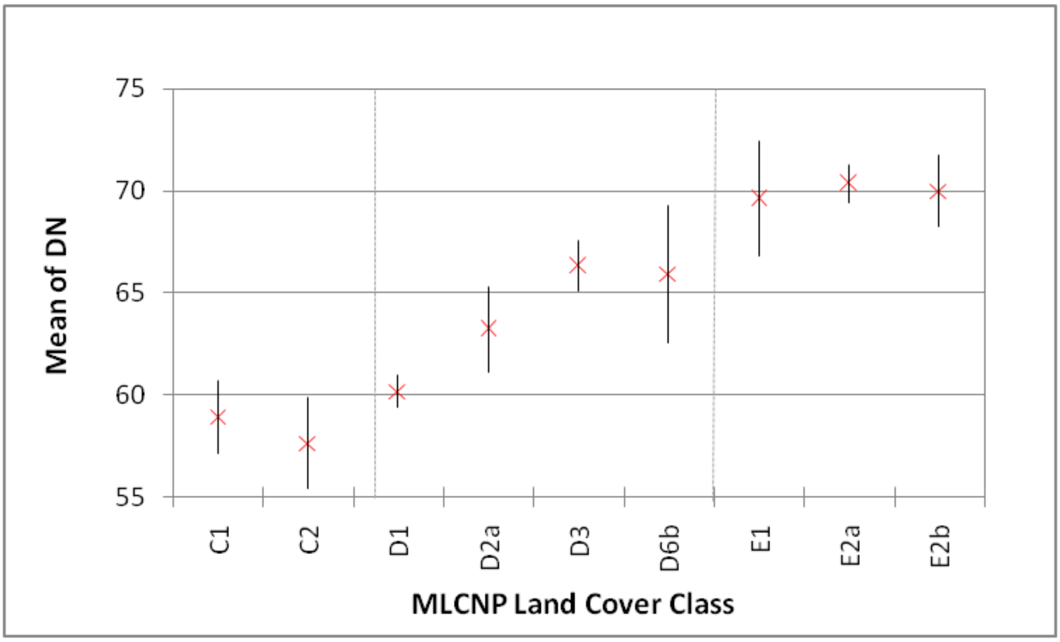
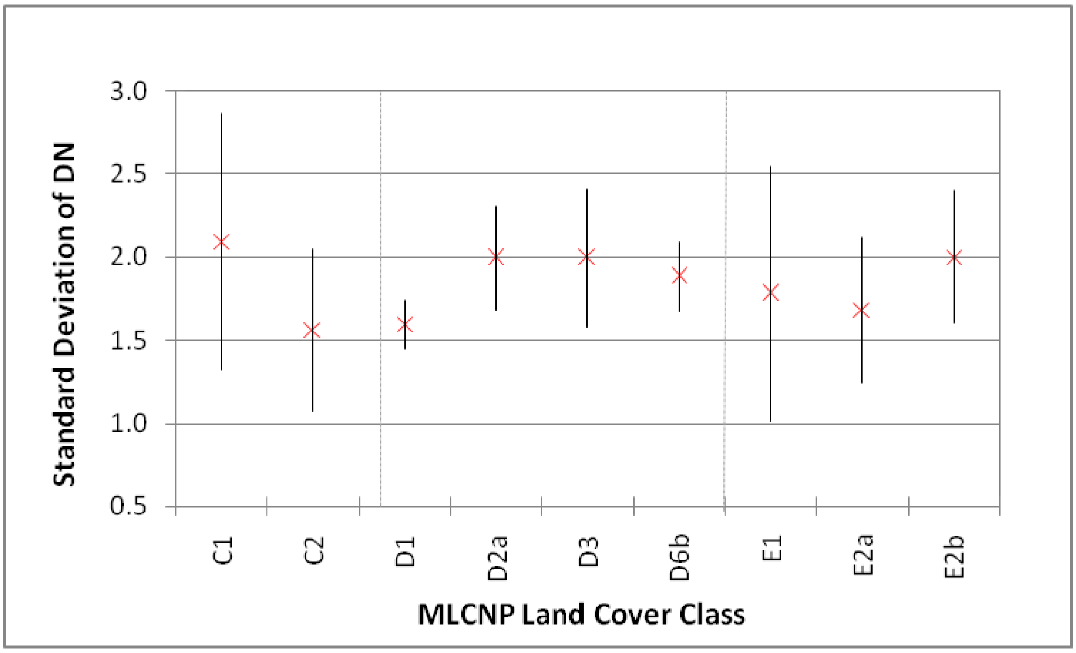


Figure 6.12: Comparison of standardised nearest neighbour MLCNP classification based on a) the mean of multi-spectral response and b) the standard deviation of multi-spectral response within image objects derived at segmentation scale 1



a) Mean of pixel DN within image objects



b) Standard deviation of pixel DN within image objects

Figure 6.13: Mean, and confidence interval range, of (a) the mean (b) standard deviation of pixel values occurring within image objects classified according to MLCNP land cover class

Notes: Plots are based on a sample of image objects; implemented during classifier training. DN values represent pixel values from band 1 (green) of the multi-spectral SPOT image.

6.4.2 Segmentation scale

Mean multi-spectral classifications were conducted on image objects derived at three pre-defined segmentation scales (section 5.4.2). Within the subset area, differing image objects, as a consequence of varying segmentation parameters, had no significant influence on overall classification accuracy (table 6.31). Full confusion matrices are included in appendix I.

Table 6.31: Comparison of the overall classification accuracy achieved for image objects derived via three alternative segmentations

Overall Classification Accuracy (%)		
Segmentation 1	**Segmentation 2**	**Segmentation 3**
73	75	70

Notes:

Each classification was based on a mean multi-spectral standardised nearest neighbour algorithm. Segmentations were derived from the following parameters: Segmentation 1: 2004 multi-spectral SPOT data, scale 25, colour 0.9, shape 0.1 (compactness 0.5 and smoothness 0.5). Segmentation 2: 2004 multi-spectral SPOT data and cadastral map, scale 25, colour 0.9, shape 0.1 (compactness 0.5 and smoothness 0.5). Segmentation 3: 2004 multi-spectral SPOT data and cadastral map, scale 15, colour 0.9, shape 0.1 (compactness 0.5 and smoothness 0.5).

As demonstrated by the per-pixel classification, user and producer accuracies vary between land cover classes as a function of vegetative composition, management and spectral characteristics. Within an object-orientated approach user and producer accuracy would also be expected to vary as a function of the segmentation scale (Bock *et al*, 2005; Dean & Smith, 2003; Lucas *et al*, 2007). Analysis of user and producer accuracy variability, as a function of major land cover class (table 6.32), demonstrated that:

- *Woodland (C)*

  This land cover was characterised by abrupt boundaries and spectrally distinct vegetation. Coniferous woodland was classified accurately across all segmentation scales (table 6.32). Lower accuracies in the broadleaf woodland reflected the per-pixel results and were expected to be a function of the small training sample fraction.

- *Upland (D)*

  Individual land cover classes of class D were highly variable in producer and user accuracy with the highest accuracies achieved in the upland heath (D1) and bracken (D3) classes. Low classification accuracies in the upland grass moor (D2a) and mosaic classes (D6a/D6b), reflected the per-pixel results (section 6.3.1), which were attributed to multi-spectral similarity between the constituents of the mosaic, and restricted training data.

  Habitats of major land cover D typically consisted of varying mixes, growth stages and mosaics of vegetation varying continuously along environmental gradients. Due to this continuum of change it would be expected that the land cover of the class would be best characterised by small entities which reflect small scale variability in habitat composition (Lucas *et al*, 2007). This trend was not observed in the current classification with similar levels of accuracy achieved across the segmentations. The lower accuracies of the individual classes, except upland heath, potentially indicated that none of the segmentations, or classification technique, best characterised the individual land covers.

- *Cultivated (E)*

  Land cover class E was composed of land covers associated with abrupt changes in vegetation composition as a result of management practices. Due to these abrupt land cover changes it was expected that a segmentation scale representative of field boundaries would have the highest classification accuracies. This trend was not strongly evident in a comparison of the segmentation scales applied as producer and user accuracies were similar across each classification.

Similarity in results across the segmentations applied may be attributed to the comparable segmentation parameters and therefore object sizes. Consequently the issue of object scale was revisited in a per-pixel comparison.

Table 6.32: Class specific user and producer accuracies (%), for the individual and major land cover classes

MLCNP Class		Segmentation 1		Segmentation 2		Segmentation 3	
		User	Producer	User	Producer	User	Producer
Individual Land Cover Classes							
Broadleaf Woodland	**(C1)**	80	44	60	33	60	33
Coniferous Woodland	**(C2)**	91	100	82	90	83	100
Upland Heath	**(D1)**	83	94	86	91	82	86
Upland Grass Moor	**(D2a)**	0	0	25	13	13	13
Bracken	**(D3)**	67	67	100	50	100	50
Bracken, Grass Mosaic	**(D6a)**	-	0	-	0	-	0
Heath, Grass Mosaic	**(D6b)**	0	0	0	0	0	0
Arable – Crop	**(E1)**	86	86	55	86	55	86
Improved Pasture	**(E2a)**	79	72	84	86	87	75
Rough Pasture	**(E2b)**	18	25	40	50	15	25
Major Land Cover Class							
Woodland	**(C)**	94	79	94	75	88	79
Upland	**(D)**	91	94	95	91	92	89
Cultivated	**(E)**	90	90	86	98	85	92

6.4.3 Spectral classification: per-pixel versus object-orientated classification

Visual comparison

A visual comparison of the per-pixel and object-orientated classifications (figure 6.14), illustrated the "peppered" appearance of the per pixel output as opposed to the homogenous parcels of the object-orientated approach. From visual interpretation of the classification outputs it was identified that each technique had captured the broad land cover patterns of the study area. However, spectral confusion was visible in both classifications (figure 6.14).

Misclassification was class and classification technique dependent. For example, while both classifications were trained on the same number of samples it was apparent that the object-orientated classification had better delineated broadleaf woodland (C1). This is a consequence of the object-orientated classification requiring fewer sample points, primarily due to each image object containing a greater number of pixels than a traditional seed-point approach (Definiens, 2006). However, a particular issue in the object-orientated classification was the misclassification of arable (E1) field boundaries as upland heath (D1). This confusion was attributed to shadow effects and variable species composition at field margins.

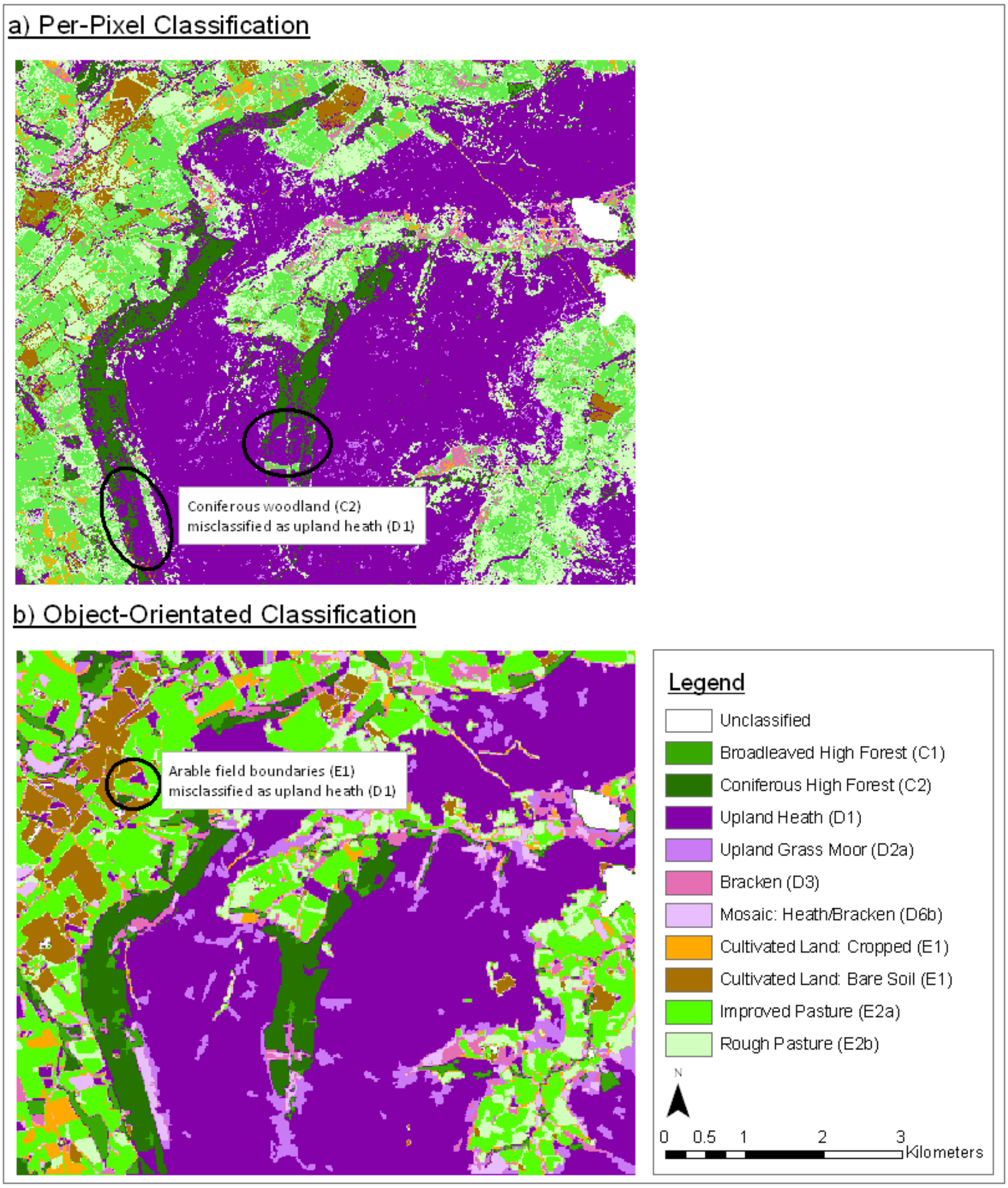


Figure 6.14: Comparison of multi-spectral classification conducted in a) a per-pixel, maximum likelihood, and b) object-orientated, standardised nearest neighbour, classification algorithm

Comparison of object-orientated and per-pixel results

Within the subset area higher overall classification accuracies were achieved with an object-orientated approach (table 6.33). However, at the 95% confidence interval, none of these increases could be described as significantly more accurate (appendix I).

Table 6.33: Comparison of overall classification accuracies for multi-spectral per-pixel and object-orientated (conducted at three segmentation scales) classification techniques

Overall Classification Accuracy (%)			
Per-Pixel	**Object-Orientated**		
Maximum Likelihood	***Segmentation 1***	***Segmentation 2***	***Segmentation 3***
65	73	75	70

As discussed in the preceding section, segmentation scale should influence classification accuracy as a function of landscape composition, habitat variability and boundary definition. In this comparison the per-pixel approach represented the smallest segmentation scale. Based on this assumption, it was hypothesised that per-pixel classifications would result in higher classification accuracies in continuous land cover types, typical of upland environments. Conversely, object-orientated approaches would be beneficial, in terms of classification accuracy, in land cover types typified by hard or abrupt boundaries.

As exemplified by segmentation 2 (table 6.34), producer classification accuracies were higher in the object-orientated approach for individual classes of the agro-pastoral land covers (E1, E2a and E2b). Rough pasture, while increasing in accuracy within the object-orientated approach, remained at a low producer accuracy.

Table 6.34: Comparison of producer accuracies for per-pixel and segmentation 2 object-orientated land cover classifications

MLCNP Class		Producer Classification Accuracies (%) Per-Pixel (Maximum Likelihood)	Object-Orientated (Segmentation 2)
Upland Heath	**(D1)**	80	91
Upland Grass Moor	**(D2a)**	0	13
Bracken	**(D3)**	67	50
Arable	**(E1)**	71	86
Improved Pasture	**(E2a)**	69	86
Rough Pasture	**(E2b)**	38	50

The JM distance, derived from the per-pixel training data (table 6.35) illustrated that rough pasture (E2b) was spectrally similar to several classes, in particular, upland grass moor (D2a), bracken (D3) and improved pasture (E2a). Similarity between these classes was attributable to the comparable vegetation species characteristics of each cover type and potential misclassification within the training data.

A distance matrix, which compares the distance between samples in the selected feature space, was derived for the object-orientated training samples. Analysis of the distance matrix (table 6.36) for rough pasture (E2b) indicated that improved pasture (E2a), upland grass moor (D2a) and bracken (D3/D6a) were very similar, as indicated by the relatively low distance values. The mean of the multi-spectral data, within image objects, was therefore not sufficient, within the current training data set limitations, to improve the definition of rough pasture (E2b) from other MLCNP classes, in particular, improved pasture (E2a).

Table 6.35: JM Distance values between rough pasture and remaining MLCNP classes, comparing SPOT5 multi-spectral bands extracted at the per-pixel training sample locations

MLCNP Class		JM Distance
Broadleaf Woodland	**(C1)**	1401
Coniferous Woodland	**(C2)**	1411
Upland Heath	**(D1)**	1369
Upland Grass Moor	**(D2a)**	1252
Bracken	**(D3)**	1268
Bracken, Grass Mosaic	**(D6b)**	1316
Arable – Crop	**(E1)**	1337
Arable – Bare Ground	**(E1)**	1410
Improved Pasture	**(E2a)**	747

Table 6.36: Distance matrices for the rough pasture (E2a) land cover, calculated from the segmentation 2 object-orientated classification

	C1	C2	D1	D2a	D3	D6b	E1 (Crop)	E1b (Bare)	E2a	E2b
C1	0	0.27	0.72	0.83	1.16	1.40	2.32	3.92	3.54	2.69
C2		0	0.78	1.79	1.54	3.51	5.10	4.27	4.81	3.82
D1			0	0.27	0.91	1.55	2.40	0.95	2.07	1.05
D2a				0	0.73	0.59	1.08	1.34	0.80	0.43
D3					0	0.50	0.81	3.37	0.42	0.45
D6b						0	0.25	3.52	0.32	0.33
E1 (Crop)							0	3.95	0.52	0.73
E1 (Bare)								0	2.09	1.96
E2a									0	0.14
E2b										0

Notes: The arable land cover (E1) is split according to fields containing crops or bare ground. The splitting of this class in the ML algorithm ensured unimodal class signatures improving class definition.

A trend of decreasing classification accuracy with increasing object size was only observed for bracken (D3); the producer accuracies for which decreased from 67% to 50% in the per-pixel and object orientated classifications, respectively (table 6.34). Comparison of the classification confusion matrices (appendix I) indicated that this decrease in producer accuracy was attributable to the introduction of confusion between bracken and its mosaic class in the object-orientated classification. As changes in accuracy were restricted to a single sample, and confusion between bracken and arable classes was also evident, it was hard to draw conclusions. However, the introduction of this type of confusion, between pure and mosaic classes, was indicative of issues in representing a continuum with image objects.

An improved producer classification accuracy of 91% for upland heath (D1) within an object-orientated approach, as opposed to 80% in the per-pixel classification (table 6.34) may be a function of implementing a mean multi-spectral feature space (Dean & Smith, 2003; Whiteside & Ahmad, 2005). Dean and Smith (2003) have demonstrated that mean spectral response accurately identifies semi-natural land cover, for a subset of image objects, as a consequence of reduced spectrally heterogeneity resulting from the averaged spectral response. In the current classification producer accuracy increases, for the upland heath (D1) and upland grass moor (D2a) land covers, were also a function of changing “confusion” between the land covers. It was proposed that the spectral similarity of the land covers and their confusion within the classifier training data especially that derived from API contributed to these misclassification errors.

6.4.4 The role of ancillary data

Digital elevation models and their derivatives

The inclusion of elevation/slope ancillary data in a per-pixel ML algorithm demonstrated a tendency to improve the accuracy of a MLCNP land cover classification (section 6.3.2). This trend was also evident in a per-pixel classification of the subset area (table 6.37), where, although not significant, overall classification accuracy increased with the inclusion of slope/elevation (appendix I).

The object orientated classifications did not replicate the per-pixel trend of increasing classification accuracy as a consequence of the inclusion of ancillary data (table 6.37). At each segmentation scale overall classification accuracies decreased or remained static as the mean DEM derived parameters were included in the feature space. Full confusion matrices are included in appendix I.

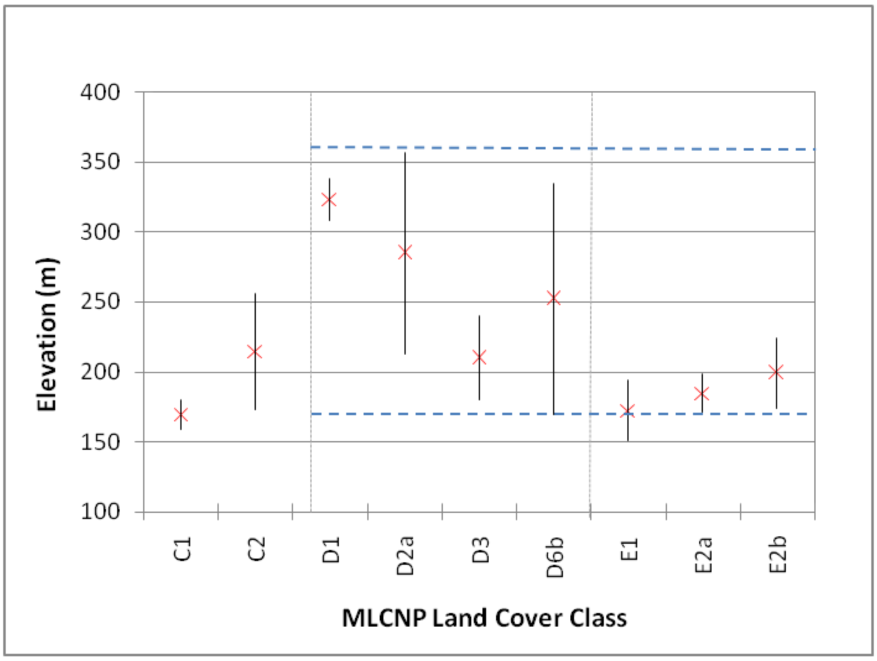
Table 6.37: Overall classification accuracies achieved via the addition of ancillary data for the per-pixel and object orientated classification approaches

Ancillary Data (Additional to Spectral bands)	**Per-Pixel**	**Object Orientated Approach: Segmentation**		
		1	**2**	**3**
None	65	73	75	70
Slope	74	73	72	69
Elevation	70	69	73	72
Slope, Elevation	71	72	72	70

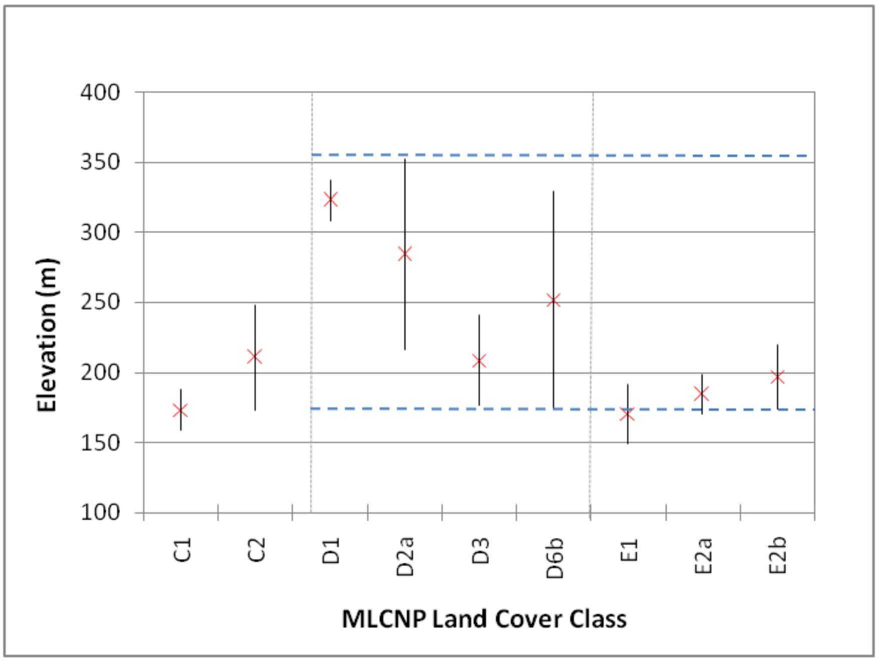
Improved classification accuracies in the per-pixel approach are attributable to the separation of land covers on the basis of characteristic slopes and elevations. Averaging of per-pixel elevation/slope values across the image object might act to mask or reduce differences between land cover types and hence class separability. To determine the influence of the averaging of elevation/slope across image objects the mean and associated confidence intervals for a sample of objects in each land cover type were plotted for segmentation scale 1 (figure 6.15 and figure 6.16). This segmentation scale was chosen subjectively to exemplify the relationships derived. For comparison this relationship was also derived, on a per-pixel basis, using sample points coincidental with the image objects.

On the basis of these plots it was concluded that, at this scale of segmentation:

- The mean and extreme elevations were reduced for all land cover classes within the subset area (figure 6.15) in comparison to the entire study area (figure 6.4).
- Within the subset area, the mean elevation values of each land cover class showed little variability between per-pixel and object derived data (figure 6.15). This was confirmed by figure 6.17, which compares the sample point elevation to mean elevation of the coincidental image object for the training sample. Clustering of the image points around the 1:1 trend-line illustrated that only small variations in elevation were expected as a consequence of averaging across the image object.
- Within the subset area, the averaging of slope across an image object did affect the mean slope values, and variability about this mean, attributed to each land cover class (figure 6.16). Comparison of sample point slope to the mean slope, for coincidental image objects (figure 6.18), illustrated that this influence was most pronounced at higher slope values where averaging across the image object tended to underestimate the slope of the associated sample point.
- The underestimation of steep slope values did not influence the potential delineation of land covers characteristic of steep slopes, that is, bracken (D3), which was characterised by significantly different mean slope values as indicated by the non-overlapping confidence intervals (figure 6.16).



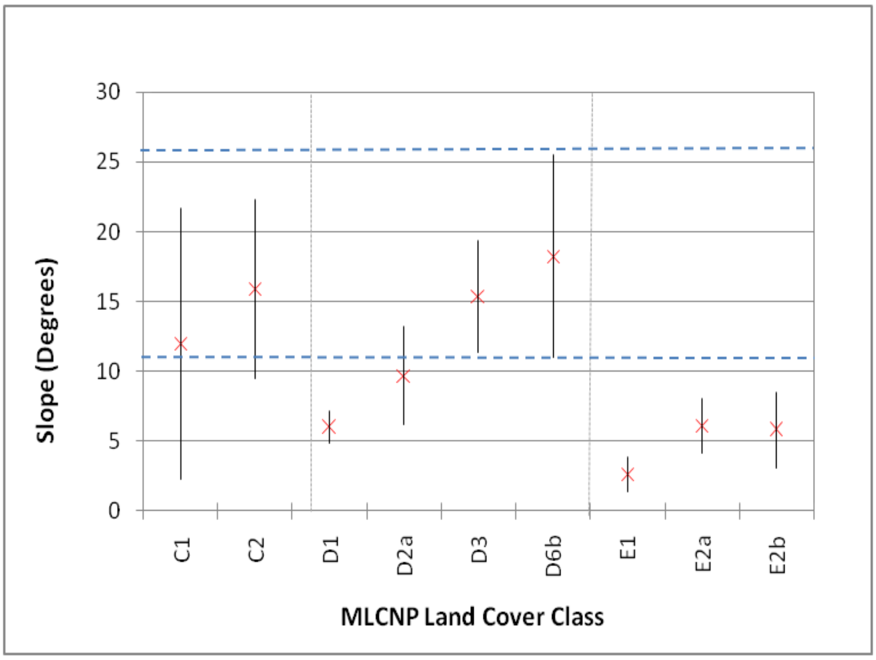
a) Per-pixel



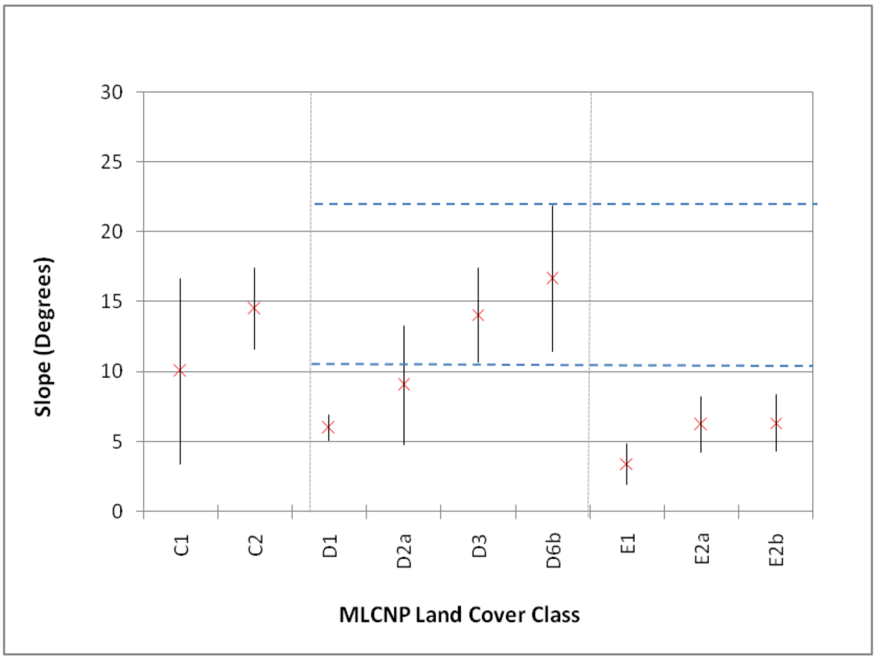
b) Object-orientated

Figure 6.15: Comparison of the average elevation, and 95% confidence intervals, for each MLCNP land cover class. Elevation values are derived, for the training samples, at (a) the pixel and (b) as the mean across the image objects, derived from segmentation 1

Notes: Blue dashed lines are added to aid discrimination of confidence interval overlap.



a) Per-pixel



b) Object-orientated

Figure 6.16: Comparison of the average slope, and 95% confidence intervals, for each MLCNP land cover class. Slope values are derived, for the training samples, at (a) the pixel and (b) as the mean across the image objects, derived from segmentation 1

Notes: Blue dashed lines are added to aid discrimination of confidence interval overlap.

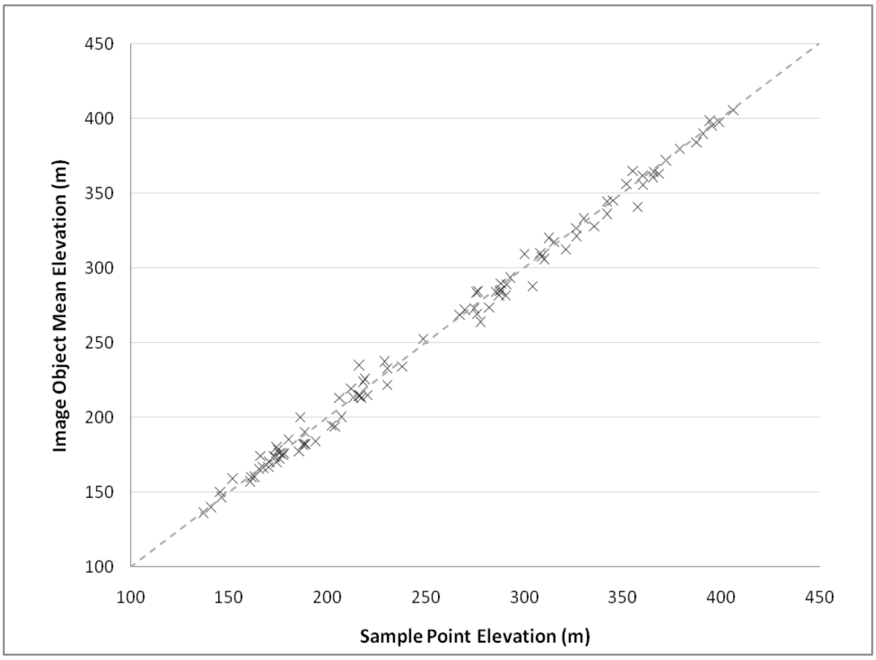


Figure 6.17: The relationship, for the training samples, between sample point elevation (pixel) and the mean elevation of the coincident image object, derived from segmentation 1

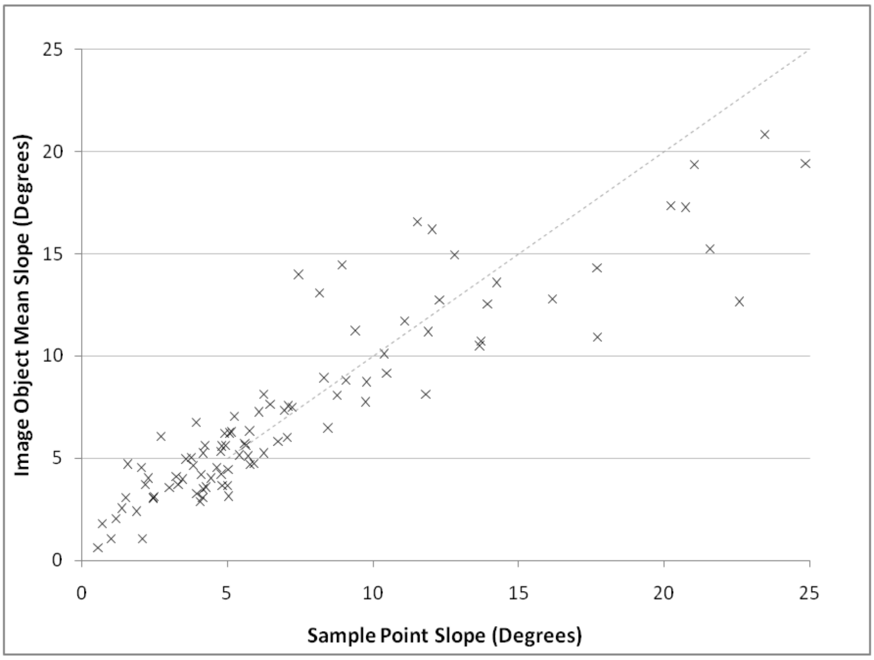


Figure 6.18: The relationship, for the training samples, between sample point slope (pixel) and the mean slope of the coincident image object, derived from segmentation 1

As distinctive land covers can be described, in terms of their elevation and slope characteristics, an increase in class specific accuracies, as a function of the inclusion of these data in the classification would be expected. From the user and producer accuracies of segmentation 1 (table 6.38), chosen to reflect the plotted relationship, it can be demonstrated that:

- The expected increase in classification accuracy for the bracken (D3) land cover was not observed. Both producer and user accuracies decreased from 67%, in the multi-spectral classification, to 50% in the multi-spectral classification including slope. Decreasing accuracy for the bracken land cover (D3) was attributable to confusion with its mosaic class (D6b), improved and rough pasture (E2a and E2b).
- Small accuracy increases were observed in the bracken mosaic land cover (D6b) via the inclusion of slope. However, accuracy changes represented only a small proportion of samples contained within the class, and confusion matrix.
- Upland heath (D1) accuracy improvements, in the classification including slope and elevation, were a consequence of the improved separation of upland heath (D1) and broadleaf woodland (C1); land covers which are distinct in terms of their characteristic elevations. Conversely, misclassification between upland heath (D1), upland grass moor (D2a) and the heath/bracken mosaic (D6b) were not resolved. On the basis of these examples, the upland heath (D1) land cover adhered to the relationships previously outlined. However, the ancillary data relationships were not consistent across classes. Upland heath (D1) remained confused with the agro-pastoral classes (E1, E2b) despite their distinctive elevations.
- The influence of slope and elevation upon classification accuracy was variable between the individual land covers of major land cover E. The arable land cover (E1) showed no variability in producer accuracy as a function of the ancillary data. This was a consequence of a tendency for the arable land cover to be confused with improved pasture (E2a); confusion which cannot be resolved on the basis of the ancillary data due to the similar elevation and slope characteristics of the land covers. Improved (E2a) and rough (E2b) pasture remained confused, within the

ancillary data classification, as was expected due to their similar slope and elevation distributions (figures 6.15 and 6.16). Small scale variability in the classification accuracy of the land covers was a consequence of variability in the confusion, typically single samples, between the pasture types (E2a and E2b) and individual classes of the upland land cover (D).

As in the per-pixel methodology, the preceding comparisons were based on a limited number of confusion matrix samples. However, on the basis of this limited data elevation and slope appeared less influential upon classification accuracy in the object-orientated approach. Variability in the ancillary data relationship was potentially a function of the limited training data, influence of API derived samples within the classifier training and application of the ancillary data within a standardised nearest neighbour algorithm, a simplistic algorithm in comparison to the ML algorithm.

Table 6.38: User and producer classification accuracies (%), derived from segmentation 1, for multi-spectral and multi-spectral plus DEM derived ancillary data classifications

MLCNP Class		Ancillary Data: Accuracies (%)							
		None		Elevation		Slope		Elevation & Slope	
		User	Producer	User	Producer	User	Producer	User	Producer
Broadleaf Woodland	**(C1)**	80	44	60	33	100	22	100	22
Coniferous Woodland	**(C2)**	91	100	82	90	91	100	91	100
Upland Heath	**(D1)**	83	94	89	86	84	91	93	95
Upland Grass Moor	**(D2a)**	0	0	0	0	0	0	0	0
Bracken	**(D3)**	67	67	75	50	50	50	43	50
Heath, Bracken Mosaic	**(D6b)**	0	0	0	0	17	33	0	0
Arable – Crop	**(E1)**	86	86	67	86	60	86	55	86
Improved Pasture	**(E2a)**	79	72	82	75	85	78	84	75
Rough Pasture	**(E2b)**	18	25	19	38	40	50	13	25

The role of additional shape features

Initial investigations were carried out to determine if class separability could be improved on the basis of parameters specific to the object-orientated approach, specifically object topology. As land cover types in the study area were characterised by differing parcel shapes, that is, rectangular, lowland fields versus irregular, upland patches, classifications were based on the image object parameters of shape index and rectangular fit (section 5.4.2).

Inclusion of the shape parameters, in addition to mean multi-spectral response, in a standardised nearest neighbour algorithm resulted in very small overall accuracy changes (table 6.39). None of these changes, between the overall accuracy of multi-spectral and multi-spectral/ancillary classifications, were significant (appendix I).

Table 6.39: Overall classification accuracies, at each segmentation scale, for multi-spectral classifications including variable shape parameters

Shape Parameter	Overall Classification Accuracy (%)		
	Segmentation 1	Segmentation 2	Segmentation 3
None	73	75	70
Shape index	71	77	69
Rectangular fit	66	75	72

Some variability in the influence of the shape features was observed between the segmentation scales. This variability would be expected due to the relationship between the shape indices and object dimensions, parameters which will vary with segmentation criteria. It is proposed that overall accuracies are similar between the segmentation scales as a consequence of the similar segmentation criteria implemented.

No class specific trends, in terms of user and producer accuracies, were identified for the segmentation scales.

The basis for the inclusion of shape features within the object-orientated classification algorithm was the proposal that land cover types of the uplands versus lowlands were characterised by objects of differing shapes. To test this hypothesis a standardised nearest neighbour classification was conducted, at segmentation scale 2, solely on the basis of the shape features (figure 6.19).

If the shape features were strongly related to landscape strata it would be expected that while specific land cover class confusion occurred land cover types would be defined in the appropriate strata. A visual interpretation of the resultant classifications (figure 6.19) indicated that while some appropriate strata classifications were evident land covers were strongly mixed in the study area.

On the basis of the limited, training data it was concluded that, at the scale of the current segmentations, shape features were not sufficiently distinct between land covers to be applied in a standardised nearest neighbour algorithm. However, their applicability in a classification hierarchy to separate land covers of differing shape and scale should be further investigated.

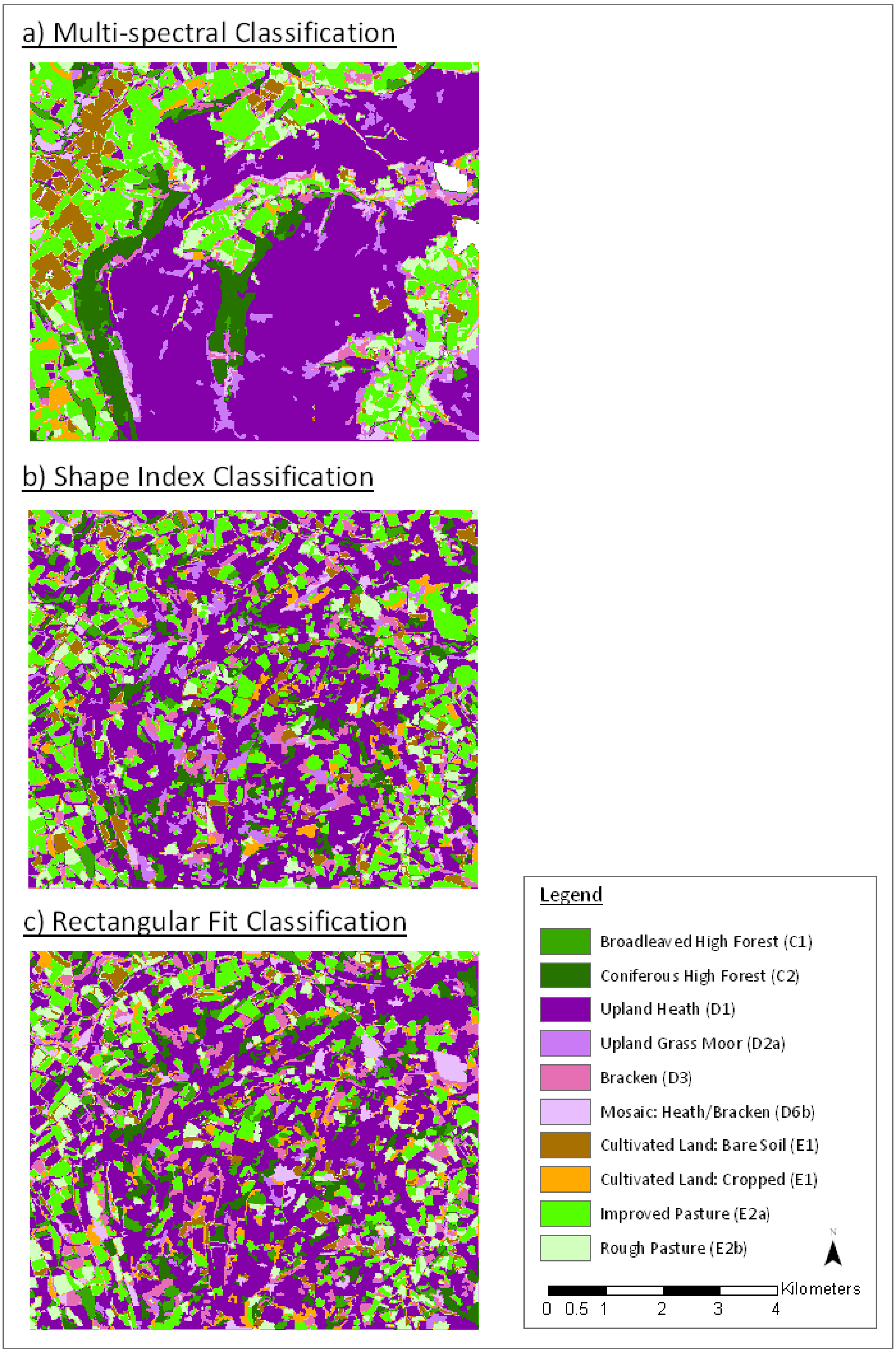


Figure 6.19: Comparison of standard nearest neighbour classifications derived from a (a) multispectral feature space, (b) shape index feature space and (c) rectangular fit feature space

6.4.5 Conclusions: object-orientated classification

Training data issues

As in the per-pixel algorithms accurate classification is dependent upon representative training samples. In addition to low sample fractions and API misclassification the object-orientated classification was influenced by an incompatibility between the point sample design and object orientated approach.

This incompatibility was exemplified by an arable field (figure 6.20) segmented into a series of image objects. The central object represented the characteristic land cover of the field, that is, the crop. Adjacent image objects represented a mix of the crop, grass buffer strips, hedgerow or shadow. Training sample points derived from API were defined to represent the object as a whole, according to the majority land cover. The influence of hedgerows, buffer strips and shadow were therefore not considered. This resulted in a disparity between the training sample point land cover and the actual land cover of the assigned image object.

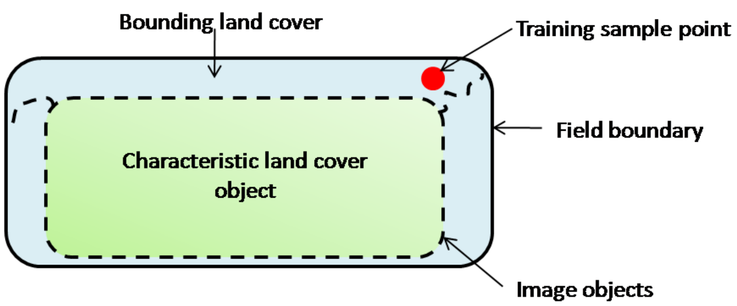


Figure 6.20: The relationship between training sample point and image objects within a field environment

The influence of scale upon classification

Results from the subset area were tentative, due to the sample size and potential training data errors, however, the per-pixel and multiple segmentation scales demonstrated the influence of object size upon classification accuracy. Determination of an appropriate scale for segmentation is an iterative, and highly subjective, process. Equally, this optimum scale is classification and, as initial investigation have illustrated, land cover dependent (Bock *et al*, 2005; Dean & Smith, 2003; Lucas *et al*, 2007). This scale/land cover dependence may best be represented by image objects of varying scale, that is, an image object hierarchy.

Class separability and the role of ancillary data

An issue highlighted in the per-pixel classification which is also evident in the object orientated classification was that of the spectral separability of land cover classes. The pre-defined classes of the MLCNP scheme were designed for the visual interpretation, as opposed to digital classification of remotely sensed data. Consequently, land cover classes were similar in their multi-spectral characteristics (Taylor *et al*, 1991c).

Derivation of slope and elevation/land cover relationships have demonstrated the potential of these ancillary data to delineate land cover types. However, inclusion of the data in the classification algorithm was not conclusive. It is proposed that sample fraction and a standardised nearest neighbour algorithm were responsible for these inconsistent results within and between segmentation scales. An advantage of the object orientated approach is the inclusion of additional feature parameters, derived from image object context and topological relations. Initial investigations have indicated that results are limited at the current segmentation scale and in a standardised nearest neighbour approach.

This research has illustrated difficulties in consistently applying ancillary data in a standardised nearest neighbour algorithm. However, improved classification via class specific descriptions, as viable in the definition of a class hierarchy, may be an important application of these data.

Recommendations for further work

To enable further development of this classification technique a number of issues need further investigation and development:

Sampling scheme

Point samples have been proven advantageous as they enable the classification of field derived attributes to multiple land cover schemes. Adaptation of the land cover attribute concept to polygons is not implicit. Consequently, the application of a point sampling scheme to image object classifier training in particular the relationship between sample point and coincident object boundaries should be investigated.

Segmentation

The influence of scale and heterogeneity parameters on the derivation of image objects and subsequent classification accuracies requires further investigation. This includes determination of an optimum segmentation scale for contrasting environments and applicability of a multi-scaled classification approach.

Parcel shrinkage

Related to segmentation scale is the concept of parcel shrinkage. Image objects, in particular those related to hard land cover boundaries, are typically characterised by a homogenous core surrounded by more spectrally variable pixels (Smith *et al*, 2000). To ensure pixels included in the classification are characteristic of the image object, and not influenced by variability at the edge of the object, several authors have recommended the exclusion of outer pixels in the derivation of the object statistics (Dean & Smith, 2003; Hinton, 1999; Smith *et al*, 2000).

Classification hierarchy

The classification hierarchy represents an alternative classification approach to that implemented in the standardised nearest neighbour algorithm (section 5.4.2). The ability of classification hierarchies to describe land cover classes on the basis of distinctive parameters has been proven beneficial in the description of land cover types (Lucas et al, 2007). However, further investigation is required to determine if sufficiently generic rule sets and class descriptions can be defined (Bock et al, 2005; Ivits *et al*, 2005). Bock *et al* (2005) state that the transfer of a classifier trained on subset areas to full images is rarely successful because of differences in the multi-spectral distribution of the data.

Object and class features

The ability of surface texture to distinguish land cover types has been demonstrated by previous studies (e.g. Bock *et al*, 2005). The applicability of this data is based on the concept that land covers containing similar species are characterised by differing textured, uneven versus uniform, surfaces. Surface texture is not viable in a standardised nearest neighbour approach, due to data quantity issues, however, a hierarchical classification approach should investigate the applicability of image object texture to land cover classification. In addition to surface texture it is recommended that the current analysis be expanded to include further parameters relating to image object shape and area.

Appropriate environments

The potential of the object-orientated approach in characteristically different environments must be critically evaluated. Initial research and current literature (Lucas *et al*, 2007; Dean & Smith, 2003) indicate that while the object-orientated approach has potential in managed environments characterised by hard boundaries such an approach may not be valid in a continuum based, semi-natural, environment unless applied at a much finer scale.

6.5 Chapter summary

The key points of this chapter are:

- Land cover attributes were classified to represent land cover classes as defined in the MLCNP, NLUD and P1 classification schemes. Classification of the field data was via a semi-automated method due to issues in defining target species, cover threshold and contextual parameters.
- Per-pixel, multi-spectral classification of the 2004 SPOT 5 image in a ML algorithm, trained on the field data classes resulted in overall classification accuracies of between 76% and 81% at the training samples.
- Visual interpretation of the classification outputs illustrated high levels of misclassification. Validation at an independent set of points (derived via API) indicated that classification accuracies were significantly lower than those achieved at the training samples.
- Relationships were demonstrated between elevation/slope/NDVI and land cover. Inclusion of these ancillary data sources within the ML algorithm improved classification accuracies. However, not all accuracy increases were significant. Accuracy improvements were classification specific, as a function of multi-spectral confusion and class specific, as a function of the ancillary data class relationship. Classifications including ancillary data were strongly influenced by the small training sample fraction which restricted classification accuracy and confusion matrix comparison.
- A significant difference was evident between the training and validation samples of all field data trained classifiers.
- The derivation of land cover class via API was demonstrated to contain misclassification errors. These errors were proven to impact upon classification accuracy.
- It is recommended that the number of training samples per class is between 10 and 30 times the number of multi-spectral wavebands (Jensen, 1986; Mather, 1999).

The influence of a sample fraction which does not meet this recommendation, upon classification accuracies, has been demonstrated

- Increasing the sample fraction reduced overall classification accuracy at the training samples. Such a decrease might be expected as further land cover variability is described. However, error was also attributed to the inclusion of API derived samples previously demonstrated to influence classifier accuracy.
- Visual interpretation indicated improved classification accuracies with increasing sample fractions. This increased accuracy was not reflected at the validation samples.
- Doubling of the training and validation sample fraction did not resolve the significant training/validation accuracy difference.
- The current training sample fraction was insufficient. Definition of the required sample fraction is complex and is related to the multi-spectral data, classification scheme, required accuracy and land cover class heterogeneity. The influence of API derived samples and validation sample fraction precluded the definition of an appropriate sample fraction on the basis of the current analysis.
- Object-orientated classification represents an alternative classification technique for land cover map reconstruction.
- Object-orientated classification tends to improve the classification accuracy of land covers which are internally homogenous and characterised by hard boundaries. However, classification improvements in semi-natural landscapes can be attributed to the reduction of land cover heterogeneity in a mean feature space.
- Relationships between ancillary data and land cover have been demonstrated irrespective of derivation of a mean object value. However, classification improvements were not evident. It was proposed that this was a consequence of the small sample fraction and standardised nearest neighbour algorithm.
- Recommendations have been made to further develop the object-orientated approach to determine the applicability of the technique. In particular a multi-scaled approach implemented within a classification hierarchy should be investigated.

Land Cover Attribute Parameterisation

Chapter 7 outlines an alternative approach to representing the field data in which the detailed land cover attribute information, as opposed to land cover class, is mapped. Advanced classification and geostatistical techniques, capable of land cover attribute parameterisation are reviewed. This review exemplifies the applicability of sub-pixel classification, in particular a fuzzy classification algorithm, to the quantification of species percentage cover within the upland stratum.

Finally recommendations regarding the applicability of advanced classification techniques to land cover attribute parameterisation are made and areas of further research outlined.

7.1 Introduction

The land cover construction methodology (chapter 6) was based on 'hard' classification techniques in which an entity, pixel or object, was assigned to a single, unique land cover class. This approach to classification:

- Potentially obscures subtle changes in land cover which do not involve a conversion from one land cover type to another.
- Underutilises the potential of remote sensing data to describe landscape mosaics and gradients.
- Obscures variability in vegetation characteristics as land cover classes are assumed to be homogenous (Defries *et al*, 2000).

The methodology described in this chapter aimed to address these issues via characterisation of the land cover attributes, as recorded during the field survey, over the entire study area.

Characterisation of land cover attributes was considered advantageous as it:

- Retains small scale variability and detail regarding vegetation composition lost at the resolution of land cover classes.
- Enables landscape managers to utilise detailed land cover data, for example, to determine if moorland stands adhere to favourable habitat conditions (Blackshall *et al* 2001).
- Results in flexibility in terms of the reconstruction of land cover classes and vegetation composition analysis.

