Assessment of Remote Sensing Attributes as Biodiversity Indicators on a European Protected Raised Bog.

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Declaration and Statements

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Of great importance to the whole project are my sponsors, Welsh Government particularly

....it has gone on for days

strumming rushes
taking up tales,
taking them on

the fall of my foot,
on tufts

a stroke of light along a law lain in under a long cloud

I accrete - lichen to limestone
sphagnum to peat ....

by Tom Pickard (extract from Lark & Merlin, 2010)

Abstract

Biodiversity is declining globally primarily because of climatic change and anthropogenic impacts. In Europe, protected sites (e.g. Natura 2000) have been established to prevent further loss of biodiversity and protect key habitats from further deterioration, including from previous detrimental management practices. In the UK and particularly Wales, even protected habitats lack a coherent management approach leaving conservation bodies to work with communities to protect their biodiversity. Few systems exist for consistently, routinely and spatially quantifying biodiversity, assessing impacts of past management and guiding and predicting the consequences of future actions, including those relating to policy. Most current monitoring systems still rely solely on field observations and field surveys with little input from very high resolution (VHR; $\leq$ 2m) airborne and space data to provide baseline data suitable for monitoring the extent and condition of habitats over time.

In order to investigate the use of VHR optical imagery for monitoring, the potential for WV2 spectral indices data to be used as indicators of condition for protected bog sites was evaluated and a method developed which could be used within a protected site monitoring system for monitoring both flora and fauna distributions. In developing an approach this study focuses primarily on the protected lowland raised bog at Cors Fochno where encroachment by grass species (primarily *Molinia caerulea* and *Phragmites australis*) over decades, coupled with management actions focusing on conserving the integrity of the bog system, has led or is anticipated to lead to transitions in state with consequences on biodiversity, particularly species richness, distributions and abundance.

Field spectroradiometer data was used to develop a method for identifying optimum months of the year and best indices for species discrimination on Cors Fochno protected site that can later be used within a system for accurate classification of species. Methods developed, and ecological information from field data, were used with WV2 data acquired over 3 time periods (March, July and November) to produce a multiscale classification (LCCS to species level) of Cors Fochno SSSI and it's surrounding landscape suitable for use within a monitoring system. Within the SSSI WV2 satellite derived parameters (spectral indices and classified dominant plant species) that relate to environmental variables relevant to invertebrate habitat suitability and invertebrate plant food sources were used to test associations with selected invertebrate species and assemblages assessed and map habitat suitability.

An ANOVA F-ratio method provided a successful method to assess the distinctive phenological differences between spectral data of the key lowland raised bog plant species.

It demonstrated the importance of phenological data for selecting the best months and the best spectral indices for species discrimination and was used with success to select optimum WV2 imagery acquisitions for a more successful species classification. Classification of varying scales, from landscape to species level, was carried out effectively with good overall accuracies (over 81%) by using LCCS and an adapted EODHaM system classification method. This enabled the use of indices values as input using the best indices and image acquisition times for species discrimination, along with ecological information gathered in field surveys. WV2 satellite derived spectral indices, and WV2 satellite derived dominant plant species classified using the developed system which were indicative of the ecological gradients of the lowland raised bog, were used to show associations between invertebrate data (*Araneae, Coleoptera* and *Diptera*) sampled across the bog and were shown to be useful as invertebrate diversity and distribution indicators. This research demonstrates that spectral indices derived from VHR optical imagery can be used as indicators of the composition, structure and functional diversity of a lowland raised bog.

A key component was the development of a framework for sampling the SSSI. From these observations and models, a conceptual framework for creating a baseline which can be used and developed for quantifying losses and gains in biodiversity as a function of satellite-observed changes in habitat extent and condition was proposed. Through this approach, a better understanding of the drivers and impacts (both actual and potential) of change is anticipated with direct benefits for conservation, sustainable use of the environment and environmental and agricultural policy.

List of publications linked to this research

Journals

Harris A, Charnock R, Lucas, R. M. (2015), Hyperspectral remote sensing of peatland floristic gradients. Remote Sensing of Environment. DOI: 10.1016/j.rse.2015.01.029

Lucas R, Blonda P, Bunting P, Jones G, Inglada J, Arias M, Kosmidou V, Petrou Z, Manakos I, Adamo M, Charnock R, Tarantino C, Mucher C, Jongman, Kramer R, Arvor D, Honrado P, and Mairota P. (2014), The Earth Observation Data for Habitat Monitoring (EODHaM) System. International Journal of Applied Earth Observation and Geoinformation. DOI: 10.1016/j.jag.2014.10.011

Reports

Mairota P, Boccaccio L, Cafarelli B, Labadessa R, Leronni V, Blonda P, Lovergine F, Pasquariello G, Honrado J, Lucas R, Charnock R, Bailey M, Nagendra H, Niphadkar M, Kosmidou V. (2012), D6.4 Landscape pattern analysis, BIOSOS Project Report Deliverable 6.4.

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Chapter 1

Introduction

Across the world there are a diverse range of habitats and landscapes that have been shaped for centuries by human activity. This activity has often resulted in the loss of many significant habitats and consequently the species and biodiversity that they support. As multiple pressures on fragile habitats increase worldwide, so important areas of biodiversity require comprehensive mapping and monitoring to underpin and inform programmes of protection. In recent decades remote sensing has grown to become a key tool to map and investigate these habitats, but only with improvements in methodology and resolution will it become possible to map and monitor species distributions and biodiversity with greater spatial accuracy. This research investigates the significance of remote sensing and its application for monitoring a major protected raised bog habitat in Wales: Cors Fochno.

1.1   Protected habitats and biodiversity, 1992 to present

In 1992 in recognition of declining trends the UK agreed and signed up to the Rio Earth Summit programme (Convention on Biological Diversity or CBD) to develop a 'Biodiversity Action Plan'. From this the first 'UK Biodiversity Action Plan' (UK BAP) was published in 1994. This delivered action plans for aiding recovery of the most threatened species and habitats while national reports were produced every three to five years (Defra, 2007). Following devolution in Wales in 1998, the Welsh Government (WG) developed it's own strategies for biodiversity, conservation and the environment

(JNCC, 2012b) although these were incorporated into a shared vision adopted in 2007 for future work at a UK level.

Documentation to support this included the EU Gothenberg agreement (in 2001) which was an implementation agreement for the CBD target to halt the loss of biodiversity by 2010. With the failure to meet the target of halting the loss of biodiversity by 2010 Wales has now adopted a new target to reverse biodiversity declines by 2026 and is obliged to meet the Achi CBD 2020 target. A UK Post 2010 Biodiversity Framework was developed with the launch of a new EU Biodiversity Strategy (EUBS)

In 1992 the EC Directive on the Conservation of Wild Birds (EU, 2009) and the EC Directive on the Conservation of Natural Habitats and Wild Flora and Fauna (EU, 1992) also established a legislative framework for protecting and conserving Europe's wildlife and habitats (Sundseth, 2014). Central to this policy was the creation of a coherent ecological network of protected areas across the EU, known as NATURA 2000. This network comprises of Special Protection Areas (SPAs) to help conserve vulnerable birds (listed in Annex 1 of the Birds Directive) and Special Areas of Conservation (SACs) for the conservation of other rare species and threatened natural habitats (under the Habitats Directive). These areas exist to provide a high level of protection to 69 species and 55 habitats that are threatened internationally.

Within Wales Natura 2000 consists of a total of 20 SPAs for vulnerable birds and 92 SACs for other rare species and threatened natural habitats all managed by Natural Resources Wales (JNCC, 2012a). Along with areas across Europe, they form an unparalleled network of international importance. While some Natura 2000 species and habitats are thriving, in over 50% of occurrences they are declining and in poor condition. For this reason focused and coordinated action is essential.

The Natura 2000 programme will identify pressures and plan the actions that are required to significantly improve the condition of these features, safeguarding them for the future. This work requires comprehensive monitoring of habitats and species important to each

site and should include monitoring of surrounding landscapes to inform on external pressures to the protected habitats. The Natura 2000 programme will also be used to inform the Wales Prioritised Action Framework in order to achieve the European Union's Biodiversity Strategy (EUBS) to 2020. With these targets in mind, the WG are keen to progress with monitoring and protecting biodiversity and recognise that more research and evidence is required to support these efforts. It is hoped that this PhD will in part, address this requirement for research and evidence into 'Assessment of Remote Sensing Attributes as Biodiversity Indicators'

1.2   Current status of ecosystems and protected sites in Wales

Current 'State of the Environment' assessments are presented biannually in Wales and are an initial attempt at systematically monitoring Welsh biodiversity. The 2012 'State of the Environment' report stated that these sites appeared to be stable or showed no clear trend. However it is apparent that biodiversity indicators are still under development and are yet to be defined (Statistical Directorate 2009). Each protected site in Wales is currently monitored but the methods are somewhat dependant on a variety of factors including the site, funds, and individual choices of assessments with some sites having far more attention than others. At present, monitoring of biodiversity is not consistent, with only some species and taxonomic groups having long-term monitoring data whilst others are not regularly monitored (Blackstock et al., 2012). The direct drivers of biodiversity change (and loss) in Wales include land-use change (particularly agricultural intensification and softwood afforestation in Wales); pollution; climate change and invasive species.

From these reports it is clear that consistent, permanent monitoring schemes needs to be introduced, in particular for monitoring habitat response to degradation or restoration

within a site. Of equal importance are responses of a site to external drivers of change such as agricultural and forestry activity, which may border or surround the site. This information can then be used to assess biodiversity losses or gains and provide further input into management practices as well as informing policy makers who are creating policies that determine the impact of external practices on these sites.

In Wales, in order to identify which of the pressures or drivers of change are affecting protected sites, improved detailed monitoring and surveillance of each site is required. Inventories of existing levels and spatial patterns of biodiversity are essential for short-term as well as long-term management strategies. For terrestrial sites the objectives of management are provided as part of a Core Management Plan which also includes the results of monitoring and advice on any action required.

As recognised in the UK National Ecosystems Technical report (Blackstock et al., 2012), ongoing scientific assessments are needed to assess the impacts of development and environmental change on the biodiversity and landscapes of Wales. These requiring sustainable and effective monitoring procedures.

Species inventories, when repeated over time, are used as a tool to monitor the loss or gain of species in protected sites (Droege et al., 1998). However, these inventories are time consuming and costly and methods used to collate these inventories are not without issues. Species inventories for many sites are often concentrated on specific areas without good spatial coverage of a site. They can be sparse due to funding and time limitations or due to site conditions (difficult to traverse), so that the true distribution and richness patterns particularly of the rare and indicator species are often unknown. Information on richness patterns, distributions and rare and indicator species as well as inventories of invertebrates would be invaluable to conservation and monitoring of a protected site (McGeoch et al., 2011a).

1.3 Current earth observation systems for monitoring biodiversity

Internationally it was recognised that a lack of integration and unbalanced coverage in biodiversity observation systems and environmental datasets needed to be addressed. Systems and networks were required to integrate biodiversity information systems from ground sourced field data to remote sensing data. The Group on Earth Biodiversity Observation Network (GEOBON) was initially formed in 2008 by government agencies and intergovernmental and international organizations to address these issues. GEOBON is working internationally to create a global monitoring network integrating masses of biological information with data and forecast on climate, anthropogenic change and other threats to biodiversity. These data can then be used to provide valuable information for addressing policy as well as providing an open-access platform for sharing biodiversity data, methods and tools. The current lack of integration of this data can impede the work of policymakers' and conservation managers'. Interlinking ground and satellite data through GEOBON should improve policymakers and conservation managers plans and have the capability to assess the effectiveness of their actions.