Development of this methodology concentrated on a review of advanced classification techniques. The specific objectives of this element of the research were to:

- Review advanced classification techniques capable of detailed vegetation parameter mapping.
- Test the implementation of a selection of these techniques.
- Make recommendations for the further development of the land cover parameterisation methodology.

7.2 Sub-pixel classification techniques

7.2.1 Introduction

Traditional classification techniques, termed 'hard' classifiers, assign each pixel a single unambiguous label (Mather, 1999b). Such an assignment is appropriate for classes which occur in a mosaic of discrete mutually exclusive parcels and where the assumption that each pixel comprises a single class is valid (Foody, 1996). 'Hard' classification techniques become invalid when the assumption of a single class per pixel is violated. This is attributable to gradual changes between vegetation classes and pixels which straddle two or more homogenous land covers. In both situations the pixel is mixed, that is, it contains more than one land cover type (Foody, 1996; Lucas *et al*, 2002).

A remote sensing image pixel records the spectral characteristics of the corresponding ground area. A pixel containing a single land cover class reflects the spectral response characteristic of that land cover type (Wang, 1990). However, the spectral response of a pixel containing multiple land cover classes will be a function of the radiant flux of multiple surface features (Lucas *et al*, 2002; Wang, 1990). In general, a pixel will show increased similarity to land cover classes contributing greatest to its surface area (Wang, 1990). Sub-pixel classification techniques therefore estimate the proportion of each land cover type within a mixed pixel based on the composite spectral response (Lucas *et al*, 2002). It should be noted that estimates of component proportions give no indication of a pixels spatial structure (Bastin, 1997).

7.2.2 Spectral mixing analysis

Encompassing a range of techniques spectral mixing analysis (SMA) is based on the assumption that spectral variation within a pixel can be modelled as a combination of the spectral responses of several "pure" surface materials or end-members (Theseira *et al*, 2002). A common means to model the contribution of each end-member is to assume a linear relationship between pixel response and class contributions termed linear mixture modelling (Mather, 1999b).

Within linear mixture modelling (LMM) class proportions, contributing to mixed pixel spectral response, are estimated via inversion of the linear mixture equations through least-square regression while restricting the sum of pixel proportions to one (Metternicht & Fermont, 1995). Inclusion of a proportion restriction is termed a constrained model; the model can also be implemented in unconstrained and semi-constrained formats (Mather, 1999b; Metternicht & Fermont, 1995).

A unique solution to the least square regression is only feasible where the number of end-members is less than or equal to the number of multi-spectral wavebands within the satellite imagery (Lucas *et al*, 2002; Metternicht & Fermont, 1995). To circumvent this restriction a multiple end-member approach has been developed. The approach is based on the assumption that while several land cover classes exist within the study area only a small number are likely to occur in a single pixel (Eastman, 2006).

Consequently, all possible end-member combinations are tested in each pixel and the single combination which best models the composite pixel spectral response identified (Theseira *et al*, 2002).

A limitation of LMM is the assumption that pixel spectral response is a linear combination of component response and includes no multiple reflections (Mather, 1999b). Such an assumption is unlikely to be valid in remote sensing images with a strong three-dimensional component (Bastin, 1997) or in shaded/wet areas (Lucas *et al*, 2002). Such multiple reflections require more sophisticated models, for example ANNs, to capture the complexity of the mixture in the pixel (Lillesand & Kiefer, 2000).

7.2.3 Probalistic methods: maximum likelihood classifier

The maximum likelihood (ML) algorithm is typically used as a 'hard' classification technique. However, in doing so 'soft' classification information provided by the technique is excluded. Such an approach is wasteful of information (Wang, 1990).

The ML algorithm can be adapted to provide three measures related to class membership and pixel composition: the probability density function, typicality and posterior probability (Foody *et al*, 1992; Foody, 1996). The probability density function, the basis of the ML algorithm, represents the probability of a pixel belonging to a specific class. Typicality is derived from the Mahalanobis distance, the distance between the centroid of the class and pixel in the feature space. Finally, posterior probability indicates the strength of membership, of a particular pixel, to a single class compared to all other classes (Foody & Trodd, 1993).

Although a simple sub-pixel classifier the ML algorithm is not appropriate for all applications due to the assumption that data display a Gaussian normal distribution (Foody, 1996). Several authors have also concluded that while correlated with land cover proportion, results from the 'soft' ML classification tend to be similar to 'hard' classification outputs (Bastin, 1997). These weaknesses potentially limit the mapping of land cover class probability with the ML algorithm (Foody, 1996).

7.2.4 Fuzzy classifiers

Fuzzy classifiers are one of a range of non-parametric classifiers which are advantageous if the assumptions of probabilistic methods regarding data distribution cannot be satisfied (Foody, 1996; Lucas *et al*, 2002). Fuzzy classifiers derive a measure of membership: the degree to which a given pixel resembles the specified class (Mather, 1999b). Consequently, pixels have partial/multiple memberships to all the candidate land cover classes (Zhang & Kirby, 1997).

Membership grades, which vary between zero and one, are positively related to the degree of similarity between the pixel and specified class (Lucas *et al*, 2002). The degree of fuzziness in this membership is determined by the shape of the function used to describe the class. A step function consisting of two values, zero and one, contains no fuzziness; the element is included or excluded from the class. Conversely, a sigmoid function introduces a fuzzy edge to the class described by a band where elements transfer from being fully included (one) to fully excluded (zero) (Bastin, 1997). The closer a membership grade to one the more similar the pixel to that class (Bastin, 1997).

Fuzzy C-means classifier

The fuzzy C-means (FCM) classifier is widely reported in remote sensing literature and has been demonstrated to yield fuzzy membership values which are significantly correlated to actual land cover proportion (Fisher & Pathirana, 1990; Foody & Trodd, 1993; Foody, 1996).

FCM is a non-hierarchical clustering algorithm in which pixels are iteratively moved between classes so as to minimise the generalised least-squared error (Fisher & Pathirana, 1990). Mathematical derivation of the FCM algorithm is outlined by Bezdek *et al* (1984) (see also Fisher & Pathirana, 1990; Foody, 1996). Implementation of the algorithm requires definition of two parameters: a weighting component (m) and measure of dissimilarity.

The degree of fuzziness incorporated in class partitions is controlled by the weighting component. A weighted component (m) of one would result in a ‘hard’ classification.

Equally, increasing values of the parameter (*m*) result in an increasingly fuzzy classification output (Foody, 1996). The measure of dissimilarity is derived as the distance between a pixel and class centroid. The form of this derivation is dependent upon specification of a weighted matrix which controls the shape of the output. Common measures include the Euclidean, diagonal and Mahalonobis distance (Lucas *et al*, 2002). The FCM algorithm can be implemented in an unsupervised (Mather, 1999b) or supervised (Foody, 1993; Lucas *et al*, 2002) mode.

Within the FCM algorithm class membership is relative, that is, membership is calculated with respect to all defined classes (Foody, 2000). Pixels belonging to an untrained class, even if that class is spectrally distinct, will display membership values partitioned between the trained classes (Foody, 2000). As a result, the presence of untrained classes has been demonstrated to degrade FCM accuracy (Foody, 2000).

In the presence of untrained classes Foody (2000) recommends relaxation of the probabilistic constraint of the FCM algorithm, the constraint which requires membership to total 100%. The resulting possibilistic component algorithm, possibilistic C-means (PCM), derives fuzzy membership values independently for each class. Membership values therefore represent some degree of absolute similarity and are not influenced by untrained classes (Foody, 2000).

7.3 Sub-pixel classification example

The applicability of sub-pixel classifiers to characterise land cover attributes was tested in the upland strata. An upland focus was selected due to the demonstrated applicability of sub-pixel techniques in the habitats characterised by ecotones, intergrading boundaries, as typical of this environment (Foody & Trodd, 1993).

7.3.1 'Pure' species/habitat definition

A requirement of the sub-pixel classifiers, as with other classification techniques, is a training data set on which class signatures can be developed. In sub-pixel classification these training data should represent 'pure' examples of each class.

Sub-pixel elements: species versus species associations

When mapping species top cover, the theoretical ideal would be a class relating to each species found in the study area. Such an approach would allow the derivation of percentage cover estimates for each species.

As stated previously, sub-pixel algorithms require sufficient 'pure' class examples to describe the land cover class and provide classifier training data. A 'pure' class example was considered to be a field survey sample dominated by a single plant species. If a species dominance threshold was defined at 80% top cover only seven of the species/plant groups, as recorded by the field survey, were represented. Consequently, it was not feasible to characterise land cover attributes at the species scale recorded during the field survey.

It was concluded that species dominant at one or more samples covered sufficient spatial extent to be detected within the SPOT 5 imagery and hence represent a single class in subsequent classifications. Species which did not dominate a sample, and therefore pixel, could not, however, be represented by a unique class. Characterisation of these sub-dominant species required the definition of species groupings. This analysis proposed the grouping of species into habitats based on typical field associations.

The definition of spatially associated species

Various techniques for determining common species associations were tested including ordination, within the Twinspan software (Hill & Šmilauer, 2005), and multiple clustering algorithms.

Twinspan

Twinspan (two-way indicator species analysis) is an extension of indicator species analysis (Shaw, 2003) which was developed to simultaneously classify species and sample units (McCune & Grace, 2002). The program can be categorised into two main processes. Firstly, a classification of samples and secondly, based on this sample classification, a classification of species to reflect their ecological preferences (Hill & Šmilauer, 2005). Twinspan in effect creates dichotomies, divisions which divide data into non-overlapping, mutually exclusive parts. This dichotomy is developed via repeated division of a correspondence analysis ordination (McCune & Grace, 2002).

Theoretically, Twinspan should be operated on presence/absence data (McCune & Grace, 2002). However, the introduction of pseudospecies enables the inclusion of quantitative data (Hill & Šmilauer, 2005). Pseudospecies are based on the concept that quantitative information i.e. proportion cover, can be retained as scaled data.

A major advantage of the Twinspan software is the presentation of both samples and species in a condensed two-way table (Hill & Šmilauer, 2005; McCune & Grace, 2002). A primary criticism of the software is an inability to represent data containing multiple gradients (McCune & Grace, 2002; Shaw, 2003). Where the single environmental gradient of the Twinspan software is violated groupings of species are, typically, better represented via clustering analysis (McCune & Grace, 2002).

Iterative testing of the Twinspan software on the basis of presence/absence and pseudo-species data resulted in inconsistent groupings of both the species and samples. Modifications to the input dataset, via the grouping of similar but less abundant and removal of infrequent species, did not resolve these inconsistent groupings. It was therefore concluded that inconsistent groupings within the data were a consequence of the inability of the software to describe complex environmental gradients; species were expected to vary across more than one environmental gradient. Consequently, Twinspan results were excluded from further analysis.

Clustering algorithms

Cluster analysis is performed with the objective of assigning objects into discrete groups based on their similarity. Clustering techniques can be defined as hierarchical versus non-hierarchical and agglomerative versus divisive. Non-hierarchical algorithms result in independent clusters whereas hierarchical clusters are related into progressively larger clusters. Agglomerative algorithms proceed from the assumption that each object represents a single cluster: these are progressively grouped into larger clusters. Conversely, divisive algorithms initiate with a single cluster that is repeatedly divided. Two clustering algorithms, selected due to software availability, were compared in the current analysis; the joining tree and k-means algorithms.

The joining tree algorithm is an agglomerative clustering approach. The clustering similarity measure implemented was Euclidean distance. The Euclidean distance between clusters can be defined according to several criteria, for example, the distance between the gravitational centre of clusters, two nearest or two furthest objects (StatSoft, 2007). The current analysis used a single linkage or nearest neighbour approach in which the distance between clusters was defined as the distance between the two closest objects (StatSoft, 2007).

The K-means classifier aims to define K clusters with the greatest possible distinction. Computationally the algorithm starts with K random clusters between which objects are moved iteratively with the aim of minimising variation within and maximising variation between clusters (StatSoft, 2007). Variability calculations were based on an analysis of variance (ANOVA), which evaluated the between-group variability against the within-group variability and maximised the ANOVA significance.

Cluster analysis

Cluster analysis was an iterative process, based on the percentage cover and presence/absence field data, during which the clustering parameters were modified in an attempt to improve cluster formation. Clusters were assessed according to their relevance for subsequent sub-pixel classification and the rejection of obvious misclassifications based on knowledge of typical species associations.

Clusters derived on the basis of species were strongly influenced by the percentage cover and frequency of species occurrence. Consequently, species of similar cover proportions were grouped irrespective of their spatial associations. Equally, clusters were limited in their ability to manage species known to occur in multiple habitats. To resolve these issues cluster analysis was based on the grouping of samples. Species characteristics within each sample point cluster were subsequently identified via inspection of the field survey dataset.

The joining tree clustering algorithm was advantageous as no prior assumptions were required regarding the optimum number of clusters. However, successive iterations illustrated that, as a consequence of an unlimited cluster number, small scale variability between samples was emphasised resulting in a high number of inappropriate clusters. Within the K-means algorithm the resultant number of clusters was controlled through the K parameter; the optimum number of clusters. This parameter was estimated via a factor analysis.

Factor analysis is an analytical technique used to detect structural relationships within data (StatSoft, 2007). The factor loadings, derived from principal components analysis (PCA), were plotted on axes normalised and rotated to maximise variability within the data. Nine potential habitats, or species associations, were extracted from the factor analysis (figure 7.1) along two broad gradients, dry to wet (factor 1) and burnt to fully recovered stands (factor 2).

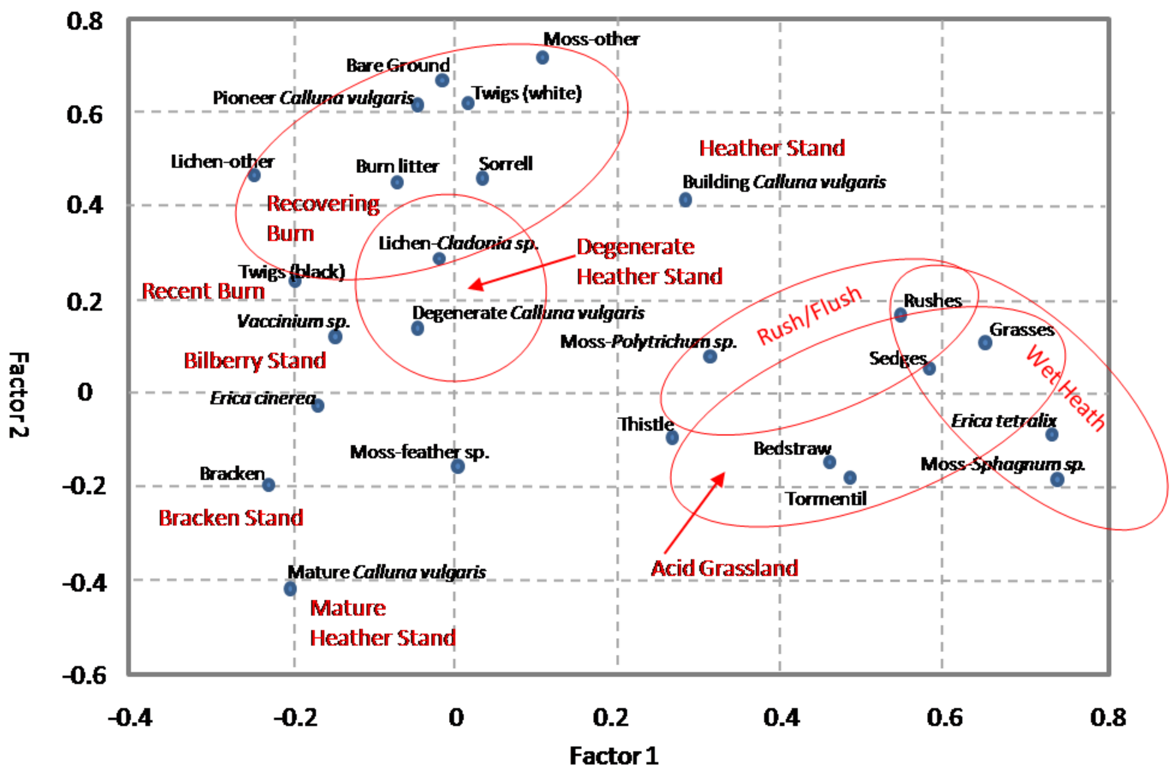


Figure 7.1: Factor analysis, based on PCA, plotted on normalised axes rotated to maximise variation within the data. Potential species association are superimposed.

Notes: Potential habitats, or species associations, are annotated in red text.

An 11 cluster K-means algorithm, based on the percentage top cover field data, was performed to assign each sample point to an appropriate cluster. Eleven clusters were used, instead of the 9 habitats identified in the factor analysis, to encompass potential land cover mosaics.

In 10 of the resultant 11 clusters the samples were easily aligned to the habitats identified in the factor analysis. In the remaining cluster variability between samples was high. This mixed class led to a further 10 class iteration of the cluster algorithm to determine if cluster variability could be resolved. In fact results of this iteration were poor, demonstrating increased variability within all clusters.

While the 11 cluster solution was judged the best iteration, inspection of the clusters revealed that several contained a number of potentially discrete habitats. The samples contained in these mixed clusters were re-clustered, based on a K-means algorithm, to determine if splitting of the original cluster could be justified. This process is exemplified by the subdivision of cluster 2, which contained all samples indicative of burning (black twigs), according to whether the burn contained any vegetative recovery (table 7.1). This iterative procedure resulted in the description of 19 potential species associations (table 7.1). This high number of species associations was a consequence of the representation of both ‘pure’ and mosaic habitats within the field data samples.

As fuzzy classifier training was based on single ‘pure’ pixels a species/habitat was required to dominate at least one pixel to be included in the subsequent classification. This pure class example could contain a single species or represent a group of species, frequently found in association, at a scale where the association dominates a pixel. Eight ‘pure’ habitats, known to dominate the field data samples and hence SPOT 5 pixels, were extracted from the species associations identified in the cluster analysis (table 7.1). These ‘pure’ habitat examples were:

- Grass dominated moor
- *Erica tetralix*, grass and sedge moor
- Recent burn
- Mature *Calluna vulgaris*
- Rush (*Juncus*) species
- Recovering burn
- Building *Calluna vulgaris*
- Bracken (*Pteridium aquilinum*)

Table 7.1: Text descriptions of the 11 sample clusters, and subsequent cluster splits, derived via k-means cluster analysis.

Cluster	Indicator Species	Cluster Division	Description
1	Grasses Rushes *Erica tetralix*	**A**	**RUSH MIXES** (Rush species greater than 20% cover but not dominant)
		B	**WET MOOR** (*Erica tetralix* present, rush species less than 5%)
		C i	**GRASS MIXES** (Grass not dominant, but mixed with a variety of species)
		C ii	**GRASS DOMINANT MOOR** (Grass dominant over other species)
2	Black twigs (Recent burn)	**A**	**RECENT BURN NO VEGETATIVE RECOVERY** (No vegetation)
		B	**RECENT BURN WITH VEGETATIVE RECOVERY** (Black twigs, indicative of recent burns, with some vegetative recover, species vary)
3	Mature *Calluna vulgaris*	**-**	**MATURE CALLUNA STAND** (*Calluna vulgaris* dominates top cover)
4	White twigs (Recovering burn)	**-**	**RECOVERY BURN** (White or bleached twigs indicate recovering burn, vegetation is variable, typical species are *Vaccinium species*, pioneer *Calluna vulgaris* and moss species)
5	*Calluna vulgaris* *Vaccinium sp*.	**-**	**MIXTURE – CALLUNA VACCINIUM** *(Vaccinium species*, *Calluna vulgaris* mosaic)
6	Rush (*Juncus*) sp.	**-**	**RUSH** (Rush sp. dominate)
7	*Calluna vulgaris* Sedges Bare ground	**A**	**MIXTURE – CONTAIN SEDGE** (*Calluna vulgaris,* grass mix which contains sedges)
		B	**MIXTURE – CALLUNA** (Mix of species - *Calluna vulgaris* greatest proportion)
		C	**CALLUNA STAND – BARE GROUND** (*Calluna vulgaris* stand, but stand contains bare ground)
		D	**MIXTURE – CALLUNA, GRASS** *(Calluna vulgaris* intermixed with grass)
		E	**MIXTURE – CALLUNA, OTHER** (*Calluna vulgaris* mixed with other species, for example, bracken)
8	Pioneer *Calluna vulgaris*	**-**	**RECOVERY BURN** (Segregated from previous recovery burns on basis of a high proportion of pioneer *Calluna vulgaris*)
9	*Vaccinium sp*.	**-**	**VACCINIUM STAND** (*Vaccinium species* dominate top cover)
10	Building *Calluna vulgaris*	**-**	**BUILDING CALLUNA STAND** (*Calluna* vulgaris dominates top cover)
11	Bracken	**-**	**BRACKEN** (*Pteridium aquilinum* dominates top cover)

Habitat/species composition

Classes containing a single species were directly comparable to the field data, therefore, the species top cover proportion at each sample was known. Conversely, classes defined to contain a mix of species required aggregation of the field data, which contained the proportion cover of each species, to the scale of the habitat. To ensure consistent derivation of habitat proportions the following rules were adopted:

- Multiple habitats could not occur in a single quadrat.
- Species identified as being sufficiently dominant as to be considered a class, *Calluna vulgaris*, *Vaccinium species* and bracken, could not occur in a derived habitat proportion.
- Habitats could contain the same species for example, grasses, rushes and sedges but the proportion of these species and presence/absence of indicator species determined the habitat to which they contributed (figure 7.2).
- Habitats were hierarchical in their derivation (figure 7.2). For example, if moss and bare ground contributed to greater than 50% of the top cover the sample was classified as a recovery burn irrespective of the presence/absence of *Erica tetralix*.

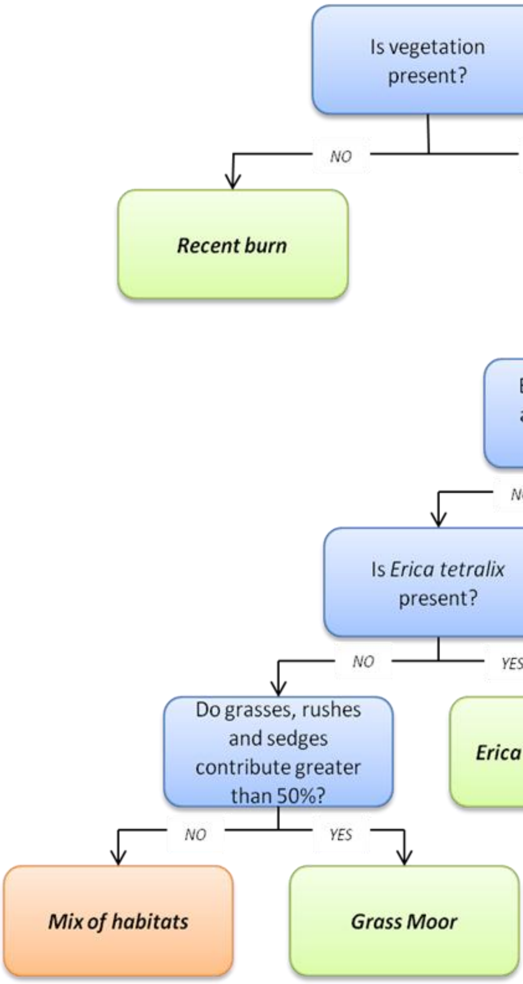


Figure 7.2: Conceptual diagram illustrating the rules implemented for the derivation of habitat proportions from the species level field data.

Class separability

In order for classes, species or habitats, to be successfully identified within a sub-pixel algorithm, between class multi-spectral variability must be maximised and within class multi-spectral variability minimised. Classes should therefore be trained on 'pure' class examples, samples at which the class represents 100% of the top cover, and defined to be spectrally separable.

The constraint that 'pure' samples must contribute to 100% of the top cover was found to be restrictive in terms of the resultant number of training samples. Maximisation of the dominance threshold was therefore balanced against the resultant number of training samples.

Visual comparisons of sample spectral plots, of increasing top cover dominance, for the *Calluna vulgaris*, bracken and recovery burn classes demonstrated that samples with top cover dominance values between 80 and 90% varied significantly from those greater than 90%. It was therefore concluded that a higher 90% top cover dominance threshold should be implemented.

In the remaining classes a threshold of 90% could not be applied due to the resultant low number of training samples. *Erica tetralix* moor, at a threshold of 80% contained four samples; these samples were sufficiently similar to enable inclusion in a single class. The grass moor and *Vaccinium species* classes did not contain sufficient samples to enable training at high top cover dominance; a threshold of 50% was required to enable sufficient training samples. This lower dominance threshold increased within class variability as a consequence of the varying species composition of each sample.

To ensure compatibility with sub-pixel classifier training class separability analysis was based on single pixels; those pixels spatially coincident with the field samples. Spectral separability was assessed, within the 2004 SPOT 5 image, using Euclidean distance; JM distance was not viable due to the small sample fraction (table 7.2). Interpretation of Euclidean distance, as a separability measure, is complex as distances are not standardised to a known scale. However, low Euclidean distance values (table 7.2), indicative of class overlap, were evident between:

- The building and mature structural stages of *Calluna vulgaris*.
- The recent and recovering burn habitats. A low Euclidean distance between these land covers was attributed to their similar compositions which were dominated by bare earth and charred heather plants. Small proportions of vegetative recovery were considered insufficient to enable full separation of the classes on the basis of their multi-spectral characteristics.

Table 7.2: Euclidean distances between proposed upland habitat classes.

	BCV	Bracken	Recent Burn	ET moor	Grass moor	MCV	Recovery burn	*Vaccinium* species
BCV*	0	64	26	10	22	6	27	25
Bracken		0	79	66	48	67	80	39
Recent Burn			0	17	32	29	8	42
ET moor*				0	20	15	18	27
Grass moor					0	27	32	11
MCV*						0	30	29
Recovery Burn							0	42
***Vaccinium* species**								0

*Notes: Distances are calculated based on the combination of the four SPOT 5 multi-spectral bands.*Abbreviations: building Calluna vulgaris (BCV), Erica tetralix, grass and sedge moor (ET moor) and mature Calluna vulgaris (MCV)*

- The *Vaccinium species* and grass moor habitats. Spectral similarity between these habitats was attributed to the lower dominance thresholds implemented in the definition of 'pure' training samples and resultant mixed habitats.

As a consequence of their spectral similarity, as determined by a low Euclidean distance, the structural stages of *Calluna vulgaris* were agglomerated to a single class. Further class and threshold modifications were not viable due to the minimal training data available.

Class definitions

On the basis of the previous analysis the following classes were defined for inclusion in the sub-pixel classification:

Bracken: Bracken (*Pteridium aquilinum*) was represented as a single species. A threshold top cover of greater than 90% was applied in the definition of 'pure' samples.

Calluna vulgaris: This class contained all stages of *Calluna vulgaris* growth. A threshold of top cover greater than 90% was applied in the definition of 'pure' samples.

Vaccinium species: This class contained bilberry (*Vaccinium myrtillus*) and cowberry (*Vaccinium vitis-idaea*) which were combined due to the low spatial extent of cowberry. To ensure sufficient training data the threshold for 'pure' samples was defined as a top cover of greater than 50% within this species association.

Recent burn, no vegetation recovery: This land cover type was defined as areas burnt during the current season. Recent burns were characterised by charred heather plants, ash and no vegetative recovery.

Moss, bare ground dominant: This habitat represented the recovery of moorland stands after burning. Vegetative recovery was less than 50% of the top cover. Typical vegetation types of the habitat were pioneer/early building *Calluna vulgaris*, *Vaccinium species*, sedges, lichen and mosses. Habitat composition was strongly influenced by recovery duration. A threshold top cover of greater than 90% was applied in the definition of 'pure' samples.

Erica tetralix moor: Vegetation species typical of this habitat were *Erica tetralix*, sedge species and a mix of grasses and moss species. *Erica tetralix* was the main indicator of the habitat and could be abundant. Pure class examples were defined as those samples at which *Erica tetralix* was present and the composite species contributed to greater than 80% of the top cover.

Grass dominant moor: Various species were present in this habitat although grass, rush and sedge species were dominant, contributing to at least 50% of the top cover. Although similar in species composition, grass dominant moor was segregated from *Erica tetralix* moor on the basis of the presence/absence of *Erica tetralix*.

7.3.2 Sub-pixel classification: methodology

Classification techniques

Sub-pixel classification encompasses a range of techniques and algorithms (section 7.2). Of these techniques the current research considered those available within the IDRISI Andes software (Eastman, 2006) including:

- *BAYCLASS*

An extension of the maximum likelihood classifier, this algorithm expresses the posterior probability of belonging to each constituent class according to Bayes' theorem.

- *BELCASS*

A complex sub-pixel classifier based on Dempster-Shafer theory. An advantage of this classifier compared to classifiers such as BAYCLASS, is the recognition that classes in addition to those trained can exist (Eastman, 2006).

- *FUZCLASS*

Based on fuzzy set theory this classifier is conceptually an extension of the minimum distance classifier. Fuzzy set membership is determined by the distance between the spectral vector of the pixel and the mean class vector.

- *UNMIX*

This classifier is based on a linear mixture model. To enable the classification of imagery which contains insufficient bands, relative to the required number of end-members, the IDRISI Andes software contains two hybrid mixture modelling techniques. The first hybrid technique identifies constituent end members via a probability based (BAYCLASS) algorithm, the second tests all possible combinations of end-members.

A fundamental difference between the sub-pixel classifiers is the training data statistics (mean, variance and covariance) incorporated within the algorithm. The current training data contained a limited number of 'pure' class samples preventing derivation of the variance and covariance matrices. Consequently, algorithms based on these variables, BAYCLASS and BELCLASS, were not feasible. Linear mixture modelling does not incorporate variance or covariance statistics. However, the limited number of multi-spectral bands within the SPOT 5 imagery restricted the number of end-members and hence applicability of this algorithm. While hybrid techniques were available these were not applicable as a probability guided technique could not be implemented and exhaustive end member testing was not recommended for signatures derived from training data (Eastman, 2006). Consequently, the only sub-pixel classifier tested was fuzzy classification (FUZCLASS).

Standardised Z score

A requirement of the FUZCLASS algorithm is the definition of a distance parameter (Z). Specified as a standardised score (Z) this distance influences the proportion of pixels assigned a membership value of zero, for example, a distance of 1.96 would force 5% of pixels to have a fuzzy membership of zero (Eastman, 2006). A Z score of 1.96 was implemented in the FUZCLASS algorithm following recommendations that the parameter fall between 1.5 and 3 (Bezdek *et al*, 1984; Bastin, 1997; Lucas *et al*, 2002).

Accuracy assessment

Sub-pixel classification accuracy measures can be subdivided into two categories according to whether they are based on hard or soft classification results.

Hard classification accuracy assessment techniques

Accuracy measures in this category are based on the assumption that the classification output contains a single class which is compared to a reference dataset also containing a single class. Derivation of a single class, for each pixel, is achieved via hardening of the sub-pixel classification output. Hardening is a maximisation process whereby a pixel is labelled according to the class with the highest probability or membership grade (Zhang & Kirby, 1997). The accuracy of the hardened classification is calculated via confusion matrices and associated statistics (section 5.4.1).

Typically, when hardening a sub-pixel classification, no consideration is given to the difference between the membership functions of the first and second most probable classes. Where these probabilities are similar assignment to the second most probable class could also be considered correct (Congalton & Green, 1998). Congleton and Green (1998) demonstrated the inclusion of this concept into the confusion matrix via the development of a rule set which encompasses data that are absolutely correct, absolutely incorrect and acceptable within the fuzziness of the current classification. In such a confusion matrix the off-diagonal elements contain two separate values; the first value represents those samples which although incorrect are acceptable, the second value those samples which are incorrect.

Soft classification (fuzzy) accuracy assessment techniques

A limitation of all hard accuracy assessment techniques is that they make no assessment of the sub-pixel classifier in terms of the strength of class membership and partitioning of membership across classes. Consequently, a range of complex techniques have been developed to assess the accuracy of the fully fuzzy output of sub-pixel classification techniques including entropy/cross-entropy (Foody, 1995; Zhang & Kirby, 1997), similarity/dissimilarity indices (Townshend, 2000), kernel-based statistics (Atkinson, 1999) and fully fuzzy confusion matrices (Binaghi *et al*, 1999).

For ease of implementation and interpretation simple measures of accuracy were advocated in the current research. Assessments of the correspondence between ground estimates of percentage cover and membership grade were based on scatter plots and derivation of the correlation coefficient (Bastin, 1997; Foody, 1996, 2000).

7.3.3 Fuzzy classification results

The FUZCLASS algorithm, trained on the pre-defined habitat classes and a standardised z score of 1.96, was implemented to classify the 2004 SPOT5 image. The resultant classification outputs illustrated the normalised fuzzy membership of each pixel to each habitat (figure 7.3).

Visual interpretation of the classification outputs (figure 7.3) illustrated that high/low membership values were approximately coincidental with the broad land cover trends of the study area; bracken and V*accinium species* dominated slopes and *Calluna vulgaris* and *Erica tetralix* dominated moorlands. However, classification errors were evident within these broad land cover trends. Examples include the overestimation of *Vaccinium species* and confusion between recent and recovering burns.

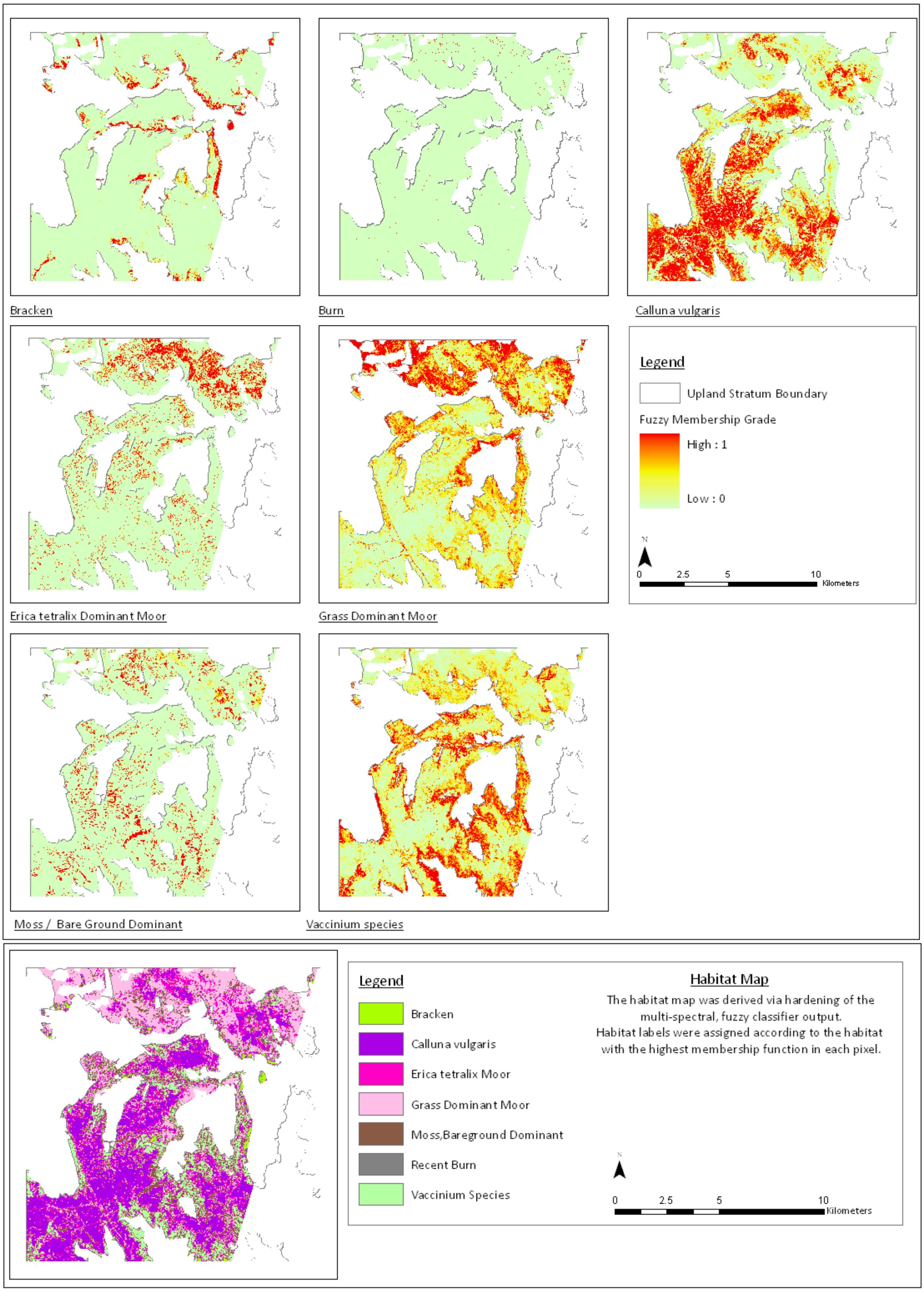


Figure 7.3: Membership grades for each habitat derived from a multi-spectral, fuzzy classifier parameterised on a standardised Z score of 1.96.

Hardening of the classification output enabled derivation of a confusion matrix at the 'pure' (training) samples (table 7.3). The confusion matrix indicated an overall classification accuracy of 73%, although class specific user and producer accuracies were variable. As the confusion matrix (table 7.3) was based on a restricted number of samples the interpretation of trends was limited. However, habitat spectral similarity, as highlighted by low Euclidean distances between classes (section 7.3.1) was evident. This was exemplified by confusion between the *Vaccinium species*/grass moor classes and the spatially associated classes of *Calluna vulgaris* and bracken; a consequence of training the *Vaccinium species*/grass moor classes on mixed pixels which inevitably contain the target and spatially associated habitats.

Expansion of the confusion matrix to include all field data samples, classified according to the habitat with the highest top cover proportion, resulted in a significant drop in overall accuracy from 73% to 59% (appendix J). This significant drop in accuracy was attributed to both error in the fuzzy classification and the introduction of error as a consequence of hardening the classification output and field data. To resolve this issue the confusion matrix was modified to consider the first and second most probable species (table 7.4). The resultant increase in overall classification accuracy to 68%, from 59%, illustrated the influence of classification hardening in the presence of multiple, equally dominant, species.

Table 7.3: Confusion matrix, derived at the 'pure' samples, comparing the hardened fuzzy classification to field data derived habitat.

Hardened fuzzy classification	Reference data								
	Bracken	Recent burn	*ET moor*	Grass moor	*Calluna vulgaris*	Moss/ bare ground	*Vaccinium species*	Total	*User Accuracy (%)*
Bracken	4						1	5	***80.0***
Recent burn		1						1	***100.0***
ET moor			3					3	***100.0***
Grass moor			1	2	2	1	1	7	***28.6***
Calluna vulgaris					11		1	12	***91.7***
Moss bare ground		1				5		6	***83.3***
Vaccinium species				2	1		4	7	***57.1***
Total	4	2	4	4	14	6	7	41	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***50***	***75***	***50***	***79***	***83***	***57***		***73***

Table 7.4: Confusion matrix, including all field data samples, comparing the first and second most probable habitats as derived from a multi-spectral fuzzy classification and field data.

Fuzzy classification	Reference data								
	Bracken	Recent burn	*ET moor*	Grass moor	*Calluna vulgaris*	Moss/ bare ground	*Vaccinium species*	Total	User Accuracy (%)
Bracken	4						1	5	***80***
Recent burn		1						1	***100***
ET moor			4			1		5	***80***
Grass moor	2		2	4	7	2,2	1,0	20	***35***
Calluna vulgaris			2	1	32	4	1,0	40	***82.5***
Moss bare ground		1,0			1	8		10	***90***
Vaccinium species	1,1			1,1	2,5	1	5	17	***29.4***
Total	8	2	8	7	47	18	8	98	***Overall Accuracy (%)***
Producer Accuracy (%)	***62.5***	***100***	***50***	***71***	***72.3***	***55.6***	***87.5***		***68***

Note: Producer and user accuracies are calculated to incorporate both correct and acceptable classification outputs

To make an assessment of the partitioning of fuzzy membership grades the actual habitat proportion, as recorded by the field survey, was plotted against the fuzzy membership grade in the coincident pixel, this was repeated for each habitat (figure 7.4). The correlation coefficients between fuzzy membership grade and habitat top cover were derived for each habitat (table 7.5).

Table 7.5: Correlation coefficient between ground proportion and fuzzy membership grade for each habitat class.

Habitat/Species	Correlation Coefficient
Bracken	0.82
Calluna vulgaris	0.61
Vaccinium species	0.49
Recent burn	0.96
Moss/bare ground dominant	0.64
***Erica Tetralix* moor**	0.66
Grass dominant moor	0.33

On the basis of the scatter plots (figure 7.4) and correlation coefficient values (table 7.5) it was demonstrated that:

- Fuzzy membership values had a significant tendency to underestimate the ground proportion of the bracken and *Erica tetralix* moor habitats. This relationship was reversed for the grass moor habitat.
- Fuzzy membership values had increased error, in comparison to the field data, at low cover proportions. This insensitivity at low cover proportions was particularly evident for the *Vaccinium species,* grass moor and *Calluna vulgaris* habitats. The *Vaccinium species* and grass moor habitats illustrated a tendency to be overestimated by fuzzy membership grade at low cover proportions. This was attributed to the training of the classes on mixed, as opposed to pure samples; a consequence of the lower dominance thresholds applied. *Calluna vulgaris* was not recorded in the image at ground proportions less than 10%.

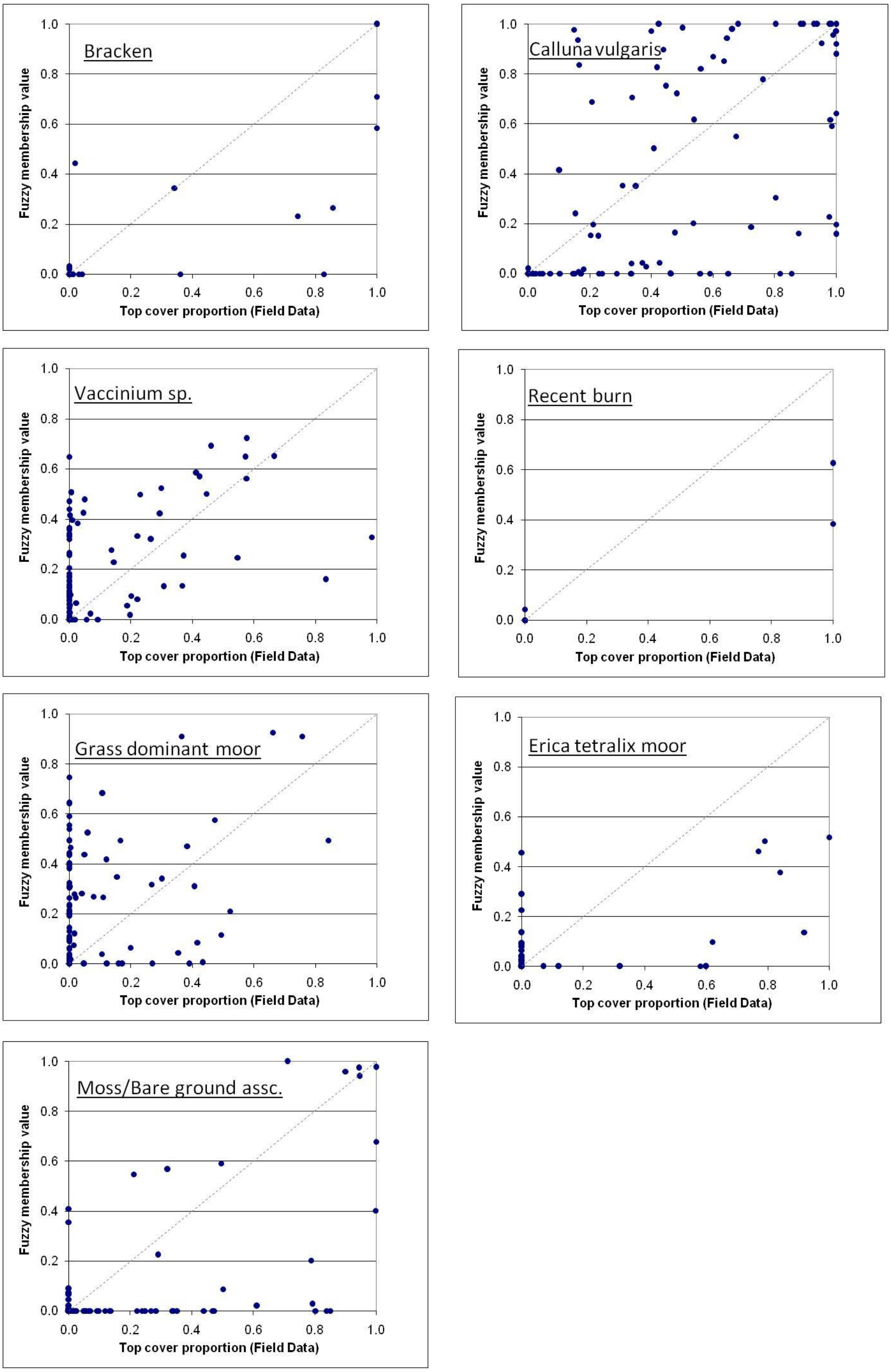


Figure 7.4: Scatter plots comparing habitat proportion derived from the field data and fuzzy membership grade for each habitat class.

- Membership grades for the moss/bare ground habitats consistently under-estimated cover proportions; this was evident at a range of cover proportions.
- Correlation coefficients were lowest for those classes trained on a low cover dominance threshold, for example, grass moor and *Vaccinium species.* Bracken and recent burn, which are the most spectrally distinct classes (table 7.2), had the highest correlation coefficient values (table 7.5). However, it should be noted that the correlation coefficients were influenced by the limited number of non-zero samples.

7.3.4 Sub-pixel classification conclusions

An assessment of habitat composition, irrespective of cover proportion or membership grade, demonstrated exact correspondence between the FUZCLASS algorithm and field survey data at only 5% of samples. However, at only 1% of samples was there no habitat correspondence. The inappropriate inclusion/exclusion of habitats at the remaining 94% of samples was indicative of significant multi-spectral confusion between classes. This was attributed to the limited training sample, low dominance thresholds applied and multi-spectral similarity of habitat classes.

Misclassification has been demonstrated to result in the overestimation of the *Vaccinium* species and grass moor classes where they occur at low cover proportions. Due to the methodological constraint that class proportions sum to 100% it was inherent that error in one component would impact upon remaining components (Lucas *et al*, 2002). Consequently, within the current sample, fuzzy membership grades were only weakly correlated to cover proportion.

This analysis has demonstrated the reliance of sub-pixel classification upon exclusive, exhaustive, spectrally distinct classes. This concurs with studies by Bastin, (1997); Foody, (1993); Metternicht & Fermont, (1995) and Lucas *et al*, (2002). Equally, the success of sub-pixel classification is related to the quality of end-member training data (Lucas *et al*, 2002; Wang, 1990). Insufficient 'pure' training samples of high dominance thresholds have been demonstrated to impact upon sub-pixel classification accuracy.

Further research

End-member selection: species versus habitats

A requirement of all sub-pixel classification techniques is that the constituent land cover classes (end-members) are spectrally separable (Bastin, 1997; Foody & Trodd, 1993; Metternicht & Fermont, 1995; Lucas et al, 2002). However, Townshend (2000) has noted that the definition of spectrally separable end-members is not easy and potentially impossible for complex, highly variable vegetation communities; community characteristics typical of the upland stratum.

The spatial and spectral resolution of SPOT 5 precludes the training, on 'pure' samples, of unique classes for each species or vegetation type. The appropriate agglomeration of species to spectrally separable habitats is therefore a fundamental element of further research.

Despite the inability of the current analysis to define spectrally separable species associations' the literature demonstrates the measurement of fine-scale upland habitat characteristics on the basis of remote sensing data (Mehner *et al*, 2004; Morton, 1986; Wardley *et al*, 1987; Weaver, 1987). Specific to sub-pixel applications spectrally separable habitats have been demonstrated by Foody and Trodd (1993) who demonstrated the spectral separability of wet and dry heath within a airborne thematic mapper image.

Sample design

The inclusion of poor quality and a limited number of training samples has been demonstrated to influence sub-pixel classification (Lucas *et al*, 2002; Wang, 1990). A significant limitation of the current point sampling frame was the limited number of 'pure' samples contained within the field data.

Modifications to the current sample design are required and must critically evaluate the advantages and disadvantages of an increased sample fraction and hence increased probability of ‘pure’ class examples (Buchanan *et al*, 2005), versus a targeted, transect sampling strategy (Foody, 1993).

Where insufficient ‘pure’ class examples exist in the sample fraction the potential of incorporating fuzziness into classifier training should be assessed (Foody, 1997; Wang, 1990). Such an approach would enable the incorporation of mixed pixels, of known cover proportions, into classifier training. Such a utility is provided via the FUZSIG module of IDRISI (Eastman, 2006).

Classification algorithm

Several studies have demonstrated that the most appropriate classification algorithm is likely to be application and data specific (Bastin, 1997; Foody & Trodd, 1993; Foody, 1996; Lucas *et al*, 2002). The current research was limited to a single sub-pixel classification algorithm due to a lack of appropriate training data. Consequently, in the event of an increased training data set, multiple sub-pixel algorithms should be tested. The importance of untrained classes within these classification algorithms is a fundamental concept of sub-pixel classification which should be fully explored.

7.4 Statistical parameterisation techniques

The remainder of this chapter considers alternative techniques which have the potential to characterise land cover attributes. These include statistical parameterisation techniques based on the derivation of a relationship to explain spatial variability in the land cover attribute.

7.4.1 Univariate estimation of the primary variable

Univariate approaches are based only on the variable of interest, the primary variable.

Interpolation and geostatistical techniques

Interpolation methods include a range of techniques where an estimate of the primary variable, at an unknown location, is derived from surrounding primary variable samples. Interpolation methods are extensive but can be broadly categorised as local/global, exact/approximate, gradual/abrupt and deterministic/stochastic (Heywood *et al*, 2002).

Deterministic methods of interpolation create a surface from a set of sample points on some degree of similarity (local interpolators) or smoothing approach (global). Objections to deterministic interpolation methods are firstly, the inability of the algorithms to determine the number of samples, shape, size and orientation of interpolation neighbourhoods required to produce an accurate estimate of the primary variable and secondly, a lack of error (uncertainty) estimates associated with the interpolated values (Burrough & McDonnell, 1998).

Geostatistics, stochastic interpolation techniques, differ from deterministic methods in that they recognise that variability in the primary attribute is often too complex or irregular to be modelled by a simple, smooth mathematical function (Burrough & McDonnell, 1998).

Kriging methods, a form of geostatistical analysis, are based on the theory of regionalised variables (Clark, 1982). Regionalised variable theory assumes that the spatial variation of a variable can be described via three elements: a structural component, having a constant mean or trend, a random but spatially correlated component and a spatial uncorrelated or residual noise component (Clark, 1982).The character of these spatially correlated elements is quantified via a semi-variogram. Once plotted a model is fitted to the semi-variogram. This model quantifies spatial autocorrelation in the data.

Parameters of the spatial autocorrelation model determine the calculation of the kriging weights and via the kriging equations the predicted value of the variable at the unsampled locations. Kriging equations are adapted from the standardised technique according to trends in the primary variable, the description of these trends and data format of the primary variable (Johnston *et al*, 2001). Kriging methods include ordinary, simple, universal, indicator, disjunctive and probability (Burrough & McDonnell, 1998).

The applicability of geostatistical techniques to species cover mapping has been demonstrated by Yallop (2002). Yallop (2002) investigated the role of sample lag size, neighbourhood inclusion and sample support size on the ordinary kriging model when mapping the cover proportion of a single salt marsh species (*Limonium vulgare*). This investigation demonstrated that the spatial resolution of sample points included in the kriging model should be approximately 5m. The applicability of the derived kriging model to map the cover proportion of a range of salt marsh species, sampled at 10m resolution, was subsequently demonstrated (Yallop, 2002).

Despite the success of previous studies (Yallop, 2002) univariate geostatistics were not recommended for the current research due to the required sample resolution. Yallop (2002) advocates a sample resolution of 10m or less. This differs significantly to the sample resolution of the field data which is at least 950m. This significant difference in sampling resolution can be attributed to the areal extent of each study. Within a 210km^2 study area, as exemplified by this research, a sampling resolution of 10m and resultant 2 million samples would severely impact the logistic viability of the current field survey design.

7.4.2 Accounting for a secondary variable

A second set of techniques can be defined in which improved estimates of the primary variable are inferred at unknown locations by inclusion of one or more secondary variables. This secondary variable can be a cheap to measure covariable, a variable which enables study area stratification or the output from a physical/empirical spatial model proven to be a driving process in the variability of the primary variable (Burrough & McDonnell, 1998).

In relation to the current research the secondary variable is considered to be a multi-spectral remote sensing image or spectral vegetation indices (SVI) such as NDVI. This remote sensing data represents a secondary variable which varies with habitat composition, is relatively cheap to measure and is known across the entire study area.

Linear regression

A straightforward approach is to model the relationship between the secondary and primary variables. Derivation of the primary variable is then based on the rescaling of the input surface, secondary variable, via the established relationship.

The most simplistic form of relationship model is a linear regression (equation 7.1). Development of this model requires measurement of the primary (p) and secondary (a) variables at the same spatial locations (x).

$$p(x_i) = \beta_0 + \beta_1 a_1(x_i) + \beta_2 a_2(x_i) \ldots \beta_x a_x(x_i) + \varepsilon \qquad \textbf{Equation 7.1}$$

Where the primary variable (p) and secondary variable (a) are both measured at the same location (x) β represents a coefficient of the model and ε the error term, calculated as the difference between the predicted and true value.

Source: Dungan, 1998

Remote sensing studies typically implement an ordinary least squared (OLS) approach to linear regression (equation 7.1) (Cohen *et al*, 2002). An assumption of OLS regression is that no measurement errors are contained in the primary or secondary variables and observations are independent; an invalid set of assumptions in many vegetation remote sensing applications (Cohen *et al*, 2002; Miller *et al*, 2007). To resolve issues regarding error in the primary and secondary variables several authors have proposed more complex regression relationships (Cho *et al*, 2007; Cohen *et al*, 2002; Curran & Hay, 1981; Fernandes & Leblanc, 2005). Increased regression complexity may result from improved regression models and/or the inclusion of additional secondary variables.

Except for the requirement that the primary and secondary variables are known at the same locations the regression approach is aspatial (Dungan, 1998). Consequently, sample point location and geometry is not considered in determination of the primary variable (Dungan, 1998; Goovaerts, 1999). Such an approach amounts to assuming that the primary variables are independent of each other (Goovaerts, 1999).

Foody (2004) evaluating the spatial dependency of species richness and temperature/precipitation/NDVI for sub-Saharan avifauna concluded that the relationship between the variables was spatially variable and scale dependent. Consequently, the average impression provided by the global model does not accurately represent local variability (Foody, 2004). This relationship variability, and spatial dependency concepts, can be incorporated into the regression relationship via geographically weighted regression (GWR).

GWR encompasses local variability in the relationship between regression variables creating models which vary spatially (Miller *et al*, 2007). In GWR, observations are weighted according to their proximity to the test location. This modelling approach is based on a moving kernel window technique (Fotheringham *et al*, 2000). Where the assumption of spatially stationarity is violated, a situation typical of vegetation parameters, GWR has been proven to produce significantly improved estimation accuracies (Kupfer & Farris, 2006; Propastin *et al*, 2006; Wang & Tenhunen, 2005).

Adapted kriging

Kriging techniques represent an alternative approach to linear regression. As standard kriging techniques are univariate the algorithms must therefore be adapted to account for a secondary variable. Several adapted kriging techniques are presented in the remote sensing literature including, stratified kriging (Goovaerts, 1999), simple kriging with varying local means (Goovaerts, 1998; 1999), kriging with external drift (Goovaerts, 1998; 1999), kriging combined with regression (Knotters *et al*, 1995) and cokriging (Angerer *et al*, 2004; Atkinson *et al*, 1992; Dungan, 1998; Dungan et al, 1999; Goovaerts, 1999; Wang *et al*, 2004). Of these techniques, cokriging was found to be the most reported.

Cokriging

Cokriging introduces one or more secondary variables into the kriging equations so that the cokriging estimate is a linear combination of neighbouring primary and secondary data. Cokriging minimises estimation error variance by exploiting cross-correlation between multiple variables (Isaaks & Srivastava, 1989). An assumption of cokriging is that variability in the spatial patterns of the primary and secondary variables are related (Dungan, 1998); in fact cokriging has been demonstrated to be most successful when the variables used are related by a common physical process (Burrough & McDonnell, 1998).

Cokriging analysis can be subdivided into three major processing steps: the independent determination of semi-variograms for the primary and secondary variables and the derivation of the cross covariance between the variables (Angerer *et al*, 2004). Derivation of the cross covariance enables an assessment of the dissimilarity of the data points according to the distance which separates them (Johnston *et al*, 2001). A requirement of cokriging is that the sample fraction contains sufficient collocated measurements, of the primary and secondary variables, to model the spatial covariance of each variable and cross covariance (Dungan, 1998). An advantage of remote sensing is the availability of a complete grid of ancillary data which allows for complete description of spatial autocorrelation in this variable (Dungan, 1998).

Various cokriging algorithms are available as a function of the form of the primary and secondary variables. Possible cokriging techniques include ordinary, simple, universal, indicator, probability, disjunctive, collocated and standardised (Burrough & McDonnell, 1998; Goovaerts, 1999; Wackernagel, 1998). Of particular interest to remote sensing studies are collocated and standardised kriging. Collocated cokriging equations are based on the definition of an economical neighbourhood when the secondary variable is available everywhere in the study area in comparison to a sparsely sampled primary variable (Wackernagel, 1998). Standardised cokriging rescales the secondary variable so that its mean is equal to that of the primary variable. This standardisation increases the contribution of the secondary variable and can prevent anomalous estimates (Goovaerts, 1999).

The applicability of cokriging techniques has been related to the strength of correlation between the primary and secondary variables. Dungan (1998) demonstrated that the inclusion of a secondary variable within linear regression or cokriging did not increase classification accuracy, over ordinary kriging, until the correlation coefficient between the variables was greater than 0.6. Equally, cokriging provided the most accurate solution until the correlation coefficient between the variables was greater than 0.89 when linear regression provided the most accurate output (Dungan, 1998).

Secondary variable conclusions

It is proposed that the inclusion of a secondary variable is a requirement of statistical techniques for land cover attribute parameterisation due to the scale of extrapolation.

Work in this field, both linear regression and geostatistics, has primarily focussed on the mapping of biophysical parameters. Consequently, site specific regression relationships are evident between pixel radiance, in various wavebands or vegetation indices, to biophysical parameters including biomass (Atkinson *et al*, 1994; Cho *et al*, 2007; Egan *et al*, 2000 Friedl *et al*, 1994; Hansen & Schjoerring, 2003; Phinn et al, 1996), leaf area index (Atkinson *et al*, 1994; Cabot *et al*, 1995; Chen & Chilar, 1996; Cohen *et al*, 2003; Wang *et al*, 2005) and canopy cover (Boyd *et al*, 2002; Cohen *et al*, 2003).

Despite the applicability of remote sensing data to cokriging studies they are less frequent particularly in relation to vegetative parameters (Atkinson *et al*, 1994). However, where correlation coefficients between variables are low, for example, in existing linear regression relationships, Dugan (1998) advocates the use of cokriging which has been demonstrated to improve predictions. This was confirmed by Atkinson *et al* (1994) in a comparison of the relationship between NDVI and green leaf area index for spring barley. The authors concluded that even though correlation between the variables was too low to allow regression, cokriging with remote sensing imagery was of value due to spatial cross correlation between the variables.

Further research

The ability of a secondary variable to improve predictions of the primary variable is dependent upon the definition of appropriate secondary variables which are proven to co-vary with or be related to the primary variable. Ideally, these secondary variables should be easier and cheaper to measure than the primary variable and be known at a greater number of locations.

Secondly, the inclusion of spatial dependency (geostatistics) as a predictive tool depends on whether:

- There is a spatial dependency in the distribution of the vegetation.
- The primary variable sampling interval and intensity are appropriate in relation to the scale of the spatial dependency (Miller *et al*, 2007).

Semi-natural habitats

A significant proportion of the studies outlined have considered a single crop (Hansen & Schjoerring, 2003) or woodland stands (Chen & Chilar, 1996; Wang *et al*, 2005). The applicability of the techniques to multiple, detailed vegetative classes and semi-natural vegetation which is characterised by a complex reflective response (Armitage *et al*, 2000) therefore requires further testing.

Sample design, observation scale

Methods based on spatial dependency (geostatistics) are sensitive to the scale of observations and remote sensing data. Biotic processes which influence vegetation composition/cover but occur at the scale similar to or less than the spatial coverage of a sample point will not be detectable (Miller *et al*, 2007). Equally, the sampling interval must be related to spatial dependency in the primary variable. A sampling interval which is too small will result in too many observations. However, a sampling interval which is too large will result in observations with no detectable spatial dependence (Miller *et al*, 2007).

Geostatistical techniques were excluded from the current analysis as it was concluded that the current sample frame interval did not incorporate spatial dependency. Due to the large sampling interval, samples closer together did not have an increased probability of being similar. Modifications to the sample frame interval and the analysis of spatial dependency relationships between upland species are therefore required as the basis of any further research.

7.5 Other techniques

The current review is not exhaustive as a broad range of techniques exist which are potentially applicable to this mapping approach. Perhaps the most relevant of these techniques are ANNs. The applicability of ANNs to sub-pixel land cover mapping has previously been demonstrated by Atkinson *et al* (1997). Atkinson *et al* (1997) compare the ANN, fuzzy c-means and linear mixture modelling algorithms in a land cover classification of NOAA-AVHRR imagery. Of the classification algorithms considered the ANN was demonstrated to be the most accurate and least sensitive to the number of land cover classes defined (Atkinson *et al*, 1997). This study considered land cover class, as opposed to land cover attributes, and is applied at a significantly greater spatial resolution (1.1km pixels) than the current study. However, Mills *et al* (2006) have demonstrated the applicability of ANNs to high spatial resolution imagery.

Mills *et al* (2006) investigate the applicability of ANNs to classify sub-pixel 'upland' land cover composition on the basis of IKONOS imagery (4m pixels). The authors conclude that the ANN algorithm results in classification accuracies higher than those of traditional classification methods (Mills *et al*, 2006). However, due to the high spectral variability of the land cover classes, particularly within the high spatial resolution IKONOS data, the ANN performed unsuccessfully when applied to regions outside the training data area (Mills *et al*, 2006). This study highlights the potential of ANNs within land cover composition mapping, however, it also highlights current limitations of ANNs as regards training data requirements and training complexity. It is in the context of these exemplified studies and existing literature (for example, Civico, 1993; Paruelo & Tomasel, 1997) that further research into the ability of ANNs to characterise land cover attributes from medium resolution remote sensing imagery is proposed.

7.6 Chapter summary

The key points of this chapter are:

- The mapping of land cover attributes, as opposed to land cover class, is advocated as it retains small scale variability and detail regarding vegetation composition. This enables detailed landscape management and flexibility in the definition of land cover classes.
- Analysis was conducted to exemplify fuzzy classification techniques to the mapping of species top cover in the upland stratum. On the basis of the current data it was demonstrated that:
    - Sub-pixel classification is reliant upon the definition of spectrally distinct land cover classes. Equally, sufficient 'pure' class samples are required to ensure accurate classification.
    - At the resolution of the current data each species or plant group, as recorded by the field survey, could not be trained as an independent class. Therefore, cluster analysis techniques were used to define common species associations or habitats.

    - The resultant habitats were not spectrally distinct as a consequence of the limited sample set, low dominance thresholds applied and habitat definitions which contained similar species.
    - Multi-spectral confusion resulted in the inaccurate identification of habitat composition and habitat proportions being weakly correlated to membership grade.
- Development of sub-pixel techniques within this method requires research into:
    - End-member selection and the definition of spectrally distinct species associations.
    - An appropriate sample design to ensure a high proportion of 'pure' class examples.
    - Alternative classification algorithms including the derivation of absolute rather than relative membership grades.
- While univariate statistical techniques have been demonstrated in small scale vegetation studies it is proposed that they are inappropriate at the current scale of analysis.
- Multivariate statistical techniques represent a potential classification technique.
- The development of multivariate techniques to map land cover attributes requires research into:
    - The correlation between land cover attributes and remote sensing variables within semi-natural habitats.
    - Determination of the spatial dependency of variables.
    - Definition of an appropriate sample plot size and sampling interval to incorporate spatial dependency into the sample design while still ensuring a design which is logistically viable.

Conclusions and Implications

This final chapter draws together the key findings of the current research into land cover mapping. The methodologies developed are discussed with reference to the research aim and novel aspects of the research identified.

In addition to key findings, the chapter considers the implications of the research to the operational use of land cover maps within the NYMNPA. The advantages of the land cover attribute approach within an operational context and potential barriers to uptake are considered.

Finally, the implications of novel aspects of this research to the wider remote sensing community are discussed. The applicability and transferability of the land cover attribute approach to future local, regional and national remote sensing projects is examined.

8.1 Key findings

Traditionally land cover surveys have required the delineation and classification of vegetation assemblies in the field, to represent homogenous land cover classes. This approach to field survey has been proven to be subjective, inconsistent and error prone (Cherrill & McClean, 1999). To improve the objectivity, repeatability and consistency with which land cover surveys are conducted it is proposed that field survey measurements should be reduced to the recording of easily identified parameters within objective measurement techniques. Consequently, this research has developed a disaggregated, novel approach to field survey based upon land cover attributes; the parameters typically used to delineate land cover classes.

Within the current research land cover attributes were extracted from existing land cover definitions to ensure compatibility between the field survey measurements and target classification schemes. To minimise the field survey effort a subset of five botanical attributes were recorded during the field survey: species composition, top cover, height, structure and density. Remaining attributes were excluded from the field survey as suitable ancillary data surrogates could be identified.

The measurement techniques implemented were developed and tested via a pilot study to ensure objective, repeatable measurements. It was concluded that each attribute should be recorded within a 1m x 1m quadrat. However, four quadrats were included at each sample location to ensure measurements were representative of the sample site and equivalent to the dimensions of a SPOT5 pixel.

A within quadrat point sampling frame was identified as the best method to collect the required quadrat based measurements. Research conducted by Armstrong (1998), Dungan and Coughlan (1999) and Webster and Oliver (2001) concluded that a systematic sampling frame was most applicable to the remote sensing techniques proposed in the current research. However, concerns regarding the representativeness and logistic viability of the design were highlighted (Kent & Corker, 1992). A comparison of clustered and systematic point sampling frames demonstrated that, within the study area, the systematic sample design was representative, in terms of the land cover sampled, and logistically viable at the current sampling fraction.

The recording of land cover attributes is advantageous as it enables the subsequent derivation of a land cover class on the basis of objective parameters and thresholds. This ensures a classification procedure which is objective, transparent and open to retrospective analysis. The applicability of land cover attributes to act as building blocks for the derivation of land cover class has been demonstrated via classification of the field survey samples to the MLCNP, NLUD and P1 classification schemes. This construction was possible due to the pre-defined association between the land cover attributes and target classification schemes. The accuracy achieved in classifying the land cover attributes could not be determined in the current research, due to the lack of a suitable reference dataset. Proposed further research would collocate the measurement of land cover class and land cover attributes to validate the consistency and accuracy with which classification rules, target species and thresholds could be defined.

Integration of the classified field survey, remote sensing and ancillary datasets to construct MLCNP, NLUD and P1 land cover maps has been demonstrated using a per-pixel ML algorithm. Within the current research, classification accuracies, independent of ancillary data inclusion, of 81%, 80% and 76% have been demonstrated for the MLCNP, NLUD and P1 classification schemes, respectively. However, the same classifications are significantly less accurate at the validation samples which achieve accuracies of only 52%, 59% and 45%, respectively. These significant accuracy differences have been demonstrated to be a function of a small sample fraction which was not representative of the study area. Consequently, a requirement for an increased training and validation sample fraction has been proven.

Object-orientated classification techniques have been demonstrated as an alternative means of representing the landscape within the land cover map construction methodology. Derivation of the MLCNP land cover map, for a subset area, indicated that classification accuracies approaching 75% could be achieved, at three segmentation scales, using this approach. A relationship between classification accuracy, segmentation scale and land cover characteristics has been identified. Consequently, further research is required to identify the optimum scale of image object definition within each land cover type.

A conclusion which can be drawn from this research is that the separation of the per-pixel and object-orientated classification techniques is too simplistic an approach for land cover map construction. Consequently, a hybrid approach which combines pixels and objects at multiple classification scales should be investigated. Secondly, classification within a classification hierarchy, as opposed to a mathematical algorithm, should be examined. It is argued that this hierarchy will enable the inclusion of more complex classification concepts including: multi-temporal images which encompass the distinct seasonal characteristics of individual land covers; additional ancillary datasets including, for example, soil, geology and climate; contextual information in the form of topographic relationships and surface texture. The advantages of a multi-scaled, hierarchical classification approach have been demonstrated by Lucas *et al* (2007).

Further research, as outlined in sections 6.3.5 and 6.4.5, is required to validate and develop the land cover construction methodology into an operational procedure. However, this research has demonstrated the validity of this methodology for the mapping of land cover attributes. The method is considered advantageous, in comparison to standard land cover mapping techniques, as it:

- Enables the derivation of land cover class on the basis of discrete attributes, removing subjectivity in land cover class delineation.
- Provides flexibility in land cover class definition subsequent to field survey. Land cover attributes are not tied to any particular land cover scheme consequently, land cover definitions can be modified from existing schema or designed to meet user specific applications. The only limitation is that definitions are based on the attributes collected.
- Is efficient in terms of field survey effort as multiple land cover maps can be derived from a single set of field data.
- Enables the independent classification of multiple land cover schemes eliminating any dependence on the conversion of maps, between classification schemes, using semantic relationships.

Despite these advantages the construction methodology outlined represents the subdivision of the landscape into discrete, homogenous land cover parcels. It is in this subdivision and reliance upon standard classification techniques that the construction methodology suffers from the same limitations and issues as standard land cover maps. Of particular relevance are:

- The assumption that each mapped entity contains a single land cover class.
- The definition of discrete land cover classes which change at hard boundaries. Consequently, the intergrading of species and associated small scale variability in vegetation composition are not considered.

- The assumption of the classification algorithms that land cover classes are spectrally distinct and relatively homogenous. Where land cover classes are defined on the basis of small scale variability, management regime and landscape characteristics, as opposed to their spectral reflectance characteristics, this assumption is unlikely to be valid resulting in misclassification.

- The aggregation of the detailed field data to represent land cover classes. Such an aggregation underutilises the potential of remote sensing data to describe detailed landscape variability, mosaics and gradients.

These disadvantages have the potential to limit the applicability of the resultant land cover maps to landscape management and monitoring within the user community. Consequently, an alternative classification approach in which the land cover attributes are parameterised across the entire study area has been considered. Land cover attribute parameterisation represents the 'ideal' approach to land cover mapping in terms of providing a flexible mapping solution. Flexibility in the mapping approach results from retention of the disaggregated field survey data, this is advantageous as it:

- Retains small scale variability and detail regarding vegetation composition lost at the resolution of land cover classes.

- Enables subsequent derivation of land cover classes, if required, within a GIS. This GIS provides an environment for the combination and delineation of the continuous parameters into land cover classes. Such an approach ensures no observer bias or subjectivity and offers flexibility in land cover class definition.

The applicability of sub-pixel classification and geostatistical techniques to the parameterisation of land cover attributes, in particular top cover, has been reviewed. The methodologies were further exemplified by a sub-pixel classification of the upland stratum.

From this, it can be concluded that the definition of spectrally separable species/habitats is fundamental to the advancement of this classification methodology. The accurate identification of all vegetation to the species level is unlikely to be achieved with medium spatial/spectral resolution sensors. It is in this context, as exemplified in the current research, that spectrally separable habitats must be defined. This definition is complex and forms the basis of proposed further research (section 7.3.4).

The inclusion of the current field data within two distinct classification methodologies demonstrates the flexibility of the land cover attribute approach. Based on data from a single field survey land cover classification has been achieved at multiple classification scales, i.e. sub-pixel, pixel and object, and in relation to multiple classification schema. This multi-scaled approach has the potential to:

- Allow the differential treatment of areas within the remote sensing image as a function of landscape characteristics.
- Provide flexibility in terms of the land cover classification scheme and classification scale applied thus ensuring a land cover product which better meets the users' requirements.

It is these criteria which enable the approach outlined to tackle the issues of inappropriate scales, inappropriate schema, consistency and boundary delineation identified within current land cover mapping approaches (section 1.3).

8.2 Research implications

8.2.1 User community

Land cover maps form an integral part in managing and monitoring the vegetative resource of the NYMNP (section 2.2.1). A mapping approach based on the recording of land cover attributes is advantageous, in the context of these objectives, as it enables flexibility in the mapping approach in terms of both land cover class definition and classification scale. This flexibility enables the user to tailor the classified output to their specific management requirements. This flexibility in approach is exemplified by:

- A multi-scaled land cover map in which variable levels of detail are mapped as a function of the landscape characteristics and mapping emphasis. For example, within studies of upland habitat condition detailed species composition information can be retained in the upland areas, within the limitations of the parameterisation methodology. Conversely, the lowland areas, where potentially less detail is required, can be mapped as broad land cover classes within an object-orientated approach.

- The definition of user specified land cover classes thus enabling the creation of land cover maps which implement the same class definitions as existing surveys, for example, P1 or MLCNP, and ensuring compatibility in analysis.

The fundamental advantage of the land cover attribute approach is the provision of this mapping flexibility from a single field survey. It should also be noted that this detailed field survey also provides an objective, baseline dataset of vegetation composition, at the sample sites, for longitudinal studies.

Despite the demonstrated advantages of the land cover attribute approach, within the NYMNP, potential barriers to the uptake of the methodology can be identified. Of particular importance are:

The measurement intensity

As stated previously the fundamental advantage of land cover attributes is the flexibility in mapping provided by a single field survey. However, the objective measurement of attributes is resource intensive in comparison to traditional land cover survey approaches. Successful implementation of an operational land cover attribute survey within the entire National Park is, it is proposed, reliant upon the integration of the survey protocol within standard vegetation monitoring activities of the NYMNPA, for example, the upland heath habitat surveys.

The definition of spectrally distinct land cover classes

Botanical land cover attributes formed the basis of this research to ensure compatibility with current land cover mapping classification schemes. These attributes were therefore not defined on the basis of their multi-spectral properties and cannot be considered discrete remote sensing elements. Consequently, a fundamental requirement of the classification methodologies is that land cover attributes are aggregated to represent spectrally distinct land cover classes. This requirement may necessitate a compromise between the users 'ideal' classification scheme and definition of land cover classes detectable at the current spatial and spectral resolution of the remote sensing data.

Classification accuracy

Remote sensing applications typically aim to achieve overall classification accuracies approaching 80% (Mather, 1999b). Such accuracies have been achieved within the current research. A stated accuracy of 80% may seem insufficient for many applications within the NYMNP limiting uptake of the land cover map. In resolving this barrier there is a requirement to put this accuracy into context with the currently used land cover maps of the area. For example, Cherrill and McClean (1999) have demonstrated surveyor subjectivity and the potential for mapping errors within P1 habitat surveys. Within field surveys it is not uncommon for accuracies to be unstated, typically due to the lack of an appropriate reference. However, remote sensing surveys tend to be explicit in the accuracy achieved. This can lead to an inappropriate assumption that remote sensing surveys are of low accuracy and not suitable for the intended application.

Interpretation and analysis of the classified land cover map.

The operational use of land cover maps resulting from the classification methodologies must consider the implications of the stated accuracies and classification techniques implemented upon subsequent analysis and interpretation. This care of interpretation is particularly relevant where classes represent a mixture of land cover classes as a consequence of multi-spectral similarity or mixed pixels.

This need for appropriate analysis is exemplified by consideration of the NYMNP Management Plan objective that the spatial extent of habitats be routinely monitored (NYMNP, 1998b). While products resulting from the current methodologies are able to respond to this objective the analysis must consider the input data. The creation of an updated P1 habitat map has been demonstrated within the current analysis. However, this map should not be considered directly comparable to current P1 habitat mapping due to the different accuracies and survey methodologies employed in deriving these products. Consequently, the maps should not be compared spatially, via thematic overlay processes, to identify areas of land cover change.

On the basis of these observations it can be concluded that the successful implementation of the land cover attribute methodology requires management of the users' expectations in terms of their requirements and the levels of mapping achievable within a remote sensing context.

8.2.2 Remote sensing community

Following Friedl *et al* (2001) current ecological remote sensing techniques can be split into two branches, the mapping of discrete vegetation habitats and the mapping of land surface bio-physical parameters. It is proposed that within the remote sensing community the measurement of land cover attributes, during field survey, has traditionally been associated with the second of these branches, the mapping of land surface bio-physical parameters. This research has demonstrated that the recording of land cover attributes is equally applicable to the first of these branches; the mapping of discrete vegetation habitats.

It is proposed that the attribute approach to land cover survey should be adopted more widely within the remote sensing community as firstly, it ensures the measurement of objective parameters removing the emphasis of subjective decision making from the field surveyor and secondly, it provides a flexible reference database. The flexibility of this reference database has been demonstrated via integration of the land cover attributes and remote sensing data within multiple classification schemes and at multiple classification scales.

Widespread adoption of the land cover attribute approach will ultimately be determined by the transferability of the methodology, which was developed in a relatively small study area and on a limited number of sampled land cover types, to larger/alternative regions. The transferability of the approach, for example in the context of a national land cover mapping approach, is proposed to be a function of:

Extension of the field survey protocol

Extension of the land cover attribute approach requires the field survey protocol to encompass a greater variability of land covers and vegetative species, for example, the inclusion of woodland samples will introduce large shrub and tree species. The 1m x 1m quadrat, as implemented in the current field survey, is designed for small shrub and grass species. Consequently, it is not a viable technique for the measurement of land cover attributes within, for example, woodland or scrub.

Further research is therefore required to determine the most appropriate data collection methods for the quantification of land cover attributes within diverse landscapes. Fundamental to this research is the definition of a field survey protocol which ensures consistency and ease of use while being able to measure species characterised by highly distinct structures and scales of variability. In such circumstances a modifiable field survey protocol, similar to the extended window of observation applied within the LUCAS survey (Bertin *et al*, 2003), is proposed.

Sample fraction and logistic viability

Application of the land cover attribute approach is reliant upon the definition of a representative sample fraction which retains its logistic viability. The current research has demonstrated that, in certain circumstances, the systematic sampling grid is logistically viable. It was concluded that this logistic viability was a function of the high proportion of access routes intersecting the region. Further research into the transferability of a systematic sample design, in terms of its logistic viability at an improved sample fraction, within differing landscapes is required.

In conclusion, this research has proven that the measurement of land cover attributes is a viable approach to land cover survey. Land cover attributes have been demonstrated to provide a flexible reference dataset which supports the integration of remote sensing data at a variety of scales, i.e. sub-pixel, pixel and object, and within multiple classification schemes.

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Land Cover Classification Scheme Descriptions

This appendix outlines the schema and land cover class definitions of the CORINE, Land Cover Map 2000, Monitoring Landscape Change in the National Parks, National Land Use Database and Phase 1 Habitat Survey classification schemes.

CORINE

1. Artificial Surface		
Urban fabric	Continuous urban fabric Discontinuous urban fabric	1.1.1 1.1.2
Industrial, commercial, transport	Industrial or commercial units Roads/railways and associated land Sea ports Airports	1.2.1 1.2.2 1.2.3 1.2.4
Mines, dumps and construction site	Mineral extraction sites Dumps Construction sites	1.3.1 1.3.2 1.3.3
Artificial non-agricultural vegetated surfaces	Green urban areas Sport and leisure facilities	1.4.1 1.4.2
2. Agriculture		
Arable land	Non-irrigated arable land Permanently irrigated land Rice fields	2.1.1 2.1.2 2.1.3
Permanent crops	Vineyards Fruit trees and berry plantations Olive groves	2.2.1 2.2.2 2.2.3
Pastures	Pastures	2.3.1
Heterogeneous agriculture	Annual crops with permanent crops Complex cultivation patterns (arable-pasture mix) Principally agriculture with significant natural vegetation Agro-forestry areas	2.4.1 2.4.2 2.4.3 2.4.4
3. Forest and semi-natural areas		
Forests	Broadleaved forest Coniferous forest Mixed woodland	3.1.1 3.1.2 3.1.3
Scrub or herbaceous vegetation	Natural grassland Moors and heathlands Sclerophylous vegetation Traditional woodland – scrub	3.2.1 3.2.2 3.2.3 3.2.4
Open spaces; little or no vegetation	Beaches and dunes Bare rock Sparsely vegetated areas Burnt areas Glaciers and perpetual snow	3.3.1 3.3.2 3.3.3 3.3.4 3.3.5
4. Wetlands		
Inland wetlands	Inland marshes Peat bog	4.1.1 4.1.2
Coastal wetlands	Salt marshes Salines Intertidal flats	4.2.1 4.2.2 4.2.3
5. Water bodies		
Continental waters	Water courses Water bodies	5.1.1 5.1.2
Marine waters	Coastal lagoons Estuaries Sea and ocean	5.2.1 5.2.2 5.2.3

Adapted from: Bossard et al (2000)

LAND COVER MAP 2000 (LCM2000)

BH	LCM Target class	LCM Subclasses	Variants
22. Inshore sublittoral	Sea / Estuary	Sea / Estuary	sea
13. Standing water/canals	Water (inland)	Water (inland)	water (inland)
20. Littoral rock	Littoral rock and sediment	Littoral rock	rock, rock with algae
21. Littoral sediment		Littoral sediment	mud, sand, sand/mud with algae
		Saltmarsh	saltmarsh, saltmarsh (grazed)
18. Supra-littoral rock	Supra-littoral rock and sediment	Supra-littoral rock	rock
19. Supra-littoral sediment		Supra-littoral sediment	shingle, shingle (vegetated), dune, dune shrubs
12. Bogs	Bogs (deep peat)	Bogs (deep peat)	bog: shrub, grass/shrub, undifferentiated (all on deep peat)
10. Dwarf shrub heath	Dwarf shrub heath (wet / dry)	Dense dwarf shrub heath	dense ericaceous, gorse
		Open dwarf shrub heath	open ericaceous
15. Montane habitats	Montane habitats	Montane habitats	montane
1. Broad-leaved woodland	Broad-leaved wood	Broad-leaved / mixed woodland	deciduous, mixed, open birch, scrub
2. Coniferous woodland	Coniferous woodland	Coniferous woodland	conifers, felled, new plantation
4. Arable & horticultural	Arable and horticultural	Arable cereals	barley, maize, oats, wheat, cereal (spring), cereal (winter),
		Arable horticulture	arable bare ground, carrots, field beans, horticulture, linseed, potatoes, peas, oilseed rape, sugar beet, mustard, non-cereal (spring), unknown
		Non-rotational horticulture	orchard, arable grass (ley), setaside (bare), setaside (undifferentiated)
5. Improved grassland	Improved grassland	Improved grassland	intensive, grass (hay/ silage cut), grazing marsh
	Neutral / calcareous semi-natural / rough grasslands	Setaside grass	grass setaside
6. Neutral		Neutral grass	rough grass (unmanaged), grass (neutral / unimproved)
7. Calcareous		Calcareous grass	calcareous (managed), calcareous (rough)
8. Acid	Acid grass and bracken	Acid grass	acid, acid (rough), acid with Juncus, acid with *Nardus/Festuca/Molinia*
9. Bracken		Bracken	bracken
11. Fen, marsh and swamp	Fen, marsh and swamp	Fen, marsh, swamp	swamp, fen/marsh, fen willow
17. Built up areas, gardens	Suburban and urban	Suburban/rural developed	suburban/rural developed
		Continuous Urban	urban residential/commercial, urban industrial
16. Inland rock	Inland Bare Ground	Inland Bare Ground	despoiled, semi-natural
20 relevant BHs	16 target classes	26 target/subclasses	72 target/subclasses/variants

Source: Fuller et al (2002)

MONITORING LANDSCAPE CHANGE IN THE NATIONAL PARKS (MLCNP)

Woodland and forests		
Broadleaved high forest	**C1**	Area greater than 0.25 hectares, wider than 20metres and having a tree canopy of at least 20 per cent by area. At least 80 per cent of the canopy should be of broadleaved species.
Coniferous high forest	**C2**	Areas greater than 0.25 hectares, wider that 20 metres and having a tree canopy cover of at least 20 per cent. At least 80 per cent of the canopy should be of coniferous species.
Mixed high forest	**C3**	Areas greater than 0.25 hectares that are wider than 20 metres and have a tree canopy of at least 20 per cent by area. Composed of an intimate mixture of broadleaved and coniferous species where the minority group comprise more than 20 per cent.
Scrub	**C4**	Areas with diffuse boundaries with less than 20 per cent cover by area of mature timber species with a rough understory of shrubs and grasses. Tress such as birch, alder, willow and hazel must be less than 3.5 metres high, although shrubs such as Blackthorn and Hawthorn may be higher.
Clear felled/new plantings in forest areas	**C5**	Areas with distinct boundaries, generally integral with stands of high forest that have recently been felled or planted. Evidence of logging, rowing up of trash and drainage may be present.
Moor and heath		
Upland heath	**D1**	Areas with greater than 80 per cent cover of heather and/or bilberry species. Characteristically found on acid heathland soils, steep rocky hillsides and crags, and peat covered moorlands, this type may be burned in patches or strips for grouse moor. Areas that have been burnt, but which it can be assumed will regenerate as heath, are included.
Upland grass moor	**D2**	Unenclosed upland areas with greater than 80 per cent cover of grass species. Two sub categories are identified:
Grass moor *Blanket peat grass moor*	*D2a* *D2b*	Which may include fescues, bents, purple moor grass and matt grass. Overlaying a peat substrate, usually found on plateaux, dominated by cotton-grass. These areas are in general unenclosed for the purpose of controlling livestock grazing, although property boundaries around large areas may be present.
Bracken	**D3**	Areas having at least an 80 per cent cover of bracken, which is an invasive species characteristically found on steep slopes extending along valley sides. Bracken is very variable in appearance depending on the time of year. Up to June it is identifiable from the presence of last year's residue of dead plant material, having a characteristic russet-brown colour. After June it appears green and bushy.
Unenclosed lowland areas	**D4**	Lowland areas that are not enclosed for stock control purposes. Two sub-categories are identified:
Rough grassland *Heath*	*D4a* *D4b*	Unenclosed lowland areas dominated by grass species Unenclosed lowland areas dominated by mixed heath species e.g. gorse.

Upland mosaics	**D6**	Areas of transition between upland heath (D1) and other moor and heath categories. Three sub categories are identified:
Heath/upland grass moor *Heath/bracken* *Heath/blanket peat grassland*	*D6a* *D6b* *D6c*	The boundary with heath will be drawn where heath species comprise 80 per cent of the cover and with the other categories where they in turn constitute more than 80 per cent of the cover.
Eroded areas	**D7**	Two sub-categories are identified:
Areas of eroding peat *Areas of eroding mineral soils*	*D7a* *D7b*	In upland situations where bare peat is the dominant cover type, or where there is heavy dissection by eroding channels to give a mosaic appearance. The associated cover types are variable.
Coastal heath	**D8**	Areas of mixed heath species along coastal slopes and exposed headlands. The lower limits of coastal heath are G2b or G3 categories, or the sea. The upper limits are C and E categories or when the change to D1 can be interpreted. The upper limits may be somewhat subjective in the transition to D1.
Agro-pastoral land (enclosed farmland)		
Cultivated land	**E1**	Areas of ploughed and cropped land, including cereals, ley grasses, legumes, field vegetables, potatoes and root crops, rape and fodder crops. The category also covers market gardens, orchards, etc. Ley grasses are difficult to discern and impossible after the first year when they will be classified as E2a (improved pasture). They are indicated by drilling rows, uniformity of species composition and are usually to be found in situations where there is arable cropping.
Grassland	**E2**	Areas that show evidence of being enclosed for stock control purposes. Two sub-categories are identified.
Improved pasture *Rough pasture*	*E2a* *E2b*	Grassland that is intensively managed for grazing and/or fodder production. Characterised by significantly modified swards produced by the use of fertilisers, herbicides, drainage and/or occasional reseeding. Species such as rushes, thistles and bracken are normally eradicated but could be present in small quantities. However, daisies, buttercups etc, may be present. It does not cover grass leys and generally occurs with the limits of mechanical operations. The sward may be lumpy due to uneven fertilisation from cow pats and may have artificial boundaries caused by strip grazing. From spring to late summer cutting for hay or silage may occur. Enclosed areas subject to little or no management, Characterised by a high density of native grasses and often containing invasive species such as bracken, bramble, thistle, rushes and scattered trees. Tussocks may also be evident. Generally occurs on steep slopes, poorly drained sites and soils of low fertility. Frequently includes area that can be accessed by farm machinery, indicating that it may have been managed in the past. Both categories can and do exist within the same field and in such cases they are separated.

Water and wetland		
Open water, coastal	**F1**	The boundary of this category will be taken as the mean low water mark. If photography coincides with high tide the area between the low tide mark and the water boundary on the photography will be mapped as F1.
Open water. inland	**F2**	Natural and man-made water bodies greater than 0.25 hectares in extent, this category does not include rivers.
Wetland vegetation	**F3**	Areas of vegetation that are controlled by the permanent or frequent periodic presence of water. Three sub-categories are identified.
Peat bog *Freshwater marsh* *Salt marsh*	*F3a* *F3b* *F3c*	
Rock and coastal land		
Bare rock	**G2**	Any significant areas of bare rocks, such as scree, cliffs and limestone pavements. Only the plan area is mapped, so large but near-vertical cliffs may cover a small area when mapped, or even be missed. The sub-categories are:
Inland bare rock *Coastal bare rock*	*G2a* *G2b*	 When it is sea cliffs or rock exposed to coastal erosion
Other coastal features	**G3**	This category includes a variety of coastal features. These may not be mapped if photography coincides with high tide. As in the case of category F1, the solution will be map areas visible on the photography and to subsequently interpret changes with caution, depending on the tidal state of the two sets of photography. The sub-categories are:
Dunes *Sand beach* *Shingle beach* *Mudflats*	*G3a* *G3b* *G3c* *G3d*	

Developed land		
Built-up land	**H1**	Two sub-categories are identified.
Urban land	*H1a*	Areas of buildings, including gardens, car parks, etc, and urban open spaces such as parks, playing fields, etc. Any settlement consisting of more than one group of buildings will be included.
Major transport routes	*H1b*	Transport routes that cover a significant area, defined as multi-carriageways roads, functioning multi-track railways, railyards, and airports. Grass verges obviously associated with the transport routes are included.
Quarries, working and derelict land	**H2**	Two sub-categories are identified
Quarries and mineral workings	*H2a*	Where these are active and still in regular use.
Derelict land	*H2b*	Disused quarries and mineral workings, and other significantly disturbed land that would need reclamation before it could be used.
Isolated rural developments	**H3**	Developments consisting of only one group of buildings but covering an area greater than 0.25 hectares. Two sub-categories are identified:
Farmsteads	*H3a*	A farmhouse and associated farm buildings
Other	*H3b*	Any other type of isolated rural development e.g. garages and public houses etc.
Unclassified land	**I**	Areas that cannot be legitimately included in any other category e.g. rivers or areas that cannot be reliably identified on the photographs due to cloud, shadow, military restrictions, lack of photographic coverage etc.

Notes: The nomenclature implemented for the upland grass moor sub-classes differs to that of the final MLCNP project. The final MLCNP project implemented the following class nomenclature: Upland grass moor – D2b and Blanket peat grass moor – D2d.

Source: Taylor et al (1991a)

NATIONAL LAND USE DATABASE (NLUD)

Cropped land (CO10)		
Field crops	**CO11**	Land under annual tillage including cereals, brassicas, root crops, legumes and other non-horticultural field crops (i.e. linseed, sunflower). Includes land ploughed in readiness for sowing
Fallow land	**CO12**	Land left untilled or unsown. Includes fallow land unused as part of agricultural rotation. Agricultural land for which there is no obvious intended change of use, but where the former use has been temporarily neglected (for up to 3 years)
Horticulture	**CO13**	Small plots of widely differing crop types within a small area, often several crops within one field e.g. soft fields (e.g. currants, blackberries, raspberries), vegetables, vineyards, hops, flowers. Includes crops grown under cloches, low plastic tunnels and greenhouses. Excludes cabbage, potatoes, sugar beet and legumes classified as field crops (CO11).
Orchards	**CO14**	Areas with planted trees which are, or have been, used for the harvesting of tree fruit crops. Often forming a distinctive block and displaying a highly organised (often grid) pattern of planting. Includes trees and shrubs grown as nursery stock for transplanting.
Grass (CO20)		
Improved grass	**CO21**	Areas of intensively managed grass that show evidence of enclosure for stock control purposes and/or use for fodder/hay, and evidence of improvement by use of fertilisers, pesticides, drainage or re-seeding, usually being dominated by a single grass species. Species such as rushes, thistles and bracken are normally eradicated. Include recently sown grass leys within the last five years at most, characterised by evidence of ploughing and bare soil between grass plants.
Unimproved grass	**CO22**	Areas of unimproved and natural grass which have not undergone agricultural improvement by way of application of fertilisers, pesticides, drainage or reseeding so as to significantly alter the sward composition although may be subject to intermittent grazing. May be enclosed or unenclosed and may occur in both lowland and upland settings. In upland areas includes semi-natural ‘downland’ grass and coarse ‘moorland’ and mountain grass.
Recreational and amenity grass	**CO23**	Areas of recreational and amenity grass e.g. parks, grassed surfaces, large lawns, playing fields, golf courses. Areas of non-agricultural mown grass e.g. airfields, race courses, gallops and grassed campsites and caravan parks.

Woodland and shrub (CO30)		
		Woodland is defined as an area of trees, where a tree is a woody species capable of achieving >5m in height and 25% canopy cover under favourable growing conditions.
Conifer woodland	**CO31**	An area of trees (with a minimum width of 20m) where 80% or more of the tree canopy is of coniferous species. Includes conifer woodland on dunes.
Mixed woodland	**CO32**	An area of mixed coniferous and broadleaved trees (with a minimum width of 20m) where both comprise >20% of the tree canopy. Includes mixed woodland on dunes
Broad-leaved woodland	**CO33**	An area of trees (with a minimum width of 20m) where 80% of the tree canopy is of broadleaved species. Includes broadleaved woodland on dunes. Includes stands of coppiced trees.
Shrub	**CO34**	Consisting predominantly of low woody plants and bushes, often with tree regeneration and brambles where canopy cover is >50%
Heathland and bog (CO40)		
Heathland	**CO41**	Land dominated by dwarf shrub and heath species (>25%) such as heather, gorse and bilberry; occurring in both lowland and moorland settings. Includes dune heath which occurs of consolidated and flattened dunes and areas of exposed peat. Excludes montane heath (CO44).
Bracken	**CO42**	Areas dominated by continuous bracken. Excludes area of unimproved grassland with patches of bracken (CO22).
Bog	**CO43**	Bog occurs on deep peat where the water table is usually at or just below the surface. Includes the vegetation of blanket bogs on hills and uplands and raised bogs of the lowlands, and is often characterised by the presence of sphagnum moss.
Montane	**CO44**	Dwarf heath, sedge, rush and snow bed vegetation communities at high elevation (i.e. above the 'treeline') usually with a wind-cut or prostrate appearance, Includes moss and lichen dominated heaths of mountain summits.
Inland rock (CO50)		
Inland rock	**CO51**	Vertical or near vertical inland rock cliffs. Areas where >50% of the land surface is covered by rock, including rock outcrops, limestone pavement, scree, block litter and mountain-top debris.
Water and wetland (CO60)		
Standing water	**CO61**	Areas of still open water e.g. lakes, canals, ponds, mere, water filled gravel pits and reservoirs. Includes silted-up areas with associated vegetation of reeds, rushes and willow (as long as the area of open water is >40% of the total).
Running water	**CO62**	Channels of moving water, including rivers and streams.
Freshwater marsh	**CO63**	Land with water-tables at or near the surface for prolonged periods of the year; generally low lying and frequently in association with stretches of open water. The range of vegetation is very wide and can include reeds, reed-grass, sedges and rushes, often with tall herbs. Some scatter alder and/or willow can also be present.

Coastal features (CO70)		
Sea and coastal waters	**CO71**	Open sea and coastal waters. Includes estuaries inland to the point where the waterway becomes strongly constricted to the normal width of the river. Excludes inter-tidal sand and mud (CO72).
Inter-tidal sand and mud	**CO72**	Unvegetated areas of sand and mud between the mean high and low water marks. Includes sandy and pebble/gravel shores. Excludes rocky shores (CO75)
Salt marsh	**CO73**	Vegetated inter-tidal sand, silt or mud with many sinuous creeks and channels colonised by salt tolerant grasses. Includes all flowering plant communities which are submerged by high tides at some stage of the annual cycle.
Dunes	**CO74**	Onshore wind-carried sand deposits arranged in cordons of ridges parallel to the coast. Includes inland windblown sand deposits. Either open or with semi-natural grassland. Excludes wooded dunes classified as woodland (CO31 - CO33), dune grassland used as unimproved grass (CO22) and dune heath, classified as heathland (CO41).
Coastal rock and cliffs	**CO75**	Applies to shores where the rocks and cliffs comprise outcropping base-rock. Includes unvegetated rocky/boulder shores (possibly seaweed-covered) consisting of shattered rock or boulders.
Buildings and structures (CO80)		
Building	**CO81**	A substantial and permanent construction with a roof and walls for giving shelter e.g. house, office, shop, warehouse, factory, church, barn.
Other built structure	**CO82**	Any built structure with a roof e.g. pylon, water tower, telecommunications mast. A minor construction which may be roofed but that is not intended for habitation e.g. covered walkway, bridge, kiosk.
Permanent made surfaces (CO90)		
Metalled roadway	**CO91**	Permanent metalled way for cars, buses, lorries and other road vehicles. Metalling includes any artificial surface including asphalt, concrete/brick paviours, granite sets and gravel.
Railway	**CO92**	Specially prepared strip of ground and supporting formation (ballast etc.) on which metal rails are laid on sleeper for trains to run on i.e. the permanent way. Includes land essential to enable the track to operate e.g. cuttings, embankments and the full extent of bridges.
Pathway	**CO93**	Paved surface by the side of the carriageway for use by pedestrians. Includes any made strip of ground specifically for pedestrian or cycle use.
Other made surface	**CO94**	Extensive and permanently developed surfaces (excluding roadways, railways and pathways) e.g. areas of tarmac or concrete, all-weather surfaces, paved civic spaces.
General land surfaces (C100)		
Multiple surface	**C101**	Any composite surface comprising a mixture of artificial and natural elements e.g. a garden or landscaped area adjacent to a building.
Bare surface	**C102**	Areas with no dominant vegetation cover. Excludes tilled land (CO11) and fallow land (C012)

Notes: The land cover classification only is included.

Source: Harrison (2006)

PHASE 1 HABITAT SURVEYS (P1)

Woodland and scrub (A)			
1 Woodland			Woodland is defined as vegetation dominated by trees more than 5m high when mature, forming a distinct, although sometimes open canopy. Dominant species should be coded and the understorey and ground layer target noted. Distinct blocks of woodland, whether broadleaved or coniferous, should be mapped separately whenever possible. The definitions of the main categories are:- • Broadleaved woodland: 10% or less conifer in the canopy; • Coniferous woodland: 10% or less broadleaved in the canopy; • Mixed woodland: 10-90% of either broadleaved or conifer in the canopy. The approximate proportions of the two types should be target noted. If the cover of trees is less than 30% the area should be shown as scattered trees on the appropriate background colour. Where the cover is higher than 30% but there are sizeable open spaces or rides, these should be target noted to describe the ground flora. **Semi-natural woodland** Semi-natural woodland comprises all stands which do not obviously originate from planting. The distribution of species will generally reflect natural variations in the site and its soil. Both ancient and more recent stands are included. Woodland with both semi-natural and planted trees should be classified as semi-natural and planted trees should be classified as semi-natural if the planted trees account for less than 30% of the canopy composition, but as plantation if more than 30% is planted. In cases where it is doubtful whether or not a wood should be classified as semi-natural, target notes giving details of origin and species composition are essential. **Plantation woodland** All obviously planted woodland of any age should be included in this category, with the exception of those types mentioned previously. Orchards should be mapped by placing green hatching over the OS symbols (which should be added where missing), and target notes made giving tree species and details of any conservation interest. Ornamental tree gardens and arboreta should be included here, and target noted where necessary.
Broadleaf	Semi-natural Plantation	**A1.1.1** **A1.1.2**	
Coniferous	Semi-natural Plantation	**A1.2.1** **A1.2.2**	
Mixed	Semi-natural Plantation	**A1.3.1** **A1.3.2**	

2 Scrub	Dense/continuous Scattered	**A2.1** **A2.2**	Scrub is seral or climax vegetation dominated by locally native shrubs, usually less than 5m tall, occasionally with a few scattered trees. Dominant species should always be coded. The ground flora under scattered scrub should be coded or target noted. The following should, amongst others, be included in this category:- • *Ulex europaeus, Cyrisus scoparius* and *Juniperus communis* scrub; • Stands of *Rubus fruticosus* and *Rosa canina*; • Montane scrub with *Salix lapponum*, *S. lanata*, *S. myrsinites*, *S. arbuscula* or *S. phylicifolia*; • Stands of mature *Crataegus monogyna*, *Prunus spinosa* or *Salix cinerea*, even if more than 5m tall; • All willow carr less than 5m tall; all *Salix cinerea* carr; • Stands of *Myrica gale* more than 1.5m tall. The following should not be included in this category:- • Very low *Salix herbacea* (see heathland), *Salix repens* (see dune slack, H6.4), or *Myrica gale* (see mire, E); • *Ulex gallii* or *Ulex minor* (see heathland D); • Hedges (see J2); • Stands of young trees or stump regrowth less than 5m high, where these represent more than 50% of the immature canopy cover; • Stands of introduced shrub species (see J1.4); • Scrub on dunes (see H6.7).
3 Parkland/scattered trees	Broad-leaved Coniferous Mixed	**A3.1** **A3.2** **A3.3**	Tree cover must be less than 30% to warrant inclusion in this category. For scattered trees over pasture (as in parkland), or over heath, bog, limestone pavement, etc, the green dot symbol should be superimposed on the appropriate habitat colour. The density of dots should be varied in proportion to the density of trees. Dominant species should be coded. Exotic trees should be target noted. Lines of trees forming windbreaks or avenues should be marked as a series of dots with the dominant species code.
4 Recently felled woodland	Broad-leaved Coniferous Mixed	**A4.1** **A4.2** **A4.3**	The only areas of felled trees which should be included in the category are those whose future land use is uncertain, for instance when it is not clear whether they are to be replanted or used for crops. The dominant species which have been felled should be coded and the codes placed in parentheses.

Grassland and marsh (B)

This category includes both areas of herbaceous vegetation dominated by grasses and certain wet communities dominated by *Juncus* species, *Carex* species, *Filipendula ulmaria* or by other marsh herbs. For grasslands where there is a greater than 25% cover of dwarf shrub heaths see heathland (D), for emergent stands of tall reed-grasses see swamp (F1), for coastal grasslands see saltmarsh (H2), dune (H6) and maritime cliff and slope (H8).

Most grasslands have been subjected to some degree of agricultural improvement by repeated grazing, mowing, fertilising, drainage or herbicide treatment. It is important to try to distinguish unimproved and semi-improved from improved grasslands. However, these grassland types form a continuum, so that it is not possible to define each with precision, especially as species critical for their definition are often only observable for a short season in the year. Agricultural improvement usually results in a decrease in the floristic diversity of the sward and dominance by a few quick-growing grasses such as *Lolium perenne, Holcus lanatus* and *Festuca rubra*. The resulting sward composition is likely to vary with intensity of treatment and with the composition of the original sward, so careful field training is necessary to define and maintain the boundaries between these categories. However, residual difficulties are bound to occur.

Unimproved grassland

Unimproved grasslands are likely to be rare, especially in the lowlands. They may be rank and neglected, mown or grazed. They may have been treated with low levels of farmyard manure, but should not have had sufficient applications of fertiliser or herbicide, or have been so intensively grazed or drained, as to alter the sward composition significantly. Species diversity is often high, with species characteristic of the area and the soils and with a very low percentage of agricultural species.

Semi-improved grassland

Semi-improved grassland is a transition category made up of grasslands which have been modified by artificial fertilisers, slurry, intensive grazing, herbicides or drainage, and consequently have a range of species which is less diverse and natural than unimproved grasslands. Such grasslands are still of some conservation value. Semi-improved grassland may originate from partial improvement of acid, neutral or calcareous grassland and should be mapped as such.

1 Acid grassland	Unimproved Semi-improved	**B1.1** **B1.2**	Grassland in this category is often unenclosed, as on hill-grazing land, and occurs on a range of acid soils (pH less than 5.5). It is generally species-poor, and often grades into wet or dry shrub heath, although it must always have less than 25% dwarf shrub cover (see heathland, especially D5 and D6). Pioneer annual-rich calcifuge communities on dry sandy soils are included in this category, as are wet acidic grasslands typified by species just as *Juncus squarrosus* (but see marsh-marshy grassland, B5). The following are indicative of acidic conditions when frequent or abundant: *Deschampsia flexuosa, Nardus stricta, Juncus squarrosus, Galium saxatile*, and *Rumex acetosella*.
2 Neutral grassland	Unimproved Semi-improved	**B2.1** **B2.2**	Typically enclosed and usually more intensively managed than acid or calcareous grassland (except on roadside verges), this category encompasses a wide range of communities occurring on neutral soils (pH 5.5-7.0). The following are indicative of neutral conditions when frequent or abundant: *Alopecurus pratensis, Arrhenatherum elatius, Cynosurus cristatus, Dactylis glomerata, Deschampsia cespitosa, Festuca arundinacea* and *Festuca pratensis. Lolium perenne* may be present, but when abundant it is indicative of improved grassland (see B4).