A European branch, the European Biodiversity Observation Network (EUBON) was formed. The main objective of EUBON is to create significant input from Europe into the GEOBON. The recent (2008-2012) European Biodiversity Observation Network project (EBONE) focused on developing an effective system integrating these as a pilot for GEOBON.

Despite these recent initiatives a JNCC report (2011) stated that evidence gaps still exist in information, location, extent, and condition of habitats. Of particular importance to the protection of conservation sites was the development of methods that can ensure more targeted fieldwork and biodiversity surveillance despite constrained resources (JNCC

report 2011). Remote sensing data could be instrumental in providing methods that can ensure more targeted surveillance.

To ensure observation networks and increasingly sophisticated integrated systems are improved the capabilities of new technologies such as high resolution remote sensing satellite systems need to be researched and investigated. To address these needs two European Framework (FP7) projects were set up to explore and develop a potential earth observation system for monitoring of Natura 2000 sites in Europe (Lang et al., 2015). The 'multi-scale service for monitoring Natura 2000 habitats of European community interest' (MS.MONINA) and the 'biodiversity multi-source monitoring system: from space to species (BIOSOS)' project. Of particular interest to this research is the BIOSOS developed system, named EO Data for Habitat Monitoring (EODHaM) (Lucas et al., 2015). This system integrates remotely sensed data from satellite sensors and ground sourced data to create both landcover and habitat classes and is based on expert knowledge elicited from botanists, ecologists, remote sensing experts and management authorities (Blonda et al., 2012). This system has been designed to incorporate multi-image data to provide seasonal, temporal change and spatial distribution data to provide a classification of vegetation. EODHaM has capability within this method to extract spectral, structural and spatial information that have the potential to act as biodiversity indicators. It is recognised that further processes need to be developed to investigate the use of these links at site level.

1.4 General benefits and reasons for using remote sensing data

Despite decades of development the use of remote sensing for accurate, detailed and complete conservation status assessment and monitoring of natural habitats, such as required in the European Natura 2000 context, is still rarely exploited (Spanhove et al.,

2012).

Remote sensing techniques need to be further developed to identify and monitor features indicative of favourable or unfavourable condition (Medcalf et al., 2012). These features can be monitored depending on what they represent (e.g. high amounts of non-photosynthetic vegetation (NPV) retrieved from winter images could represent areas of invasive species such as *Molinia caerulea* and *Phragmites australis*). The JNCC report 2011 (JNCC, 2011) made recommendations for future work to include mapping of among other factors, habitat context and measures that supported the assessment of the condition of these sites (e.g. the amount of NPV) or habitat types (e.g. dry heath, wet heath, humid heath).

Although the EODHaM system has mainly been tested and used for vegetation classification it has the potential to be adapted further and can be used to provide valuable data and variables that are important to the monitoring of protected sites. The potential for variables that relate to invertebrate associations has not yet been fully recognised and more research to guide the selection of these is required. Remote sensing data could be used to extrapolate records either in the form of vegetation classifications and/or habitat suitability models (HSM) or species distribution models (SDM) of flora and fauna. These can indicate further areas where species may occur and, in turn, greatly improve our knowledge of their distribution and vulnerability.

Remote sensing can act as a powerful tool to assess the extent and condition of habitats and associated species diversity as well as quantifying losses, degradation or recovery associated with specific events or processes (Nagendra et al., 2013). By understanding some of the associations derived from the remote sensing data we can start to understand the implications of changes to extent and condition of ecosystems.

Remote sensing data can be used to help target field surveys (Medcalf et al., 2012) thereby reducing costs, and can be used to extrapolate into areas that may be difficult or dangerous to access. Forming a baseline from which one can assess change or make

predictions is imperative to monitoring processes. This requires good spatial coverage in order to obtain a clear picture of all ecosystem processes occurring. Remote sensing can play a key role in establishing these baselines.

Once a baseline is created for flora and fauna remote sensing can provide a spatial tool for both assessment of change and to predict the effects of change. This could provide further valuable information on losses and gains of biodiversity to either inform policy, planning or management of protected sites. Sustained observations are essential in Wales for key environmental parameters that impact on ecosystems and human health, and are predictive of environmental progress and sustainability. This includes research to refine the suite of indicators for the Wales Environment Strategy and the Natural Environment Framework.

1.5 Key considerations

1.5.1 Vegetation classification

Remote sensing data is often used to create a vegetation classification which may be used to produce further habitat suitability maps for a species. However, systems have not developed sufficiently to provide an overall flora and fauna monitoring capability that can be used to provide information on the flora and fauna representative of the effects of ecological gradients which may represent effects of degradation. These ecological gradients can influence the presence of species and species assemblages (Del Rio Mora, 2014).

A vegetation classification can provide a wealth of data for monitoring purposes however, the connections between species or habitat data and other biodiversity needs to be made. Monitoring vegetation or plant species just because they are easy to monitor is insufficient. For example what a species stands for is important to assess in order

to understand what a change in its abundance means (Jongman, 2013). Vegetation species abundance and dominance can relate to ecological gradients as well as to the abundance of fauna species (Grime et al., 2007). Recognising these ecological gradients in vegetation classifications can provide recordable features that are indicative of favourable and unfavourable conditions. Very often these gradients can be recognised by looking at the vegetation present (Grime et al., 2007). Although vegetation mapping and classification using remote sensing is widely practised there is less emphasis placed on recording species that may relate to these ecological gradients. The typical output of a system such as EODHaM is a vegetation classification, however, there are numerous other outputs that can be extracted that could be used to provide associations with fauna (Lucas et al., 2015). Both vegetation classifications and biophysical parameters (e.g. vegetation indices) could prove important in providing associations with other flora or fauna biodiversity.