3 Calcareous grassland	Unimproved Semi-improved	**B3.1** **B3.2**	These grasslands are often unenclosed, not managed intensively, and occur on calcareous soils (pH above 7.0). *Dryas octopetala* communities are included. Where the grass is tall, the dominant species is usually either *Brachypodium pinnatum* or *Bromus erectus*, whilst species indicative of short, close-grazed and species-rich calcareous turf are *Koeleria macrantha, Avenula pratensis, Sesleria albicans, Helianthemum nummularium, Sanguisorba minor* and *Thymus praecox.*
4 Improved grassland		**B4**	Improved grasslands are those meadows and pastures which have been so affected by heavy grazing, drainage, or the application of herbicides, inorganic fertilisers, slurry or high doses or manure that they have lost many of the species which one could expect to find in an unimproved sward. They have only a very limited range of grasses and a few common forbs, mainly those demanding of nutrients and resistant to grazing. The following signs usually indicate substantial improvement:- • Bright green, lush and even sward, dominated by grasses (though poaching causes unevenness); • Low diversity of forb species; • More than 50% *Lolium perenne*, *Trifolium repens* and other agricultural species. Fields which have been reseeded in the past and have since become somewhat more diverse are included in this category, but recently reseeded monoculture grassland such as rye grass leys, with or without clover, should be classified under cultivated land (J1).
5 Marsh/marshy grassland		**B5**	This is a diffuse category covering certain *Molinia* grasslands, grasslands with a high proportion of *Juncus* species, *Carex* species or *Filipendula ulmaria*, and wet meadows and pastures supporting communities of species such as *Caltha palustris* or *Valeriana* species, where broadleaved herbs, rather than grasses, predominate. The category differs from swamp (F1) in that the latter has a water table distinctly above the substratum for much of the year and is dominated by reed grasses or large sedges. Unlike marginal vegetation (F2), marsh/marshy grassland occurs on more or less level areas, rather than on the banks of watercourses. It differs from flush (E2) in that bryophytes are not a conspicuous component of the vegetation, also flushes always have a flow or seepage of water through them. If *Sphagnum* is abundant, refer to the mire classification (E).
6 Poor semi-improved		**B6**	Where there is a large amount of semi-improved grassland it may be useful to split this category into 'good semi-improved' and 'poor semi-improved'. This sub-division is optional. Good semi-improved grassland will have a reasonable diversity of herbaceous species, at least in parts of the sward, and is clearly recognisable as acid, calcareous or neutral in origin. Such grassland should be left in the semi-improved categories of acid, neutral and calcareous grassland (B1.2, 2.2 and 3.2). Poor semi-improved grassland will have a much more restricted list of species and, being more improved; it is more likely to resemble a species poor neutral grassland.

Tall herb and fern (C)			
1 Bracken	Continuous Scattered	**C1.1** **C1.2**	Areas dominated by *Pteridium aquilinum*, or with scattered patches of this species.
2 Upland species-rich ledges		**C2**	This ledge vegetation contains species such as *Angelica sylvestris, Filipendula ulmaria, Solidago virgaurea, Athyrium filix-femina, Trollius europaeus* and *Crepis paludosa.* Areas supporting this habitat are nearly always too small to map and consequently must be target noted.
3 Other	Tall ruderal Non-ruderal	**C3.1** **C3.2**	**Tall ruderal** (C3.1) This category comprises stands of tall perennial or biennial dicotyledons, usually more than 25cm high, of species such as *Chamerion (Chamaenerion) angustifolium, Urtica dioica* and *Reynoutria japonica.* Dominant species should be coded. See also ephemeral/short perennial (J1). **Non-ruderal** (C3.2) Non-wooded stands of species such as *Oreopteris limbosperma, Athyrium felix-femina, Dryopteris* species or *Luzula sylvatica* should be included in this category. Dominant species should always be coded.

Heathland (D)			
Heathland includes vegetation dominated by ericoids or dwarf gorse species, as well as ‘heaths’ dominated by lichens and bryophytes, dwarf forbs, *Carex bigelowii* or *Juncus trifidus*. Generally occurring on well-drained acid soils, heathland is further distinguished from mire (E) by being arbitrarily defined as occurring on peat less than 0.5 m thick (but see flood-plain mire E3.3). Dominant species should always be coded. See also dune heath (H6.6) and coastal heathland (8.5).			
1 Dry dwarf shrub heath	Acid Basic	**D1.1** **D1.2**	Vegetation with greater than 25% cover of ericoids or small gorse species in relatively dry situations forms this category. *Calluna vulgaris, Vaccinium myrtillus, Erica cinerea, Ulex minor* and *Ulex gallii* are typical of lowland dry dwarf shrub heath, *whilst Empetrum nugrum, Empetrum hermaphroditum, Arctostaphylos uva-idaea* are found in upland heaths. Acid heaths usually occur on deep podsols developed on base-deficient sands, gravels and clays. Basic heaths are much more restricted in extent, and may be recognised by the presence of herbs characteristic of chalk grassland and open habitats.
2 Wet dwarf shrub heath		**D2**	As with dry dwarf shrub heath (D1), this vegetation type has more than 25% cover of ericoids and/or small *Ulex* species. However, it differs from D1 in that *Molinia caerulea* is often abundant and it generally contains some *Sphagnum compactum* or *Sphagnum tenellum* and less frequently other *Sphagna.* In transitions to mires, the proportion of *Sphagna* will increase and the species composition will change, often with *Sphagna papillosum* and *Sphagnum subnitens* becoming more frequent. *Erica tetralix* is common in wet dwarf shrub heath and is often present in significant quantity. *Trichophorum cespitosum* is occasionally present at lower levels. Macrolichens such as *Cladonia portentosa (impexa), C. arbuscula* and *C uncialis* may be locally abundant. The abundance of *Molina* and *Erica tetralix* decreases in the transition from wet to dry heath. See also wet heath/acid grassland mosaic (D6) and wet modified bog (E1.3).
3 Lichen/bryophyte heath		**D3**	This category comprises bryophyte and lichen-dominated heaths of mountain summits and lowland situations such as the East Anglian Breckland. Bryophytes and/or lichens must be dominant and there must be less than 30% vascular plant cover.
4 Montane heath/dwarf herb		**D4**	This is rather diverse grouping of montane heath and snow-bed vegetation types. Included in this category are heaths dominated by *Carex bigelowii* and *Juncus trifidus*, also dwarf forb communities of *Alchemilla alpine, Silene acaulis, Sibbaldia procumbens* and *Saxifraga* species. Montane dwarf shrub heath should not be included, but should be classified under D1 or D2; *Dryas octopetala* communities should be classified under calcareous grassland
5 Dry heath/acid grassland mosaic		**D5**	This represents a common mixture of dry heath (D1) and acid grassland (B1), to be found on hill and moorland, and the category has been specified only for ease of mapping. The relative proportions of each type of habitat should be target noted.
6 Wet heath/acid grassland mosaic		**D6**	Vegetation mosaics similar to D5, but involving a mixture of wet heath (D2) with acid grassland (B1), make up this category. Again, the proportions of each habitat type should be target noted

Mire (E)			
1 Bog	Blanket bog Raised bog Wet modified Dry modified	**E1.6.1** **E1.6.2** **E1.7** **E1.8**	Unmodified bog (blanket bog and raised bog) consists of *Sphagnum*-rich vegetation, lying on peat more than 0.5 m deep, with the water table at or just below the surface and no input of water from the surrounding land. Modified bog contains little or no *Sphagnum*. **Blanket bog** (E1.6.1) Blanket bog comprises *Sphagnum*-rich vegetation on deep peat, forming a blanket over both concave and convex surfaces, on level to moderately sloping ground in the uplands. It is widespread in the north and west of Britain, where it may be fragmentary or very extensive. The drainage is usually diffuse and undisturbed blanket bog often shows a hummock-and hollow structure, with *Sphagnum*-rich pools in the hollows. Blanket bog includes watershed mires, saddle mires, terrace bog and valleyside mire and may also include other mire types, where these occur within a blanket bog complex. **Raised bog** (E1.6.2) Raised bogs are found on estuarine flats, river flood plains and other level areas with impeded drainage in the lowlands, also at moderate altitudes, where they may grade into blanket mire. Many raised bogs overlie sites of glacial lakes which become infilled. In a classic raised bog, a structure now rare in Britain, the peat is several metres deep and has accumulated to form a distinctly raised dome, with peat depth greatest in the centre and decreasing towards the edges, which are marked by the more steeply sloping mire margin. Drainage tends to flow around the mire, forming a lagg stream, and the drier sloping margins of the mire may carry lagg woodland, which should be mapped as woodland. **Wet modified bog** (E1.7) This category comprises modified bog vegetation with little or no *Sphagnum*, often with bare peat and patches of *Trichophorum cespitosum* and/or *Molinia caerulea*. Ericoids may be abundant, sparse or absent. This vegetation is mainly found on drying and degraded blanket bogs and cut-over raised bogs. It may resemble wet heath (D2), but is distinguished by having a peat depth greater than 0.5 m. **Dry modified bog** (E1.8) The vegetation of dry modified bog is dominated by *Calluna vulgaris* and other ericoids, or by *Eriophorum vaginatum*, on peat more than 0.5m deep. *Sphagnum* is notably absent.

2 Flush/spring	Acid/neutral Basic Bryophyte dom.	**E2.1** **E2.2** **E2.3**	These types of minerotrophic mire are termed soligenous because they are associated with water movement. They may or may not form peat, but where they do, the peat is often less than 0.5m deep. Flushes occur on gently-sloping ground, are often linear or triangular and may include small watercourses. They may be extensive or too small to map, in which case they should be target noted. When flushes feed a fen (E3) they should be target noted and mapped as an integral part of the mire complex, unless they are very large and distinct, when they may be individually mapped. Flushes typically have an open or closed ground layer of *Sphagnum* and/or bryophytes, together with small sedges and *Juncus* species. The presence of a well developed bryophyte ground layer and the lack of dominant grasses distinguish flush habitats from marshy grassland and from wet acid, neutral and calcareous grasslands. Thus, a habitat with *Juncus effuses* over herbs and grasses is a marsh/marshy grassland (B5). Complex mosaics of grassland and flush are quite common, particularly in the uplands, and should be mapped according to the most prevalent habitat, with the proportions of each recorded in a target note. **Acid/neutral flush** (E2.1) These typically support species-poor vegetation consisting of a *Sphagnum* carpet overlain by *Carex* or *Juncus* species. Characteristic moss species include *Sphagnum recurvum, S. palustre* and *S. auriculatum.* Overlying vegetation may consist of small *Carex* species (*Carex echinata, C. nigra* or *C. curta*), *Carex rostrata, Juncus acutiflorus, J. effuses, J. squarrosus*, or *Eriophorum angustifolium*. Dominant species should be coded. **Basic flush** (E2.2) Basic flushes typically support a carpet of pleurocarpous brown mosses, often without *Sphagnum*, overlain by a conspicuous small sedge layer, *Carex flacca, Schoenus nigricans* or a mixed-herb layer. Characteristic pleurocarpous mosses include *Scorpidium, Campylium, Drepanocladus* and *Calliergon* species, whilst characteristic herbs include *Eleocharis quinqueflora, Eriophorum latifolium* and *Carex lepidocara.* **Bryophyte-dominated spring** (E2.3) This habitat occurs only in the immediate vicinity of up-wellings and it usually consists of spongy mats or small mounts dominated by bryophytes such as *Cratoneuron* or *Philonotis* species. Areas which fall within this category are normally too small to map and should be target noted. Flushes occurring downslope of a spring should be mapped if they are large enough.

3 Fen	Valley mire Basin mire Flood-plain	**E3.1** **E3.2** **E3.3**	Fens are defined as minerotrophic mires, usually over peat more than 0.5m deep (but see E3.3). The water table is at or just below the surface. Three main types of fen can be distinguished, using topographical rather than vegetational criteria. 'Poor fen' contains acid water (pH 5 or less) and short vegetation with a high proportion of *Sphagnum*. 'Rich fen' contains more calcareous water (pH above 5), *Sphagnum* is often absent and the vegetation usually includes patches of tall plants and species such as *Juncus subnodulosus*, *Schoenus nigricans* and *Carex lepidocarpa*, characteristic of base-rich situations. **Valley mire** (E3.1) A valley mire develops along the lower slopes and floor of a small valley and receives water from springs and seepages on the valley sides, feeding a central watercourse. Such a fen can be distinguished from a flush because the former is a complex, whereas a flush is a discrete single feature, usually of limited extent. Valley mires are often dominated by acidophilous vegetation containing *Sphagnum* species, *Carex* species and ericoids. However, vegetation typical of base-rich conditions can also occur, for instance *Schoenus nigricans* and *Juncus subnodulosus*. Floating mats of mosses and sedges may be present. Acid watercourses often contain *Hypericum elodes* and *Potamogeton polygonifolius*. **Basin mire** (E3.2) This type of fen develops in a waterlogged basin and contains very little open water. The water table within the basin is level, but small flushes may occur around the edges and there is a limited through-flow of water. The vegetation may be dominated by *Sphagnum* species, together with *Carex rostrata* and ericoids, or by tall swamp plants such as *Phragmites australis*, *Schoenoplectus (Scirpus) lacustris*, *Typha* species and, in base-rich situations, *Cladium mariscus*. **Flood-plain mire** (E3.3) This type of fen forms on a river or stream flood-plain which is waterlogged and, typically, inundated periodically. The substrate may be peat, mineral or a mixture of both. The range of vegetation types is similar to that of a basin mire (E3.2).
4 Bare peat		**E4**	Patches of bare peat more than 0.25 ha in extent (that is, approximately 50m x 50m) should be mapped. Peat hagging and areas of eroding peat haggs should be target noted. Commercial peat-workings are included in this category.

Swamp, marginal and inundation (F)			
1 Swamp		**F1**	Swamp contains tall emergent vegetation typical of the transition between open water and exposed land. Swamps are generally in standing water for a large part of the year, but may occasionally be found on substrates that are seldom immersed, as in the later stages of the seral succession to marshy grassland. Species composition varies according to the trophic status of the water, the substrate type, etc. Note that vegetation dominated by *Molinia caerulea*, *Filipendula ulmaria*, mosses, small *Carex* species or *Juncus* species, should be classified as marsh/marshy grassland (B5) or flush (E2), as appropriate. Swamp vegetation includes both mixed and single species stands of *Typha* species, *Phragmites australis*, *Phalaris arundinacea*, *Glyceria maxima*, *Carex paniculata, C. acutiformis, C. rostrata* or other tall sedge. Single-species stands are usually found in deeper water and should be indicated with species codes. Strips of swamp vegetation narrower than 5m bordering watercourses should be classified as marginal vegetation (F2.1).
2 Marginal/inundation	Marginal Inundation	**F2.1** **F2.2**	**Marginal vegetation** (F2.1) This category encompasses all narrow strips of emergent vegetation occurring on the (often steep) margins of lowland watercourses, where the water table is permanently high. Bands of tall vegetation wider than 5m should be classified as swamp (F1). Marginal vegetation is typically open and contains plants such as *Glyceria* species, *Rorippa* species, *Apium nodiflorum, Berula erecta, Oenanthe* species, *Galium palustre, Nasturtium officinale, Myosotis* species, *Veronica* species, *Alisma* species, *Sparganium erectum, Carex riparia, Juncus effuses* and *Juncus inflexus*, also small stands of taller plants such as *Phragmites australis, Typha* species and *Phalaris arundinacea*. Areas of such vegetation will be too small to map, so should be target noted. **Inundation vegetation** (F2.2) This category includes open and innately unstable communities that are subject to periodic inundation, as found on sorted or unsorted silts, sands and gravels of river beds and islands and on the draw-down zone around pools, lakes and reservoirs. A wide variety of species occur in such communities, including *Polygonum* species, *Juncus bulbosus, Bidens species, Agrostis stolifera* and *Alopecurus geniculatus*, as well as many ruderal species.

Open Water (G)			
Open water is defined as water lying beyond the limits of swamp or emergent vegetation, although it may contain submerged, free-floating or floating-leaved vegetation. The dominant species of any such vegetation should be coded, and the salinity of the water, whether fresh or brackish, indicated if possible. Where aquatic vegetation is present in quantity but there is insufficient room to code all abundant species, a target note should be provided.			
1 Standing water	Eutrophic Mesotrophic Ogliotrophic Dystrophic Marl Brackish	**G1.1** **G1.2** **G1.3** **G1.4** **G1,5** **G1.6**	Standing water includes lakes, reservoirs, pools, flooded gravel pits, ponds, water-filled ditches, canals and brackish lagoons.
2 Running water	Eutrophic Mesotrophic Ogliotrophic Dystrophic Marl Brackish	**G2.1** **G2.2** **G2.3** **G2.4** **G2.5** **G2.6**	Running water comprises rivers and streams. The direction of flow should be indicated by an arrow.

Coastland (H)			
1 Intertidal	Mud/sand Shingle/cobbles Boulders/rock Zostera beds Green algal beds Brown algal beds	**H1.1** **H1.2** **H1.3** **H1.(1-2).1** **H1.(1-3).2** **H1.(1-3).3**	The codes for *Zostera*, green algal beds or brown algal beds should, where appropriate, be superimposed over the relevant Ordnance Survey symbols (mud/sand; shingle/cobbles, boulders/rocks).
2 Saltmarsh	Saltmarsh/dune interface Scattered plants Dense/continuous	**H2.3** **H2.4** **H2.5**	**Saltmarsh/dune interface** (H2.3) Vegetation peculiar to this area, characterised by species such as *Frankenia laevis* or *Suaeda fruticosa*, should be mapped wherever large enough, and always target noted. **Scattered plants** (H2.4) The dominant species should be coded. **Dense/continuous** (H2.6) Dominant species should be coded, particularly noting *Spartina* where it is abundant. Areas of inland saltmarsh should be included in this category.
3 Shingle above high tide mark		**H3**	Target note any vascular plants or lichen vegetation that may occur.
4 Boulders/rocks above high tide mark		**H4**	Target note as for H3
5 Strandline vegetation		**H5**	This type of vegetation occurs as an open community on the drift line and is characterised by species such as *Cakile maritime*, *Honkenya peploides*, *Rumex crispus*, *Salsola kali*, *Atriplex* species and *Beta vulgaris* ssp. *maritime*. In contrast to fore dunes, *Elymus farctus* (*Agropyron junceiforme*) is characteristically sparse or absent. Target note where feasible, stating whether the substrate is shingle or rock

6 Sand-dune	Dune slack Dune grassland Dune heath Dune scrub Open dune	**H6.4** **H6.5** **H6.6** **H6.7** **H6.8**	**Dune slack** (H6.4) Dune slacks are valleys in hollows between dune ridges, where the water table is close to the surface for at least several months in the year, leading to marshy vegetation. *Ammophila arenaria* is usually absent. Characteristic species are *Salix repens, Hydrocotyle vulgaris, Dactylorhiza* species and *Epipacyis palustris*. Saline slacks should be classified as saltmarsh (H2). **Dune grassland** (H6.5) All grassland occurring on consolidated and flattened dunes should be classified in this category. Generally, little *Ammophila arenaria* will be present. Machair should be included here. **Dune heath** (H6.6) All heathland occurring on consolidated and flattened dunes should be included in this category. *Calluna* is usually the dominant ericoid, with *Erica cinerea* and *Erica tetralix* also common. *Carex arenaria* is often present and lichens, particularly *Cladonia* species, are often abundant. Occasionally, juniper may be present. Use yellow crosses for scattered heath. **Dune scrub** (H6.7) All scrub occurring on consolidated and flattened dunes should be included in this category. *Hippophae rhamnoides* is a characteristic species. Use green crosses for scattered scrub. **Open dune** (H6.8) This category comprises the three early successional stages of dune formation, less stable and with lower vegetation cover than H6.4-H6.7. Fore dune: unstable, usually low ridges of sand on the foreshore, often with a very open plant cover. *Elymus farctus* is strongly characteristic, often dominant, and sometimes the only species present; *Honkenya peploides, Atriplex* species and *Cakile maritima* are typically associated species; *Ammophila arenaria* may be present in small quantities, but should not be dominant.

8 Maritime cliff and slope	Hard cliff Soft cliff Crevice/ledge vegetation Coastal grassland Coastal heathland	H8.1 H8.2 H8.3 H8.4 H8.5	**Maritime hard cliff** (H8.1) These are cliffs formed of rock (including chalk) with less than 10% vascular plant cover. The type of rock should be target noted. Vegetated cliffs should be mapped using the relevant vegetation code and target noted. **Maritime soft cliff** (H8.2) These are cliffs formed of mud or clay with less than 10% vascular plant cover. The type of substrate should be target noted. **Crevice and ledge vegetation** (H8.3) This category comprises vegetation, occasionally sparse, but covering at least 10% of the cliff surface, occurring in crevices or on ledges on steep cliffs. The communities present should be described with a target note, taking care to record whether the vegetation is influenced by the use of the cliffs by birds, as may be indicated by species such as *Beta vulgaris*. Vegetation occurring in the splash zone at the base of cliffs should be included here. **Coastal grassland** (H8.4) These are grasslands which include maritime species and which occur on shallow slopes or level areas by the sea, often on cliff tops (but see dune grassland - H6.5). Indicator species include *Scilla verna*, *Plantago maritime* and *Armeria maritima*. *Festuca rubra* is often dominant. Other species may include *Hieracium pilosella*, *Anthyllis vulneraria*, *Lotus corniculatus*, *Galium verum* and *Thymus praecox*. **Coastal grassland** (H8.5) All heathlands which include maritime species and which occur on shallow slopes, or even level areas, by the sea should be included in this category (but see dune heath - H6.6). Indicator species include *Scilla verna*, *Armeria maritima*, *Jasione Montana*, *Plantago maritima* and *Plantago coronopus*. *Calluna vulgaris* is often dominant; *Erica cinerea* and dwarf *Ulex* species are frequently present. Coastal heathland often occurs just inland of coastal grassland and, like that category, frequently occurs at the top of cliffs.

Rock exposure and waste (I)			
1 Natural			**Inland cliff** (I1.1)
Inland cliff	Acid/neutral	**I1.1.1**	This category is defined as rock surfaces over 2m high and sloping at more than 60°. Vegetated cliffs with more than 10% vascular plant cover are not included, but should be mapped using the relevant vegetation code, and target noted as necessary.
	Basic	**I1.1.2**	
Scree	Acid/neutral	**I1.2.1**	**Scree** (I1.2)
	Basic	**I1.2.2**	Scree is defined as an accumulation, usually at the foot of a cliff, of weathered rock fragments of all sizes, mostly angular in shape. This category includes large boulders (boulder scree) which should be mapped using enlarged red dots.
Limestone pavement		**I1.3**	**Limestone pavement** (I1.3) This comprises a near horizontal surface, usually of Carboniferous Limestone, which is irregularly corrugated and furrowed by solution and often cut by deeper and more regular fissures (grikes), which correspond to naturally occurring joints within the rock.
Other exposure	Acid/neutral	**I1.4.1**	**Other exposure** (I1.4) Exposed rock on mountain tops and in river beds should, for example, be included in this category.
	Basic	**I1.4.2**	
Cave		**I1.5**	**Cave** (I1.5) Any natural recess, large enough to enter and with a complete ceiling, should be mapped as cave and any features of interest target noted. Large crevices and deep narrow gullies should not be included here, but should be mapped under 'other'.
2 Artificial	Quarry	**I2.1**	The boundaries of quarries, spoil heaps, mines or refuse tips should be outlined in red. Covering vegetation, if abundant, should be coded as appropriate, under grassland, scrub, etc, or target noted if sparse.
	Spoil	**I2.2**	**Quarry** (I2.1) Excavations such as gravel, sand or chalk pits and stone quarries should be included in this category. Target note the mineral or ore which has been, or is being, extracted. If the site is water-filled, map as open water and target note previous use.
	Mine	**I2.3**	**Spoil** (I2.2) Includes abandoned industrial areas and tips of waste material such as coal mine spoil and slag. Spoil heaps within quarries should be included in I2.1. Target note the type of spoil. **Mine** (I2.3) Mark the area on the map and target note any features of interest.
	Refuse tip	**I2.4**	**Refuse-tip** (I2.4) Target note any vegetation of interest, if it covers an area too small to map, and code the dominant species.

Miscellaneous (J)			
1 Cultivated/disturbed land	Arable Amenity grassland Ephemeral/short Perennial Introduced shrub	**J1.1** **J1.2** **J1.3** **J1.4**	**Arable** (J1.1) This includes arable cropland, horticultural land (for example, nurseries, vegetable plots, flower beds), freshly ploughed land and recently reseeded grassland, such as rye grass and rye-clover leys, often managed for silage. **Amenity grassland** (J1.2) This comprises intensively managed and regularly mown grasslands, typical of lawns, playing fields, golf course fairways and many urban 'savannah' parks, in which *Lolium perenne*, with or without *Trifolium repens*, often predominates. The sward composition will depend on the original seed mixtures used and on the age of the community. Herbs such as *Bellis perennis*, *Plantago major* and *Taraxacum officinale* may be present. If the amenity grassland has a sward rich in herbs, it may be possible to classify it as semi-improved acidic, neutral or calcareous grassland, as appropriate. In such cases, the area concerned should be mapped as the specific grassland type and its amenity use target noted. **Ephemeral/short perennial** (J1.3) Short, patchy plant associations typical of derelict urban sites, quarries and railway ballast, should be classified here. The land must be freely draining, and usually has shallow stony soil. The vegetation typically lacks a clear dominant species, but consists of a mixture of low-growing plants, often less than 25 cm high, such as *Plantago major*, *Ranunculus repens*, *Trifolium repens*, *Medicago lupulina*, *Tussilago farfara*, *Leucanthemum vulgare* and *Senecio* species, or of taller species such as *Sisymbrium* or *Melilotus* species. Parts of fields containing similar communities, such as areas around gates, should not be included, but should be classified as grassland (B). See also tall ruderal (C3.1). **Introduced shrub** (J1.4) This is vegetation dominated by shrub species that are not locally native, whether planted or self-sown. Common introduced shrubs include species of *Buxus*, *Cornus*, *Laurus*, *Ligustrum*, *Rhododendron* and *Symphoricarpus*. Formal beds of shrubs such as of *Hypericum calycinum*, *Cotoneaster*, heaths and dwarf conifers should be included here. Introduced shrubs forming an understorey in woodland should be mapped as woodland (A1) and target noted. Introduced shrub on sand dunes should be classified as dune scrub (H6.7). See also scrub (A2).

Source: JNCC (1993)

References

Bossard M, Feranec J & Otahel J (2000) *CORINE land cover technical guide: Addendum 2000*, Technical Report Number 40, European Environment Agency

Fuller R.M, Smith G.M, Sanderson J.M, Hill R.A, Thomson A.G, Cox R, Brown N.J, Clarke R.T, Rothery P & Gerard F.F (2002) *Land Cover Map 2000: Draft Final Report*, Centre for Ecology and Hydrology.

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Land Cover Attribute Derivation

To ensure compatibility land cover attributes measured in the field were extracted from land cover definitions taken from widely used land cover mapping schema.

This appendix outlines the attributes identified as being responsible for the delineation of land cover parcel boundaries within the Phase 1 (JNCC, 1993), Land Cover Map 2000 (Fuller et al, 2002), NLUD (Harrison, 2006), CORINE (Bossard et al, 2000), MLCNP (Taylor et al 1991), NVC (Cooper, 1997; Elkington et al, 2001; Hall et al, 2001) classification schemes and the Natural England Favourable Habitats Management Plan (Blackshall et al, 2001).

Attributes are classified as being floristic, physiological, environmental or structural to aid comparison.

CORINE

Floristic information:

- Presence/absence of particular species

Physiological information:

- Coniferous/deciduous vegetation

Structural information:

- Percentage cover, abundance
- Height
- Canopy closure
- Productivity

Environmental information:

- Presence/absence of artificial surfaces, buildings etc
- Land use
- Land management
- Soil type
- Evidence of soil erosion
- Elevation
- Seasonal water inundation

LAND COVER MAP 2000 (LCM2000)

Floristic information:

- Presence/absence of particular species

Physiological information:

- Coniferous/deciduous vegetation
- Seasonal characteristics of the vegetation

Structural Information:

- Vegetation height
- Percentage cover, abundance
- Area of the feature

Environmental Information:

- Management practices
- Soil acidity
- Peat depth
- 'Context'
- Presence/absence of artificial surfaces, buildings etc.

MONITORING LANDSCAPE CHANGE IN THE NATIONAL PARKS (MLCNP)

Floristic Information:

- Presence/absence of particular species

Physiological information:

- Broadleaf/deciduous woodland

Structural Information:

- Species height
- Percentage cover
- Canopy cover
- Area/width/length of land cover class

Environmental Information:

- Enclosed versus un-enclosed
- Elevation - upland versus lowland vegetation

PHASE 1 HABITAT SURVEY (P1)

Floristic Information:

- Presence/absence of particular species

Physiological information:

- Broadleaf/deciduous woodland

Structural Information:

- Species height
- Percentage cover

Environmental Information:

- Soil pH
- Peat depth
- Water table height
- Topographical and elevation considerations
- Management practices

NATURAL ENGLAND FAVOURABLE HABITATS MANAGEMENT PLAN

1a) Sub-Montane Dry Dwarf-Shrub Heath, Typical Calluna Dry Heath

- Percentage cover/dominance of key species.
- Number of dwarf shrub species in the area and their relative dominance.
- Presence of bryophytes (i.e. lichen) below or in between shrubs.
- The amounts of dwarf shrub at each stage of the age cycle.
  (At least 25% of the management unit in the late or mature/degenerate age)
- The amount of burning.
- Light grazing impacts (maximum 5% of grazing unit should show signs of current moderate or heavy grazing).
  Indicators of light grazing:
    - Only tips of plant removed by grazing.
    - Less than 33% long shoots show signs of grazing (only considered in early spring).
    - Species flowering.
    - Bush canopy should be open and not a tightly packed mass of contorted shoots. No drumstick, topiary or carpet growth forms should be evident.
    - No uprooted seedlings.
    - Negligible bare ground.

1b) Sub-Montane Dry Dwarf-Shrub Heath, Dry Heath with *Ulex gallii*

Same as above but also include:

- The percentage cover of *Ulex gallii* (western gorse).

2) Wet Heath

- Types of species present, dominance and percentage cover.
- The number of species and their relative abundance.
- The presence of byrophtyes.
- Age classes of *Calluna vulgaris.*
- Graminoid cover, types of species and percentage cover.
- Light grazing.

3) Blanket and Upland Raised Mires

- Bryophytes should be abundant and include *Sphagnum* species.
- The percentage cover of dwarf shrubs, sphagnum and other species present.
- The number of dwarf shrub species.
- Graminoid cover (grasses) must not be dominant over dwarf shrubs.
- Little/no bare ground.
- No erosion or limited local instances.
- Light grazing impacts.

References

Blackshall J, Manley J & Rebance M (2001) *The Upland Management Handbook*, English Nature Science No.6

Bossard M, Feranec J & Otahel J (2000) *CORINE land cover technical guide: Addendum 2000*, Technical Report Number 40, European Environment Agency

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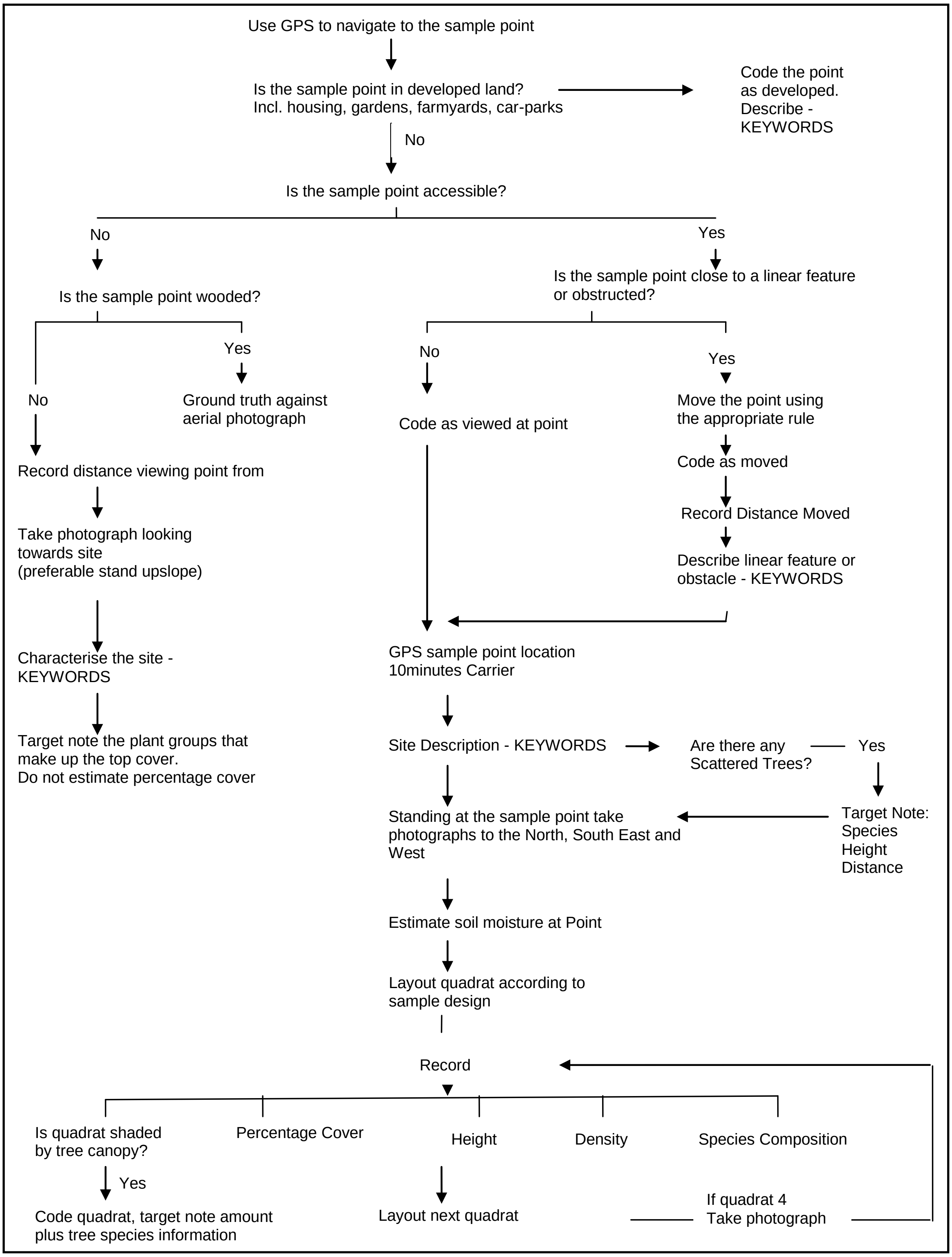
Field Survey Protocol

This appendix outlines the field survey protocol implemented during the full field survey. This protocol was developed, subsequent to a pilot field survey, to ensure consistency between samples and surveyors. For each land cover attribute the protocol details the measurement technique and data collection rules implemented.

FIELD SURVEY PROTOCOL: FLOW DIAGRAM



MOVING SAMPLE POINTS DUE TO LINEAR FEATURES/OBSTACLES

SAMPLE POINTS SHOULD BE MOVED IF:

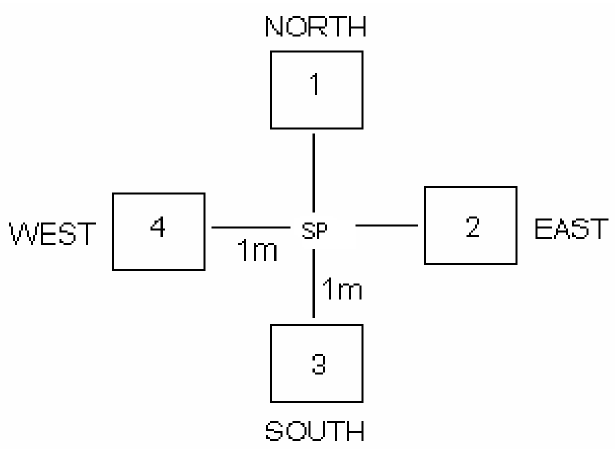
- THEY **ARE ON** A LINEAR FEATURE
- THEY ARE IN **CLOSE PROXIMITY** TO A LINEAR FEATURE
    - Defined as a zone 3 x average HEIGHT of that feature
- ANY **OBJECT RESTRICTS** THE LAYOUT OF THE QUADRATS

MOVE THE SAMPLE POINT **PERPENDICULAR** TO THE LINEAR FEATURE TO A DISTANCE WHICH IF **3 TIMES THE VERTICAL FEATURE HEIGHT** OR A **MINIMUM OF 3 METRES** IF THE FEATURE HAS NO HEIGHT.

Rules

- Sample point locations should be shifted if they fall:
  On or within a zone 3 times the vertical height of the linear feature, if the vertical feature has no height then the zone should be considered to be 3 metres wide
- If the linear feature has width measurements should be taken from the edge of the feature.
- If moving the sample point according to this rule intersects another linear feature, the sample point should be placed centrally between the two linear features in order to minimise the influence of both.
- The linear feature/obstruction from which the sample point is moved must be described.

QUADRAT LAYOUT



SAMPLE POINT INFORMATION

1. GPS Location

Naming Conventions:

Rover: R “*date – ddmmyy*”

Point Features: SMP “*sample point ID*”

2. Site Photographs

Photograph order: NORTH

EAST

SOUTH

WEST

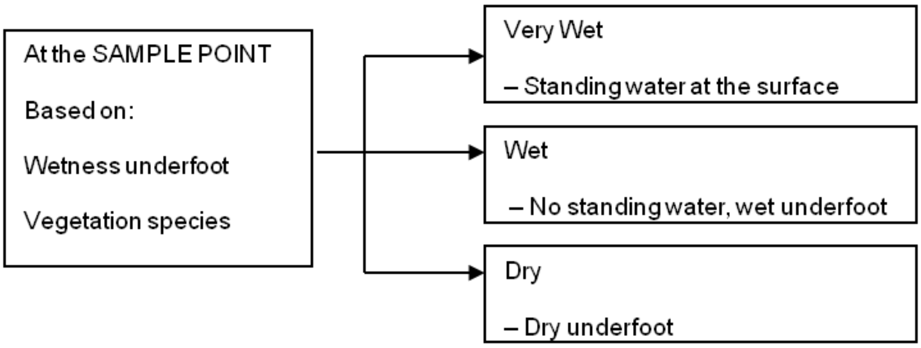
Naming convention: “*Sample point ID*” _N

“*Sample point ID*” _E

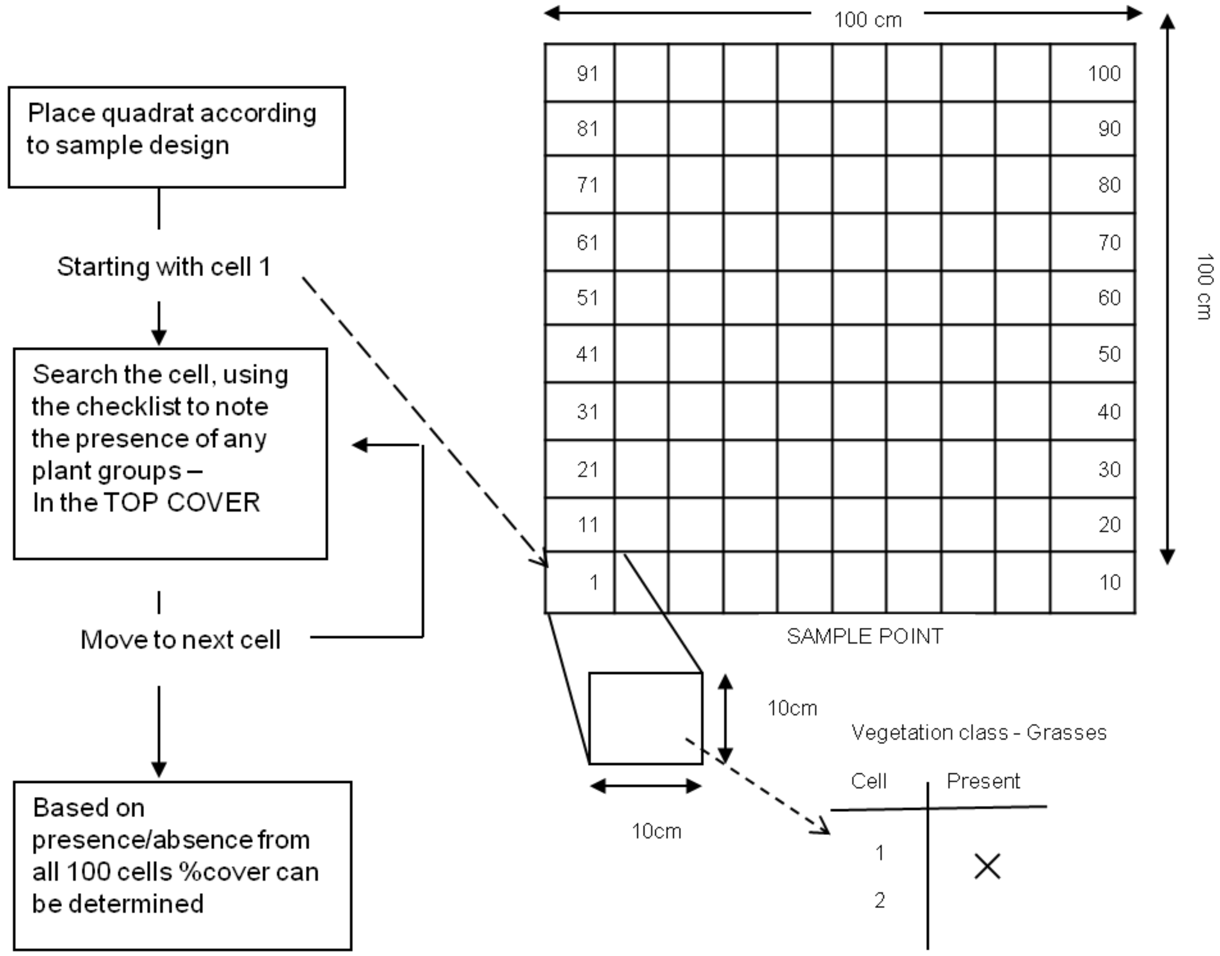
“*Sample point ID*” _S

“*Sample point ID*” _W

3. Soil Moisture



PERCENTAGE COVER



Rules:

- Every quadrat should be split into one hundred 10 cm x 10 cm cells, which should be consistently numbered.
- Each cell must be searched systematically and any plant groups present in the top cover noted.
- The top cover plants do not have to be rooted in the quadrat, if any part of the plant falls within the quadrat it should be included in the top cover.
- If two or more plant groups are present in the cell both should be noted.
- Every 4th quadrat at each sample point should be photographed, from directly above, to allow calibration and accuracy assessment of the results.
- Percentage cover should be calculated using the number of cells in which a plant group has been noted as being present. In order to prevent percentage cover values exceeding 100%, if two or more vegetation classes are present in a cell the one percent of that cell is proportioned between the plant groups.
  For examples: Two plant groups each counts as 0.5%

PERCENTAGE COVER – PLANT GROUPS

The following levels of identification should be applied:

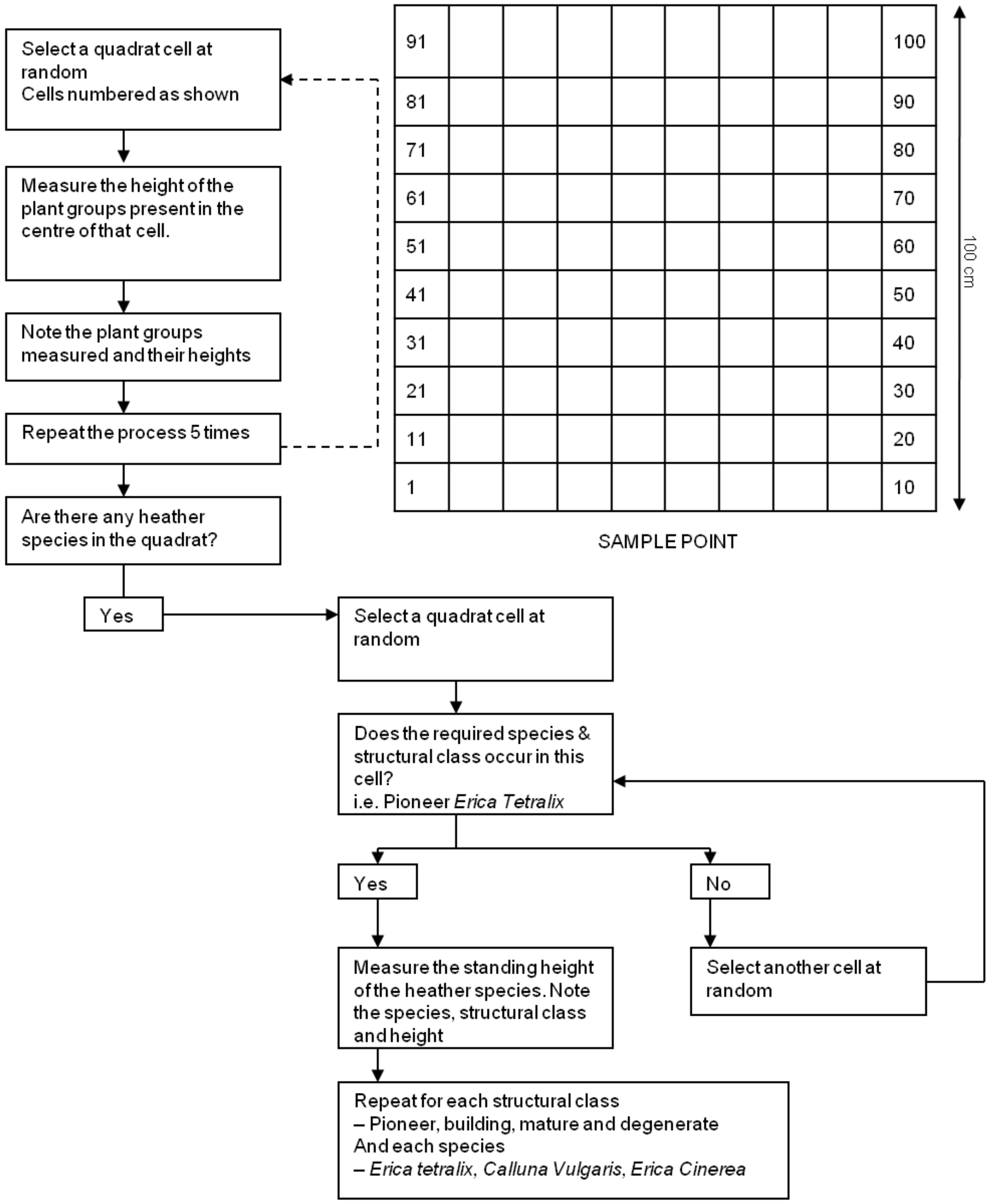
Family/Groups	Genus	Species
Grasses	Bedstraws – *Galium sp*.	All shrub sp. [2]
Rushes	Thistles – *Cirsium sp*.	
Sedges	Buttercups – *Ranunculus sp*.	
Mosses – "Feather"	Chickweeds – *Stellaria sp*.	
Mosses – *Polytrichum*	Dandelions – *Taraxacum sp*.	
Mosses – Sphagnum	Clovers – *Trifolium sp*.	
Mosses – Other		
Lichen – *Cladonia*	All Flowering plants[1]	
Lichen - Other		

Notes:

[1] *If any flowering plant cannot be identified to the genus level the group – other flowering plants should be applied.*

[2]*Ericaceous sp. and Calluna sp. should also be split into structural groups*

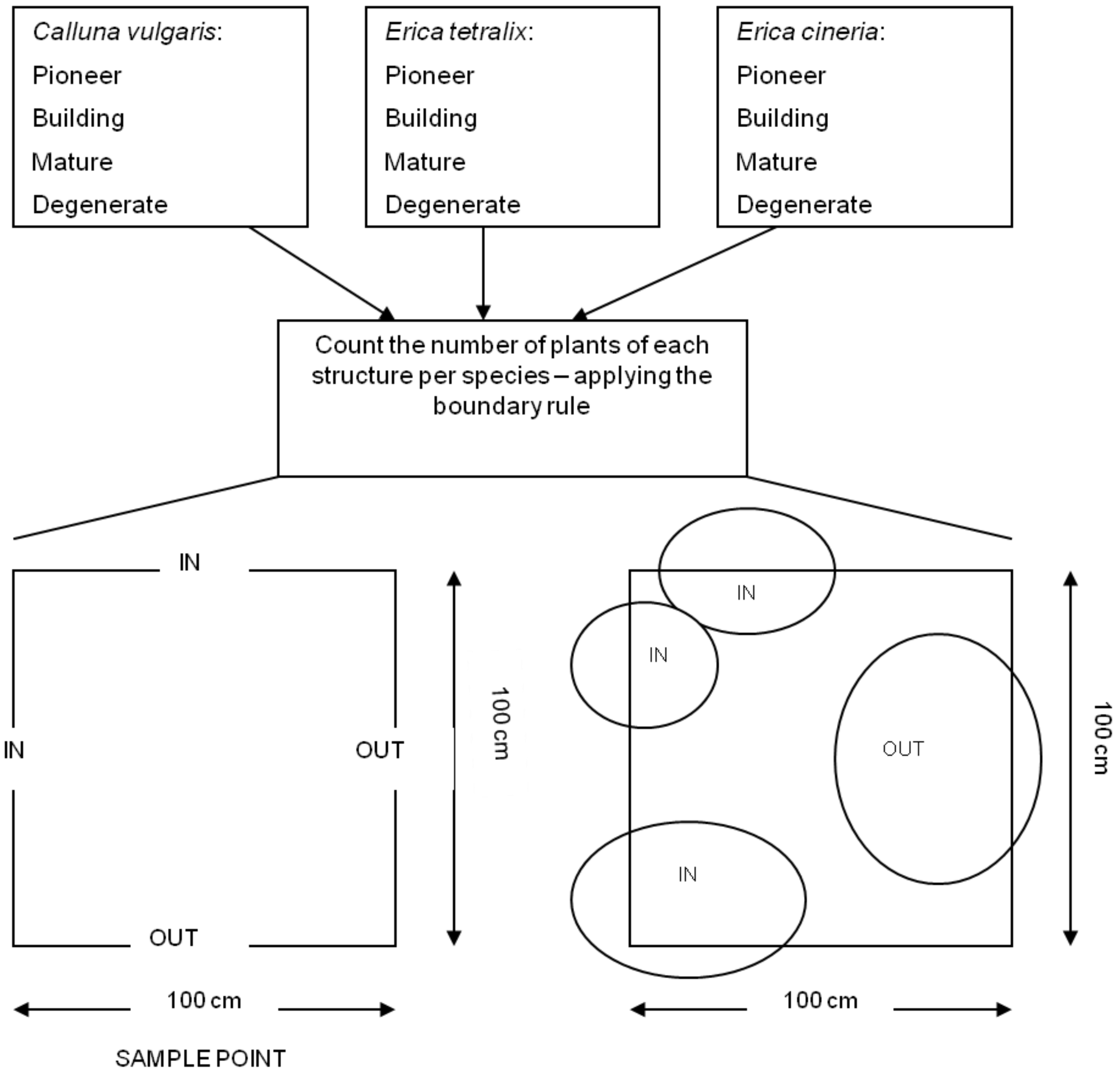
VEGETATION HEIGHT



<u>Rules</u>

- Height should be measured to the top of the leaf – not flowering head if the two vary.
- If the heather species does not form the top cover, this should be target noted along with the height of the top cover vegetation class.
- Measurement subdivision should be at 2cm.
- Vegetation classes lower than 2cm in height should be recorded as zero – indicative of ground cover.

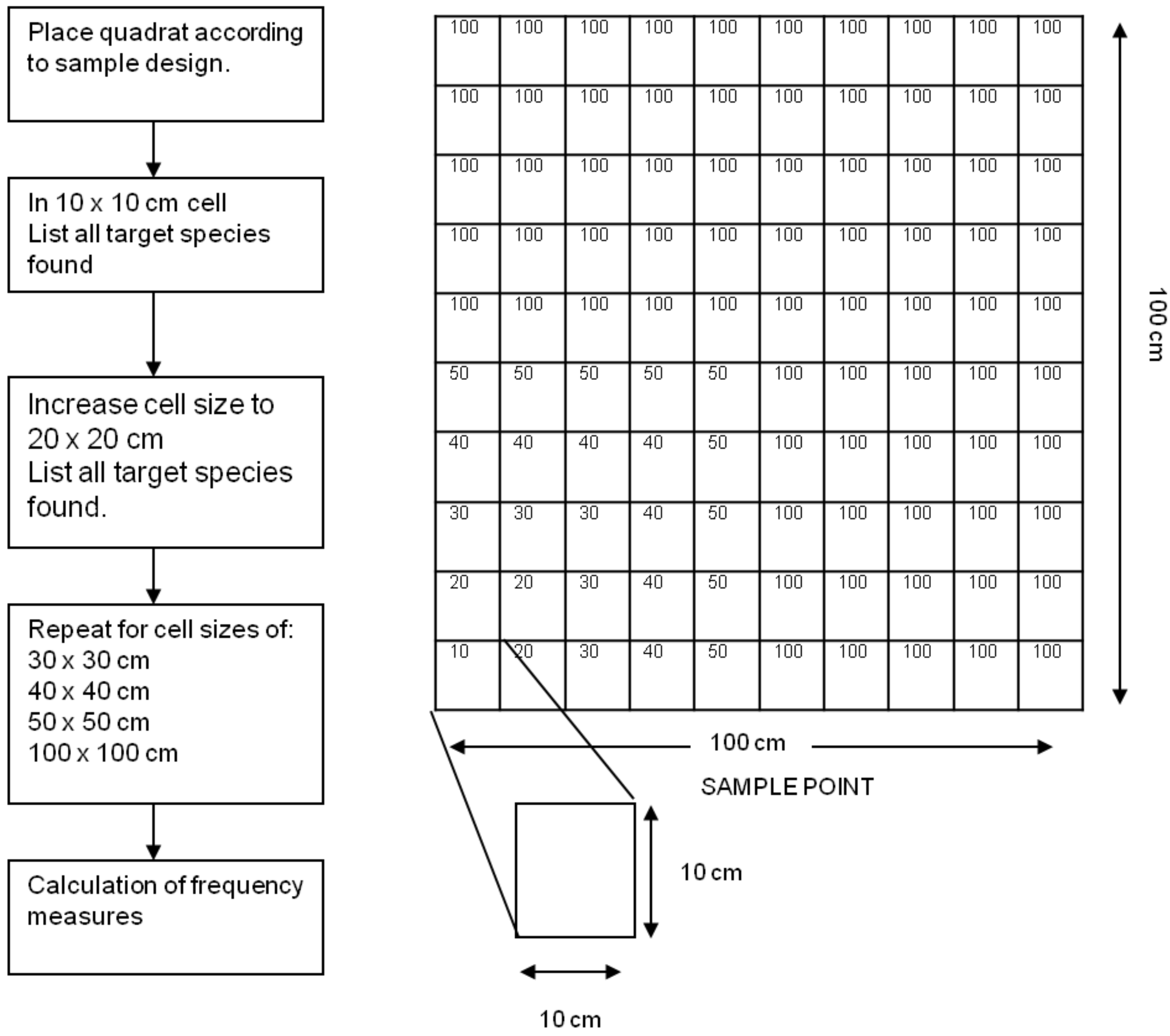
DENSITY



Rules

- The boundary rule illustrated should always be applied, even if the recorded number of plants is dramatically reduced.
- Plants which touch both an "in" and "out" boundary should be included in the quadrat total.
- The in/out boundaries should always be orientated as shown above relative to the sample point.

SPECIES COMPOSITION



Rules

- The 10 x 10 cm cell must always be placed in the same location, relative to the sample point.
- If any part of the target species is in the cell, it should be recorded it does not have to be rooted in the cell.
- Seedlings which cannot be identified accurately as target species should be ignored.

SPECIES COMPOSITION – TARGET SPECIES

Common Name	Latin Name	Comments
Shrubs		
Heathers[1]	*Erica tetralix* *Erica cineria* *Calluna vulgaris*	
Bilberry	*Vaccinium mytillus*	
Cowberry	*Vaccinium vitis-idaea*	
Crowberry	*Empetrum nigrum*	
Gorse	*Ulex europaeus*	
Bracken	*Pteridium aquilinum*	
Grasses		
Rye Grass	*Lolium perenne*	Indicative of agricultural improvements
Yorkshire Fog	*Holcus lanatus*	
Red Fescue	*Festuca rubra*	
Wavy Hair Grass	*Deschampsia flexuosa*	Indicative of acidic soil conditions
Matt Grass	*Nardus stricta*	
CocksFoot	*Dactylis glomerata*	Indicative of neutral soil conditions
Crested Dogstail	*Cynosurus cristatus*	
False Oat Grass	*Arrhenatherum elatius*	
Tor-Grass	*Brachypodium pinnatum*	Indicative of calcareous soil conditions
Crested Hair-grass	*Koeleria macrantha*	
Purple Moor Grass	*Molinia caerulea*	Can indicate overgrazing
Common Bent	*Agrostis capillaris*	
Sedges		
Cotton Grasses: Hairstail Common	 *Eriophorum vaginatum* *Eriophorum angustifolium*	Indicative of wet heath
Deer Grass	*Trichophorum cespitosum*	
Rushes		
Heath Rush	*Juncus squarrosus*	
Flowering plants		
Sheep's Sorrell	*Rumex acetosella*	Indicative of acidic soil conditions
Heath Bedstraw	*Galium saxatile*	
Daisy	*Bellis perennis*	Indicative improved grassland
Rosebay Willow Herb	*Chamerion angustifolium*	Indicative tall herb community
Nettles	*Urtica sp.*	Indicative nutrient enrichment
Dandelions	*Taraxacum sp.*	Indicative improved grassland
Buttercups	*Ranunculus sp.*	
Clovers	*Trifolium sp.*	
Common Sorrell	*Rumex acetosa*	
Tormentil	*Potentilla erecta*	Indicative unimproved grassland
Mosses and Lichens		
Moss – Feather	*Hylocomium sp.* *Plerozium sp.* *Hyprium sp.*	
Moss – Sphagnum	*Sphagnum sp.*	
Moss – Polytrichum	*Polytrichum sp.*	
Lichen	*Cladonia sp.*	

Notes:

[1] Heather species (Erica sp. and Calluna sp.) should be split according to their structural groups.

WOODLAND

ALL WOODLANDS in which SAMPLE POINTS FALL should be VISITED

GROUND TRUTH INFORMATION WHICH SHOULD BE RECORDED ON THE AERIAL PHOTOGRAPHS:

- CHANGE IN WOODLAND BOUNDARY/TREE AREA
- DEMARCATED STANDS – INCLUDING SPECIES COMPOSITION

IN ADDITION THE FOLLOWING INFORMATION SHOULD BE RECORDED

- SPECIES

As tracks are followed through the woodland species encountered should be listed.

- HEIGHT

The height of a subset of mature trees should be recorded.

ENSURE THAT TREES ARE:

  - Mature
  - Reflect a cross section of species
  - Representative of the stand height
  - Level
  - On flat ground

ENSURE THAT BOTH THE TOP AND BOTTOM OF THE TREE ARE CLEARLY VISIBLE.

KEYWORD LISTINGS

1. Linear Features Or Sample Point Obstructions

1.1 Linear Features

a) Feature type

Access:
Road
Rail
Path
Track
Bridleway

Water:
River
Stream

Boundaries:
Fence
Wall
Hedge
Strip woodland

Drainage:
Ditch – Dry
Ditch – Wet

Trees:
Strip woodland
Woodland edge

b) Feature height

Height:
0 - 1m
1 - 3m
3 - 5m
5m +

1.2 Obstructions

Water:
Pond
Reservoir

Management:
Grouse Butt
Silage Bags
Sheep dip
Feeding station

2. Description Of Developed Surfaces

Buildings:
Housing
Farming – Barns
Commercial building
Others

Others:
Gardens

3. Survey Information

Weather:

Raining	Clear	Still	Dry	Cold
Drizzle	Overcast	Breezy	Sunny	Warm
Showers	Misty	Windy	Sunny	Hot
Thundery	Poor visibility	Strong wind	Intervals	
Sleet				
Hail				
Snow				

4. Site Characteristics

Topology:	**Aspect:**
Flat	South Facing
Moderate slope	North Facing
Steep slope	East Facing
	West Facing
Bottom of slope	
Mid slope	
Top of slope	
Undulating	
Hummocks	

Geology/soils:

Rocky outcrops	
Bare Earth	
Compaction	
Erosion →	Rills/Gullies
	Crusts
	Slumping
	Deposition
	Puddles
	Sheet Wash
	Creep

Proximity to open water:

Spring	
Stream	
River →	Fast flowing
Pond	Slow Flowing
Lake	Still
Reservoir	

Miscellaneous:

Litter/Brash
Animal disturbance i.e. burrowing
Overhead wires

5. Management

Grouse:	Grouse Butts
	Shooting Posts
	Burning
	Mineral supplements
Bracken Control:	Trampling
	Spraying
	Cutting
	Burning
	Dead fronds – no evidence control
Livestock:	Rabbits
	Grouse
	Cattle
	Sheep
	Horses
Artificial Drainage:	Ditches
Recreation activities:	Footpath
	Bridleway
	Other - Specify
Enclosure:	Unenclosed
	Enclosed
Grazing:	
Light	Fenced/walled
Moderate	Supplement feeding
Heavy	Poaching
	Trampling
	Up-rooted plants
	Topiary/drumstick/carpet
	Grasses short
	Bilberry grazed
	Cotton grass grazed
	Matt grass grazed
	Bare ground
Fertilizer/Herbicide Treatments:	Bright Green Appearance
	Low species diversity

Mown/cut
Cultivated
Peat extraction
Scrub Invasion
Bracken Invasion
Irrigated
Logging
Orchard
Neglected

EQUIPMENT LIST

Quadrat	- 1m x 1m - 10cm subdivisions - Collapsible design
Measuring stick	- Solid measure - Length: 1.3m - Subdivisions: 2cm
Flag	- Height c.150cm
Hand lens	- Suitable for vegetation identification
pH Meter	
Clinometer	
Standard 30m measuring tape	
Compass	
Digital Camera	
Binoculars	
Notebook	
GPS	
Field Documentation:	- 1: 50,000 and 1: 10,000 topographic maps - 1: 5,000 aerial photography *Sample point locations visible* - Woodland aerial photography (Printed) - Field survey protocol - Vegetation identification keys - Access/land ownership information - Random number table

The Measurement of Percentage Cover

This appendix outlines analysis undertaken to determine the influence of measurement technique upon percentage cover estimates. Analysis was based on data collected during the pilot study. This data set contained percentage cover measurements resulting from visual estimates, undertaken independently by two surveyors, and via the pin frame technique.

Comparisons considered include (a) surveyor bias, (b) the influence of reduced pin frames and (c) differences between the visual and pin frame techniques.

VISUAL ESTIMATION: OBSERVER DIFFERENCES

During the pilot study, visual estimates of percentage top cover, after initial training, were made independently by two field surveyors. These duplicated measurements allowed the influence of observer upon percentage cover estimates to be assessed.

A one-way analysis of variance (ANOVA) was constructed to test if any significant differences existed between surveyor estimates (figure D1). This test was based on commonly occurring species, to ensure sufficient data, and excluded any sites at which the species being analysed was completely absent. It must be noted that interpretation of the ANOVA results was restricted as the pilot study data contained a limited number of samples. Consequently, the assumptions of the statistical techniques were not met.

The null hypothesis, that percentage cover estimates were significantly different according to surveyor or site, was only rejected in relation to sites (figure D1). Consequently, on the basis of the pilot study data, it can be concluded that while species cover would be expected to vary as a function of site a species dependent difference between surveyors was not evident.

It should be noted that this conclusion masked large differences, of up to 20%, between surveyors at the quadrat level (figure D2). These surveyor differences were particularly evident at intermediate levels of cover. As the level of analysis in subsequent remote sensing and GIS processing is the sample point, the quadrat level data were agglomerated to the scale of the sample point. At this scale surveyor difference, and therefore scatter about the one-to-one line, was reduced (figure D3).

On the basis of these plots and the ANOVA it was concluded that firstly, while there was a tendency for surveyors to differ in their visual estimates of percentage cover, particularly at intermediate levels of cover, these differences were not significant. Secondly, quadrat scale surveyor differences tended to ‘average out’ when agglomerated to the sample.

Bilberry

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	0.1	0.1	0.00	0.978
site.position	4(1)	30985.6	7746.4	42.85	<.001
assessor.site.position	4(1)	90.4	22.6	0.13	0.972
Residual	30(6)	5423.5	180.8		
Total	39(8)	36499.6			

Bracken

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	0.7	0.7	0.00	0.947
site	1	21816.5	21816.5	146.93	<.001
assessor.site	1	2.6	2.6	0.02	0.895
site.position	8(2)	56016.0	7002.0	47.16	<.001
assessor.site.position	8(2)	75.4	9.4	0.06	1.000
Residual	60(12)	8909.0	148.5		
Total	79(16)	83183.0			

Building Calluna vulgaris

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	6.3	6.3	0.04	0.851
site	1	3755.0	3755.0	20.97	<.001
assessor.site	1	7.8	7.8	0.04	0.836
site.position	9(1)	32054.1	3561.6	19.89	<.001
assessor.site.position	9(1)	496.5	55.2	0.31	0.970
Residual	66(6)	11817.7	179.1		
Total	87(8)	47796.1			

Pioneer Calluna vulgaris

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	9.12	9.12	0.23	0.632
site	1	1502.58	1502.58	38.14	<.001
assessor.site	1	2.81	2.81	0.07	0.790
site.position	9(1)	11965.54	1329.50	33.75	<.001
assessor.site.position	9(1)	158.14	17.57	0.45	0.905
Residual	66(6)	2600.00	39.39		
Total	87(8)	16101.27			

Figure D1: ANOVA results comparing visual estimates of common species, bilberry, bracken and *Calluna vulgaris*, by two surveyors (assessor).

*Notes: Sites (sample locations) and assessors (visual estimates made by the surveyors) are compared in an ANOVA. The data treatment structure applied was assessor *(site/position). Tests in which the null hypothesis, that all sites and assessors are the same, can be rejected at the 95% confidence level are highlighted in red.*

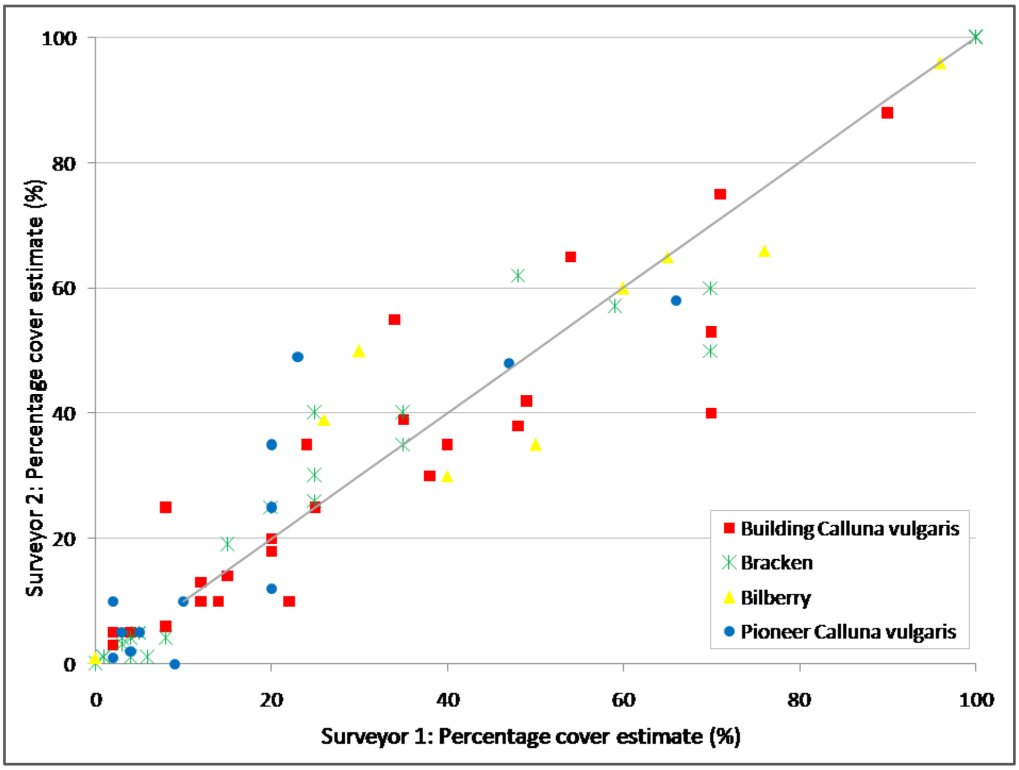


Figure D2: A comparison of surveyor percentage cover estimates, within a quadrat, for differing species

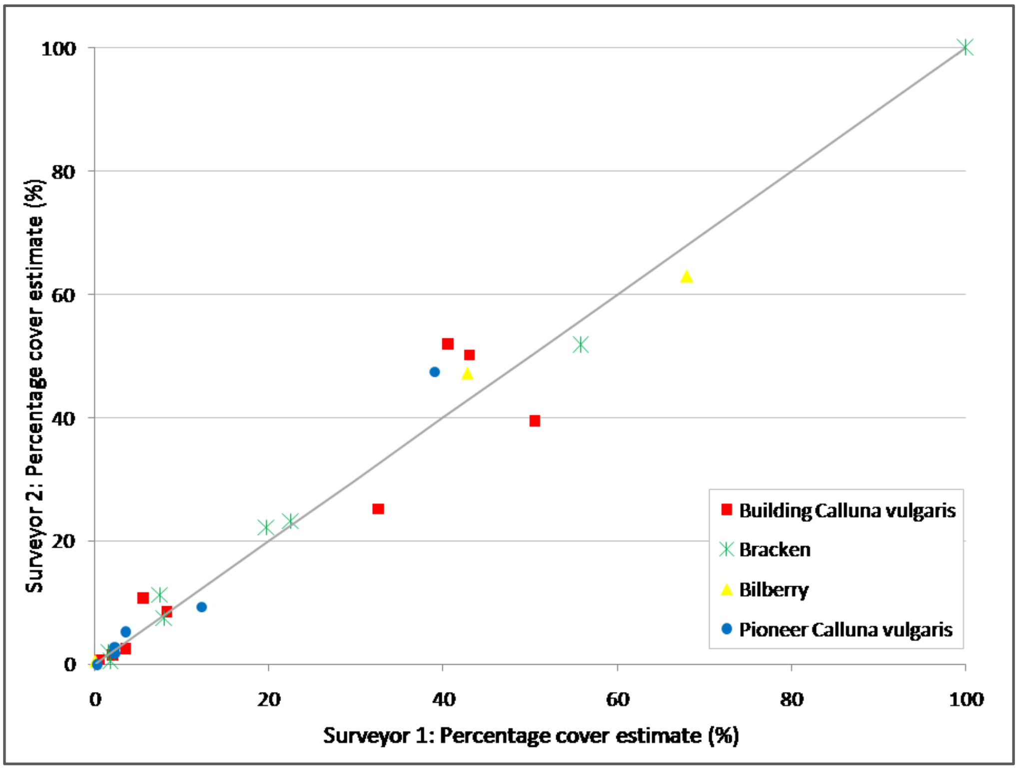


Figure D3: A comparison of surveyor percentage cover estimates, at the sample point, for differing species

Factors which influence visual estimates

From the observed surveyor differences and field notes it was concluded that visual estimations of percentage cover were influenced by:

- *Vegetation structure, size and floristic characteristics*

Small, rare species which covered a small spatial extent in the quadrat had a greater probability of being overlooked by either surveyor. This was particularly evident for indistinct species which lacked flowering heads. Methodical searching of each quadrat cells was found the most effective way to ensure all plant species were recorded.

- *Cover proportion*

Estimates of percentage cover tend to differ at intermediate levels of cover (figure D2).

- *Mixing*

Surveyor estimates of top cover tended to be similar in quadrats characterised by 'blocky' species cover. Where species dominate quadrat segments top cover can be determined with a high degree of accuracy. A consequence of species mixing was increased subjectivity in top cover estimates and an increased tendency for surveyor estimates to differ.

- *Top cover determination*

Quadrats composed of multiple vegetation layers required a subjective judgement, by the surveyor, in determining the species contributing to the top vegetation layer.

- *Weather conditions and time of day*

The weather and time of day were found to influence light conditions at the site and therefore visual percentage cover estimates. Equally, long hours in the field and adverse weather conditions influenced surveyor motivation and therefore the accuracy of recorded data.

PIN FRAME TECHNIQUE: FRAME REDUCTION

Implementation of the 10 pin frames as required by the field protocol was found to be prohibitively time consuming. Consequently, measurements were reduced. At moorland sites percentage cover was recorded in 5 pin frames. These frames represented either the odd or even frame locations, selected at random, in the quadrat.

To determine if bias was introduced as a function of a reduced number of pins or selection of odd/even frames a synthetic dataset was produced for all samples at which a full 10 frame dataset was available. An ANOVA analysis (figure D4), comparing results obtained with 10, as opposed to 5 frames, at moorland sites for common species concluded that the null hypothesis could not be rejected. Therefore, on the basis of the synthetic dataset no significant bias could be proven as a function of reduced pin frame measurements.

At grassland sites the required 10 pin frames were reduced to 25 pins in a randomly selected quadrant of the quadrat. The impact of data collection at 25 pins, as opposed to 100 pins, at grassland sites could not be statistically tested due to insufficient data being available. However, visual interpretation of quadrat photographs indicated that the quadrant selected although representative of the sample site was typically, unrepresentative of the entire quadrat.

SAMPLE BASED ON EVEN NUMBERED FRAMES

Bilberry

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
pins	1	1.8	1.8	0.00	0.961
Residual	18	13228.0	734.9		
Total	19	13229.8			

Bracken

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
pins	1	0.4	0.4	0.00	0.974
Residual	18	7635.3	424.2		
Total	19	7635.8			

Building Calluna vulgaris

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
pins	1	0.	0.	0.00	0.984
Residual	18	20499.	1139.		
Total	19	20500.			

SAMPLE BASED ON ODD NUMBERED FRAMES

Building Calluna vulgaris

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
pins	1	0.	0.	0.00	0.985
Residual	18	20917.	1162.		
Total	19	20917.			

Bracken

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
pins	1	0.1	0.1	0.00	0.992
Residual	18	7776.5	432.0		
Total	19	7776.6			

Bilberry

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
pins	1	0.2	0.2	0.00	0.987
Residual	18	12997.6	722.1		
Total	19	12997.8			

Figure D4: ANOVA results comparing cover estimates of common species, bilberry, bracken and *Calluna vulgaris*, derived in 5 (odd/even) as opposed to 10 pin frames.

Notes: On the basis of the ANOVA analysis the null hypothesis, that the 10 frame and 5 frame results are the equivalent, cannot be rejected at the 95% confidence level.

Factors which influence pin frame estimates

The accuracy with which pin frame measurements could be collected was found to be dependent upon:

- *Vegetation structure*

In short ground cover the pin frame technique was an ideal means of estimating percentage cover. However, as vegetation became taller and increasingly dense the pin frame technique became impractical.

- *Species identification*

Errors were introduced into data collection where the species hit by the pin could not be easily identified. This error was particularly evident for grass species as identification on the basis of leaves was complex and recognition of the associated flowering head impractical.

- *Missing species*

Frames located at regular intervals within the quadrat demonstrated a tendency to miss species which occurred at low cover proportions.

COMPARISON OF THE VISUAL ESTIMATION AND PIN FRAME TECHNIQUES

Finally, an ANOVA test was constructed to determine if any significant bias could be identified between the two cover estimation techniques, that is, visual estimation and the pin frame.

Results from the ANOVA analysis (figure D5 and D6) indicated that while differences in species cover would be expected as a function of site no significant differences were proven, at the quadrat level, as a function of the measurement technique; the null hypothesis could not be rejected. However, it should be noted that the datasets on which the tests were performed were limited and assumptions of the statistical technique not met. Consequently, the results were considered indicative only.

Plotting of the quadrat data pairs illustrated that while no significant difference was found between the techniques this masked large disparities between the visual, particularly those made by surveyor 1, and pin frame estimates (figure D7). Aggregation of quadrat data to the sample point reduced variability between the techniques, as evident by decreased scatter of observation pairs about the one-to-one line (figure D8). A trend evident in these plots (figure D8) is one of higher percentage cover estimates in the pin frame technique.

SURVEYOR 1

Bilberry

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	102.8	102.8	0.40	0.531
site.position	5	33579.1	6715.8	26.23	<.001
assessor.site.position	3(2)	172.6	57.5	0.22	0.878
Residual	30(6)	7682.5	256.1		
Total	39(8)	38007.6			

Bracken

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	51.1	51.1	0.37	0.543
site	1	21038.5	21038.5	154.00	<.001
assessor.site	1	2.3	2.3	0.02	0.898
site.position	9(1)	58386.1	6487.3	47.49	<.001
assessor.site.position	7(3)	450.0	64.3	0.47	0.852
Residual	60(12)	8197.0	136.6		
Total	79(16)	81574.0			

Building Calluna vulgaris

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	314.2	314.2	1.83	0.181
site	1	5434.8	5434.8	31.62	<.001
assessor.site	1	0.7	0.7	0.00	0.949
site.position	10	36354.9	3635.5	21.15	<.001
assessor.site.position	8(2)	382.4	47.8	0.28	0.971
Residual	66(6)	11345.5	171.9		
Total	87(8)	53034.9			

Pioneer Calluna vulgaris

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	85.54	85.54	2.10	0.152
site	1	623.31	623.31	15.30	<.001
assessor.site	1	169.03	169.03	4.15	0.046
site.position	10	5185.13	518.51	12.72	<.001
assessor.site.position	8(2)	781.72	97.72	2.40	0.025
Residual	66(6)	2689.50	40.75		
Total	87(8)	9503.95			

Figure D5: ANOVA results comparing cover estimates of common species, bilberry, bracken and *Calluna vulgaris*, by surveyor one (visual estimate) and the pin frame.

*Notes: Sites (sample locations) and assessors (surveyor 1 and the pin frame) are compared in an ANOVA. The data treatment applied was structure assessor *(site/position). Tests in which the null hypothesis, that all sites and assessors are the same, can be rejected at the 95% confidence level are highlighted in red.*

SURVEYOR 2

Bilberry

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	66.0	66.0	0.26	0.617
site.position	5	33612.9	6722.6	26.08	<.001
assessor.site.position	3(2)	122.5	40.8	0.16	0.923
Residual	30(6)	7732.5	257.8		
Total	39(8)	37163.9			

Bracken

Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	51.2	51.2	0.35	0.554
site	1	21637.6	21637.6	149.72	<.001
assessor.site	1	1.4	1.4	0.01	0.922
site.position	9(1)	55745.9	6194.0	42.86	<.001
assessor.site.position	7(3)	368.7	52.7	0.36	0.919
Residual	60(12)	8671.5	144.5		
Total	79(16)	80854.8			

Building Calluna vulgaris

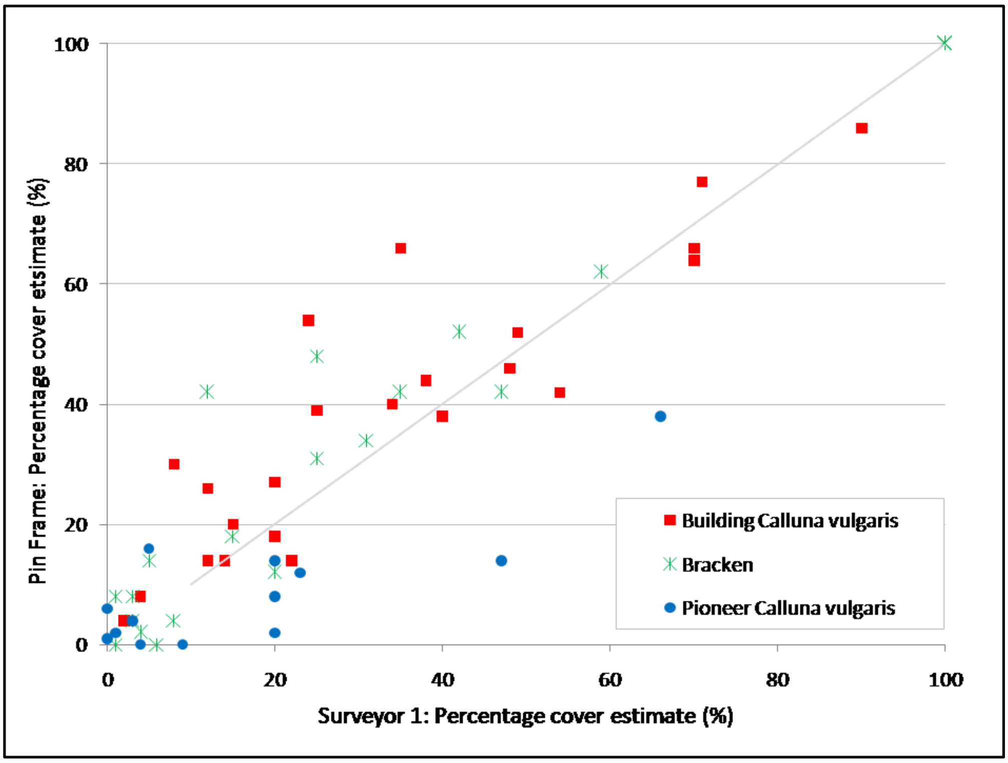
Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	339.6	339.6	2.18	0.144
site	1	5302.1	5302.1	34.07	<.001
assessor.site	1	29.8	29.8	0.19	0.663
site.position	10	35201.3	3520.1	22.62	<.001
assessor.site.position	8(2)	495.8	62.0	0.40	0.918
Residual	66(6)	10269.7	155.6		
Total	87(8)	50512.4			

Pioneer Calluna vulgaris

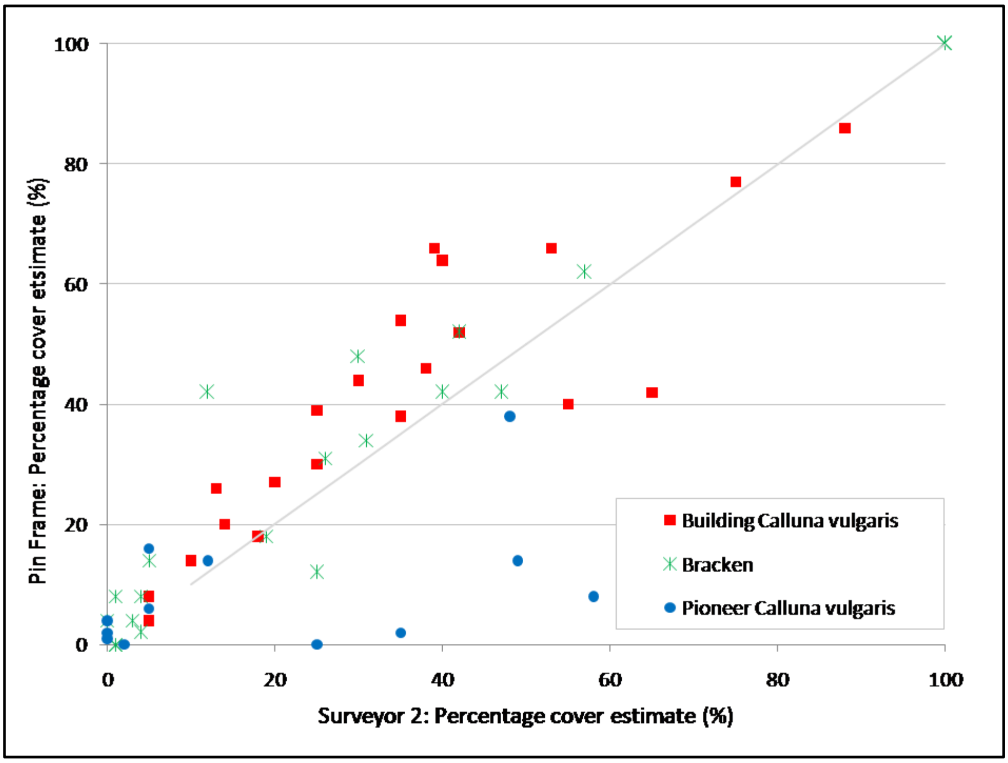
Source of variation	d.f.(m.v.)	s.s.	m.s.	v.r.	F pr.
assessor	1	132.11	132.11	5.03	0.028
site	1	685.96	685.96	26.12	<.001
assessor.site	1	238.72	238.72	9.09	0.004
site.position	10	6875.36	687.54	26.18	<.001
assessor.site.position	8(2)	1443.26	180.41	6.87	<.001
Residual	66(6)	1733.50	26.27		
Total	87(8)	11056.32			

Figure D6: ANOVA results comparing cover estimates of common species, bilberry, bracken and *Calluna vulgaris*, by surveyor two (visual estimate) and the pin frame.

*Notes: Sites (sample locations) and assessors (surveyor 2 and the pin frame) are compared in an ANOVA. The data treatment applied was structure assessor *(site/position). Tests in which the null hypothesis, that all sites and assessors are the same, can be rejected at the 95% confidence level are highlighted in red.*

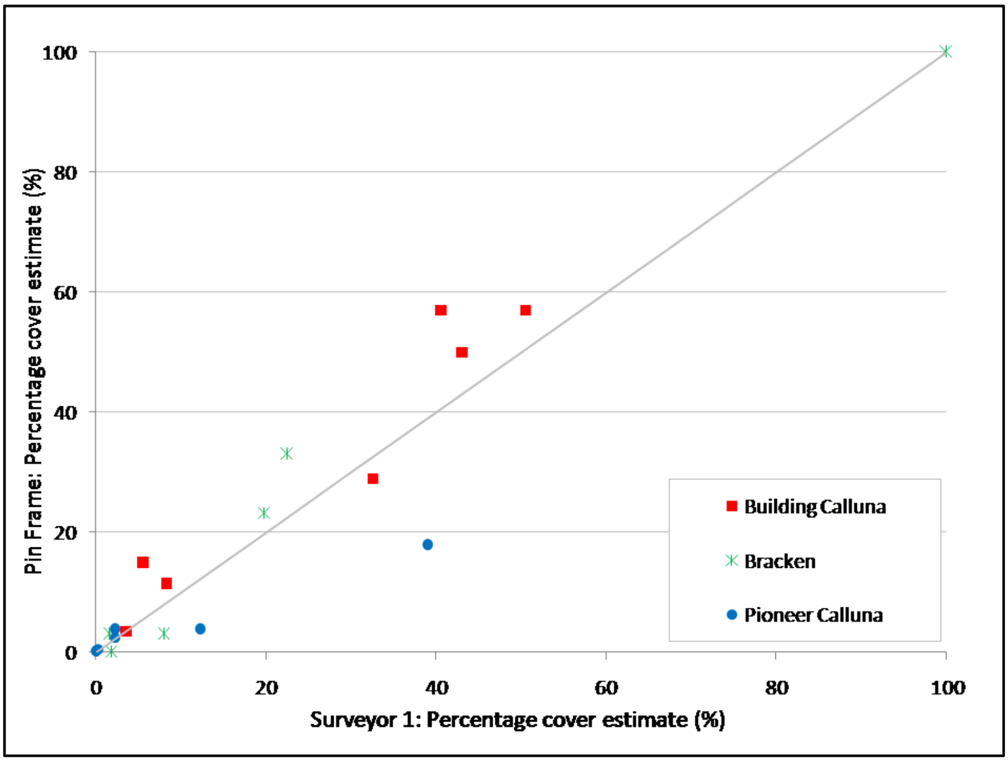


a) Surveyor one estimates are compared to the pin frame technique

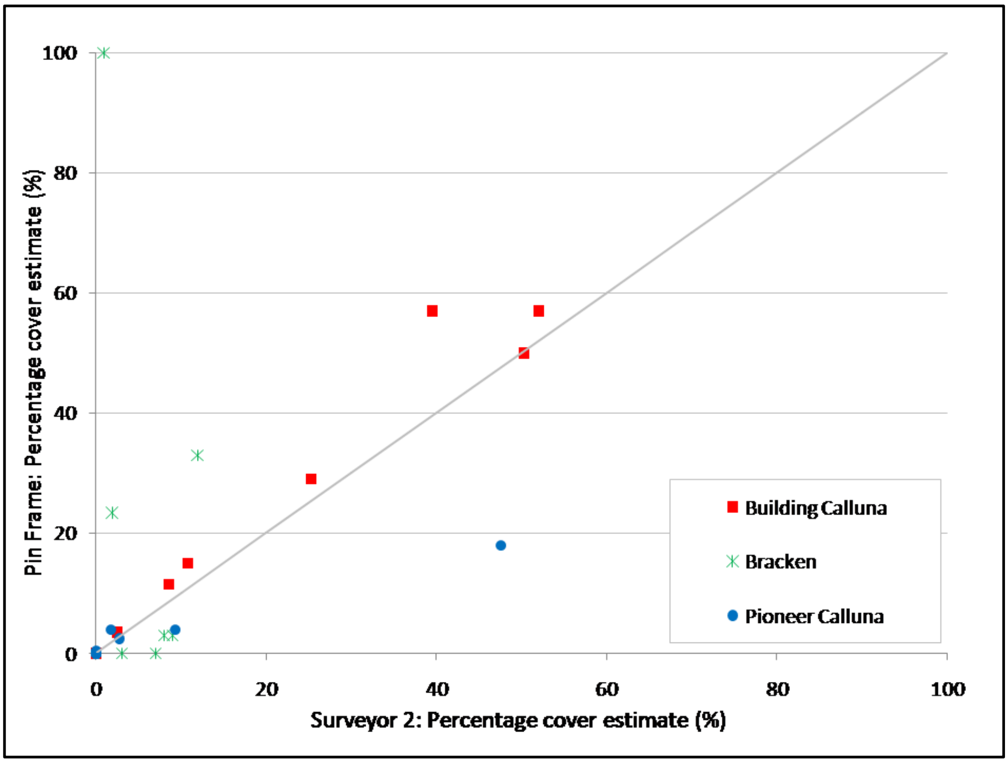


b) Surveyor two estimates are compared to the pin frame technique

Figure D7: A comparison of percentage cover derived from visual estimates (surveyors (a) 1 and (b) 2) and the pin frame, within a quadrat, for differing species



a) Surveyor one estimates are compared to the pin frame technique



b) Surveyor two estimates are compared to the pin frame technique

Figure D8: A comparison of percentage cover derived from visual estimates (surveyors (a) 1 and (b) 2) and the pin frame, at the sample, for differing species

APPENDIX E

Field Data Collection Application

The appendix describes a bespoke application developed to enable data collection as per the field survey protocol. Following a review of potential data storage formats and programming environments the structure of the application and implemented relational database design are outlined.

Implementation of the field survey protocol within a digital application

Traditionally data collection has taken the form of paper and ink note-taking. However, with the advent of pocket PC devices it is now feasible to collect data in the field in a digital format. This is particularly true with the integration of pocket PC devices and GPS units. This digital data capture has several advantages over traditional note taking.

Efficiency

Digital data capture is both more efficient in the field and in subsequent data processing. In the field there is no requirement for paper field sheets, prone to damage in the rain, or extensive note taking. Following the field survey time-consuming database creation and data input is eliminated.

Better error handling

Using traditional note taking, error can be introduced both in the field, when the surveyor records the wrong information, and in the data input stages, due to transcription/typing errors or incorrect interpretation of field notes. If field data is recorded digitally, data processing is reduced to a minimum restricting the introduction of errors into the dataset. Errors are still feasible as the surveyor inputs data. However, the collection program can be designed with inbuilt error checking in an attempt to minimise such mistakes.

Consistency

While traditional field data collection sheets can be designed to ensure that surveyors are consistent in notation there is often room for deviation or a failure to record data in all the required data fields. Collection programs can be designed to ensure all required data is recorded in the correct format and at an appropriate level of detail.

A better use of resources

The implemented field survey recorded measurements at approximately 960 quadrats. If it was assumed that each quadrat required a field data collection sheet of 4 pages, the resultant 3840 sheets of paper represented a considerable resource and cost.

While there are a number of advantages to digital data capture there are several disadvantages when compared to traditional note taking.

Data backup

If data is collected in a paper format, a hard copy of the results is automatically available should the subsequently created digital data be corrupted, damaged or lost. If the original data is collected digitally this hard copy is unavailable making file backup in multiple, secure locations vital.

Data format

If data is collected on paper, a copy that anyone can read is automatically available, this is not true if digital data is collected in an inappropriate format. While data conversion is often possible, the implications and the potential for data loss should be considered.

Digital data capture requirements

The requirements of the digital data capture program used within the field survey were:

- A logical approach which stepped the surveyor through the field survey protocol.
- Ease of use, on a PDA, within a field environment.
- Functionality which ensured standardisation in data collection.
- Compatibility with a small-footprint device, in particular the Trimble GeoXT.
- Functionality to enable efficient data backup and storage.

Additionally any data capture program was required to manage:

- The hierarchical nature of the data collection by accommodating data recorded at the scale of the point, quadrat and sub-quadrat.
- The variety of vegetation parameters collected.
- The large datasets which were generated.

Data format and storage options

Prior to the development of the field survey application, the most appropriate data format for field data storage was considered. This was of primary importance as the format chosen would influence the application development environment. Potential data storage options were compared against the digital data capture requirements.

ESRI Shapefile

ArcPad is a scaled down version of ArcGIS intended for use with handheld computers. Within ArcPad there are a set of development tools which enable the development of a field data collection application. Such an application can be integrated with the ArcPad GPS tools to allow both spatial and attribute data storage within a single ESRI shapefile.

Program creation in ArcPad is targeted towards data collection and therefore the interface was easily adapted to meet the specific requirements of the field survey. However, the flat structure of the shapefile attribute table was not ideally suited to the hierarchical nature of the field data.

TerraSync Rover File

In addition to the recording of GPS data the TerraSync software provides functionality to enable attribute recording. This functionality is available via the data dictionary utility. The data dictionary provides a template for data collection which prompts the user for feature specific attribute data during GPS data collection.

Development of a TerraSync data dictionary, as a means of field data collection, was advantageous as it allowed the integration of the spatial and attribute data at each sample. However, the flat structure of a TerraSync attribute table and the numerous data entry fields required for the current survey were limitations regarding development of the application in this environment.

Databases

The primary advantage of a database is the ability to store complex data in a series of relational tables.

Microsoft Access database (.mbd)

Microsoft Access is a commonly used relational database provided with Microsoft Office. Features which made this file structure suitable for the storage of field data included:

- A widely recognised and used data format.
- An ability to create multiple tables to represent the hierarchal levels of data collection.
- An ability to relate tables through common fields.
- Inbuilt error checking capabilities.
- Automated data queries for data extraction.

Microsoft Access would seem to provide an ideal structure and format in which to store the field data, however, the program is not compatible with small-footprint devices due to the resources required by the application. Pocket Microsoft Access (*.cdb*), a scaled down version of the software compatible with small foot-print devices, has been available in the past. However, this has now been withdrawn by Microsoft.

Although the Microsoft Pocket Access software is no longer available the compacted database file format (*.cdb*) is still recognised by Microsoft ActiveSync and the Windows CE operating system. Consequently, it is possible to implement this file structure in a stand-alone program developed to act as an interface between the surveyor and database file.

SQL Server CE 2.0

SQL Server CE is a compact relational database designed for mobile devices. The structure of SQL Server CE is designed to allow integration with the .Net Compact Framework via the visual studio programming languages. While this software could provide an alternative to Microsoft Access it was not available for this research project.

Commercially available, Pocket PC specific databases.

A number of independent companies now design and promote database software targeted to the small-footprint device, for example, HanDBase (DDH Software, 2004) and SprintDB (KaioneSoft, 2004).

Available applications range in their complexity, output data format and database structure. A review of these software concluded that the applications were not suitable for the research due to concerns regarding program specific developments, the output data format and file compatibility.

<u>Data Format Conclusions</u>

Of the formats considered, the most appropriate and those available to the project were ArcPad, TerraSync and Microsoft Access. The characteristics of each of these data format options, in terms of the application requirements, are compared in table E1.

While ArcPad and TerraSync had the advantage of GPS integration the hierarchical nature of the field data at the scale of the sample point, quadrat and sub-quadrat, was best managed by the multiple related tables offered by the Microsoft Access database structure.

Table E1: A comparison of field data storage options

Requirement	ArcPad	TerraSync	Microsoft Access
GPS integration	√	√	(√)
GPS Post-processing	x	√	x
Allow field data entry *(Standard tools)*	x	√	x
Allow field data entry *(Additional programming)*	√	x	√
Hierarchical data structure *(Relational tables)*	x	x	√
Trimble GPS device specific	x	√	x
Output file format	Shapefile (.shp)	Trimble rover file (.ssf)	Compact Microsoft Access (.cdb)

To enable implementation of the Microsoft Pocket Access data format a standalone field survey program was developed to enable interaction between the compact database file (*.cdb*) and the surveyor. GPS data, the spatial location of the sample point, was collected independently of the field survey data using the TerraSync software.

It should be noted that GPS integration could be achieved in the interface developed, however, this is not simple and the recording of complex GPS signals, in terms of carrier and code signal information for post-processing, was not viable within the context of this research.

Database programming and small footprint devices

The small-footprint device used in this study was the Trimble GeoXT unit. This unit combines a Trimble GPS receiver with a hand-held computer running the Windows CE.Net 4.2 operating system.

Application development targeting the Windows CE operating system

Programs or applications for Windows CE or Pocket PCs must be developed in an environment which targets the appropriate operating system and small-footprint device. Targeted programming ensures that the developed application only implements that functionality best suited to the device typically characterised by limited CPU power, memory and bandwidth connectivity. Windows CE.Net 4.2 is compatible with the EVC++, C#.Net and VB.Net programming languages; the field survey application was developed in VB.Net

'Inthehand' wrapper, Pocket Access and ADOCE

A limitation in the functionality of the .Net compact framework is that the local database tools only support SQL Server CE 2.0 and not Pocket Access (*.cdb*). To enable interaction between the developed user interface and Pocket Access database an additional wrapper and ActiveX control were required.

ADOCE 'Inthehand' is a commercially available wrapper which plugs the gap between the programming language (VB.Net) and Pocket Access enabling read/write access to windows databases from the .Net compact framework. The wrapper is a combination of .Net classes and an unmanaged C++ dynamic link library which bridges to the ADOCE ActiveX control. This ActiveX control, Microsoft ADOCE 3.1, enables communication with the Pocket Access database.

Field survey application

Design

The design of the field survey application was centred on the following elements:

Field survey protocol

The field survey application was designed to step the surveyor through the field survey protocol. In this way the application prohibited the surveyor from missing steps in the protocol hence ensuring all appropriate data were collected. This step through design was achieved via a series of switchboard forms which, by asking the surveyor questions regarding the sample point, ensured the appropriate forms for data collection were displayed (figure E1).

To ensure clarity in data collection each element of the field survey protocol was presented to the surveyor in an individual form. The field data resulting from each field protocol element were stored in separate tables of the Pocket Access database.

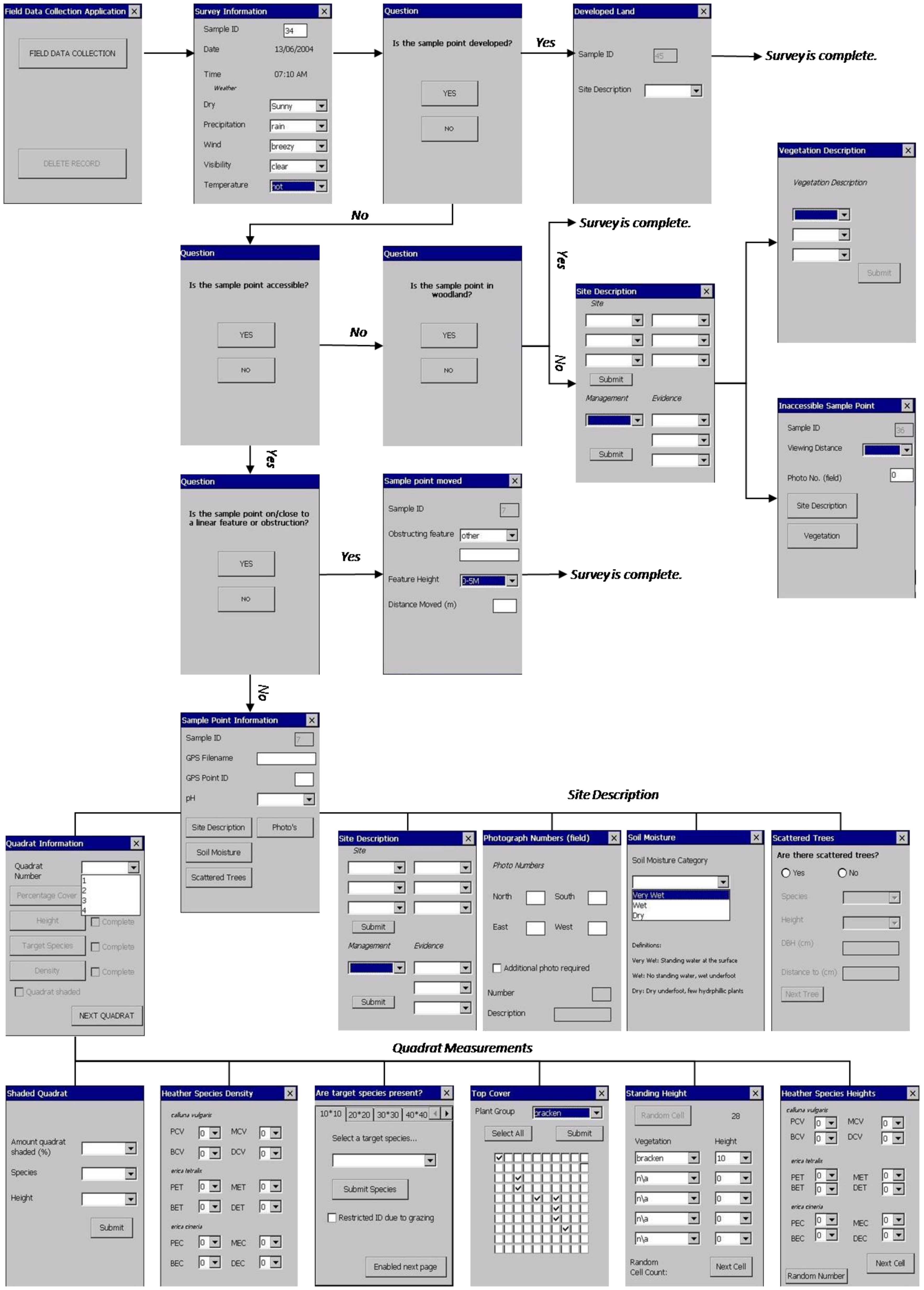


Figure E1: Construction of the field survey program

Standardised input

The field survey application was designed to ensure consistency and standardisation in data input as defined within the field survey protocol. This was achieved by limiting user input, wherever possible, to a standard set of descriptors or keywords. For example, in the case of the soil moisture parameter a standard set of descriptors were provided to the surveyor in the form of a drop-down list (figure E2). Consistent data collection was further promoted by the inclusion of 'help' sections within the field survey application. Figure E2 illustrates the inclusion of soil moisture definitions in the data input form to ensure consistent interpretation of the parameter keywords.

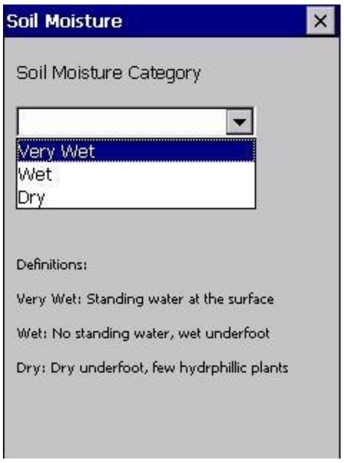


Figure E2: Characterisation of the soil moisture parameters, an example of data input standardisation.

Error checking

Error checking was an important element of the field survey application to ensure results were consistent, within accepted bounds, and collected at an appropriate level of detail. Error checking was applied to data input elements to ensure that:

- All required information was entered.
- Duplicated entries were not accepted (figure E3).
- Measurements were within acceptable value ranges.
- Measurements were taken in the correct format.

This was achieved via various programming elements including data entry masks, data conversion and record checks.

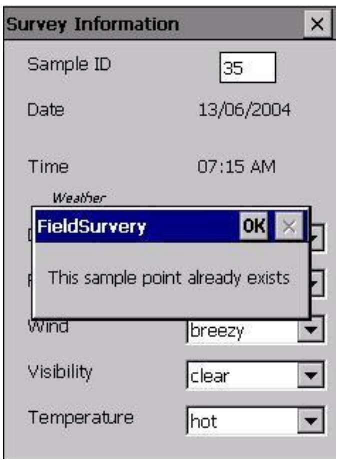


Figure E3: Error checking example, the surveyor cannot proceed as the sample point already exists in the database

Form design

Forms, used in the application, were designed to ensure:

- Suitability for display on the GeoXT device.
- Suitability for use with the input stylus of the GeoXT. This was achieved by placing controls to ensure that double taps did not influence running of the application.
- Clarity as to which parameter was being measured and how it should be recorded.

Database structure

The field data were stored in a Microsoft Pocket Access structure which was converted to the standard Microsoft Access file format (*.mdb*) via the ActiveSync software.

The field data database was constructed to ensure each field survey parameter was recorded within an independent table. This resulted in 13 tables (outlined below). Tables were related by a field containing a unique identification number constructed from the sample and quadrat identification numbers.

The field survey application was designed to create independent databases according to the date of survey. This separation of results, into survey days, minimised the memory resources required on the GeoXT for storage of the database and promoted prompt download and therefore backup of the collected field data. Database naming was standardised to FieldData_*"Dateofsurvey"*.

Field survey application properties

The field survey application properties are summarised in table E2.