1.5.2   Fauna associations

Although habitat suitability models and species distribution models have been used to extrapolate known fauna species' habitats using remote sensing data, there are still many gaps in knowledge of how variables extracted from satellite imagery can be applied, and how effective they may be. Focus has been placed on mapping mammalian, bird and plant species (Pettorelli et al., 2011; Swatantran et al., 2012; Coops and Catling, 2002) with little research on invertebrate distribution. Invertebrate habitat suitability modelling is often carried out to locate areas of pestilence where crops or vegetation have been damaged *en mass* (Huang et al., 2008; Eklundh et al., 2009). On balance the study of possible invertebrate associations made using satellite derived data is still in its infancy.

Landcover maps derived from remote sensing used in habitat suitability models are often not detailed enough to provide any valuable associations with fauna (Bradley and Fleish-

man, 2008a; Eyre et al., 2003). For areas where very high resolution satellite imagery is used maps of more dominant species may be made (Burai et al., 2015; Lane et al., 2014) and a fauna species occurrence can be associated with a single vegetation species (e.g. caterpillars). However, many fauna species do not rely on one specific plant species and may be better predicted by other environmental variables. Predictive powers of models can be improved by adding continuous data relating to vegetation structure, productivity and phenology which may influence the quality of habitat for some species (Bradley and Fleishman, 2008a). Studies have been done using vegetation indices (Buermann et al., 2008; Lafage et al., 2013; Lassau et al., 2005) and LiDAR (Hill and Hinsley, 2015; Müller and Brandl, 2009) to provide more continuous data than vegetation classifications alone. These combinations have proved to be more effective than stand alone vegetation classification variables.

HSMs and SDMs usually focus on individual distributions although recent developments are recognising that they may be developed to produce effective distributions of whole communities (Guisan and Rahbek, 2011; Bonthoux et al., 2013; Harris, 2015), thereby providing a more accurate picture of ecosystem interactions.

Functional groups of biodiversity are now becoming of interest to policy makers as it is now being recognised that the linking of functional groups with habitats and vegetation may produce effective measures of biodiversity assessment. It would therefore be useful if links could be made between properties derived from satellite data and functional groups (e.g. Plant Senescence Reflectance Index which indicates the amount of dead vegetation or litter and invertebrate detritus feeders).

HSMs and SDMs also help to provide more spatially consistent information on a species and can be used as a predictive tool to aid management.

1.5.3 Plant phenology

In order to use the best satellite imagery for input into a system the most suitable dates for acquisition are required. The phenology of plant species plays an important role in vegetation classifications (Hill et al., 2010; Lucas et al., 2010) and effects the distribution of fauna species (Regniere and Nealis, 2002; Regniere, 2003). In Wales and Britain as a whole there are dramatic seasonal variations throughout the year and this seasonal variation can also vary from year to year. Microclimates, differences in altitude, coastal positioning etc. all have an influence on the seasonal growth patterns of plant species. These seasonal differences can have major impacts on any classifications recorded from satellite imagery causing inaccuracies at larger scales (Xie et al., 2008). A system is required that can make use of these phenological differences in vegetation species to aid vegetation species discrimination. They can also be used to gain further information on the ecological responses of species, and could prove to be particularly useful in determining areas of more competitive invasive species from the endemic less productive native species. The phenology of a plant species is also of importance to many invertebrate species (Loranger et al., 2012; Prishchepov et al., 2012) and information derived from satellite data regarding a plant's phenology could be useful for forming associations.

1.6 Choice of study site

The UK National Ecosystem Report highlights that further research is urgently required to assess the overall extent and condition of the UK's peatlands and peat soils and how land management, especially grazing, burning and tree planting, impacts on carbon storage and the loss of carbon as carbon dioxide and methane (Blackstock et al., 2012). Both raised and blanket bogs are on the UK BAP priority habitat list -2007 (JNCC,

2011) and are areas of focus for protection and prevention of degradation.

Increases in drainage to bog areas along with drainage and nitrogen deposition from surrounding areas can have serious consequences for the future of a peatland. Increases in these can cause serious peat deterioration. Encroachment by species such as Molinia, which further dry out areas of peat and assist in changing the flora and fauna diversity of the area, can also seriously shrink the peatland so reducing its size.

Climate change is also of major concern as this is often rapid and reduces the ability of environments to adapt, with dire consequences for the associated and endemic species present. Many of these species, e.g. sphagnum, are what regulate the peatlands by producing further layers of peat and so perpetuating the storage of carbon, another important consideration aside from the preservation of Carbon sinks.

One of the largest European low raised bogs of national and international importance, Cors Fochno, was selected for this study. It is a protected Ramsar site, NNR, SSSI, SAC, SPA, and Natura 2000 site and supports many rare and endemic species.

As this is a relatively flat area it means that many issues which confound remote sensing imagery are removed or reduced (e.g. topographical shading, orthorectifying and atmospheric correction issues). Atmospheric conditions such as water vapor content and aerosols (related to visibility) can vary more across a scene in upland bog areas. Key parameters for atmospheric correction, namely aerosol optical thickness (AOT; related to visibility) and water vapour change with respect to elevation. Being a flat site enables a single model parametrisation to be used for the atmospheric correction, greatly simplifying the correction process. Areas with hills and or cliffs around them are also prone to shadowing effects in imagery. Using a bog site that is flat with no nearby surrounding hills removes some of these issues and this means more focus can be placed on the methods and interpretation of results obtained from research, allowing greater focus on the flora and fauna monitoring methods. Cors Fochno, as with many bogs, is also an area for which remote sensing imagery is virtually the only safe way to map

vegetation and fauna in areas that are extremely fragile, difficult or dangerous to access and monitor. The main difficulties are the danger and difficulties of traversing the peat due to the possibility of sinking, and the fact that the vegetation is easily damaged under foot and consists of rare flora and fauna species that should not be disturbed. Already much of the recorded fauna data derives mainly from the verges of the bog or from along the easily accessible boardwalk area. Remote sensing data along with habitat suitability models and species distribution models is vital in extrapolating data to areas that are not accessible in order to get a truer picture of the distributions of fauna and flora on this protected site.