Table E2: Summary of the field survey application properties

Field survey application properties	
Development environment	Visual Basic.Net
Database	.CDB (.MDB upon conversion)
Targeted operating system	Windows CE .NET 4.2
Targeted processor	ARM
Required files	Keywords.Cdb (Located in 'my documents') ADOCE.net IntheHand wrapper ADOCE 3.1 ActiveX component
Output files	FieldData*"Date of survey"*.cdb

References

DDH Software (2004) *HanDBase*, http://www.ddhsoftware.com/handbase.html (Available April 2008)

KaioneSoft (2004) SprintDB, http://www.kaione.com/ (Available April 2008)

Database Structure

Table Name	Description
Top Cover	Percentage top cover of species occurring within each quadrat surveyed
Density (Heather Species)	The number of heather plants (categorised according to species and structural stage) occurring within each quadrat surveyed
Development	The description of sample points falling on developed surfaces
Heights: Heather	The height of heather species in the quadrat as recorded per the field survey protocol
Heights: Species	The height of plant groups in the quadrat as recorded per the field survey protocol
Inaccessible Sample	A generalised description of sample points which could not be surveyed
Quadrat Information	A description of the quadrat identified according to the sample and quadrat position
Scattered Trees	A description of scattered tree (if present) surrounding the sample point
Shaded Quadrat	A description of trees (if present) shading the quadrat
Sample Point Moved	Information outlining the factors responsible for sample points being moved spatially to ensure full quadrat layouts (as described in the field survey protocol)
Sample Point Description	A description of the sample point and the surrounding area
Survey Information	Details regarding the survey date and conditions at the time of survey
Target Species	Records of the presence/absence of target species with each quadrat surveyed

Table descriptions

COVER

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
QID	Unique sample point and quadrat identification number		Integer	
PLANTGRP	Keyword - plant species for which cover is being recorded		Text	plantgroups
CELL1 - 100	Code - identifies if the plant group is present/absent in the cell	**1** : Yes **0** : No	Integer	

DENSITY (Heather Species)

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
QID	Unique sample point and quadrat identification number		Integer	
PCV	Approximate number of pioneer *Calluna vulgaris* plants		Integer	
BCV	Approximate number of building *Calluna vulgaris* plants		Integer	
MCV	Approximate number of mature *Calluna vulgaris* plants		Integer	
DCV	Approximate number of degenerate *Calluna vulgaris* plants		Integer	
PET	Approximate number of pioneer *Erica tetralix* plants		Integer	
BET	Approximate number of building *Erica tetralix* plants		Integer	
MET	Approximate number of mature *Erica tetralix* plants		Integer	
DET	Approximate number of degenerate *Erica tetralix* plants		Integer	
PEC	Approximate number of pioneer *Erica cinerea* plants		Integer	
BEC	Approximate number of building *Erica cinerea* plants		Integer	
MEC	Approximate number of mature *Erica cinerea* plants		Integer	
DEC	Approximate number of degenerate *Erica cinerea* plants		Integer	

DEVELOPMENT

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
DEVTYPE	Keyword - Development type		Text	Development

HEIGHTS: HEATHER

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
QID	Unique sample point and quadrat identification number		Integer	
CELLNO	Random cell in which measurements are being taken		Integer	
PCV	Height of pioneer *Calluna vulgaris* (if present) in cell centre		Integer	
BCV	Height of building *Calluna vulgaris* (if present) in cell centre		Integer	
MCV	Height of mature *Calluna vulgaris* (if present) in cell centre		Integer	
DCV	Height of degenerate *Calluna vulgaris* (if present) in cell centre		Integer	
PET	Height of pioneer *Erica tetralix* (if present) in cell centre		Integer	
BET	Height of building *Erica tetralix* (if present) in cell centre		Integer	
MET	Height of mature *Erica tetralix* (if present) in cell centre		Integer	
DET	Height of degenerate *Erica tetralix* (if present) in cell centre		Integer	
PEC	Height of pioneer *Erica cinerea* (if present) in cell centre		Integer	
BEC	Height of building *Erica cinerea* (if present) in cell centre		Integer	
MEC	Height of mature *Erica cinerea* (if present) in cell centre		Integer	
DEC	Height of degenerate *Erica cinerea* (if present) in cell centre		Integer	

HEIGHTS: SPECIES

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
QID	Unique sample point and quadrat identification number		Integer	
CELLNO	Random cell in which the measurements are being taken		Integer	
SP1	Keyword - first species found in cell centre		Text	plantgroups
HGT1	Height of species 1		Integer	
SP2	Keyword - second species found in cell centre (if present)		Text	plantgroups
HGT2	Height of species 2 (if present)		Integer	
SP3	Keyword - third species found in cell centre (if present)		Text	plantgroups
HGT3	Height of species 3 (if present)		Integer	
SP4	Keyword - fourth species found in cell centre (if present)		Text	plantgroups
HGT4	Height of species 4 (if present)		Integer	
SP5	Keyword - fifth species found in cell centre (if present)		Text	plantgroups
HGT5	Height of species 5 (if present)		Integer	

INACCESSIBLE SAMPLE

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
WOOD	True/False – is the sample point inaccessible due to woodland?		Text	
VIEWDIST	Code - indicates distance from which sample point viewed	**0** : < 10 m **1** : 10 - 20 m **2** : 20 m +	Integer	Viewdist
PHOTOFIELD	Photo file name/number in field		Integer	
PHOTONAME	Photo file name/number post fieldwork		Text	
ASPECT	Keyword - site aspect		Text	Sitedesc
SLOPE	Keyword - description of slope angle at the sample point		Text	Sitedesc
SLOPELOC	Keyword - sample point location in relation to the slope		Text	Sitedesc
GEOLOGY	Keyword - description of rocky outcrops at the sample point		Text	Sitedesc
PROXWATER	Keyword - description of water features (if present)		Text	Sitedesc
MISC	Keyword - additional information regarding sample point area		Text	Sitedesc
MANAGE1	Keyword - landscape management: description and evidence		Text	Management + Manageevid
MANAGE2	Keyword - landscape management two (if present)		Text	Management + Manageevid
MANAGE3	Keyword– landscape management three (if present)		Text	Management + Manageevid
VEGDESC	Keyword - generalised description of vegetation at sample point		Text	VegInacc

QUADRAT INFORMATION

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
QUAD	Quadrat number (1 - 4)		Integer	
QID	Unique sample point and quadrat identification number		Integer	
SHADED	True/False - is the quadrat shaded by any shrub or tree species?		Text	
Q4PHOTO	Photograph name/number in field - taken of quadrat 4		Integer	

SCATTERED TREES

Field Name	***Description***	***Codes***	***Data Type***	***Related Keyword Table***
SMPID	Unique sample point identification number		Integer	
SPECIES	Keyword - tree/shrub species		Text	Treesp
HEIGHT	Code - approximate tree height (m)	**0** : 0 - 5 m **1** : 5 - 10 m **2** : 10 m +	Integer	
DBH	Tree diameter at breast height (m)		Integer	
DISTTO	Distance (m) between sample point and tree base		Integer	

SHADED QUADRAT

Field Name	***Description***	***Codes***	***Data Type***	***Related Keyword Table***
SMPID	Unique sample point identification number		Integer	
QID	Unique sample point and quadrat identification number		Integer	
SPECIES	Keyword - tree/shrub species shading the quadrat		Text	Treesp
HEIGHT	Height (m) of species shading quadrat	**0** : 0 - 5 m **1** : 5 - 10 m **2** : 10 m +	Integer	
AMOUNT	Proportion of quadrat (%) obscured by tree/shrub		Integer	

SAMPLE POINT MOVED

Field Name	***Description***	***Codes***	***Data Type***	***Related Keyword Table***
SMPID	Unique sample point identification number		Integer	
DESCFEAT	Keyword - Feature obstructing the sample point		Text	Feattyp
HGT	Code - approximate height of feature (m)	**0** : 0 - 5 m **1** : 5 - 10 m **2** : 10 m +	Integer	Feathgt
DISTMOVED	Distance sample point moved away from obstructing feature		Integer	
OTHER	Description of obstructing feature (if appropriate keyword not available)		Text	

SAMPLE POINT DESCRIPTION

Field Name	*Description*	*Codes*	*Data Type*	*Related Keyword Table*
SMPID	Unique sample point identification number		Integer	
GPSFILE	GPS filename		Text	
GPSID	Identification number for sample point recorded in GPS file		Text	
SOILMOIST	Code - soil moisture conditions at the sample point	**1** : Very Wet **2** : Wet **3** : Dry	Text	
PHOTON	Photograph name/number in field - taken facing north		Integer	
PHOTOS	Photograph name/number in field - taken facing south		Integer	
PHOTOE	Photograph name/number in field - taken facing east		Integer	
PHOTOW	Photograph name/number in field - taken facing west		Integer	
PHOTOEXTRA	Name/number of additional photographs taken and feature description		Text	
SCATTREES	True/False - is sample point surrounded by scattered trees?		Text	
ASPECT	Keyword - site aspect		Text	Sitedesc
SLOPE	Keyword - slope angle at the sample point		Text	Sitedesc
SLOPELOC	Keyword - sample point location relative to the slope		Text	Sitedesc
GEOLOGY	Keyword - description of rocky outcrops at the sample point		Text	Sitedesc
PROXWATER	Keyword - description of water features (if present)		Text	Sitedesc
MISC	Keyword - additional information regarding sample point area		Text	Sitedesc
MANAGE1	Keyword - landscape management: description and evidence		Text	Management + Manageevid
MANAGE2	Keyword - landscape management two (if present)		Text	Management + Manageevid
MANAGE3	Keyword– landscape management three (if present)		Text	Management + Manageevid

SURVEY INFORMATION

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
DATE	Date of survey		Text	
TIME	Time of survey		Text	
PRECIP	Keyword - Record current weather, precipitation state		Text	Weather
DRY	Keyword - Record current weather, amount of sunshine		Text	Weather
VISIBLE	Keyword - Record current weather, visibility		Text	Weather
WIND	Keyword - Record current weather, wind strength		Text	Weather
TEMP	Keyword - Record current weather, temperature		Text	Weather

TARGET SPECIES

Field Name	Description	Codes	Data Type	Related Keyword Table
SMPID	Unique sample point identification number		Integer	
QID	Unique sample point and quadrat identification number		Integer	
CELL	Proportion of quadrat being searched.		Integer	
RESTRICTID	Yes/no - is target species identification restricted		Text	
ET	Yes/no - is *Erica tetralix* present in the search area?		Text	
EC	Yes/no - is *Erica cinerea* present in the search area?		Text	
CV	Yes/no - is *Calluna vulgaris* present in the search area?		Text	
BIL	Yes/no - is bilberry present in the search area?		Text	
COW	Yes/no - is crowberry present in the search area?		Text	
CROW	Yes/no - is crowberry present in the search area?		Text	
GORSE	Yes/no - is gorse present in the search area?		Text	
BK	Yes/no - is bracken present in the search area?		Text	
RYE	Yes/no - is rye grass present in the search area?		Text	
YORKFOG	Yes/no - is Yorkshire fog present in the search area?		Text	
RFESCUE	Yes/no - is red fescue present in the search area?		Text	

TARGET SPECIES (continued)

Field Name	*Description*	*Codes*	*Data Type*	*Related Keyword Table*
WHG	Yes/no - is wavy hair grass present in the search area?		Text	
MATT	Yes/no - is matt grass present in the search area?		Text	
COCKSFOOT	Yes/no - is cocksfoot grass present in the search area?		Text	
DOGSTAIL	Yes/no - is crested dogstail grass present in the search area?		Text	
FALSEOAT	Yes/no - is false oat grass present in the search area?		Text	
TOR	Yes/no - is tor-grass present in the search area?		Text	
CRESTHAIR	Yes/no - is crested hair-grass present in the search area?		Text	
PMG	Yes/no - is purple moor grass present in the search area?		Text	
COMBENT	Yes/no - is common bent grass present in the search area?		Text	
HARESCOTTON	Yes/no - is hairstail cotton grass present in the search area?		Text	
COMCOTTON	Yes/no - is common cotton grass present in the search area?		Text	
DEER	Yes/no - is deer grass present in the search area?		Text	
HRUSH	Yes/no - is heath rush present in the search area?		Text	
SS	Yes/no - is sheep's sorrell present in the search area?		Text	
HBED	Yes/no - is heath bedstraw present in the search area?		Text	
DAISY	Yes/no - is the daisy found in the search area?		Text	
RWH	Yes/no - is rosebay willow herb found in the search area?		Text	
NETTLE	Yes/no - is nettle found in the search area?		Text	
DANDY	Yes/no - is dandelion found in the search area?		Text	
BUTTER	Yes/no - is buttercup found in the search area?		Text	
CLOVER	Yes/no - is clover found in the search area?		Text	
CS	Yes/no – is common sorrel found in the search area?		Text	
TORM	Yes/no - is tormentil found in current search area?		Text	
MFEATH	Yes/no – are feather moss species found in the search area?		Text	
MSPG	Yes/no – are *sphagnum* species found in the search area?		Text	
MPOLY	Yes/no - are *polytrichum* species found in the search area?		Text	
LICHEN	Yes/no – are lichen found in the search area?		Text	

Ancillary and Remote Sensing Data Sources

The appendix outlines the technical specifications of the remote sensing and ancillary data available to aid extrapolation of the land cover attributes, as characterised at the field survey samples, to the entire study area.

Included in this review is an assessment of the NEXTMap digital surface and terrain models. The accuracy of these data sources, against an Ordnance Survey reference surface, is outlined. Specifically the utility of the difference between the surface and 'bare earth' products in the determination of vegetation and landscape feature height is assessed.

Remote sensing data: technical specifications

SPOT 5 (Le Système Pour l'Observation de la Terre)

The SPOT 5 satellite, one of a series of SPOT satellites, was launched on the 4th May 2002. The satellite, for which the technical information is included in table F1, contains a number of data recording instruments. From this payload the research concentrated on the HRG (High Resolution Geometric) instruments.

The HRG instruments record information in 6 spectral bands each of which is situated in a different portion of the electromagnetic spectrum (table F2). The spatial resolution, smallest resolvable element, of the remote sensing data is band specific with pixel resolutions varying from 5m in the panchromatic bands to 20m in the short-wave infrared (table F2).

Table F1: Technical specifications of the SPOT 5 satellite

Platform	SPOT 5
Launch date	4th May 2002
Orbit	822km altitude, near-polar, sun-synchronous
Orbit inclination	98.7°
Orbital period	101.4 minutes
Orbital cycle	26 days
Equator crossing time	10:30am (local)
Instruments	**HRG***
	High Geometric Resolution instrument
	HRS
	High-resolution Stereoscopic imaging instrument
	VEGETATION 2

*Notes: * Two identical HRG instruments are included in the satellite payload.*
Source: SPOT Image (2007)

Table F2: Spectral and spatial resolution of the HRG instruments on board the SPOT 5 satellite

Band		Spectral Range (μm)	Spatial Resolution (m)
Panchromatic 1		0.48-0.71	5 (or 2.5)
Panchromatic 2		0.48-0.71	5 (or 2.5)
Green	**(Band 1)**	0.50-0.59	10
Red	**(Band 2)**	0.61-0.68	10
Near-Infrared	**(Band 3)**	0.78-0.89	10
Shortwave-Infrared	**(Band 4)**	1.58-1.75	20

Source: SPOT Image (2007)

UK Perspectives aerial photography

UK Perspectives flew a program to provide national (England and Wales) aerial photography coverage between 1999 and 2002. The research study area was captured over a period spanning approximately 13 months between July 2001 and September 2002.

The visible colour aerial photographs were scanned to provide digital data at a spatial resolution of 25 cm. Subsequently, the photography was orthocorrected to the British National Grid hence no further georeferencing was required. To enable data transfer the photography was supplied in an ECW (Enhanced Compression Wavelet) format.

Ancillary data: technical specifications

NEXTMap IFSAR

Elevation data available to the research project was extracted from the national NEXTMap survey. This survey, conducted by Intermap Technologies during 2002 produced DEM data via airborne interferometic synthetic aperture radar (IFSAR). IFSAR is based on radar remote sensing in which electromagnetic pulses, in the microwave portion of the spectrum (X-Band: 9.5675 GHz), are transmitted towards the earth's surface. The survey results in the creation of three products, a DSM, DTM and orthorectified image (ORI). The ORI is a greyscale image, similar in appearance to a black and white aerial photograph, constructed from the radar pulse return.

Advantages of IFSAR, and other active remote sensing systems, over traditional aerial photography, are improved data collection and processing rates, which can principally be attributed to the active illumination of the surface. This active illumination enables wide acquisition schedules, day/night operation, and due to the cloud penetration capability of microwaves, data capture in cloud covered and rainy conditions.

The NEXTMap survey utilised a Star-3i system, an across track, dual antenna IFSAR, mounted on a Learjet aircraft. The radar antennas were mounted at a known separation on the aircraft, 1 metre in the Star-3i system; this is defined as the interferometric baseline. During operation an electro-magnetic pulse is transmitted from one of the antenna. The amplitude and phase of the return pulse, as reflected from the earth's surface, is subsequently recorded at both antennas. Return pulse amplitude and phase varies as a consequence of the terrain backscatter properties and the distance between the sensor and terrain, respectively. As a consequence of the baseline return, pulses at each antenna will record slightly different path lengths. This path length variability, the phase difference, in addition to the known interferometric baseline and precise aircraft location information (location, pitch, row and yaw) forms the basis of DSM derivation. This complex process is summarised in figure F1.

The two primary products derived from the IFSAR processing chain are the orthorectified radar image (ORI) and DSM. The third NEXTMap product, the DTM, is derived from the DSM through the removal of cultural and vegetation surface features in a semi-automated process using the TerrainFit® algorithm, a hierarchical, pyramidal surface fitting approach. The base of the pyramid is fitted to the DSM. Using a moving window, of pre-defined size, the TerrainFit® algorithm then identifies local elevation minima; these minima represent the next layer of the pyramid. This process is repeated iteratively, gradually removing surface features to produce the top layer of the pyramid, the DTM (Coleman, 2001).

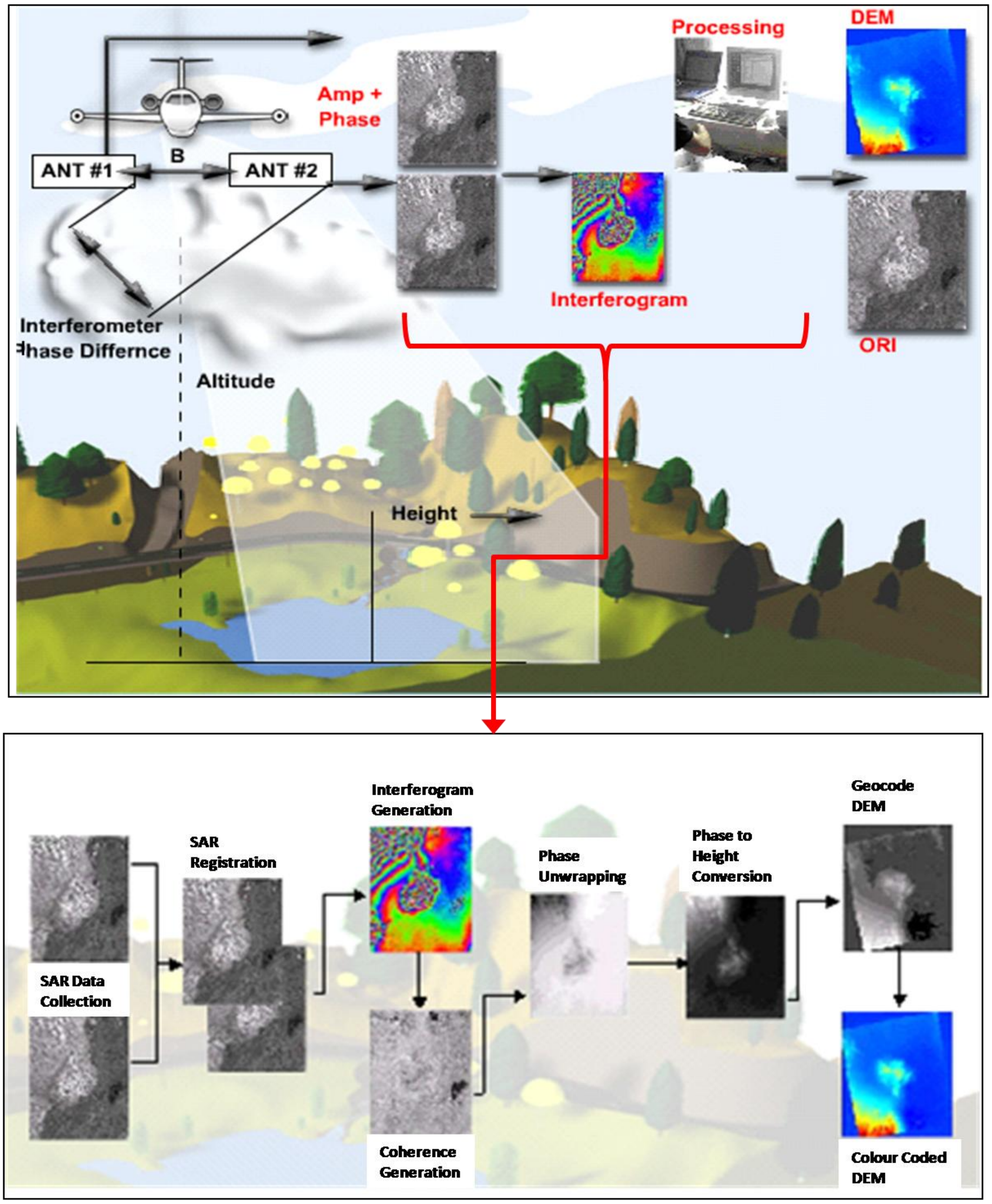


Figure F1: Summary of the NEXTMap data collection and processing chain

Source: Intermap Technologies (2006)

The NEXTMap DTM and DSM are produced at 5 metre postings (and 5m pixels), where the post represents the elevation (z) at that x, y location. The quoted accuracies for these products are included in table F3.

Table F3: The technical specifications of the NEXTMap DSM and DTM

Product	Horizontal Accuracy	Vertical Accuracy	Posting
DSM	2.5m RMSE	0.5m/1m* RMSE	5m
DTM	2.5m RMSE	1m/1.5m* RMSE	5m

**South East England and East Anglia available at 50cm vertical (DSM) and 1m vertical (DTM) resolution.*
Source: Intermap Technologies (2003)

The elevation recorded in each 5m pixel represents the combined signal of all scatterers, first surface contacts, within the sample area. Consequently, surface elevation within a pixel results from an averaging of multiple scatterers, potentially of differing heights, and interaction between these features.

NEXTMap DSM and DTM accuracy

To enable an assessment of the accuracy of the NEXTMap DSM and DTM products a reference dataset, which was assumed to contain more accurate elevation readings, was required. Data from two sources provided the basis of this reference dataset; Ordnance Survey spot heights and GPS readings collected during the field survey (table F4)

Table F4: Elevation data sources

	NEXTMap DSM	NEXTMap DTM	Ordnance Survey Spot Heights.	GPS Survey Data
Derived	IFSAR	IFSAR	Ground Survey	Ground Survey
Data Format	5m Grid	5m Grid	Points on 1:10,000	Points
Vertical Accuracy	1m	1.5m	0.1m*	1-2m**

Notes:
**Ordnance Survey (2007)*
*** Approximate accuracy*

The Ordnance Survey elevation data comprised 521 points collectively referred to as spot heights. Only those spot heights derived via ground survey were included in the DTM accuracy comparison. Heights derived from aerial photograph photogrammetric techniques were excluded due to the potentially greater error associated with these measurements. It should be noted that the spot heights were not distributed evenly across the study area (figure F2) and tended to be concentrated along linear features.

The GPS survey data were extracted from the full ground survey and represented sample locations. GPS measurements were post-processed using the coarse acquisition signal. Previous analysis (section 4.5) indicated that sub-metre accuracy was achieved in the XY dimension using this level of processing. This accuracy in the XY dimension was indicative of 1 to 2m accuracy in the Z dimension.

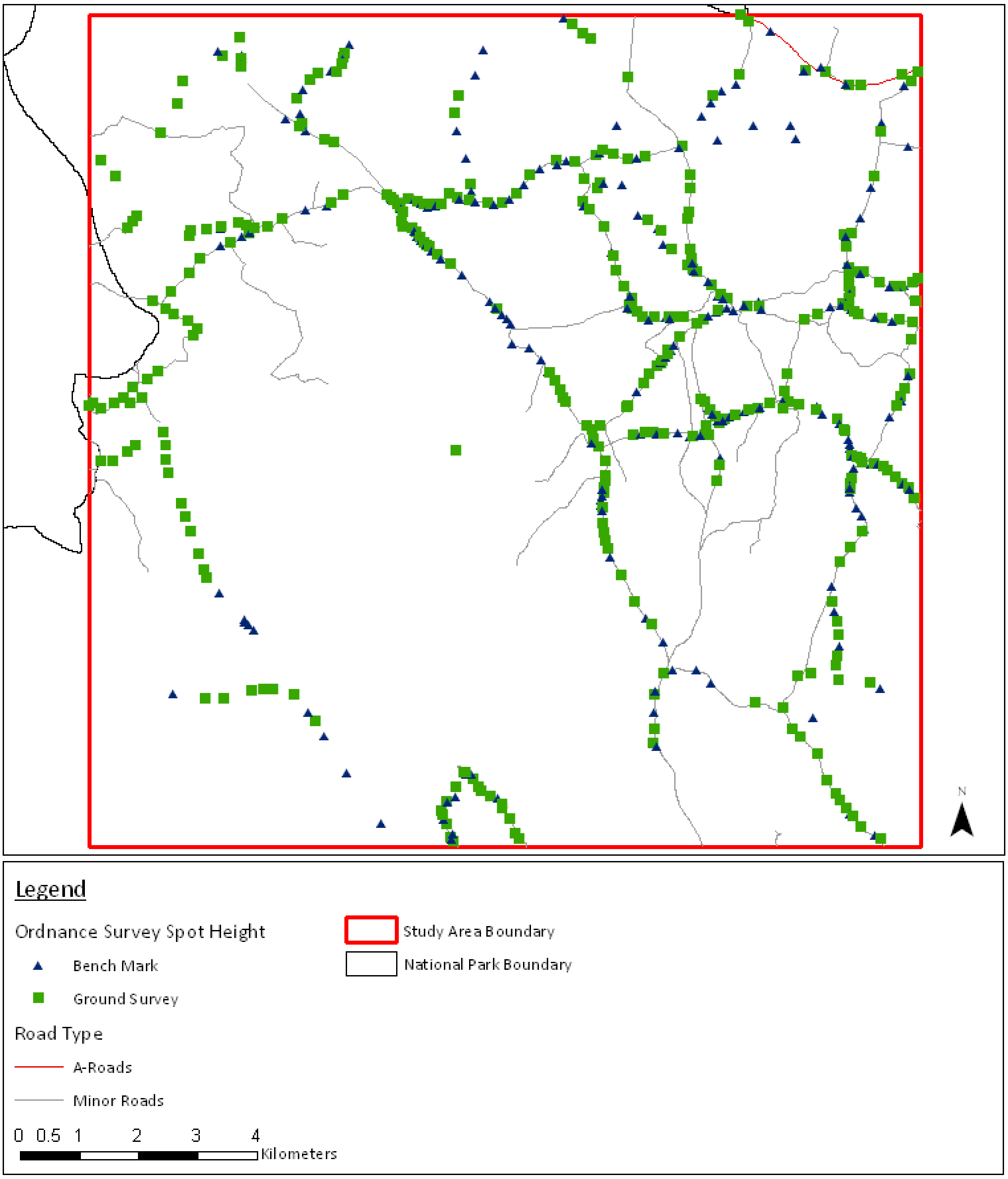


Figure F2: Spot height locations within the study area classified according to data source. Roads are also included to illustrate the distribution of spot heights relative to these features.

Previous studies (Dowman *et al*, 2005) have indicated that the accuracy of the NEXTMap DEMs is a function of land cover and slope. To enable this comparison in the current analysis, land cover at each height reference location was extracted from the 1980s MLCNP survey (Taylor *et al*, 1991). To enable simplification the MLCNP classification was generalised into 6 broad land cover categories: bracken, cultivated, developed, upland grass moor and upland heath.

Slope was derived from the NEXTMap DTM using standard GIS processing tools. The resultant surface was reclassified into five simplified slope classes (table F5).

Table F5: Generalised slope angle classification

Slope Range (°)	Slope Class	Description
0 - 5	1	Very gently sloping
5 - 10	2	Gently sloping
10 - 20	3	Moderate slope
20 - 30	4	Steep slope
30+	5	Very steep slope

DTM, spot height and GPS comparison

To ensure compatibility the Ordnance spot heights and GPS measurements were compared to the NEXTMap DTM. This comparison was made as the reference measurements represent 'bare' earth measurements as reflected, theoretically, by the DTM. The inclusion of surface features within the DSM automatically introduces bias into a comparison of heights from this surface and the reference datasets. In determining the DTM accuracy it was the accuracy of the original surface, DSM, and TerrainFit® algorithm which was being assessed.

Dowman *et al* (2005) concluded that the NEXTMap data contained systematic bias, elevations tended to be higher than the reference surface. The authors concluded this was a consequence of the larger footprint of the NEXTMap data which increased the contribution of multiple scatterers to pixel elevations.

To determine if such systematic bias was evident within the current dataset the difference between the DTM and spot height, at each sample point, was classified as being: overestimated (DTM is greater than spot height), exact (DTM equals spot height) or underestimated (DTM is less than spot height).

Of the Ordnance Survey derived reference samples the split between overestimated and underestimated values was 49.7 and 50.1%, respectively. This indicated that the DTM was not consistently above or below the spot height surface. This was further reflected at the GPS samples where the split between overestimated and underestimated values was 44% and 56%, respectively. A visual assessment of the spatial distribution of these overestimated and underestimated DTM heights indicated that they were well mixed.

While no systematic bias was evident greater variability was encountered if the samples were split according to land cover or slope (tables F6 and F7).

Chi-squared analysis was conducted to test the null hypothesis that each class contained an equal proportion of over and under estimated sample points (tables F6 and F7). This null hypothesis was rejected in the case of moderate slopes and the developed and upland heath land cover classes.

Table F6: A comparison of the number of Ordnance Survey spot height locations at which the DTM over or underestimated elevation, classified according to generalised land cover.

Generalised Land Cover	Overestimated (Count)	Underestimated (Count)	χ^2	Significantly Different
Bracken	40	32	0.8	X
Cultivated	90	81	0.4	X
Developed	40	15	11.18	√
Woodland	14	6	3.2	X
Upland Grass Moor	11	11	-	X
Upland Heath	64	116	15.02	√

Notes: Chi-square values compared the over, under estimation counts, within each class. The significant chi-squared value was 7.88 at the 95% confidence interval.

Table F7: A comparison of the number of Ordnance Survey spot height locations at which the DTM over or underestimated elevation, classified according to slope.

Slope Class	Overestimated (Count)	Underestimated (Count)	χ^2	Significantly Different
Very gently sloping	98	140	7.42	X
Gently sloping	95	93	0.02	X
Moderate slope	58	28	10.46	√
Steep slope	7	0	10	-
Very steep slope	*Insufficient Data*			

Notes: Chi-square values compared the over, under estimation counts, within each class. The significant chi-squared value was 7.88 at the 95% confidence interval.

The preceding results indicated that DTM error, in particular systematic bias, was potentially variable as a consequence of land cover and slope. To quantify this error the root mean square difference (RMSE), between the DTM and reference data, was calculated (equation F1).

Equation F1

$$RMSE = \sqrt{\frac{\sum D^2}{n}}$$

Where:

D is the DTM, reference elevation difference at the sample point

N is the number of sample points falling in the land cover or slope class

RMSE is a frequently implemented technique to describe error within DEMs. However, authors have noted that the measure may not be an appropriate descriptor of the statistical distribution of DEM error (Fisher & Tate, 2006). Equally, the measure represents a global summary statistics and therefore fails to describe the spatial structure of the error. In an attempt to quantify DTM error spatially RMSE was calculated according to slope and land cover class. It should however be noted that determining the spatial autocorrelation of error within these classes is considered beyond the scope of this research.

Considering all Ordnance Survey reference locations, the calculated RMSE value of 1.8 m, indicated that an average error of 1.8 m could be expected between the DTM and reference surface within the study area. This value, although low and similar to the stated accuracy of the dataset (1.5 m), masked increased error variability as a function of land cover and slope (table F8).

Table F8: RMSE values, comparing NEXTMap DTM to Ordnance Survey reference elevation, derived according land cover and slope characteristics.

Generalised Land Cover	RMSE	Slope Class	RMSE
Bracken	1.7	**Very gently sloping**	1.34
Cultivated	1.6	**Gently sloping**	1.49
Developed	2.13	**Moderate slope**	2.60
Woodland	4.94	**Steep slope**	5.60
Upland Grass Moor	1.57	**Very steep slope**	*Insufficient Data*
Upland Heath	1.16		

Table F8 indicated that RMSE values tended to be higher in land cover types characterised by taller vegetation or cultural features and increase with increasing slope. It should be noted that the variables, land cover and slope, were considered independently hence the influence of their interaction upon RMSE was not considered.

A comparison of the NEXTMap DTM to the GPS derived reference surface resulted in a lower overall RMSE value of 0.92m, which was also reflected for each land cover and slope class (table F9). These lower RMSE values, in comparison to the Ordnance Survey reference surface, were a function of the limited nature of the GPS dataset which, due to the field data collection method, contained only 145 points on a limited range of land cover types and slopes.

Table F9: RMSE values, comparing NEXTMap DTM to GPS reference elevation, derived according to land cover and slope characteristics.

Generalised Land Cover	RMSE	Slope Class	RMSE
Bracken	0.99	**Flat**	0.63
Cultivated	1.13	**Gently sloping**	0.85
Developed	-	**Moderate slope**	1.48
Woodland	-	**Steep slope**	-
Upland Grass Moor	-	**Very steep slope**	-
Upland Heath	0.83		

Increased DTM error with increasing slope and obstructed land covers, in particular woodland and urban features, can be attributed to the characteristics of IFSAR and the TerrainFit® algorithm.

NEXTMap literature states that DSM accuracy can be expected to degrade, significantly, on slopes greater than 10^{o} (Intermap Technologies, 2003). The magnitude of the error introduced is a consequence of the location of the slope within the swath (IFSAR look angle), slope angle, direction and aspect.

Increased error in woodland is attributable to the behaviour of the TerrainFit® algorithm. As outlined the TerrainFit® algorithm identifies elevation minima within discrete image regions. Where a large proportion of the surface is wooded variability in the surface terrain cannot be identified. Equally, drops in the canopy may be inappropriately labelled as 'bare' earth points. This error is particularly evident where wooded areas are greater than 80m in all directions (Intermap Technologies, 2003).

IFSAR errors in urban land covers are a function of radar layover, shadow and strong returns as a consequence of highly reflective surfaces. These effects are a product of the side-looking geometry of the radar which results in shadow behind and layover in front of tall objects perpendicular to the flight path. Within urban areas these characteristics typically result in the obstruction of streets, bare earth locations, perpendicular to the flight path by buildings. As in wooded areas, elevation minima in the urban area will be incorrectly identified as bare earth points by the TerrainFit® algorithm where urban areas are greater than 80m in each direction (Intermap Technologies, 2003).

In wooded and urban areas the identification of elevated 'bare' earth points due to canopy variability results in an edge effect. This edge effect is a consequence of the interpolation of the DTM from true 'bare' earth samples, adjacent to the woodland, to elevated 'bare' earth samples, in the woodland (Cliffen, 2005).

DSM, DTM differencing as a means of predicting feature heights

As stated previously the DTM is not an original product of the IFSAR survey but a derivative of DSM. As the DSM represents the first surface and the DTM the theoretical 'bare' earth the difference between the products should be indicative of the relative surface feature heights.

It should be clarified that this derived surface feature height, particularly in the case of vegetation, is only indicative of relative feature heights as the return radar pulse can represent penetration of the signal into the vegetation canopy; height measurements will therefore contain noise. Such an issue is reduced for surfaces less prone to scatter i.e. urban surfaces (Dowman *et al*, 2005).

A visual inspection of the DSM and DTM, via a series of hillshades, illustrated the inconsistent removal of surface features in DTM creation (figures F3 and F4).

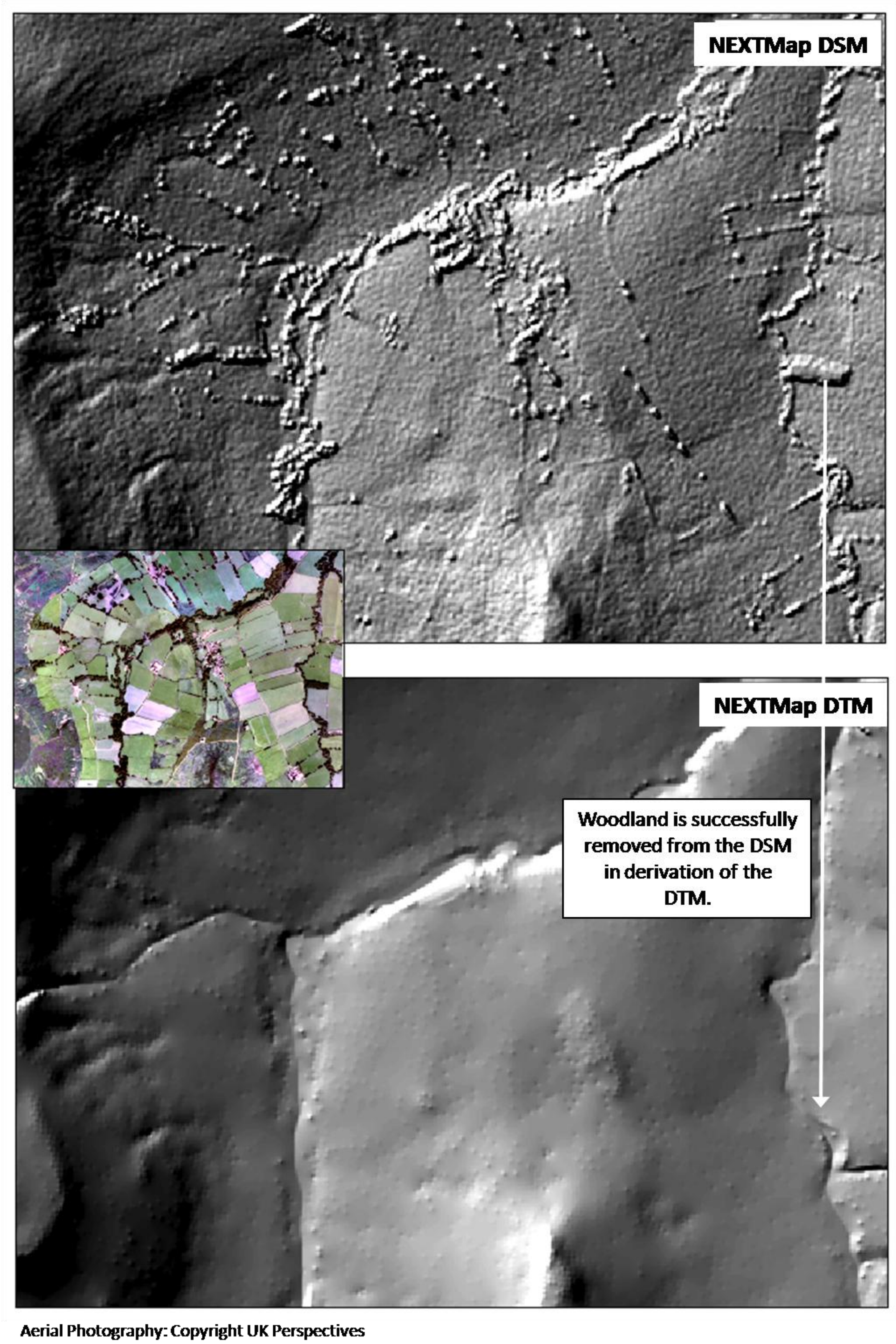
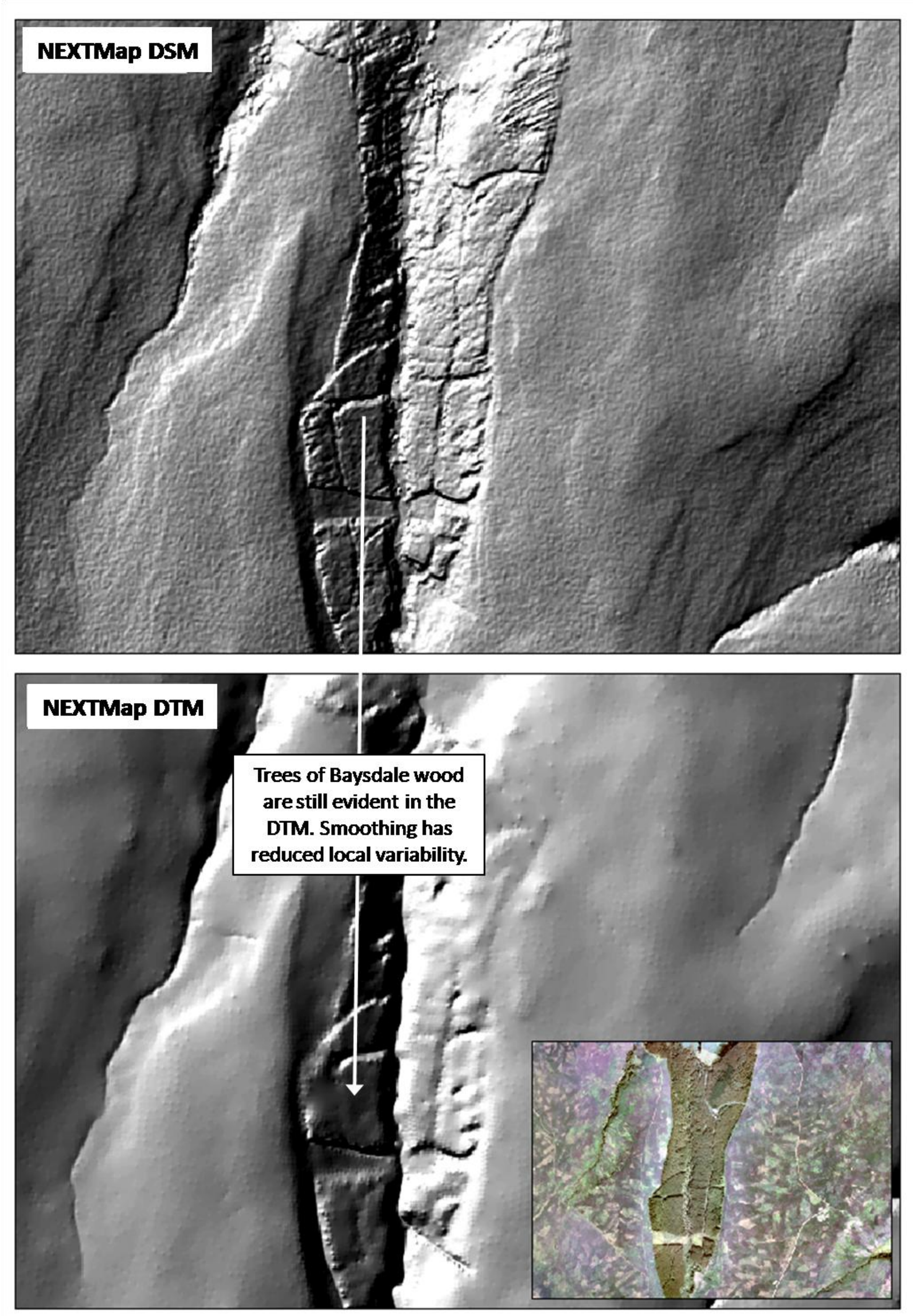


Figure F3: NEXTMap DSM and DTM hillshades for the area surrounding Westerdale.



Aerial Photography: Copyright UK Perspectives

Figure F4: NEXTMap DSM and DTM hillshades for the area surrounding Baysdale Wood.

Since the DTM surface is representative of the bare earth and DSM the first surface it would be expected that, in areas where features have surface heights, DSM elevations are greater than those in the DTM. Additionally, in areas where features have no surface height and the ground is the first reflected surface the DTM should be equal to the DSM.

As a result, if the DTM is subtracted from the DSM the resultant values should, theoretically, be greater than or equal to zero. Within the study area only 63% of the raster cells met this condition. In the remaining 37% of cells, equivalent to 73km^2, the DTM elevation was greater than that recorded in the original DSM. Intersection of these DTM cells with the MLCNP land cover map (Taylor *et al*, 1991) illustrated that these cells predominantly fell on upland heath (table F10).

Table F10: The percentage of cells, in which the DTM elevation was greater than the DSM elevation, occurring in each generalised land cover class

Generalised Land Cover	Percentage (%)
Bare Ground / Eroded	**0.17**
Bracken	**12.31**
Cultivated	**29.11**
Developed	**0.51**
Upland Grass Moor	**1.23**
Upland Heath	**50.39**
Water	**0.15**
Woodland	**6.09**

The NEXTMap literature states that the primary cause of this DTM overestimation, relative to the DSM, is the interpolation process employed during data creation (Intermap Technologies, 2003). The interpolation process is based on a discontinuous surface of "bare-earth" points extracted from the DSM via various extraction processes within the TerrainFit® algorithm. "This interpolation process by its very nature will tend to round off hill tops and infill valleys to a limited extent. This will result in differences between the DSM and DTM even in open areas where they ought to be identical" (Intermap Technologies, 2003).

This tendency to round off hill tops and infill valleys is reflected in table F10, as the highest proportion of DTM high cells occur in the cultivated and upland heath land covers. Cultivated land is, typically, isolated to valley bottoms and hence subjected to DTM infill whereas the upland heath is located on higher ground and is subjected to landscape rounding (figure F5).

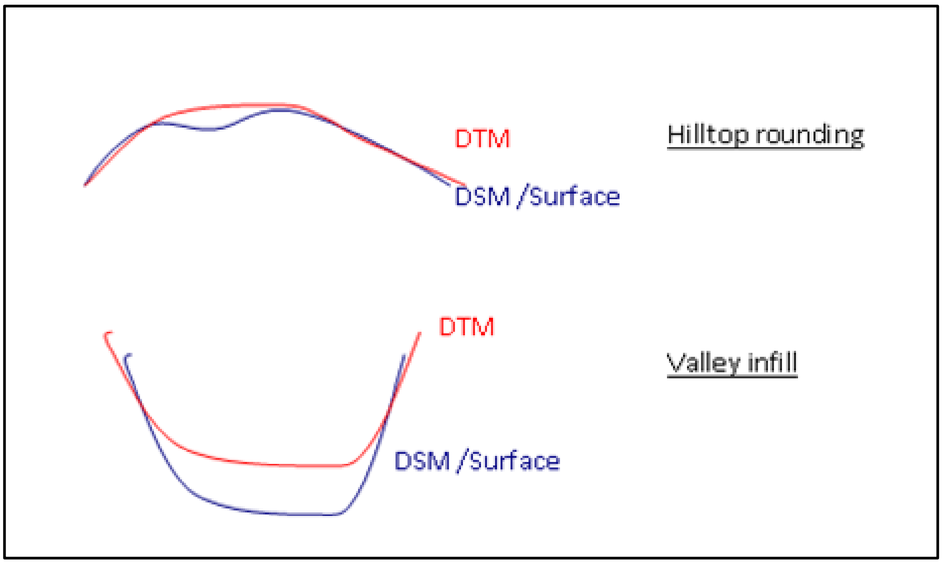


Figure F5: Hilltop rounding and valley infill as a result of 'bare earth' point interpolation during DTM derivation

These results do conflict with those of table F6 in which it was concluded that, based on the Ordnance Survey sample, elevations in upland heath illustrate a significant tendency to be underestimated in the DTM. This conflict may be a consequence of sample location relative to the hilltop.

The stated statistic of 37% DTM high cells within the study area did not consider the size of the difference between the DSM and DTM or account for those areas previously identified as containing erroneous DTM elevations. If these factors are taken into account, the core product specification of the NEXTMap products states that "in unobstructed areas where the slope is less than 10 degrees, less than 5% of the data will result in DTM high elevations of greater than 1m" (Cliffen, 2005). Repetition of the DSM:DTM difference analysis, following the method of Cliffen (2005), concluded that in unobstructed regions of the study area, located on slopes less than 10 degrees, 6.4% of the data contained DTM high elevations greater than 1m. Therefore, within the study area the core product specification was not met.

Woodland and urban area identification

A proposed utility of the DSM:DTM difference was to aid in the identification of land cover types typified by taller vegetation and cultural features in particular woodland and urban areas. The preceding analysis has indicated an association between these land cover types and increased DTM error. Propagation of this error into the DSM:DTM difference therefore had the potential to preclude the identification of these features. As the preceding analysis considered only a limited number of woodland and developed sample points, 20 and 55, respectively, the analysis was extended to consider the DSM:DTM difference within all cells classified as either woodland or urban in the MLCNP land cover map (Taylor *et al*, 1991).

Woodland Areas

Actual tree heights within the study area were not known therefore analysis of the predicted tree heights from the DSM:DTM difference was based on a visual interpretation. From this visual interpretation, (commented figures F6 to F9) it can be demonstrated that:

- Woodland identification in the DSM:DTM difference image was strongly influenced by, stand size, slope, woodland fragmentation and tree density.
- Predicted tree heights were lower than would normally be expected for mature tree species. This difference could be a function of canopy penetration or DEM error.
- Predicted tree heights showed wide within woodland variability.

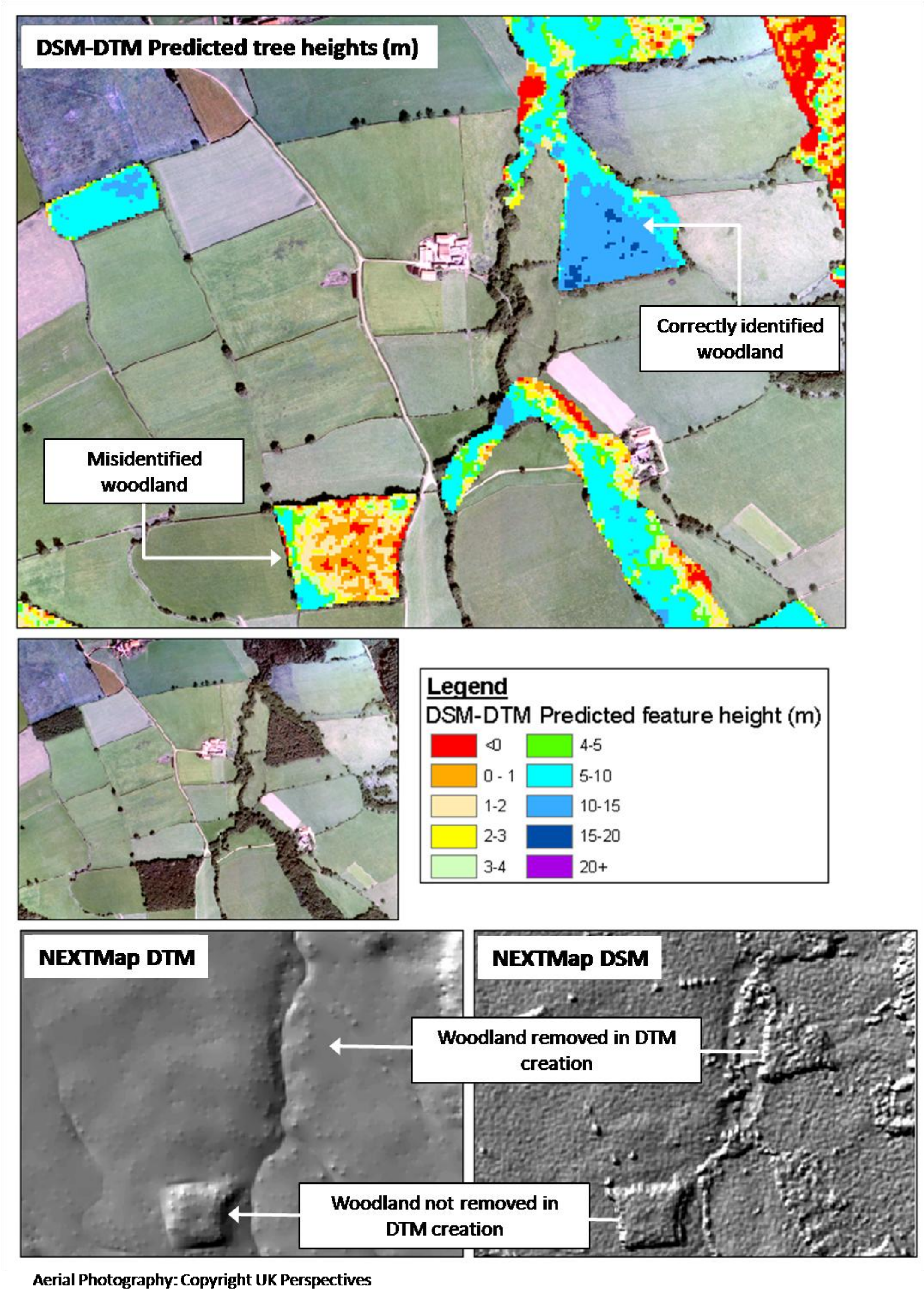


Figure F6: Predicted DSM:DTM tree heights for woodlands adjacent to Sheepfold Farm.

This figure illustrates that the identification of increased height differences in the DSM:DTM difference, associated with woodlands, was a result of the successful removal of the woodland from the DSM during DTM derivation.