In the past there has been a substantial amount of anthropogenic activity which has caused peat degradation including historic programmes of drainage and cutting (Poucher, 2009). This has led to the encroachment of invasive species such as *Molinia caerulea*. Monitoring of the progression of the invasive species and deterioration of endemic species can be useful to monitor and guide the restoration and conservation managements to prevent further degradation of the peat and habitats.

1.7 Aims and objectives

1.7.1 Aims

The aim of this study was to explore the potential for indicators of condition for protected bog sites to be derived from Earth Observation, such that a protected site monitoring system could be formed. This study focuses on VHR optical imagery (in this case WV2 data) for retrieving biophysical parameters to identify key flora species and assess their potential for identifying invertebrate community and species habitat associations.

1.7.2   Objectives

1. Develop a method using field collated spectral data for identifying optimum months of the year and best indices for species discrimination on Cors Fochno protected site that can later be used within a system for accurate classification of species using WV2 satellite data.

2. Assess the use of methods and ecological information developed for use with WV2 data acquired over 3 time periods (March, July and November) and to produce a multi-scale classification of Cors Fochno SSSI and it's surrounding landscape suitable for use within a monitoring system.

3. Use WV2 satellite derived parameters that relate to environmental variables relevant to invertebrate habitat suitability and invertebrate plant food sources to assess their associations with selected invertebrate species and assemblages.

1.7.3   Hypotheses:

1. The ANOVA F-ratio method provides a successful method to statistically show that distinctive phenological differences of key lowland plant species on a lowland raised bog are important for selecting the best months and best spectral indices for species discrimination and can be used to select optimum WV2 imagery acquisitions for a more successful species classification.

2. Classification of varying scales, from landscape to species level, can be carried out effectively with good accuracy results within one classification process, using an F-ratio method for best indices and image time selection, and ecological information gathered in field surveys to produce a system that is repeatable for improved monitoring purposes.

3. WV2 satellite derived spectral indices and WV2 satellite derived dominant plant species can be used together as invertebrate diversity and distribution indicators.

1.8   Thesis outline by chapters

1. Introduction

The reasons for the need for a monitoring system globally and nationally are discussed with potential gaps in the use of remote sensing data for this identified. The aims and objectives are outlined.

2. Background

This chapter provides a review on what biodiversity is. Current methods that use remote sensing data to assess both flora and invertebrate fauna are discussed in brief. (Each results chapter has a further review on these.)

3. Study site

This chapter establishes the study site, Cors Fochno used for this research and describes current monitoring regimes of the protected Natura 2000 site.

4. Species discrimination using field spectro-radiometer data

With a view to creating a vegetation classification in chapter 5 the research in this chapter was carried out to investigate species discrimination. Spectral data and spectral derived indices collated from ground data were investigated to determine species discrimination. Phenological differences in species were used to assess satellite acquisition suitability. A selection process for the most suitable indices that provide the best species discrimination was developed.

5. Vegetation classification

A comparison of the spectral indices from ground results in chapter 4 and the satellite derived indices was made. Using the methods and results developed in chapter 4 a vegetation classification was carried out using WV2 satellite data using a modified EOD-HaM system. A classification of the dominant species was made and its practical was

demonstrated providing condition information for reserve management purposes.

6. Evaluation of remote sensing derived attributes as invertebrate biodiversity indicators

A method for sampling ground dwelling (Aranea, Coleoptera) and aerial (Diptera) invertebrates over degradation gradients in difficult terrain was developed. Associations between invertebrate species assemblages and satellite derived vegetation data from chapter 5 (vegetation species classified and vegetation indices) were made. A single species was selected to demonstrate the systems use for mapping habitat suitability.

7. Discussion

The final discussion focuses on how this work has improved and contributed to biodiversity monitoring of protected sites.Further work and application to policy and national and international biodiversity targets are discussed.

Chapter 2

Background

2.1 Introduction

Ecosystem assessment and monitoring requires the development and application of suitable indicators. They need to be reliable and capable of simplifying complex relationships, quantifiable and transparent in order to enable an easy communication, and fit for the purpose of indication (Feld et al., 2010).

It is important that these variables are sensitive to short-term and more medium-term biodiversity change. They need to be relevant to understand the impact of drivers of biodiversity change, and if possible, to assess policy responses and should be repeatable (temporal) and scalable (spatial). They should have a biological basis and be related to biodiversity state. They should be easily measurable. They should be able to capture the different levels of biodiversity. These indicators and methods should be transferable across different sites and ecosystems. In this case they also need to be a set of variables that are not dependent on particular questions of today but relevant in the medium-term.

To assess biodiversity indicators it is important to establish what is meant by biodiversity and changes in biodiversity. Changes in biodiversity can be defined as the following:

- An increase/decrease in a population

- A change in species richness

- Loss of keystone or indicator species

- An increase in secondary, primary species, native, alien and invasive species

- A shift in species dominance

In order to investigate changes in biodiversity utilising remote sensing data a number of questions should be addressed;

Utilizing remote sensing data:

a) Do observed changes in the extent and condition of habitats reflect a change in the biodiversity and in what way?

b) What is observed that impacts directly on the biodiversity?

c) What inputs can be made to SDMs that can be used to assess change?

d) What are the effects of these changes on species assemblages?

The following background information is important to assist in formulating responses and answers to the above points and questions and is the basis of understandings of biological indicators and the linking of ecological research with remote sensing research.