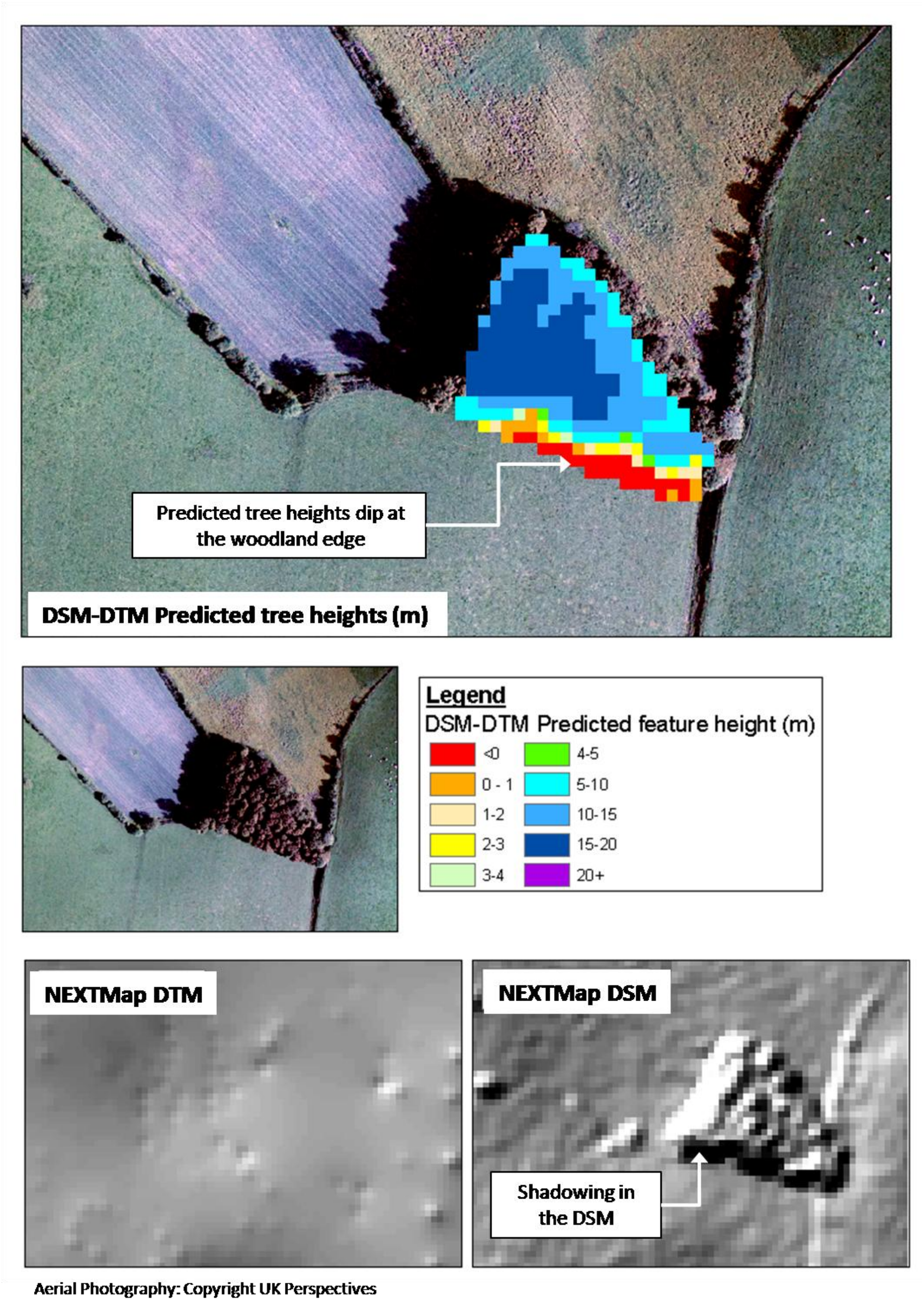


Figure F7: Predicted tree height reductions close to or at the woodland edge.

This figure illustrates woodland boundary mis-location due to a drop in predicted tree heights at the woodland edge. In the example shown this height decrease was attributable to image shadowing.

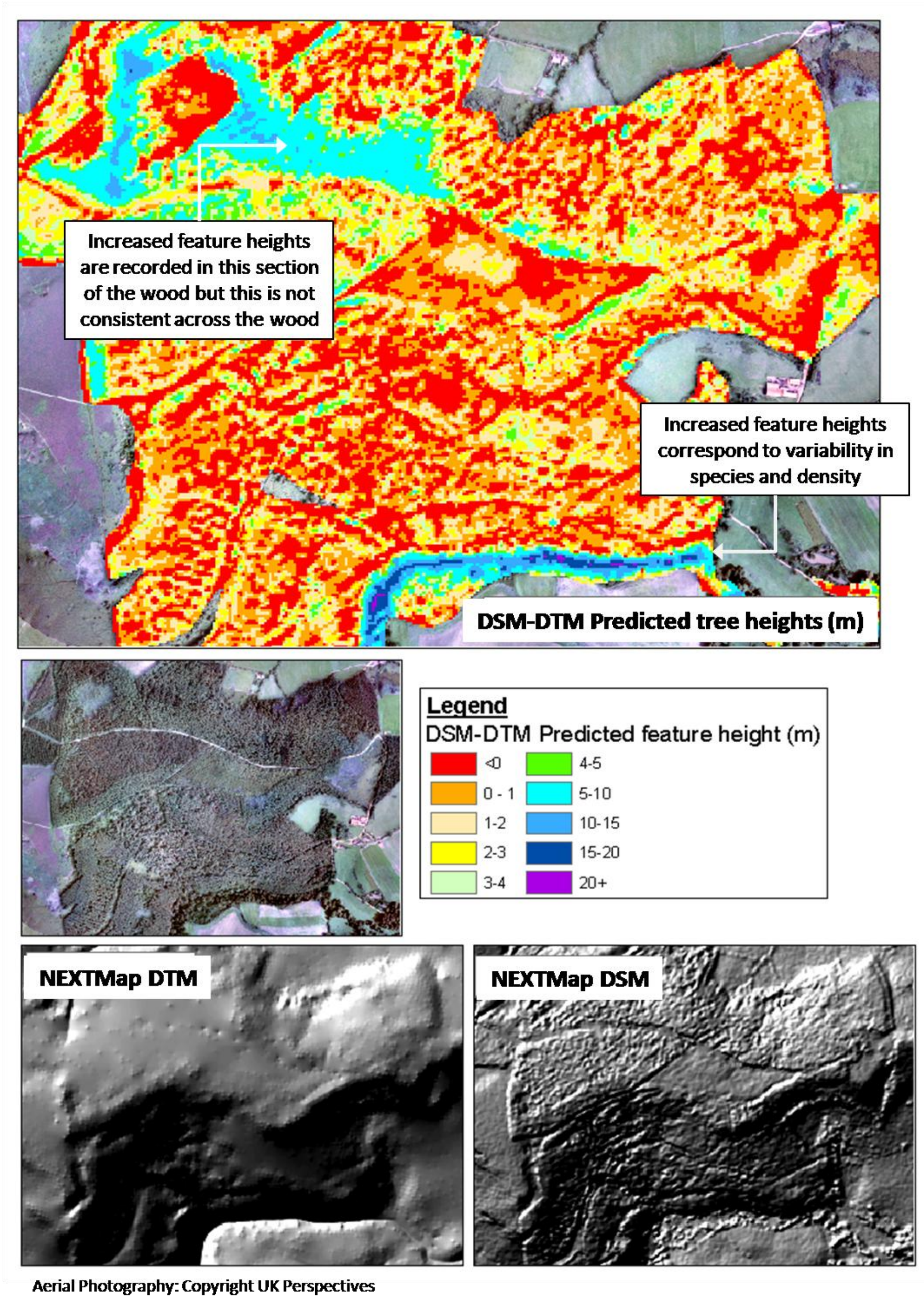


Figure F8: Within woodland variability of DSM:DTM height differences

Coate Moor Wood illustrates the inconsistency of the DSM:DTM difference and therefore tree identification within a single woodland. While the DSM:DTM difference values in the north of the woodland are indicative of trees this was not consistently achieved across the woodland potentially as a consequence of tree density and species.

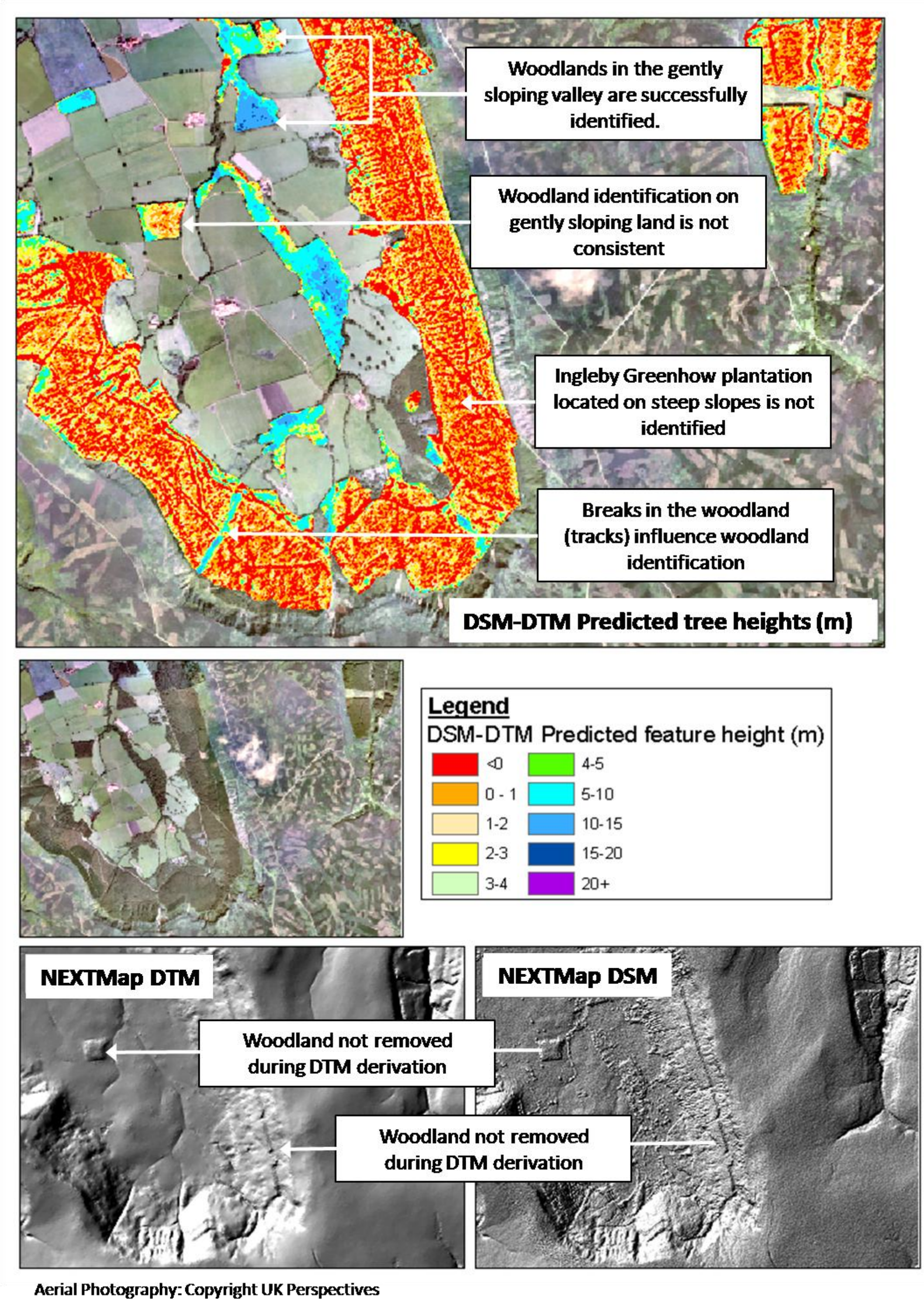
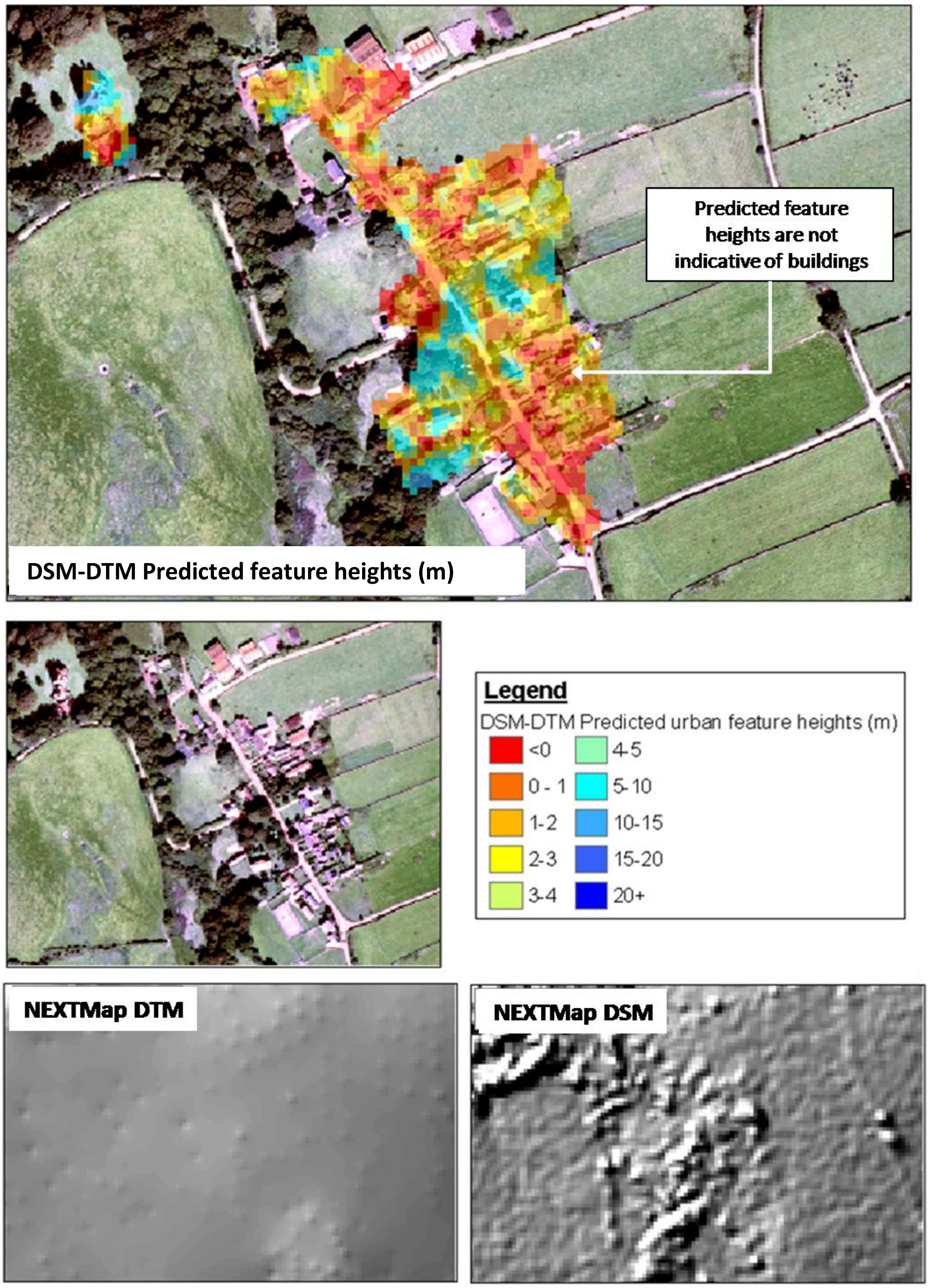


Figure F9: The influence of slope on predicted tree heights derived via the DSM:DTM difference.

The misidentification of tree species heights within Ingleby Greenhow plantation can be attributed to the steep slopes on which the plantation is located.

Urban areas

It was hypothesised that cultural features in urban areas had the potential to be more consistently identified in the DSM:DTM difference image due to the predominance of this land cover type on moderate slopes, increased fragmentation of the features (i.e. due to gardens and roads) and reduced influence of volume scattering on urban surfaces. Visual interpretation of the predicted feature heights against aerial photography (figures F10 and F11) did not support this hypothesis and illustrated that the identification of 'tall' cultural features within urban areas was inconsistent and erroneous.



Aerial Photography: Copyright UK Perspectives

Figure F10: The identification of urban areas, Westerdale, within the DSM:DTM difference

This example taken from Westerdale illustrates that while the cultural features of the urban areas appear to have been removed from the DSM in the derived DTM, the difference between the two datasets was not sufficiently great to indicate the presence of buildings.

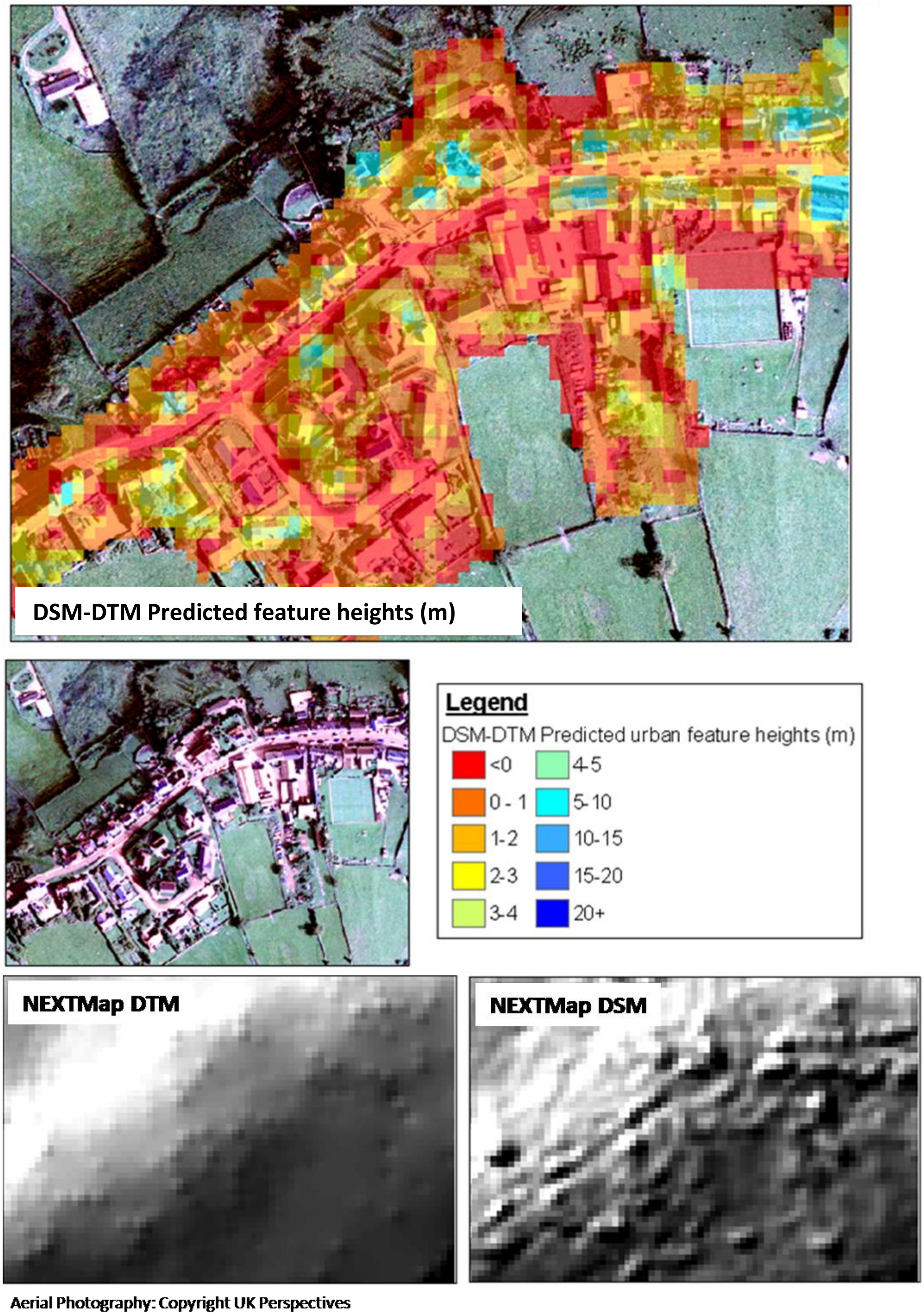


Figure F11: The identification of urban areas, Castleton, within the DSM:DTM difference.

Castleton was included due to the greater building density in this town. Increased building density did not improve the consistency with which urban features were identified in the DSM:DTM difference.

Issues arising from DTM:DSM comparison

The preceding analysis highlighted several issues in terms of the applicability of the DSM:DTM difference as an ancillary data source for the determination of land cover type or heather structure stage.

Woodland / hedgerow and isolated tree identification

- A high RMSE between the DTM and Ordnance Survey reference surface indicated that the average error expected in this land cover type was 4.94m. This average when transferred to the DSM:DTM difference had the potential to mask true and generate false height variability.
- The identification of woodlands in the DSM:DTM difference was inconsistent primarily due to the inefficient removal of woodland during DTM derivation.
- Woodland removal was strongly influenced by slope, stand size, fragmentation and tree density.
- Successful delineation of woodland areas was limited due to boundary misidentification.
- The 5m spatial resolution of the NEXTMap DSM and DTM limited the applicability of the data to isolated tree and hedgerow identification due to the generalisation of these features with surrounding elevations values.

Urban area identification

- Based on the current sample, DTM elevation in urban areas showed a significant tendency to be higher than the Ordnance Survey reference data. This, in addition to a high RMSE of 2.13m, would introduce error into the DSM:DTM difference limiting the accuracy with which cultural features could be identified in urban areas.
- Although visual interpretation appeared to illustrate the removal of buildings from the DSM during DTM creation, height differences between the surfaces were not representative of buildings. A proposed cause of this anomaly was reduced pixel

elevations as a consequence of pixel generalisation between buildings and adjacent scatterers, typically gardens.

Heather species heights

- An average RMSE of 1.16m within upland heath had the potential to mask the relative height changes between heather stands of differing structural stages.
- This error in heather height measurement was compounded by a significant tendency for DTM elevations to be underestimated within this land cover.
- DTM high values prevented height estimation in over 6% of upland heath areas.

A further issue, common to each of the land cover types, related to the restrictive nature of the NEXTMap data in respect to repeated surveys. While gradual change, between the survey date and field data collection is unlikely to be detected within the error bounds of the DEM data, catastrophic land cover change, deforestation or heather burning, subsequent to the IFSAR survey will not be reflected in the NEXTMap DEMs.

As a consequence of the outlined issues the DSM:DTM difference was not recommended as a viable ancillary data source for land cover classification. This was principally due to the inconsistent and inaccurate removal of features from the DSM during DTM derivation and hence erroneous feature heights in the DSM:DTM difference. Alternative techniques for the identification of tall surface features and associated abrupt changes within the DSM include edge detection techniques or comparison of the DSM to an alternative ‘bare’ earth model i.e. Ordnance Survey DEMs. Initial testing highlighted the potential of these techniques. However, in-depth investigation was beyond the scope of the current research.

Elevation, slope and aspect

The overall accuracy of the DTM, with respect to the Ordnance Survey reference surface, was 1.8 m. While this level of error precluded the use of the DSM:DTM difference as an ancillary data source the DTM, and its derivatives, are sufficiently accurate to characterise generalised vegetation, elevation relationships (figure F12).

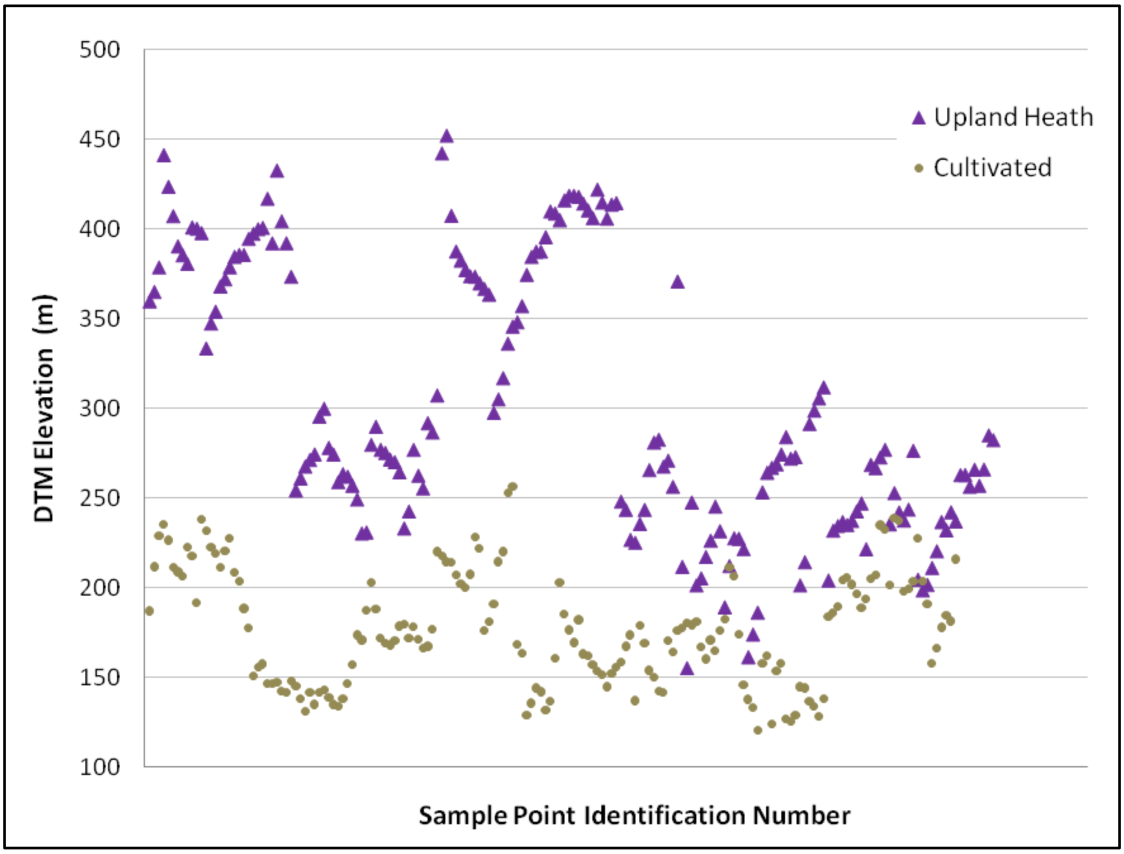


Figure F12: The land cover, NEXTMap DTM elevation relationship exemplified by the upland heath and cultivated land cover types.

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Derivation of the Kappa Statistic

This appendix outlines the derivation of the Kappa statistic and its implementation within statistical significance tests to determine if; firstly, agreement within a single error matrix is significantly greater than zero, that is, better than a random classification assignment and secondly whether two independent Kappa values, and therefore two error matrices, are significantly different.

KAPPA STATISTIC

The Kappa (KHAT) statistic is a measure of agreement calculated as the difference between actual agreement and chance agreement within an error matrix.

Statistical notation of an error matrix

Within an error matrix let the number of samples classified as belonging to category *i* be n_{i+} and n_{+j} the number of samples classified as belonging to category j in the reference dataset. Finally, let p_{ij} denote the proportion of samples in the ij^{th} cell, corresponding to n_{ij}

Kappa

Following the same notation, the derivation of the Kappa statistic and its variance is outlined below.

If actual agreement is defined as:

$$p_0 = \sum_{i=1}^{k} p_{ii}$$

And chance agreement:

$$p_c = \sum_{i=1}^{k} p_{i+}p_{j+}$$

Assuming a multi-nominal sampling model, the estimate of Kappa is given by:

$$\widehat{K} = \frac{p_o - p_c}{1 - p_c}$$

And it's variance:

$$\widehat{var}(\widehat{K}) = \frac{1}{n}\left\{\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2\left(\theta_4-4\theta_2{}^2\right)}{(1-\theta_2)^4}\right\}$$

Where:

$$\theta_1 = \frac{1}{n}\sum_{i=1}^{k} n_{ii}$$

$$\theta_2 = \frac{1}{n^2}\sum_{i=1}^{k} n_{i+}n_{+i}$$

$$\theta_3 = \frac{1}{n^2}\sum_{i=1}^{k} n_{ii}(n_{i+} + n_{+i})$$

and

$$\theta_4 = \frac{1}{n^3}\sum_{i=1}^{k}\sum_{j=1}^{k} n_{ij}\left(n_{j+} + n_{+i}\right)^2$$

A Kappa statistics is computed for each confusion matrix as a measure of the agreement between the classification and reference datasets. The value of Kappa lies between -1 and +1, however, values between 0 and 1 would typically be expected as the reference data and classification output are positively correlated. A value of 0 represents agreement due to chance only. Conversely, a value of 1 indicates complete agreement.

The Kappa statistic can be included within a significance test to determine if the agreement between the classification and reference data is significantly greater than 0, that is, better than a random classification.

The test statistic for determining the significance of a single error matrix is:

$$Z = \frac{\widehat{K}_1}{\sqrt{\widehat{var}(\widehat{K_1})}}$$

Given the null hypothesis H_0: $K_1 = 0$ and the alternative hypothesis H_1:$K_1 \neq 0$. H_0 is rejected if $Z \geq Z_{\alpha/2}$ Where $\alpha/2$ is the confidence level of a two-tailed Z test and the degrees of freedom are assumed to be infinite.

Finally, the Kappa statistics from two independent error matrices can be compared to determine if the matrices are statistically different. Let $\widehat{K}_1$ and $\widehat{K}_2$ denote the estimates of the Kappa statistics for two error matrices, numbers 1 and 2, respectively. Also let $\widehat{var}(\widehat{K_1})$ and $\widehat{var}(\widehat{K_2})$ be the corresponding estimates of variance.

The test statistic for testing if two independent error matrices are significantly different is expressed by:

$$Z = \frac{\left|\widehat{K}_1 - \widehat{K}_2\right|}{\sqrt{\widehat{var}(\widehat{K_1}) + \widehat{var}(\widehat{K_2})}}$$

Given the null hypothesis H_0:$(K_1 - K_2) = 0$ and the alternative hypothesis H_1:$(K_1 - K_2) \neq 0$

H_0 is rejected if $Z \geq Z_{\alpha/2}$

References

Text and equations are adapted from:

- Congalton R.G & Green K (1998) *Assessing the Accuracy of Remote Sensing Data: Principles and Practice*, Lewis Publishers

Per-Pixel Classification: Confusion Matrices

This appendix contains the confusion matrices resulting from the per-pixel classification (section 6.3). A per-pixel, maximum likelihood classification algorithm was tested as a means of integrating the field survey data, classified according to the MLCNP, NLUD and P1 class definitions, with multi-spectral and ancillary data sources.

MULTI-SPECTRAL CLASSIFICATIONS

Confusion matrices derived at the validation samples for the (a) MLCNP, (b) NLUD and (c) P1 classifications. Classifications result from the inclusion of the multi-spectral SPOT 5 image in a per-pixel, ML algorithm.

a) MLCNP

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1			1									2	***50***
C2		4		1	2		1						8	***50***
C4		1											1	***0***
D1	1			51	10		3	1	2	1			69	***74***
D2a				2									2	***0***
D3	2			3		4	1	3	3	3	1		20	***20***
D6a				10	8		4				1	1	24	***17***
D6b	3			1	2	1				3	2		12	***0***
E1										1			1	***0***
E2a				1						25	4		30	***83***
E2b						1							1	***0***
F3						1							1	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***80***	***0***	***73***	***0***	***57***	***44***	***0***	***0***	***76***	***0***	***0***		***52***

b) NLUD

NLUD Classification	NLUD Reference									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11							1		1	***0***
CO21		18	7		1		1	2	29	***62***
CO22	2	5	3				2	1	13	***23***
CO31			2	5	1	1	2	1	12	***42***
CO33					1		2		3	***33***
CO34	1			1				2	4	***0***
CO41			3		3		55	14	75	***73***
CO42		2	4		1			7	14	***50***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***0***	***72***	***16***	***83***	***14***	***0***	***87***	***26***		***59***

c) P1

P1 Classification	P1 Reference																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	1									2						3	***33***
A1.2.2	2	8						1		4						15	***53***
A2.1																0	***0***
B1.1				1	1	1				2					1	6	***17***
B2.2					8	3				1					1	13	***62***
B4				1	7	3										11	***27***
B5																0	***0***
C1.1	2			4	4			5	2	4	1	1	1		3	27	***19***
C1.2					1					1						2	***0***
D1.1	2	1		4				1		49	7	2				66	***74***
D2				2						6	3					11	***27***
D5																0	***0***
D6																0	***0***
E2.1	1			1				1		4	2					9	***0***
J1.1					5	5									1	11	***9***
Total	8	9	0	13	26	12	0	8	2	73	13	3	1	0	6	174	***Overall Accuracy (%)***
Producer Accuracy (%)	***13***	***89***	***0***	***8***	***31***	***25***	***0***	***63***	***0***	***67***	***23***	***0***	***0***	***0***	***17***		***45***

MULTI-SPECTRAL, SLOPE AND ELEVATION CLASSIFICATIONS: MLCNP

Confusion matrices derived at the field data samples for the MLCNP classification. Classifications result from the combination of the multi-spectral SPOT 5 image plus (a) slope, (b) elevation and (c) slope and elevation ancillary data in a per-pixel, ML algorithm.

a) Multi-spectral plus slope

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				66						1			67	***99***
D2a					3								3	***100***
D3				1		7				1			9	***78***
D6a				12			8						20	***40***
D6b						2		3					5	***60***
E1				3					7				10	***70***
E2a										27			27	***100***
E2b											4		4	***100***
F3				1								3	4	***75***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***80***	***100***	***78***	***100***	***100***	***100***	***93***	***100***	***100***		***87***

b) Multi-spectral plus elevation

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6		1									7	***86***
C4			2										2	***100***
D1				72						1			73	***99***
D2a				2	3								5	***60***
D3				1		7				1			9	***78***
D6a				6			8						14	***57***
D6b						2		3					5	***60***
E1									7				7	***100***
E2a										27			27	***100***
E2b				1							4		5	***80***
F3												3	3	***100***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***87***	***100***	***78***	***100***	***100***	***100***	***93***	***100***	***100***		***91***

c) Multi-spectral plus slope and elevation

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				79						1			80	***99***
D2a					3								3	***100***
D3						7				1			8	***88***
D6a				4			8						12	***67***
D6b						2		3					5	***60***
E1									7				7	***100***
E2a										27			27	***100***
E2b											4		4	***100***
F3												3	3	***100***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***95***	***100***	***78***	***100***	***100***	***100***	***93***	***100***	***100***		***95***

Confusion matrices derived at the validation samples for the MLCNP classification. Classifications result from the combination of the multi-spectral SPOT 5 image plus (a) slope, (b) elevation and (c) slope and elevation ancillary data in a per-pixel, ML algorithm.

a) Multi-spectral plus slope

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1												1	***100***
C2	1	5		1	1								8	***63***
C4													0	***0***
D1	2			52	15	1	4	1	2	1	1	1	80	***65***
D2a				1									1	***0***
D3	2			3		5	2	3	3	1	1		20	***25***
D6a				10	4		3				1		18	***17***
D6b	1									1	1		3	***0***
E1													0	***0***
E2a				3	1					29	4		37	***78***
E2b					1	1				1			3	***0***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***100***	***0***	***74***	***0***	***71***	***33***	***0***	***0***	***88***	***0***	***0***		***56***

b) Multi-spectral plus elevation

MLCNP Classification	MLCNP Reference													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1												1	***100***
C2		4					1						5	***80***
C4		1											1	***0***
D1	2			56	17	1	4	1	2		2		85	***66***
D2a				1									1	***0***
D3	1			4		4	1	3	3	3	1		20	***20***
D6a				8	3		3				1	1	16	***19***
D6b	1					1							2	***0***
E1				1									1	***0***
E2a	2				1					30	4		37	***81***
E2b					1	1							2	***0***
F3														***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***80***	***0***	***80***	***0***	***57***	***33***	***0***	***0***	***91***	***0***	***0***		***57***

c) Multi-spectral plus slope and elevation

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1													0	***0***
C2	1	3					1						5	***60***
C4		1											1	***0***
D1	3	1		62	19	2	4	2	2		2	1	98	***63***
D2a													0	***0***
D3				2	1	4	1	2	2	1	1		14	***29***
D6a				4	1		3				1		9	***33***
D6b	1												1	***0***
E1									1				1	***100***
E2a	2			2	1	1				31	4		41	***76***
E2b										1			1	***0***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***60***	***0***	***89***	***0***	***57***	***33***	***0***	***20***	***94***	***0***	***0***		***61***

MULTI-SPECTRAL, SLOPE AND ELEVATION CLASSIFICATIONS: NLUD

Confusion matrices derived at the field data samples for the NLUD classification. Classifications result from the combination of the multi-spectral SPOT 5 image plus (a) slope, (b) elevation and (c) slope and elevation ancillary data in a per-pixel, ML algorithm.

a) Multi-spectral plus slope

NLUD Classification	**NLUD Reference (Field Data)**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6									6	***100***
CO21	1	26	4				1	1		33	***79***
CO22	1	4	8			1	2			16	***50***
CO31				9			2			11	***82***
CO33					3					3	***100***
CO34		2				4				6	***67***
CO41	1						87	1		89	***98***
CO42		1					2	10		13	***77***
CO63							1		3	4	***75***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***79***	***67***	***100***	***100***	***80***	***92***	***83***	***100***		***86***

b) Multi-spectral plus elevation

NLUD Classification	**NLUD Reference (Field Data)**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6									6	***100***
CO21	1	27	4				1	1		34	***79***
CO22	2	4	6			1	2			15	***40***
CO31				9			2			11	***82***
CO33					3					3	***100***
CO34						4	3			7	***57***
CO41		1	1				86	1		89	***97***
CO42		1	1				1	10		13	***77***
CO63									3	3	***100***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***82***	***50***	***100***	***100***	***80***	***91***	***83***	***100***		***85***

c) Multi-spectral plus slope and elevation

NLUD Classification	NLUD Reference (Field Data)										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6									6	***100***
CO21	1	30	3				1	1		36	***83***
CO22	1	2	8			1	2			14	***57***
CO31				9			2			11	***82***
CO33					3					3	***100***
CO34						4	1			5	***80***
CO41	1	1	1				88	1		92	***96***
CO42							1	10		11	***91***
CO63									3	3	***100***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***91***	***67***	***100***	***100***	***80***	***93***	***83***	***100***		***89***

<u>Confusion matrices derived at the validation samples for the NLUD classification. Classifications result from the combination of the multi-spectral SPOT 5 image plus (a) slope, (b) elevation and (c) slope and elevation ancillary data in a per-pixel, ML algorithm.</u>

a) Multi-spectral plus slope

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11							1		1	***0***
CO21		19	11		1		1	1	33	***58***
CO22	2	7	4				3	1	17	***24***
CO31			2	6	3	1	2	3	17	***35***
CO33					1		1		2	***50***
CO34	1				1				2	***0***
CO41		1	2	1	2		56	14	76	***74***
CO42			1	1	1		1	8	12	***67***
Total	3	27	20	8	9	1	65	27	160	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***0***	***70***	***20***	***75***	***11***	***0***	***86***	***30***		***59***

b) Multi-spectral plus elevation

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	1								1	***100***
CO21		20	11	1	4				36	***56***
CO22	2	5	2				3	4	16	***13***
CO31			1	4	3	1	2		11	***36***
CO33					1		1		2	***50***
CO34				3			1	1	5	***0***
CO41		1	5		1		57	15	79	***72***
CO42		1	1				1	7	10	***70***
Total	3	27	20	8	9	1	65	27	160	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***33***	***74***	***10***	***50***	***11***	***0***	***88***	***26***		***58***

c) Multi-spectral plus slope and elevation

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11									0	***0***
CO21		20	10	1	2				33	***61***
CO22	3	6	5				5	2	21	***24***
CO31			1	5	4	1	2	2	15	***33***
CO33									0	***0***
CO34				1					1	***0***
CO41		1	4	1	2		58	15	81	***72***
CO42					1			8	9	***89***
Total	3	27	20	8	9	1	65	27	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***74***	***25***	***63***	***0***	***0***	***89***	***30***		***60***

MULTI-SPECTRAL, SLOPE AND ELEVATION CLASSIFICATIONS: P1

Confusion matrices derived at the field data samples for the P1 classification. Classifications result from the combination of the multi-spectral SPOT 5 image plus (a) slope, (b) elevation and (c) slope and elevation ancillary data in a per-pixel, ML algorithm.

a) Multi-spectral plus slope

P1 Classification	P1 Reference (Field data)																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	3															3	***100***
A1.2.2		8														8	***100***
A2.1			3													3	***100***
B1.1				4												4	***100***
B2.2					10	2									1	13	***77***
B4					5	9	1									15	***60***
B5																0	***0***
C1.1			2		2			9		2					1	16	***56***
C1.2								2	3							5	***60***
D1.1		1				1				79					2	83	***95***
D2											5					5	***100***
D5																0	***0***
D6																0	***0***
E2.1										4				4		8	***50***
J1.1					2	1				2					13	18	***72***
Total	3	9	5	4	19	13	1	11	3	87	5	0	0	4	17		***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***89***	***60***	***100***	***53***	***69***	***0***	***82***	***100***	***91***	***100***	***0***	***0***	***100***	***76***		***82***

b) Multi-spectral plus elevation

P1 Classification	**P1 Reference (Field Data)**																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	3															3	***100***
A1.2.2		8								1						9	***89***
A2.1			3												1	4	***75***
B1.1				3												3	***100***
B2.2					10	2										12	***83***
B4					4	9										13	***69***
B5																0	***0***
C1.1		1	1		1		1	10		4					1	19	***53***
C1.2				1					3							4	***75***
D1.1						1		1		71					1	74	***96***
D2										3	5					8	***63***
D5																0	***0***
D6																0	***0***
E2.1										8				4		12	***33***
J1.1			1		4	1									14	20	***70***
Total	3	9	5	4	19	13	1	11	3	87	5	0	0	4	17	181	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***89***	***60***	***75***	***53***	***69***	***0***	***91***	***100***	***82***	***100***	***0***	***0***	***100***	***82***		***79***

c) Multi-spectral plus slope and elevation

P1 Classification	P1 Reference (Field Data)																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	3															3	***100***
A1.2.2		8					1			1						10	***80***
A2.1			3												1	4	***75***
B1.1				4												4	***100***
B2.2					13	2									1	16	***81***
B4			1		4	10										15	***67***
B5																0	***0***
C1.1			1					11		1					2	15	***73***
C1.2									3							3	***100***
D1.1		1				1				82					1	85	***96***
D2										2	5					7	***71***
D5																0	***0***
D6																0	***0***
E2.1										1				4		5	***80***
J1.1					2										12	14	***86***
Total	3	9	5	4	19	13	1	11	3	87	5	0	0	4	17	181	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***89***	***60***	***100***	***68***	***77***	***0***	***100***	***100***	***94***	***100***	***0***	***0***	***100***	***71***		***87***

Confusion matrices derived at the validation samples for the P1 classification. Classifications result from the combination of the multi-spectral SPOT 5 image plus (a) slope, (b) elevation and (c) slope and elevation ancillary data in a per-pixel, ML algorithm.

a) Multi-spectral plus slope

P1 Classification	**P1 Reference**																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	1									1						2	***50***
A1.2.2	3	8						1		2						14	***57***
A2.1																0	***0***
B1.1				1		1									1	3	***33***
B2.2					8	3				1					1	13	***62***
B4				1	8	5				1						15	***33***
B5																0	***0***
C1.1	1			2	2			5	1	4	1	1			4	21	***24***
C1.2																0	***0***
D1.1	3	1		7				2	1	61	12	2	1			90	***68***
D2																0	***0***
D5																0	***0***
D6																0	***0***
E2.1				1						3						4	***0***
J1.1				1	8	3										12	***0***
Total	8	9	0	13	26	12	0	8	2	73	13	3	1	0	6	174	***Overall Accuracy (%)***
Producer Accuracy (%)	***13***	***89***	***0***	***8***	***31***	***42***	***0***	***63***	***0***	***84***	***0***	***0***	***0***	***0***	***0***		***51***

b) Multi-spectral plus elevation

P1 Classification	P1 Reference																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	1									1						2	***50***
A1.2.2	2	7								1						10	***70***
A2.1																0	***0***
B1.1																0	***0***
B2.2					8	4									1	13	***62***
B4				1	10	3				1						15	***20***
B5																0	***0***
C1.1	2			4	4	2		5	2	4		1	1		4	29	***17***
C1.2										1						1	***0***
D1.1	3	2		7				2		59	10	1				84	***70***
D2				1						2	1					4	***25***
D5																0	***0***
D6																0	***0***
E2.1								1		3	2	1				7	***0***
J1.1					4	3				1					1	9	***11***
Total	8	9	0	13	26	12	0	8	2	73	13	3	1	0	6	174	***Overall Accuracy (%)***
Producer Accuracy (%)	***13***	***78***	***0***	***0***	***31***	***25***	***0***	***63***	***0***	***81***	***8***	***0***	***0***	***0***	***17***		***49***

c) Multi-spectral plus slope and elevation

P1 Classification	P1 Reference																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1																0	***0***
A1.2.2	3	7						1		2						13	***54***
A2.1																0	***0***
B1.1																0	***0***
B2.2					11	3									2	16	***69***
B4				2	11	5										18	***28***
B5																0	***0***
C1.1	3	1		2	2	1		5	2	5		1	1		4	27	***19***
C1.2																0	***0***
D1.1	2	1		9				2		63	13	2				92	***68***
D2																0	***0***
D5																0	***0***
D6																0	***0***
E2.1										3						3	***0***
J1.1					2	3										5	***0***
Total	8	9	0	13	26	12	0	8	2	73	13	3	1	0	6	174	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***78***	***0***	***0***	***42***	***42***	***0***	***63***	***0***	***86***	***0***	***0***	***0***	***0***	***0***		***52***

MULTI-SPECTRAL AND NDVI CLASSIFICATIONS

Confusion matrices derived at the validation samples for the (a) MLCNP, (b) NLUD and (c) P1 classifications. Classifications result from the inclusion of the multi-spectral SPOT 5 imagery and NDVI in a per-pixel, ML algorithm.

a) MLCNP

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1													0	***0***
C2	1	2			1						1		5	***40***
C4		1											1	***0***
D1	1	2		64	17	2	7	1	2		1	1	98	***65***
D2a													0	***0***
D3				2		3		3		1	1		10	***30***
D6a				1	2		2				1		6	***33***
D6b	2			1	1					1			5	***0***
E1									3	1			4	***75***
E2a	3			2	1	2				30	4		42	***71***
E2b													0	***0***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***40***	***0***	***91***	***0***	***43***	***22***	***0***	***60***	***91***	***0***	***0***		***61***

b) NLUD

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	1									1	***100***
CO21		19	9		2			4		34	***56***
CO22	2	5	3				3			13	***23***
CO31			2	5	4	1	2	3		17	***29***
CO33											***0***
CO34				2			1			3	***0***
CO41		1	3		2		57	14		77	***74***
CO42		2	3	1	1		1	6		14	***43***
CO63							1			1	***0***
Total	3	27	20	8	9	1	65	27	0	160	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***33***	***70***	***15***	***63***	***0***	***0***	***88***	***22***	***0***		***57***

c) P1

P1 Classification	**P1 Reference**																
	A1.1.1	**A1.2.2**	**A2.1**	**B1.1**	**B2.2**	**B4**	**B5**	**C1.1**	**C1.2**	**D1.1**	**D2**	**D5**	**D6**	**E2.1**	**J1.1**	**Total**	***User Accuracy (%)***
A1.1.1	1															1	***100***
A1.2.2	2	7								2						11	***64***
A2.1																0	***0***
B1.1																0	***0***
B2.2					10	5		1		1					2	19	***53***
B4					7	4				1		1				13	***31***
B5																0	***0***
C1.1				5	3			4	2	2	1		1			18	***22***
C1.2										1						1	***0***
D1.1	5	2		7	1	1		3		66	12	2			1	100	***66***
D2				1												1	***0***
D5																0	***0***
D6																0	***0***
E2.1																0	***0***
J1.1					5	2									3	10	***30***
Total	8	9	0	13	26	12	0	8	2	73	13	3	1	0	6	174	***Overall Accuracy (%)***
Producer Accuracy (%)	***13***	***78***	***0***	***0***	***38***	***33***	***0***	***50***	***0***	***90***	***0***	***0***	***0***	***0***	***50***		***55***

FILTERING: MLCNP

Confusion matrices derived at the field samples following the application of a (a) 3x3 and (b) 5x5 majority filter to the multi-spectral MLCNP classification.

a) 3x3 majority filter

MLCNP Classification	**MLCNP Reference (field data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6		2									8	***75***
C4			2										2	***100***
D1				62			1			1			64	***97***
D2a				2	3								5	***60***
D3				1		7	2			2			12	***58***
D6a				9			5						14	***36***
D6b				1		2		3					6	***50***
E1				2					7				9	***78***
E2a										26			26	***100***
E2b				1							4		5	***80***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***75***	***100***	***78***	***63***	***100***	***100***	***90***	***100***	***100***		***82***

b) 5x5 majority filter

MLCNP Classification	**MLCNP Reference (field data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6		1									7	***86***
C4			2										2	***100***
D1				64			2			1			67	***96***
D2a				1	3								4	***75***
D3				1		8	2			2			13	***62***
D6a				12			4						16	***25***
D6b						1		3					4	***75***
E1									7				7	***100***
E2a										26	2		28	***93***
E2b				2							2		4	***50***
F3				2								3	5	***60***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***77***	***100***	***89***	***50***	***100***	***100***	***90***	***50***	***100***		***82***

CLASS SUBDIVISION: MLCNP

Confusion matrices derived at the field data samples for the MLCNP classification. Classifications result from splitting of Upland Heath (D1) into (a) 5, (b) 8 and (c) 10 clusters prior to inclusion in a multi-spectral, per-pixel, ML algorithm.

a) 5 cluster solution

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				74			3			1			78	***95***
D2a				2	3								5	***60***
D3				1		7	1			2			11	***64***
D6a				3			4						7	***57***
D6b						2		3			1		6	***50***
E1									7				7	***100***
E2a										25			25	***100***
E2b										1	3		4	***75***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***89***	***100***	***78***	***50***	***100***	***100***	***86***	***75***	***100***		***88***

b) 8 cluster solution

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				77			3			1			81	***95***
D2a				2	3								5	***60***
D3						7	1			2			10	***70***
D6a							4						4	***100***
D6b						2		3			1		6	***50***
E1									7				7	***100***
E2a										25			25	***100***
E2b				1						1	3		5	***60***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***93***	***100***	***78***	***50***	***100***	***100***	***86***	***75***	***100***		***89***

c) 10 cluster solution

MLCNP Classification	MLCNP Reference (Field Data)													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2										2	***100***
D1				78			2			1			81	***96***
D2a				2	3								5	***60***
D3						7	1			2			10	***70***
D6a							5						5	***100***
D6b						2		3			1		6	***50***
E1									7				7	***100***
E2a										25			25	***100***
E2b										1	3		4	***75***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***94***	***100***	***78***	***63***	***100***	***100***	***86***	***75***	***100***		***91***

Confusion matrices derived at the validation samples for the MLCNP classification. Classifications result from splitting of Upland Heath (D1) into (a) 5, (b) 8 and (c) 10 clusters prior to inclusion in a multi-spectral, per-pixel, ML algorithm.

a) 5 cluster solution

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1			1									2	***50***
C2		4		1	1								6	***67***
C4		1											1	***0***
D1				57	15		7	1	3	1		1	85	***67***
D2a				1									1	***0***
D3	3			3		4	1	3	2	3	1		20	***20***
D6a				7	5		1				1		14	***7***
D6b	3				1	1				3	2		10	***0***
E1										1			1	***0***
E2a										25	4		29	***86***
E2b						1							1	***0***
F3						1							1	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***80***	***0***	***81***	***0***	***57***	***11***	***0***	***0***	***76***	***0***	***0***		***54***

b) 8 cluster solution

MLCNP Classification	MLCNP Reference													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1												1	***100***
C2		4		1	1								6	***67***
C4		1											1	***0***
D1				60	16		9	1	3	1	1	1	92	***65***
D2a				1									1	***0***
D3	3			3		4		3	2	3	1		19	***21***
D6a				4	4								8	***0***
D6b	3				1	1				3	2		10	***0***
E1										1			1	***0***
E2a										25	4		29	***86***
E2b						1							1	***0***
F3				1		1							2	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***80***	***0***	***86***	***0***	***57***	***0***	***0***	***0***	***76***	***0***	***0***		***55***

c) 10 cluster solution

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1												1	***100***
C2		4		1	1								6	***67***
C4		1											1	***0***
D1				58	18		8	1	3	1	1	1	91	***64***
D2a				1									1	***0***
D3	3			3		4	1	3	2	3	1		20	***20***
D6a				6	2								8	***0***
D6b	3				1	1				3	2		10	***0***
E1										1			1	***0***
E2a										25	4		29	***86***
E2b						1							1	***0***
F3				1		1							2	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***80***	***0***	***83***	***0***	***57***	***0***	***0***	***0***	***76***	***0***	***0***		***54***

A-PRIORI **CLASSIFICATION: MLCNP**

Confusion matrices derived at the validation data samples for the MLCNP classification. Classification results from a multi-spectral, per-pixel, ML algorithm in which *a-priori* weights have been specified as a function of land cover class area.

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1												1	**100**
C2		5			1								6	**83**
C4													0	**0**
D1	3			63	19	1	7	1	2	1	1	1	99	**64**
D2a				1									1	**0**
D3	2			3		4	1	3	3	3	1		20	**20**
D6a				1			1						2	**50**
D6b	1			1	1	1				3	2		9	**0**
E1										1			1	**0**
E2a				1	1					25	4		31	**81**
E2b						1							1	**0**
F3													0	**0**
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***100***	***0***	***90***	***0***	***57***	***11***	***0***	***0***	***76***	***0***	***0***		***58***

CLASSIFICATIONS TRAINED ON API DERIVED SAMPLES: MLCNP

Confusion matrices derived at the training samples for the MLCNP classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on API derived land cover class.

a) Multi-spectral

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	7			1							1		9	***78***
C2		5											5	***100***
C4													0	***0***
D1				42	2								44	***95***
D2a				6	12							1	19	***63***
D3						6		1		2	1		10	***60***
D6a				15	3		7		1		1		27	***26***
D6b				1	2	1		3					7	***43***
E1				1	1		2		4	1			9	***44***
E2a					1					27	1		29	***93***
E2b				4	1					3	4		12	***33***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***0***	***60***	***55***	***86***	***78***	***75***	***80***	***82***	***50***	***0***		***68***

b) Multi-spectral plus slope and elevation

MLCNP Classification	MLCNP Reference													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	7			1	1						1		10	***70***
C2		5											5	***100***
C4													0	***0***
D1				47	3	1							51	***92***
D2a				9	14							1	24	***58***
D3				1	1	6							8	***75***
D6a				8	3		8						19	***42***
D6b								4					4	***100***
E1				1					5	1			7	***71***
E2a							1			30	1		32	***94***
E2b				3						2	6		11	***55***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***0***	***67***	***64***	***86***	***89***	***100***	***100***	***91***	***75***	***0***		***77***

<u>Confusion matrices derived at the validation (field data) samples for the MLCNP classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on API derived land cover class.</u>

a) Multi-spectral

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1		1				1		1					3	***0***
C2		3											3	***100***
C4													0	***0***
D1				41									41	***100***
D2a	1	1		18	3		3		1	2		1	30	***10***
D3						2		1		1		1	5	***40***
D6a	1		1	15			3				1	1	22	***14***
D6b				3		2							5	***0***
E1		1	1	6					4				12	***33***
E2a						2			2	24	3		31	***77***
E2b	1					2	2	1		2			8	***0***
F3														
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***50***	***0***	***49***	***100***	***22***	***38***	***0***	***57***	***83***	***0***	***0***		***50***

b) Multi-spectral plus slope and elevation

MLCNP Classification	MLCNP Reference													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	2	2						1					5	***40***
C2			1										1	***0***
C4													0	***0***
D1				54	2	1	1		1			1	60	***90***
D2a		3	1	15		1	5		2	2		1	30	***0***
D3		1				2		1		1			5	***40***
D6a				12	1	1	2	1				1	18	***11***
D6b				1		1							2	***0***
E1				1					2				3	***67***
E2a						2			1	24	4		31	***77***
E2b	1					1			1	2			5	***0***
F3													0	***0***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***67***	***0***	***0***	***65***	***0***	***22***	***25***	***0***	***29***	***83***	***0***	***0***		***54***

CLASSIFICATIONS TRAINED ON API DERIVED SAMPLES: NLUD

Confusion matrices derived at the training samples for the NLUD classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on API derived land cover class.

a) Multi-spectral

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	3								3	***100***
CO21		23	5						28	***82***
CO22		2	9				1	4	16	***56***
CO31				6				1	7	***86***
CO33			1		6		1	2	10	***60***
CO34									0	***0***
CO41			2				54	14	70	***77***
CO42			2		1	1	7	6	17	***35***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***100***	***92***	***47***	***100***	***86***	***0***	***86***	***22***		**71**

b) Multi-spectral plus slope and elevation

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	3								3	***100***
CO21		24	5						29	***83***
CO22		1	10		1		1	3	16	***63***
CO31				6					6	***100***
CO33			1		6			1	8	***75***
CO34									0	***0***
CO41			2				54	14	70	***77***
CO42			1			1	8	9	19	***47***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***100***	***96***	***53***	***100***	***86***	***0***	***86***	***33***		***74***

Confusion matrices derived at the validation (field data) samples for the NLUD classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on API derived land cover class.

a) Multi-spectral

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	1			1						2	***50***
CO21	2	21	3					1		27	***78***
CO22	2	9	6			1	9	7		34	***18***
CO31				4		2				6	***67***
CO33							1	1		2	***0***
CO34										0	***0***
CO41		2	1	1			76	1	1	82	***93***
CO42	4	1	2	3	3	2	9	2	2	28	***7***
CO63										0	***0***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
Producer Accuracy (%)	***11***	***64***	***50***	***44***	***0***	***0***	***80***	***17***	***0***		***61***

b) Multi-spectral plus slope and elevation

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	1									1	***100***
CO21	2	17	5							24	***71***
CO22	1	15	4			1	6	4	2	33	***12***
CO31				4		1				5	***80***
CO33		1		1	3					5	***60***
CO34										0	***0***
CO41	2		3	1		1	74	1	1	83	***89***
CO42	3			3		2	15	7		30	***23***
CO63										0	***0***
Total	9	33	12	9	3	5	95	12	3	181	**Overall Accuracy (%)**
***Producer Accuracy** (%)*	***11***	***52***	***33***	***44***	***100***	***0***	***78***	***58***	***0***		***61***

CLASSIFICATIONS TRAINED ON A RANDOM SAMPLE: MLCNP

Confusion matrices derived at the training samples for the MLCNP classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on a random sample frame.

a) Multi-spectral

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	4			1									5	***80***
C2		8											8	***100***
C4													0	***0***
D1				45			1			1			47	***96***
D2a				11	8		1						20	***40***
D3				1		9							10	***90***
D6a				14	6	1	7					1	29	***24***
D6b								2					2	***100***
E1									3	1			4	***75***
E2a						2				19	1		22	***86***
E2b						1				4	6		11	***55***
F3													0	***0***
Total	4	8	0	72	14	13	9	2	3	25	7	1	158	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***0***	***63***	***57***	***69***	***78***	***100***	***100***	***76***	***86***	***0***		***70***

b) Multi-spectral plus slope and elevation

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	4												4	***100***
C2		8											8	***100***
C4													0	***0***
D1				50						1		1	52	***96***
D2a				3	11								14	***79***
D3				3		12				1			16	***75***
D6a				16	3		9						28	***32***
D6b								2					2	***100***
E1									3				3	***100***
E2a						1				22	1		24	***92***
E2b										1	6		7	***86***
F3													0	***0***
Total	4	8	0	72	14	13	9	2	3	25	7	1	158	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***0***	***69***	***79***	***92***	***100***	***100***	***100***	***88***	***86***	***0***		***80***

<u>Confusion matrices derived at the validation samples for the MLCNP classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on a random sample frame.</u>

a) Multi-spectral

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3	1		1		2					1		8	***38***
C2		3											3	***100***
C4													0	***0***
D1				43	4		2		1		1		51	***84***
D2a		1		7	8				1				17	***47***
D3	4			4	3	4		1		3	1		20	***20***
D6a				13	6	1	5	3			1	1	30	***17***
D6b													0	***0***
E1							1			4			5	***0***
E2a							1		3	20	3		27	***74***
E2b				2	1					6	1		10	***10***
F3													0	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***43***	***60***	***0***	***61***	***36***	***57***	***56***	***0***	***0***	***61***	***13***	***0***		***51***

b) Multi-spectral plus slope and elevation

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1	1								1			3	***33***
C2		2											2	***100***
C4													0	***0***
D1	1	1		48	6	1	2		1			1	61	***79***
D2a		1		4	6				1				12	***50***
D3	5			5	3	4	3	1		2	2		25	***16***
D6a				11	6	1	3	2			1		24	***13***
D6b													0	***0***
E1													0	***0***
E2a				2		1	1	1	3	24	5		37	***65***
E2b					1					6			7	***0***
F3														
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***14***	***40***	***0***	***69***	***27***	***57***	***33***	***0***	***0***	***73***	***0***	***0***		***51***

CLASSIFICATIONS TRAINED ON A RANDOM SAMPLE: NLUD

Confusion matrices derived at the training samples for the NLUD classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on a random sample frame.

a) Multi-spectral

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6									6	***100***
CO21		22	5					2		29	***76***
CO22		2	6		1		11	1		21	***29***
CO31				11	1					12	***92***
CO33										0	***0***
CO34										0	***0***
CO41			5				58	1		64	***91***
CO42		1	1				3	6		11	***55***
CO63							1		2	3	***67***
Total	6	25	17	11	2	0	73	10	2	146	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***100***	***88***	***35***	***100***	***0***	***0***	***79***	***60***	***100***		***76***

b) Multi-spectral plus slope and elevation

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6									6	***100***
CO21		23	4							27	***85***
CO22		1	8		1		9	1		20	***40***
CO31				11	1					12	***92***
CO33										0	***0***
CO34										0	***0***
CO41			4				61	2		67	***91***
CO42		1	1				3	7		12	***58***
CO63									2	2	***100***
Total	6	25	17	11	2	0	73	10	2	146	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***100***	***92***	***47***	***100***	***0***	***0***	***84***	***70***	***100***		***81***

<u>Confusion matrices derived at the validation samples for the NLUD classification. Classifications result from the combination of the (a) multi-spectral SPOT 5 image and (b) multi-spectral plus slope and elevation in a per-pixel, ML algorithm trained on a random sample frame.</u>

a) Multi-spectral

NLUD Classification	NLUD Reference									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	2								2	***100***
CO21		18	9				1		28	***64***
CO22		4	4		2		5	2	17	***24***
CO31				6				1	7	***86***
CO33									0	***0***
CO34									0	***0***
CO41			2		2		55	14	73	***75***
CO42	1	3	4		3	1	2	10	24	***42***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***72***	***21***	***100***	***0***	***0***	***87***	***37***		***63***

b) Multi-spectral plus slope and elevation

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11									0	***0***
CO21	1	21	11				1		34	***62***
CO22		2	4		5	1	1	5	18	***22***
CO31				4					4	***100***
CO33									0	***0***
CO34									0	***0***
CO41			2	1			57	14	74	***77***
CO42	2	2	2	1	2		4	8	21	***38***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***0***	***84***	***21***	***67***	***0***	***0***	***90***	***30***		***62***

CLASSIFICATIONS BASED ON AN INCREASED SAMPLE FRACTION: MLCNP

Confusion matrices derived at the field samples for the MLCNP classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on increasing sample fractions: (a) fraction 2, (b) fraction 3, (c) fraction 4 and (d) fraction 5.

a) Sample fraction 2

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2	1									3	***67***
D1				49	1		1			1			52	***94***
D2a				13	2								15	***13***
D3				1		6	1			3			11	***55***
D6a				16		1	6						23	***26***
D6b						2		3					5	***60***
E1									7	3			10	***70***
E2a										18			18	***100***
E2b										4	4		8	***50***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***59***	***67***	***67***	***75***	***100***	***100***	***62***	***100***	***100***		***68***

b) Sample fraction 3

MLCNP Classification	**MLCNP Reference (Field Data)**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3												3	***100***
C2		6											6	***100***
C4			2	1		1							4	***50***
D1				46	1		1			1			49	***94***
D2a				12	2		2						16	***13***
D3						6				4			10	***60***
D6a				18		1	4						23	***17***
D6b						1		3					4	***75***
E1				1					7	3			11	***64***
E2a										18			18	***100***
E2b				2			1			3	4		10	***40***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***55***	***67***	***67***	***50***	***100***	***100***	***62***	***100***	***100***		***65***

c) Sample fraction 4

MLCNP Classification	MLCNP Reference (Field Data)													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	2			1									3	***67***
C2		6											6	***100***
C4			2	2									4	***50***
D1				42	1		2			1			46	***91***
D2a	1			11	2		1						15	***13***
D3						5	1			3			9	***56***
D6a				20		1	4						25	***16***
D6b				4		2		3			1		10	***30***
E1									7	4			11	***64***
E2a						1				16			17	***94***
E2b										5	3		8	***38***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***67***	***100***	***100***	***51***	***67***	***56***	***50***	***100***	***100***	***55***	***75***	***100***		***59***

d) Sample fraction 5

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	1	1											2	***50***
C2		5											5	***100***
C4			2	2									4	***50***
D1				40	1		2			1			44	***91***
D2a				10	2		1						13	***15***
D3						6	1	1		3			11	***55***
D6a				20		1	4						25	***16***
D6b	2			7		1		1			1		12	***8***
E1									7	10			17	***41***
E2a										12			12	***100***
E2b				1		1		1		3	3		9	***33***
F3				3								3	6	***50***
Total	3	6	2	83	3	9	8	3	7	29	4	3	160	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***83***	***100***	***48***	***67***	***67***	***50***	***33***	***100***	***41***	***75***	***100***		***54***

Confusion matrices derived at the validation samples for the MLCNP classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on increasing sample fractions: (a) fraction 2, (b) fraction 3, (c) fraction 4 and (d) fraction 5

a) Sample fraction 2

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	5			1	1	1	1						9	***56***
C2		4			1								5	***80***
C4		1						1					2	***0***
D1				48	6		1	1					56	***86***
D2a				8	3		3		1				15	***20***
D3				1		3		2		2			8	***38***
D6a				6	9		3				2	1	21	***14***
D6b	1					2				2	2		7	***0***
E1	1						1		4	2			8	***50***
E2a										22	3		25	***88***
E2b				5	2					5	1		13	***8***
F3				1		1							2	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***71***	***80***	***0***	***69***	***14***	***43***	***33***	***0***	***80***	***67***	***13***	***0***		***54***

b) Sample fraction 3

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	5			1		1	1						8	***63***
C2		4			1								5	***80***
C4		1						1					2	***0***
D1				48	4		1	1	1			1	56	***86***
D2a				7	6		3		1				17	***35***
D3	2			2	1	4		2		2			13	***31***
D6a				8	8		3				2		21	***14***
D6b						1				2	2		5	***0***
E1				1			1		3	6	1		12	***25***
E2a										20	2		22	***91***
E2b				2	2					3	1		8	***13***
F3				1		1							2	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***71***	***80***	***0***	***69***	***27***	***57***	***33***	***0***	***60***	***61***	***13***	***0***		***55***

c) Sample fraction 4

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	5			1		1	1				1		9	***56***
C2		4			1								5	***80***
C4		1		1				1					3	***0***
D1				47	4		1	1				1	54	***87***
D2a				5	6		2						13	***46***
D3	1			2		4		2		1			10	***40***
D6a				10	9		2		1		2		24	***8***
D6b	1			1		1	1			1	1		6	***0***
E1				1			1		4	6	1		13	***31***
E2a										21	2		23	***91***
E2b				1	2		1			4	1		9	***11***
F3				1		1							2	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***71***	***80***	***0***	***67***	***27***	***57***	***22***	***0***	***80***	***64***	***13***	***0***		***55***

d) Sample fraction 5

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	5										1		6	***83***
C2		4			1								5	***80***
C4		1		1				1					3	***0***
D1				46	5		1	1				1	54	***85***
D2a				4	5		3						12	***42***
D3				1		5		1		3			10	***50***
D6a				9	8		1		1		2		21	***5***
D6b	2			6	1	1	2				1		13	***0***
E1				1			1		4	7			13	***31***
E2a										19	3		22	***86***
E2b				1	2		1	1		4	1		10	***10***
F3				1		1							2	***0***
Total	7	5	0	70	22	7	9	4	5	33	8	1	171	***Overall Accuracy (%)***
Producer Accuracy (%)	***71***	***80***	***0***	***66***	***23***	***71***	***11***	***0***	***80***	***58***	***13***	***0***		***53***

CLASSIFICATIONS BASED ON AN INCREASED SAMPLE FRACTION: NLUD

Confusion matrices derived at the field data samples for the NLUD classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on increasing sample fractions: (a) fraction 2, (b) fraction 3, (c) fraction 4 and (d) fraction 5

a) Sample fraction 2

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	7	2				1	1			11	***64***
CO21	1	21	4					1		27	***78***
CO22		6	6				4			16	***38***
CO31				8						8	***100***
CO33					3		1			4	***75***
CO34	1	1	1			4	3			10	***40***
CO41		1	1				81	1		84	***96***
CO42		2		1			2	10		15	***67***
CO63							3		3	6	***50***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***78***	***64***	***50***	***89***	***100***	***80***	***85***	***83***	***100***		***79***

b) Sample fraction 3

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	7	2				2	1			12	***58***
CO21	1	26	3					1		31	***84***
CO22	1	2	7				8			18	***39***
CO31				7		1				8	***88***
CO33		1		2	3		1			7	***43***
CO34		1				2	4			7	***29***
CO41			2				75	1		78	***96***
CO42		1					3	10		14	***71***
CO63							3		3	6	***50***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
Producer Accuracy (%)	***78***	***79***	***58***	***78***	***100***	***40***	***79***	***83***	***100***		***77***

c) Sample fraction 4

NLUD Classification	NLUD Reference										
	CO11	CO21	CO22	CO31	CO33	CO34	CO41	CO42	CO63	Total	*User Accuracy (%)*
CO11	7	7	1			1	2	1		19	***37***
CO21	1	19	3							23	***83***
CO22	1	2	6				4			13	***46***
CO31				7						7	***100***
CO33		1		2	3		2			8	***38***
CO34						4	2			6	***67***
CO41		1	2				80	1		84	***95***
CO42		3					2	10		15	***67***
CO63							3		3	6	***50***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
Producer Accuracy (%)	***78***	***58***	***50***	***78***	***100***	***80***	***84***	***83***	***100***		***77***

d) Sample fraction 5

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	8	8	2			1				19	***42***
CO21		19	2					1		22	***86***
CO22	1	2	6				6			15	***40***
CO31				7						7	***100***
CO33		1		2	1		2			6	***17***
CO34					1	4	2			7	***57***
CO41		1	2				78	1		82	***95***
CO42		2			1		4	10		17	***59***
CO63							3		3	6	***50***
Total	9	33	12	9	3	5	95	12	3	181	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***89***	***58***	***50***	***78***	***33***	***80***	***82***	***83***	***100***		***75***

<u>Confusion matrices derived at the validation samples for the NLUD classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on increasing sample fractions: (a) fraction 2, (b) fraction 3, (c) fraction 4 and (d) fraction 5.</u>

a) Sample fraction 2

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	1	2					1		4	***25***
CO21		16	8						24	***67***
CO22	1	5	4		1		3	3	17	***24***
CO31				5				2	7	***71***
CO33			1		3	1	2	1	8	***38***
CO34	1			1					2	***0***
CO41			2				56	14	72	***78***
CO42		2	4		3		1	7	17	***41***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***33***	***64***	***21***	***83***	***43***	***0***	***89***	***26***		***61***

b) Sample fraction 3

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	2	2	0	0	0	0	1	0	5	***40***
CO21		19	8					1	28	***68***
CO22		2	4		1		4	2	13	***31***
CO31				5				1	6	***83***
CO33			1		3	1	2	1	8	***38***
CO34	1			1				1	3	***0***
CO41			2				55	13	70	***79***
CO42		2	4		3		1	8	18	***44***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***76***	***21***	***83***	***43***	***0***	***87***	***30***		***64***

c) Sample fraction 4

NLUD Classification	NLUD Reference									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	2	5	2				1	1	11	***18***
CO21		16	7						23	***70***
CO22	1	2	3		1		4	2	13	***23***
CO31				4				1	5	***80***
CO33			1		6	1	2	2	12	***50***
CO34			1	2					3	***0***
CO41			2				55	14	71	***77***
CO42		2	3				1	7	13	***54***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***64***	***16***	***67***	***86***	***0***	***87***	***26***		***62***

d) Sample fraction 5

NLUD Classification	NLUD Reference									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	2	5	2				1	1	11	*18*
CO21		16	7						23	***70***
CO22	1	2	3		1		4	2	13	***23***
CO31				4				1	5	***80***
CO33			1		6	1	2	2	12	***50***
CO34			1	2					3	***0***
CO41			2				55	14	71	***77***
CO42		2	3				1	7	13	***54***
Total	3	25	19	6	7	1	63	27	151	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***67***	***64***	***16***	***67***	***86***	***0***	***87***	***26***		***62***

CLASSIFICATIONS BASED ON AN IMPROVED TRAINING AND VALIDATION SAMPLE FRACTION: MLCNP

Confusion matrices derived at the field data samples for the MLCNP classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on 2 sample replicates. Classifications are labelled (a) classification i - (f) classification vi.

a) Classification i (Training replicates: field data and A)

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	6			1	2								9	***67***
C2		16											16	***100***
C4			3	1									4	***75***
D1				95	3		3			1			102	***93***
D2a				23	10		1				2		36	***28***
D3				1		11	1			5			18	***61***
D6a				28	5	1	7				2		43	***16***
D6b						2		4		1			7	***57***
E1						1			10	3			14	***71***
E2a						1				37	6		44	***84***
E2b					1					5	9		15	***60***
F3				9	1							3	13	***23***
Total	6	16	3	158	22	16	12	4	10	52	19	3	321	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***100***	***100***	***60***	***45***	***69***	***58***	***100***	***100***	***71***	***47***	***100***		***66***

b) Classification ii (Training replicates: field data and B)

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	6			3		2							11	***55***
C2		15											15	***100***
C4			2										2	***100***
D1				94	3		3			1			101	***93***
D2a				20	7								27	***26***
D3				2	1	8	1			2	2		16	***50***
D6a				28	5	2	9	1					45	***20***
D6b						3		3			1		7	***43***
E1				2	1				16	4			23	***70***
E2a						1				42	1		44	***95***
E2b						1				9	7		17	***41***
F3				4								3	7	***43***
Total	6	15	2	153	17	17	13	4	16	58	11	3	315	***Overall Accuracy (%)***
Producer Accuracy (%)	**100**	**100**	**100**	**61**	**41**	**47**	**69**	**75**	**100**	**72**	**64**	**100**		***67***

c) Classification iii (Training replicates: field data and C)

MLCNP Classification	MLCNP Reference													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	6			2	1	1				1			11	***55***
C2	1	15											16	***94***
C4			3	3			1			1			8	***38***
D1		1		91	3		3			1			99	***92***
D2a				22	5						1		28	***18***
D3	1				2	9	1			4	2		19	***47***
D6a				27	7	1	7						42	***17***
D6b				5	1	1		4	1	1	2		15	***27***
E1				3		1			10	10			24	***42***
E2a									1	32	3		36	***89***
E2b				2	1	1				9	11		24	***46***
F3				4								3	7	***43***
Total	8	16	3	159	20	14	12	4	12	59	19	3	329	***Overall Accuracy (%)***
Producer Accuracy (%)	***75***	***94***	***100***	***57***	***25***	***64***	***58***	***100***	***83***	***54***	***58***	***100***		***60***

d) Classification iv (Training replicates: A and B)

MLCNP Classification	MLCNP Reference												
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	6	1		1		1						9	***67***
C2		15										15	***100***
C4												0	***0***
D1				94	8		1	1				104	***90***
D2a		3		25	16	2	1				3	50	***32***
D3					2	10		1			2	15	***67***
D6a				24	3		7				1	35	***20***
D6b												0	***0***
E1					1				12	4		17	***71***
E2a						2				37	7	46	***80***
E2b			1	1	3					11	9	25	***36***
Total	6	19	1	145	33	15	9	2	12	52	22	316	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***79***	***0***	***65***	***48***	***67***	***78***	***0***	***100***	***71***	***41***		***65***

e) Classification v (Training replicates: A and C)

MLCNP Classification	**MLCNP Reference**												
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	8			1	1				1		1	12	***67***
C2		19										19	***100***
C4			2									2	***100***
D1		1		86	4		1					92	***93***
D2a				26	17					1	7	51	***33***
D3					1	9				3	1	14	***64***
D6a				30	8		7					45	***16***
D6b				4	1	1		2				8	***25***
E1									6	2		8	***75***
E2a						1			1	38	9	49	***78***
E2b				4	4	1				9	12	30	***40***
Total	8	20	2	151	36	12	8	2	8	53	30	330	***Overall Accuracy (%)***
Producer Accuracy (%)	***100***	***95***	***100***	***57***	***47***	***75***	***88***	***100***	***75***	***72***	***40***		***62***

f) Classification vi (Training replicates: B and C)

MLCNP Classification	MLCNP Reference												
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	7	1		1	1	3					1	14	**50**
C2		17										17	**100**
C4												0	**0**
D1		1		89	5		2					97	**92**
D2a			1	22	10	2	2				1	38	**26**
D3				1	5	4				2	4	16	**25**
D6a				28	8		5					41	**12**
D6b				1				2				3	**67**
E1	1			2	1	1			12	16		33	**36**
E2a									2	29	6	37	**78**
E2b				2	1	3				12	10	28	**36**
Total	8	19	1	146	31	13	9	2	14	59	22	324	***Overall Accuracy (%)***
Producer Accuracy (%)	***88***	***89***	***0***	***61***	***32***	***31***	***56***	***100***	***86***	***49***	***45***		***57***

<u>Confusion matrices derived at the validation samples for the MLCNP classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on 2 sample replicates. Classifications are labelled (a) classification i - (f) classification vi.</u>

a) Classification i (Validation replicates: B and C)

MLCNP Classification	**MLCNP Reference**												
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2			2	2	3		1	1	1		12	***17***
C2	2	18										20	***90***
C4							1					1	***0***
D1		1		92	4		3	1				101	***91***
D2a	1			22	9	2	1				2	37	***24***
D3				1		4				4	2	11	***36***
D6a				23	12	1	4					40	***10***
D6b	1				2	1			1		3	8	***0***
E1	1			2					9	3		15	***60***
E2a						1			2	37	6	46	***80***
E2b	1		1	2	2	1			1	14	9	31	***29***
Total	8	19	1	146	31	13	9	2	14	59	22	324	***Overall Accuracy (%)***
Producer Accuracy (%)	***25***	***95***	***0***	***63***	***29***	***31***	***44***	***0***	***64***	***63***	***41***		***57***

b) Classification ii (Validation replicates: A and C)

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1		1		4	3			1		1			10	***0***
C2	2	19		1									22	***86***
C4													0	***0***
D1				86	6		4				1		97	***89***
D2a			1	22	12	1	2			1	3		42	***29***
D3	4		1	2	4	8		1		2	2		24	***33***
D6a				28	9		2				3		42	***5***
D6b	2					1			1	1	4		9	***0***
E1				1		1			4	6			12	***33***
E2a						1			3	36	11		51	***71***
E2b					1					6	6		13	***46***
F3				7	1								8	***0***
Total	8	20	2	151	36	12	8	2	8	53	30	0	330	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***95***	***0***	***57***	***33***	***67***	***25***	***0***	***50***	***68***	***20***	***0***		***52***

c) Classification iii (Validation replicates: A and B)

MLCNP Classification	MLCNP Reference												
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3			1	3	3			1			11	***27***
C2	1	19										20	***95***
C4					2							2	***0***
D1				89	8		4				1	102	***87***
D2a				15	7		1				1	24	***29***
D3				1		6				2	3	12	***50***
D6a			1	27	9		4	1			2	44	***9***
D6b	2			5	1	2					1	11	***0***
E1						2			10	7	1	20	***50***
E2a						1			1	34	8	44	***77***
E2b					2	1		1		9	5	18	***28***
Total	6	19	1	145	33	15	9	2	12	52	22	316	***Overall Accuracy (%)***
Producer Accuracy (%)	***50***	***100***	***0***	***61***	***21***	***40***	***44***	***0***	***83***	***65***	***23***		***56***

d) Classification iv (Validation replicates: field data and C)

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1								1					1	***0***
C2	1	7											8	***88***
C4													0	***0***
D1		1		82	2		6					1	92	***89***
D2a		7	2	41	10	1	3	1		2	2		69	***14***
D3	3	1			4	9	1	1		8	3		30	***30***
D6a	2			31	3		1					2	39	***3***
D6b													0	***0***
E1				3					8	3			14	***57***
E2a						1			4	39	2		46	***85***
E2b	2		1	2	1	3	1	1		7	12		30	***40***
F3													0	***0***
Total	8	16	3	159	20	14	12	4	12	59	19	3	329	***Overall Accuracy (%)***
Producer Accuracy (%)	***0***	***44***	***0***	***52***	***50***	***64***	***8***	***0***	***67***	***66***	***63***	***0***		***51***

e) Classification v (Validation replicates: field data and B)

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	3	1				2		1	1		1		9	**33**
C2	1	14	1										16	**88**
C4										1			1	**0**
D1				81	4		3	1	6	1			96	**84**
D2a	2			25	6	3	4		1			2	43	**14**
D3						5	1	1		4	2		13	**38**
D6a			1	38	4		4					1	48	**8**
D6b				6									6	**0**
E1									1	1			2	**50**
E2a						2			3	42	1		48	**88**
E2b				3	3	5	1	1	4	9	7		33	**21**
F3													0	**0**
Total	6	15	2	153	17	17	13	4	16	58	11	3	315	***Overall Accuracy (%)***
Producer Accuracy (%)	***50***	***93***	***0***	***53***	***35***	***29***	***31***	***0***	***6***	***72***	***64***	***0***		***52***

f) Classification vi (Validation replicates: field data and A)

MLCNP Classification	**MLCNP Reference**													
	C1	**C2**	**C4**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**F3**	**Total**	***User Accuracy (%)***
C1	4			1				2					7	***57***
C2		16	1										17	***94***
C4													0	***0***
D1				89	5		3		1	1		1	100	***89***
D2a	2			19	7		2				3		33	***21***
D3				2	3	9		1		2	2		19	***47***
D6a			2	43	5		5				1	2	58	***9***
D6b				2			1						3	***0***
E1				1	1				8	10			20	***40***
E2a						2			1	30	6		39	***77***
E2b				1	1	5	1	1		9	7		25	***28***
F3													0	***0***
Total	6	16	3	158	22	16	12	4	10	52	19	3	321	***Overall Accuracy (%)***
Producer Accuracy (%)	***67***	***100***	***0***	***56***	***32***	***56***	***42***	***0***	***80***	***58***	***37***	***0***		***55***

Pair-wise Kappa comparison, for the MLCNP double replicate classifications, to determine the influence of field data and API upon overall classification accuracy at the training and validation samples

Classification Comparison	Kappa Values	
	Train Samples	Validation Samples
i - ii	0.41	1.12
i - iii	1.52	0.22
i - iv	0.22	1.52
i - v	0.72	1.47
i - vi	2.18	0.70
ii - iii	1.94	0.88
ii - iv	0.63	0.40
ii - v	1.14	0.37
ii - vi	2.60	0.40
iii - iv	1.29	1.28
iii - v	0.81	1.23
iii - vi	0.66	0.47
iv - v	0.49	0.02
iv - vi	1.94	0.80
v - vi	1.47	0.76

Notes: Red values indicate a significant difference in overall accuracy, at the 95% confidence level, between the classifications

CLASSIFICATIONS BASED ON AN IMPROVED TRAINING AND VALIDATION SAMPLE FRACTION: NLUD

Confusion matrices derived at the field data samples for the NLUD classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on 2 sample replicates. Classifications are labelled (a) classification i - (f) classification vi.

a) Classification i (Training replicates: field data and A)

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	9	3	1	0	0	1	2	0	0	16	***56***
CO21	1	48	10					3		62	***77***
CO22		7	16				8			31	***52***
CO31				16						16	***100***
CO33					7		2			9	***78***
CO34	1	2	1	1		4	5			14	***29***
CO41		1	4				148	2		155	***95***
CO42		3		1			2	19		25	***76***
CO63			1				8		3	12	***25***
Total	11	64	33	18	7	5	175	24	3	340	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***82***	***75***	***48***	***89***	***100***	***80***	***85***	***79***	***100***		***79***

b) Classification ii (Training replicates: field data and B)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	9	4				1	1		1	16	***56***
CO21	2	53	10					2		67	***79***
CO22		8	7				17	1		33	***21***
CO31				14						14	***100***
CO33	1	1		1	6		2	1		12	***50***
CO34	2	1	3	1	1	4	6			18	***22***
CO41		2	4				145	2		153	***95***
CO42		1	1	1	1		5	11		20	***55***
CO63							4			4	***0***
Total	14	70	25	17	8	5	180	17	1	337	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***64***	***76***	***28***	***82***	***75***	***80***	***81***	***65***	***0***		***74***

c) Classification iii (Training replicates: field data and C)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	10	9	2			1	2	1		25	***40***
CO21	2	46	7		1			1		57	***81***
CO22		3	12				11	1		27	***44***
CO31				17			1			18	***94***
CO33		1	2	1	6		4	2		16	***38***
CO34	2	2	2	1		5	8			20	***25***
CO41			3				152	2		157	***97***
CO42		5	6		1		4	12		28	***43***
CO63							4		3	7	***43***
Total	14	66	34	19	8	6	186	19	3	355	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***71***	***70***	***35***	***89***	***75***	***83***	***82***	***63***	***100***		***74***

d) Classification iv (Training replicates: A and B)

NLUD Classification	NLUD Reference									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	3		1						4	***75***
CO21		51	10		2			2	65	***78***
CO22	1	15	20				11	2	49	***41***
CO31		1		17	2				20	***85***
CO33					6		1	1	8	***75***
CO34									0	***0***
CO41	2	3	4				148	2	159	***93***
CO42	1	2			1		6	11	21	***52***
Total	7	72	35	17	11	0	166	18	326	***Overall Accuracy (%)***
Producer Accuracy (%)	***43***	***71***	***57***	***100***	***55***	***0***	***89***	***61***		***79***

e) Classification v (Training replicates: A and C)

NLUD Classification	**NLUD Reference**									
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**Total**	***User Accuracy (%)***
CO11	6	3			2			1	12	50
CO21		48	10		2			1	61	79
CO22	1	12	19			1	14	3	50	38
CO31		1		18	1				20	90
CO33		1	1		6		2	2	12	50
CO34									0	0
CO41		2	4	1			154	3	164	94
CO42		1	10				2	10	23	43
Total	7	68	44	19	11	1	172	20	342	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***86***	***71***	***43***	***95***	***55***	***0***	***90***	***50***		***76***

f) Classification vi (Training replicates: B and C)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6	6			1			1		14	***43***
CO21		51	6		2			2		61	***84***
CO22		7	15			1	17	2		42	***36***
CO31				17	1				1	19	***89***
CO33		1	2		5		2			10	***50***
CO34										0	***0***
CO41	3	5	6				152	1		167	***91***
CO42	1		6	1	1		5	6		20	***30***
CO63										0	***0***
Total	10	70	35	18	10	1	176	12	1	333	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***60***	***73***	***43***	***94***	***50***	***0***	***86***	***50***	***0***		***74***

<u>Confusion matrices derived at the validation samples for the NLUD classification. Classifications result from a multi-spectral, per-pixel ML algorithm trained on 2 sample replicates. Classification are labelled (a) classification i - (f) classification vi.</u>

a) Classification i (Validation replicates: B and C)

NLUD Classification	**NLUD Reference**										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	6	9	1				2			18	***33***
CO21	1	40	8		1			2		52	***77***
CO22	1	17	9		1	1	17	2		48	***19***
CO31				15	1		2			18	***83***
CO33	1		2		2			1		6	***33***
CO34			3	2	1		4			10	***0***
CO41		3	5	1			144	3		156	***92***
CO42	1	1	7		4		4	4	1	22	***18***
CO63							3			3	***0***
Total	10	70	35	18	10	1	176	12	1	333	***Overall Accuracy (%)***
Producer Accuracy (%)	***60***	***57***	***26***	***83***	***20***	***0***	***82***	***33***	***0***		***66***

b) Classification ii (Validation replicates: A and C)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	3	2	1				1			7	***43***
CO21	2	54	11		2			2		71	***76***
CO22		8	15		1	1	20	4		49	***31***
CO31		1		12	1		2			16	***75***
CO33			3	1	1		2	1		8	***13***
CO34	1	2	1	6	1		5			16	***0***
CO41			5		1		132	3		141	***94***
CO42	1	1	7		4		3	10		26	***38***
CO63			1				7			8	***0***
Total	7	68	44	19	11	1	172	20	0	342	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***43***	***79***	***34***	***63***	***9***	***0***	***77***	***50***	***0***		***66***

c) Classification iii (Validation replicates: A and B)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	5	13	2				3			23	***22***
CO21		46	11		1			3		61	***75***
CO22		5	6				5	3		19	***32***
CO31		1		16	4		2	1		24	***67***
CO33	1	1	1		2		2	2		9	***22***
CO34		1	2	1	1		4			9	***0***
CO41		2	8		2		141	2		155	***91***
CO42	1	3	4		1		3	7		19	***37***
CO63			1				6			7	***0***
Total	7	72	35	17	11	0	166	18	0	326	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***71***	***64***	***17***	***94***	***18***	***0***	***85***	***39***	***0***		***68***

d) Classification iv (Validation replicates: field data and C)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	2									2	***100***
CO21	4	45	5		1					55	***82***
CO22	6	14	16		3	3	27	5	2	76	***21***
CO31				16		2	1			19	***84***
CO33				1	1		1			3	***33***
CO34										0	***0***
CO41	1	3	4				149	2	1	160	***93***
CO42	1	4	9	2	3	1	8	12		40	***30***
CO63										0	***0***
Total	14	66	34	19	8	6	186	19	3	355	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***14***	***68***	***47***	***84***	***13***	***0***	***80***	***63***	***0***		***68***

e) Classification v (Validation replicates: field data and B)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	1	6		1				1	1	10	***10***
CO21	2	44	5					1		52	***85***
CO22	3	9	11		1	1	13	2		40	***28***
CO31				15	2	3				20	***75***
CO33	1			1	3		2	2		9	***33***
CO34										0	***0***
CO41	7	7	7			1	156	1	1	180	***87***
CO42		4	2		2		9	10	1	28	***36***
CO63										0	***0***
Total	14	70	25	17	8	5	180	17	3	339	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***7***	***63***	***44***	***88***	***38***	***0***	***87***	***59***	***0***		***71***

f) Classification vi (Validation replicates: field data and A)

NLUD Classification	NLUD Reference										
	CO11	**CO21**	**CO22**	**CO31**	**CO33**	**CO34**	**CO41**	**CO42**	**CO63**	**Total**	***User Accuracy (%)***
CO11	3	4		1	1			1	1	11	***27***
CO21	2	44	13		1			3		63	***70***
CO22	3	12	14			1	11	4		45	***31***
CO31		1		16	1	3				21	***76***
CO33				1	4		1	3		9	***44***
CO34										0	***0***
CO41	3	4	5			1	155	3	1	172	***90***
CO42		3	2		2		9	11	1	28	***39***
CO63										0	***0***
Total	11	68	34	18	9	5	176	25	3	349	***Overall Accuracy (%)***
***Producer Accuracy** (%)*	***27***	***65***	***41***	***89***	***44***	***0***	***88***	***44***	***0***		***71***

<u>Pair-wise Kappa comparison, for the NLUD double replicate classifications, to determine the influence of field data and API upon overall classification accuracy at the training and validation samples</u>

Classification Comparison			Kappa Value	
			Train Samples	Validation Samples
i	**-**	**ii**	1.93	0.51
i	**-**	**iii**	1.69	0.79
i	**-**	**iv**	0.57	0.7
i	**-**	**v**	1.2	1.09
i	**-**	**vi**	1.61	1.45
ii	**-**	**iii**	0.29	0.29
ii	**-**	**iv**	1.32	0.2
ii	**-**	**v**	0.73	0.6
ii	**-**	**vi**	0.29	0.95
iii	**-**	**iv**	1.07	0.1
iii	**-**	**v**	0.46	0.31
iii	**-**	**vi**	0.007	0.65
iv	**-**	**v**	0.6	0.41
iv	**-**	**vi**	1.02	0.76
v	**-**	**vi**	0.44	0.33

Notes: No significant differences in overall accuracy (at the training and validation samples), at the 95% confidence level, were identified between the classifications

Object-Orientated Classification: Confusion Matrices

This appendix contains the confusion matrices resulting from the object-orientated classification (section 6.4). Classifications were based on a standardised nearest neighbour algorithm and image objects derived at 3 differing segmentation scales (section 5.4.2).

<u>Comparison of the (a) mean and (b) standard deviation of object pixel values as the basis of classification at segmentation scale 1.</u>

a) Mean multi-spectral feature space

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	4						1				5	***80***
C2	1	10									11	***91***
D1	2		60	5		2	2			1	72	***83***
D2a			3								3	***0***
D3					4				2		6	***67***
D6a											0	***0***
D6b	1			1	1				2		5	***0***
E1								6	1		7	***86***
E2a				1				1	26	5	33	***79***
E2b	1		1		1	1			5	2	11	***18***
Total	9	10	64	7	6	3	3	7	36	8	153	***Overall Accuracy (%)***
Producer Accuracy (%)	***44***	***100***	***94***	***0***	***67***	***0***	***0***	***86***	***72***	***25***		***73***

b) Standard deviation multi-spectral feature space

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2		2						1		5	***40***
C2	1	5	3						6		15	***33***
D1	1	4	44	3	1	2		3	9	3	70	***63***
D2a			1							1	2	***0***
D3	4		2	2	4		1	1	3		17	***24***
D6a											0	***0***
D6b				1							1	***0***
E1	1		3	1				1	1		7	***14***
E2a			6			1	2	2	9	2	22	***41***
E2b		1	3	1	1				7	2	15	***13***
Total	9	10	65	8	6	3	3	7	36	8	154	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***50***	***68***	***0***	***67***	***0***	***0***	***14***	***25***	***25***		***44***

Confusion matrix, derived at the validation samples, resulting from the classification of (a) segmentation 1, (b) segmentation 2 and (c) segmentation 3 image objects in a mean multi-spectral feature space

a) Segmentation scale 1

Object-Orientated Classification	MLCNP Reference											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	4						1				5	***80***
C2	1	10									11	***91***
D1	2		60	5		2	2			1	72	***83***
D2a			3								3	***0***
D3					4				2		6	***67***
D6a											0	***0***
D6b	1			1	1				2		5	***0***
E1								6	1		7	***86***
E2a				1				1	26	5	33	***79***
E2b	1		1		1	1			5	2	11	***18***
Total	9	10	64	7	6	3	3	7	36	8	153	***Overall Accuracy (%)***
Producer Accuracy (%)	***44***	***100***	***94***	***0***	***67***	***0***	***0***	***86***	***72***	***25***		***73***

b) Segmentation scale 2

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3	1					1				5	***60***
C2	2	9									11	***82***
D1	1		59	5		2	2				69	***86***
D2a			3	1							4	***25***
D3					3						3	***100***
D6a											0	***0***
D6b	2			1	1					1	5	***0***
E1			1		2			6	2		11	***55***
E2a	1			1				1	31	3	37	***84***
E2b			2			1			3	4	10	***40***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***90***	***91***	***13***	***50***	***0***	***0***	***86***	***86***	***50***		***75***

c) Segmentation scale 3

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3						2				5	***60***
C2	2	10									12	***83***
D1	1		56	5		2	1			3	68	***82***
D2a			6	1						1	8	***13***
D3					3						3	***100***
D6a											0	***0***
D6b	2			1	1						4	***0***
E1			1		1			6	3		11	***55***
E2a	1		1						27	2	31	***87***
E2b			1	1	1	1		1	6	2	13	***15***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***100***	***86***	***13***	***50***	***0***	***0***	***86***	***75***	***25***		***70***

<u>Confusion matrix, derived at the validation samples, resulting from a per-pixel, multi-spectral classification of the subset area</u>

Per-Pixel Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3										3	***100***
C2	3	9									12	***75***
D1			52	6		1					59	***88***
D2a	1	1	10			2				2	16	***0***
D3	1			1	4		1		1		8	***50***
D6a											0	***0***
D6b									1		1	***0***
E1			1					5	1		7	***71***
E2a					2				25	3	30	***83***
E2b	1		2	1			2	2	8	3	19	***16***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***90***	***80***	***0***	***67***	***0***	***0***	***71***	***69***	***38***		***65***

<u>Confusion matrix, derived at the validation samples, resulting from the classification of segmentation 1 image objects in a (a) multi-spectral plus slope, (b) multi-spectral plus elevation and (c) multi-spectral plus slope and elevation feature space</u>

a) Multi-spectral plus slope

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2										2	***100***
C2	1	10									11	***91***
D1	1		59	7		1	1			1	70	***84***
D2a	1		3			2				1	7	***0***
D3	2				3		1				6	***50***
D6a											0	***0***
D6b	1		2	1	1		1				6	***17***
E1			1					6	3		10	***60***
E2a	1				1			1	28	2	33	***85***
E2b					1				5	4	10	***40***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***100***	***91***	***0***	***50***	***0***	***33***	***86***	***78***	***50***		***73***

b) Multi-spectral plus elevation

Object-Orientated Classification	MLCNP Reference										
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3	1					1				5	***60***
C2	2	9									11	***82***
D1			56	5		1	1				63	***89***
D2a	2		7			1				2	12	***0***
D3					3				1		4	***75***
D6a											0	***0***
D6b				1	1						2	***0***
E1				1				6	2		9	***67***
E2a			1		1			1	27	3	33	***82***
E2b	2		1	1	1	1	1		6	3	16	***19***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***90***	***86***	***0***	***50***	***0***	***0***	***86***	***75***	***38***		***69***

c) Multi-spectral plus slope and elevation

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2										2	***100***
C2	1	10									11	***91***
D1			62	5							67	***93***
D2a	2					2				2	6	***0***
D3	1				3		2			1	7	***43***
D6a											0	***0***
D6b	1		1	1	1						4	***0***
E1			1	1				6	3		11	***55***
E2a	1				1				27	3	32	***84***
E2b	1		1	1	1	1	1	1	6	2	15	***13***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***100***	***95***	***0***	***50***	***0***	***0***	***86***	***75***	***25***		***72***

<u>Confusion matrix, derived at the validation samples, resulting from the classification of segmentation 2 image objects in a (a) multi-spectral plus slope, (b) multi-spectral plus elevation and (c) multi-spectral plus slope and elevation feature space</u>

a) Multi-spectral plus slope

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2										2	***100***
C2	2	9									11	***82***
D1			59	5		1	1				66	***89***
D2a			4	1		2				1	8	***13***
D3	2	1			5		1			2	11	***45***
D6a											0	***0***
D6b	2		1	1	1		1		1		7	***14***
E1			1					6	4		11	***55***
E2a	1			1				1	25	2	30	***83***
E2b									6	3	9	***33***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***90***	***91***	***13***	***83***	***0***	***33***	***86***	***69***	***38***		***72***

b) Multi-spectral plus elevation

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2	1					1				4	***50***
C2	2	9									11	***82***
D1	1		58	5		1	1				66	***88***
D2a			6	1		1				1	9	***11***
D3	1				4				1	1	7	***57***
D6a											0	***0***
D6b	1			1	1						3	***0***
E1					1			6	3		10	***60***
E2a	1							1	29	2	33	***88***
E2b	1		1	1		1	1		3	4	12	***33***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***90***	***89***	***13***	***67***	***0***	***0***	***86***	***81***	***50***		***73***

c) Multi-spectral plus slope and elevation

Object-Orientated Classification	MLCNP Reference											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2										2	***100***
C2	2	9	1								12	***75***
D1			59	5							64	***92***
D2a			3	1		3				1	8	***13***
D3	3	1			5		2			2	13	***38***
D6a											0	***0***
D6b	1		1	1	1				1		5	***0***
E1			1					6	5		12	***50***
E2a	1			1				1	27	2	32	***84***
E2b							1		3	3	7	***43***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***90***	***91***	***13***	***83***	***0***	***0***	***86***	***75***	***38***		***72***

<u>Confusion matrix, derived at the validation samples, resulting from the classification of segmentation 3 image objects in a (a) multi-spectral plus slope, (b) multi-spectral plus elevation and (c) multi-spectral plus slope and elevation feature space</u>

a) Multi-spectral plus slope

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	1	1					1				3	***33***
C2	3	9									12	***75***
D1			56	5		1				2	64	***88***
D2a			7	1		2				1	11	***9***
D3	3				3						6	***50***
D6a											0	***0***
D6b	1			1			1		1		4	***25***
E1			1					6	3		10	***60***
E2a	1		1	1	3				26	1	33	***79***
E2b							1	1	6	4	12	***33***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***11***	***90***	***86***	***13***	***50***	***0***	***33***	***86***	***72***	***50***		***69***

b) Multi-spectral plus elevation

Object-Orientated Classification	MLCNP Reference											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2										2	***100***
C2	2	10									12	***83***
D1	2		57	4		2	1				66	***86***
D2a			5	1						2	8	***13***
D3	1				3		1			1	6	***50***
D6a											0	***0***
D6b				1							1	***0***
E1			1		2			6	3		12	***50***
E2a	2		1						28	1	32	***88***
E2b			1	2	1	1	1	1	5	4	16	***25***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***100***	***88***	***13***	***50***	***0***	***0***	***86***	***78***	***50***		***72***

c) Multi-spectral plus slope and elevation

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	1	1					1				3	***33***
C2	3	9									12	***75***
D1			55	4		1					60	***92***
D2a	1		8	1		1	1			1	13	***8***
D3	1				4					1	6	***67***
D6a											0	***0***
D6b	1			1					1		3	***0***
E1			1					6	2	1	10	***60***
E2a	1				2				28	1	32	***88***
E2b	1		1	2		1	1	1	5	4	16	***25***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***11***	***90***	***85***	***13***	***67***	***0***	***0***	***86***	***78***	***50***		***70***

Confusion matrix, derived at the validation samples, resulting from the classification of segmentation 1 image objects in a (a) multi-spectral plus shape index and (b) multi-spectral plus rectangular fit index feature space

a) Multi-spectral plus shape index

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	4	1					2				7	***57***
C2	1	9									10	***90***
D1	2		58	5		2				1	68	***85***
D2a			4							1	5	***0***
D3					3				2		5	***60***
D6a											0	***0***
D6b	1		1	1					1		4	***0***
E1				1	1			6	2		10	***60***
E2a				1	1			1	27	3	33	***82***
E2b	1		1		1	1	1		4	3	12	***25***
Total	9	10	64	8	6	3	3	7	36	8	154	***Overall Accuracy (%)***
Producer Accuracy (%)	***44***	***90***	***91***	***0***	***50***	***0***	***0***	***86***	***75***	***38***		***71***

b) Multi-spectral plus rectangular fit index

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2	2					1				5	***40***
C2	1	8									9	***89***
D1	1		56	5		1	1			1	65	***86***
D2a	1		6			1				1	9	***0***
D3	1				3				1		5	***60***
D6a											0	***0***
D6b	1			1	1						3	***0***
E1				1				6	3		10	***60***
E2a			1	1	2			1	24	3	32	***75***
E2b	2		2			1	1		8	3	17	***18***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***22***	***80***	***86***	***0***	***50***	***0***	***0***	***86***	***67***	***38***		***66***

Confusion matrix, derived at the validation samples, resulting from the classification of segmentation 2 image objects in a (a) multi-spectral plus shape index and (b) multi-spectral plus rectangular fit index feature space

a) Multi-spectral plus shape index

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3						1				4	***75***
C2	2	10									12	***83***
D1			60	4		2	2				68	***88***
D2a			2	1						2	5	***20***
D3	2				4				1		7	***57***
D6a											0	***0***
D6b	2			1					2	1	6	***0***
E1			1		1			6			8	***75***
E2a					1			1	31	1	34	***91***
E2b			2	2		1			2	4	11	***36***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***100***	***92***	***13***	***67***	***0***	***0***	***86***	***86***	***50***		***77***

b) Multi-spectral plus rectangular fit index

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3						2				5	***60***
C2	2	10									12	***83***
D1	1		59	5		2				1	68	***87***
D2a			3	1						1	5	***20***
D3					3				1		4	***75***
D6a											0	***0***
D6b	2			1	1				1	1	6	***0***
E1	1		1		1			6	1		10	***60***
E2a				1	1			1	30	1	34	***88***
E2b			2			1	1		3	4	11	***36***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***100***	***91***	***13***	***50***	***0***	***0***	***86***	***83***	***50***		***75***

<u>Confusion matrix, derived at the validation samples, resulting from the classification of segmentation 3 image objects in a (a) multi-spectral plus shape index and (b) multi-spectral plus rectangular fit index feature space</u>

a) Multi-spectral plus shape index

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	2	2					1			1	6	**33**
C2	2	7									9	**78**
D1	1	1	60	4						1	67	**90**
D2a			2	1		2				1	6	**17**
D3	1				1		1		1		4	**25**
D6a											0	**0**
D6b	1			1	1				1		4	**0**
E1			1		1			6	1		9	**67**
E2a	2				3			1	26	1	33	**79**
E2b			2	2		1	1		6	4	16	**25**
Total	9	10	65	8	6	3	3	7	35	8	154	***Overall Accuracy (%)***
Producer Accuracy (%)	**22**	**70**	**92**	**13**	**17**	**0**	**0**	**86**	**74**	**50**		***69***

b) Multi-spectral plus rectangular fit index

Object-Orientated Classification	**MLCNP Reference**											
	C1	**C2**	**D1**	**D2a**	**D3**	**D6a**	**D6b**	**E1**	**E2a**	**E2b**	**Total**	***User Accuracy (%)***
C1	3	1					2				6	***50***
C2	2	8									10	***80***
D1	1		59	5		1			1	2	69	***86***
D2a			3	1							4	***25***
D3		1			2				2		5	***40***
D6a											0	***0***
D6b	1			1	2						4	***0***
E1			1					6			7	***86***
E2a	1		1	1	2			1	27	1	34	***79***
E2b	1		1			2	1		6	5	16	***31***
Total	9	10	65	8	6	3	3	7	36	8	155	***Overall Accuracy (%)***
Producer Accuracy (%)	***33***	***80***	***91***	***13***	***33***	***0***	***0***	***86***	***75***	***63***		***72***

APPENDIX J

Sub-pixel Classification: Confusion Matrices

This appendix contains the confusion matrices resulting from the sub-pixel classification (section 7.3). The sub-pixel classifier, implemented via the FUZCLASS algorithm, was tested on the upland strata of the study area. The classifier was trained on a combination of species and habitat classes defined to represent 'pure' class examples.

Confusion matrix, derived for all field samples, for the sub-pixel classification implemented via the FUZCLASS algorithm

Hardened fuzzy classification	**Reference data**								
	Bracken	**Recent burn**	***ET moor***	**Grass moor**	***Calluna vulgaris***	**Moss/ bare ground**	***Vaccinium species***	**Total**	***User Accuracy (%)***
Bracken	4						1	5	***80***
Recent burn		1						1	***100***
ET moor			4			1		5	***80***
Grass moor	2		2	4	7	4	1	20	***20***
Calluna vulgaris			2	1	32	4	1	40	***80***
Moss bare ground		1			1	8		10	***80***
Vaccinium species	2			2	7	1	5	17	***29***
Total	8	2	8	7	47	18	8	98	***Overall Accuracy (%)***
Producer Accuracy (%)	***50***	***50***	***50***	***57***	***68***	***44***	***63***		***59***

Note: The reference class, at each field survey sample, is defined as the class with the highest top cover proportion