2.2 Biodiversity

2.2.1 What is biodiversity and why measure it

Due to pressures from anthropogenic and or natural disturbances on biodiversity it is increasingly important to assess biodiversity using easily measured appropriate variables. To establish which variables to use, an understanding of the attributes, layers and spatial contexts of biodiversity is required in order to extract useful and meaningful indicators of biodiversity. When trying to assess biodiversity or develop biodiversity indicators it is important to establish what biodiversity means and why we need to measure it. Biodiversity (biological diversity) reflects the number, variety and variability of living

organisms and how these change from one location to another and over time. Biodiversity includes diversity within species (genetic diversity), between species (species diversity), and between ecosystems (ecosystem diversity) (Magurran and McGill, 2011).
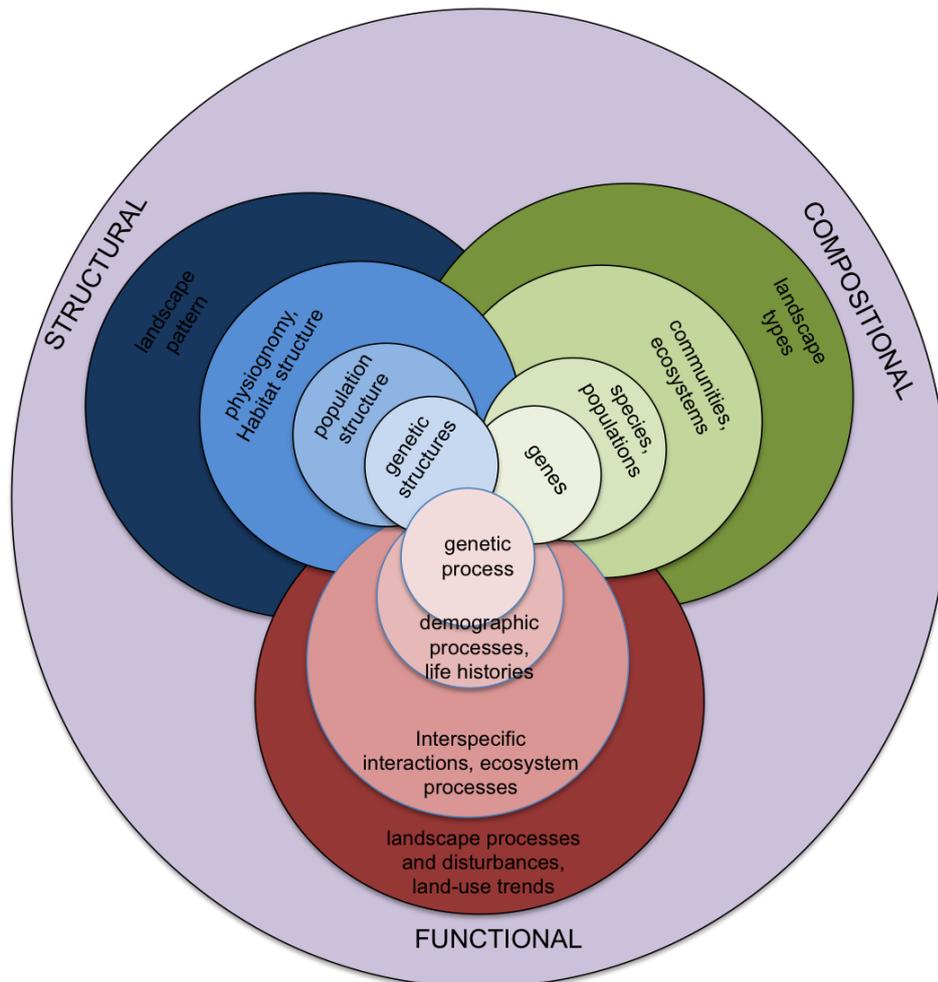
Figure 2.1: Compositional, structural, and functional biodiversity shown as interconnected spheres, each encompassing multiple levels of organisation. This conceptual framework may facilitate selection of indicators that represent the many aspects of biodiversity that warrant attention in environmental monitoring and assessment programs (adapted from Noss (2008)).

2.2.2   Characteristics of biodiversity

There are three primary attributes of biodiversity - composition, structure and function (Noss, 2008). These three attributes together determine the biodiversity of an area

(Figure 2.1). Compositional attributes describe the biodiversity components of an area (e.g. species composition, habitat types), structural attributes relate to the physical organisation (patterns) and size of a habitat, and functional attributes outline the processes affecting life within the area such as disturbance and predator-prey relationships. These three characteristics of biodiversity are all interdependent of each other (Noss, 2008).

Indicators			
	Composition	**Structure**	**Function**	**Inventory and Monitoring Tools**
Regional Landscape	Identity, distribution, richness, and proportions of patch (habitat) types and multipatch landscape types; collective patterns of species distributions (richness, endemism)	Heterogeneity; connectivity; spatial linkages, patchiness; porosity; contrast; grain size; fragmentation; configuration; juxtaposition; patch size frequency distribution; perimeter-area ratio; pattern of habitat layer distribution	Disturbance processes (areal extent, frequency or return interval, rotation period, predictability, intensity, severity, seasonality); nutrient cycling rates; energy flow rates; patch persistence and turnover rates; rates of erosion and geomorphic and hydrologic processes; human land-use trends	Aerial photographs (satellite and conventional aircraft) and other remote sensing data; Geographic Information System (GIS) technology; time series analysis; spatial statistics; mathematical indices (of pattern, heterogeneity, connectivity, layering, diversity, edge, morphology, autocorrelation, fractal dimension)
Community – Ecosystem	Identity, relative abundance, frequency, richness, evenness, and diversity of species and guilds; proportions of endemic, exotic, threatened, and endangered species; dominance-diversity curves; life-form proportions; similarity coefficients; C4:C3 plant species ratios	Substrate and soil variables; slope and aspect; vegetation biomass and physiognomy; foliage density and layering; horizontal patchiness; canopy openness and gap proportions; abundance, density, and distribution of key physical features (e.g. cliffs, outcrops, sinks) and structural elements (snags, down logs); water and resource (e.g. mast) availability; snow cover	Biomass and resource productivity; herbivory, parasitism, and predation rates; colonization and local extinction rates; patch dynamics (fine-scale disturbance processes), nutrient cycling rates; human intrusion rates and intensities	Aerial photographs and other remote sensing data; ground-level photo stations; time series analysis; physical habitat measures and resource inventories; habitat suitability indices (HIS, multispeices); observation, censuses and inventories, captures, and other sampling methodologies; mathematical indices (e.g. of diversity, heterogeneity, layering dispersion, biotic integrity)
Population – Species	Absolute or relative abundance; frequency; importance or cover value; biomass; density	Dispersion (microdistribution); range (macrodistribution); population structure (sex ratio, age ratio); habitat variables (see community-ecosystem structure, above); within-individual morphological variability	Demographic processes (fertility, recruitment rate, survivorship, mortality); metapopulation dymanics; population genetics (see below); population fluctuations; physiology; life history; phenology; growth rate (of individuals); acclimation; adaptation	Censuses (observations, counts, captures, signs, radio-tracking); remote sensing; habitat suitability index (HIS); species-habitat modelling; population viability analysis

Figure 2.2: Indicator variables for inventory, monitoring and assessing terrestrial biodiversity at three levels of organisation, including a sampling of inventory and monitoring tools and techniques (adapted from Noss (2008)).

2.2.3 Biodiversity hierarchy

Biodiversity hierarchy presents another perspective of biodiversity and consists of regional landscapes, community-ecosystem, species-population, and genetic levels (Noss, 1983).

Regional landscapes refer to the complexity of land forms, vegetation types and land uses (Urban et al., 1987). Landscape features such as patch size, heterogeneity and connectivity can control species composition and abundance and population viability of sensitive species (Noss and Harris, 1986).

At community-ecosystem level, an ecosystem is an entire system of biotic and abiotic components that interact in the same place. These include a wide range of biological, physical and chemical processes. All of these have influence on each other creating a delicate balance that can easily change in one direction or the other if any of these components are altered or change in any way. At a smaller micro scale, the population-species level, community ecology analyses parts of the ecosystems focus on species interactions, diversity and distributions within the ecosystems.

Giving species interactions a spatial perspective places them in a context in which their interactions with ecosystem processes may be assessed (Jones and Lawton, 1995). The way in which the measures of biodiversity vary over space and time is a key feature of biodiversity, and therefore only assessments using these dimensions can provide insights into the relationships between changes in biodiversity and changes in ecosystem functioning (Naeem et al., 1999).

Combining as many of these perspectives of ecological systems as is possible should improve the prediction of ecosystem assessment and function with the combination allowing ecologists to consider biodiversity as a driver of ecosystem functioning (Naeem et al., 1999).

2.3   Biodiversity indicators

Indicators of biodiversity are required to help prioritize and conserve habitats (Sarker, 2002) and are often used to inform in decision making in land use planning. They are needed to help determine and monitor management goals, to identify actual or potential stressors on biodiversity, to assess impacts on biodiversity and to analyse habitat conditions, which allow for comparisons over time.

2.3.1   What are biodiversity indicators?

The definition of biodiversity in itself is far too simple and it is far better to define components of biodiversity in order to 'provide a framework for identifying specific, measurable indicators to monitor change and assess overall status of biodiversity' (Noss, 2008). An indicator is, in effect, a surrogate for biodiversity that uses variables or attributes to represent the distribution and abundance of species and communities and is used as an indicator of the well-being of ecological systems. They are variables that provide quantitative data to measure the state of biodiversity (e.g., rarity, threat), impacts on biodiversity (sensitivity to change), or drivers of biodiversity change (natural versus man-made change).

It is not possible to measure and document the complete biodiversity of an area (Freudenberger and Harvey, 2003) and it is impossible for a single measure to capture all dimensions of the compositional, structural and functional attributes of biodiversity adequately. However, it is imperative that there is a link between management aims and indicators and the types and levels of biodiversity (Ferris and Humphrey, 1999). It is recommended to use indicators that focus on both key habitats as well as species (Landres et al., 1988) and that the indicators should include compositional, structural and functional biodiversity at multiple levels; i.e. regional landscape, community-ecosystem and population-

species (Figure 2.2) (Noss, 2008). A similar approach has been followed and applied to biodiversity monitoring by the Government for South Australia (Figure 2.3).

Biodiversity Attributes

components patterns processes

Genes	Genetic structure of population species	Genetic process
Populatio n species	Population structure and distriution	Demographi c processes and life histories
Communities ecosystem	Habitat types Habitat architecture	Interaction among species ecosystem processes
Landscape types	Landscape patterns	Landscape processes and disturbances Land use trends Hydrological processes

The Biodiversity Hierarchy

genes

species

ecosystems

landscapes

Increasing level of biological complexity

Increasing level of biological complexity

Figure 2.3: Attributes (components, patterns and processes) of the biodiversity hierarchy (adapted from Peck (1998)).

Biodiversity can also be estimated using species richness. This approach involves extensive field surveys. However, remote sensing can be a better option to estimate biodiversity using higher taxa and environmental surrogates thus minimizing extensive field surveys. This is particularly important in areas that are inaccessible or difficult to reach and where fragility and diversity or heterogeneity is the major constraint, as with Cors Fochno.

Biodiversity is a dynamic feature of ecosystems that changes in response to a wide range of natural and anthropogenic influences. The relationship between these influences on biodiversity is complex (Murthy et al., 2003). For example specialisation of a population is a precondition for sensitivity to habitat change (Pearson, 1994; Ferris and Humphrey,

1999). Remote sensing data has become an important tool with which to investigate the spatial and temporal dynamics of these systems. Historical archives of aerial and satellite data can also be used to help monitor changes and assess land management processes and drivers of change.

2.3.2   Suitability and sensitivity of an indicator

There are many aspects that one needs to consider when selecting and using a suitable indicator. Selection of an indicator can depend on issues at stake and the relevance of the indicator to management questions. Questions relevant to management or policy may steer the selection of indicators. The question can be posed as 'what are we monitoring and why?' (Noss, 2008). The indicator should have the capacity to differentiate between natural and anthropogenic changes.

Indicators need to be repeatable and reproducible and suitable for statistical analysis. Initial baseline values are required to serve as a reference, which are applicable at different scales and represent many habitats. Indicators need to correlate with the biodiversity and it is important to know the ecology of any species that may be used as indicators. It is important to know of interrelationships between indicators and species/groups present (Lindenmayer and Margules, 2000). Another factor equally important is the feasibility of using certain indicators such as time or the cost of investigation.

An assessment based on a combination of a number of indicators is often the most effective way of assessing the biodiversity within a landscape or ecosystem. Zebisch et al. (2004) assessed biodiversity of a landscape by using six indicators, with two for each attribute: composition, structure and function. From this study they found that the most sensitive indicators were compositional attributes, and that irregularities where one attribute changed more than another were beneficial for determining management impacts.

2.3.3 Other biodiversity measures

Explaining patterns of species diversity at the species level is one of the most complex problems in ecology because diversity is usually the outcome of many contributing factors whose relative importance varies with spatial and temporal scale (Diamond, 1988). Species composition is possibly more important to monitor than species richness as it is the dominant or most abundant species that are usually the key species drivers of an ecosystem. Species richness and number of distinct plant functional types are measures that are often used to assess biodiversity. Estimates of turnover are also important although very difficult to do accurately due to the lack of data available. However, this is where RS data can allow some of these gaps to be filled. There are three terms of biodiversity over spatial scales known as alpha, beta and gamma diversity (Whittaker, 1972).

Alpha diversity is the diversity within a particular habitat or ecosystem. This is usually known as the number of different species present in an ecosystem or area. However, it is not just the number of species that create the diversity. Diversity depends also on evenness which compares the similarity of the population size for each of the species present. Species numbers recorded across a transect across transition areas can be used to provide a measure of alpha diversity of each habitat/vegetation type across the gradients.

There are several indices created to measure species biodiversity; the most popular are the Simpson Index and the Shannon Index. These indices focus on the relative species richness and abundance and/or the pattern of species distribution. These biodiversity indices can be used for identifying areas of high natural or human disturbance (Magurran and McGill, 2011).

Beta diversity can be used to compare different sampling areas. Measures of biodiversity are often used to compare two ecosystems or to determine changes over time in a given

region. Beta diversity measures the present status and changes of species diversity between ecosystems or areas. The number of taxa that are unique to each of the ecosystems are compared. Beta diversity can be used in temporal studies and can indicate the spatial turnover of species composition across habitats and environmental gradients.

2.4 Monitoring vegetation

2.4.1 Vegetation maps

Vegetation is often considered to be the best single biodiversity surrogate for habitat and ecosystems (Lindenmayer et al., 2014). Different land cover and vegetation classification approaches vary in their potential to provide information and useful detail. It is imperative to perform validation of these classification results to estimate and to improve vegetation classification (Kerr and Ostrovsky, 2003b). Miller (2000) stated that vegetation is often used to indicate particular habitats. However, a habitat is much more complex and does in fact describe an area with a combination of resources (e.g. food, cover and water) and environmental conditions, that allows a given species or population to survive and reproduce. Habitat is in this therefore linked to a species, or species group, that share the same ecological requirements. Bunce et al. (2008) define habitat as an element of the land surface that can be consistently defined spatially in the field in order to define the principal environments in which organisms live.

Traditionally, vegetation mapping and information about vegetation condition and composition have been collected using ground based assessments, usually on protected sites for the purpose of monitoring (Gibbons and Freudenberger, 2006). However, remote sensing of protected sites can provide conservation managers with up to date data within and around the sites. It can provide detailed information regarding habitat status pro-

viding information on land cover and its vegetation structure. With the help of high resolution satellite imagery, vegetation of different biodiversity rich regions can be studied in both time and space. As well as producing detailed vegetation maps this data has been used to significantly improve species distribution modelling, species richness modelling, alpha diversity, beta diversity, and measures of both productivity and heterogeneity (Gillespie et al., 2008). Examples of biodiversity surrogates can include maps of ecological communities (Lindenmayer et al., 2014). Different representative vegetation patches can be sampled using ecological surveys and remote sensing imagery, and results can be extrapolated on a regional scale. Essential to the use of vegetation as an indicator/measure is a correlation or link between it and the biological diversity of that particular vegetation. Vegetation maps produced by remote sensing methods can increase the accuracy of maps of associated species distributions (Briggs and Freudenberger, 2006). However, although vegetation maps are frequently used for indicating biodiversity associations, they cannot necessarily on their own act as indicators of biodiversity (Burgman and Lindenmayer, 1998).

2.4.2 Classification systems

To work well within a remote sensing system and for use within programs developed for analysis of satellite imagery, it is best to use or incorporate a classification system that correlates well with remote sensing methods, as well as one that uses characteristics which equate to data that can be extracted from the remote sensing data.

Plant functional types are often used to classify plants according to their physical, phylogenetic and phenological characteristics in order to develop vegetation maps and models. The most important approaches to plant functional groupings are based on the use of functional characteristics. Functional grouping of species allows us to simplify biodiversity to components that can identify patterns or processes, and effects and interactions between species at different levels of organization (Duckworth et al., 2000). Plant

functional types and their traits are useful measures that aid the understanding of the ecological processes of competition and succession. They are fundamental to understanding changes over time showing interactions between components of biodiversity of plant communities and ecosystems and can provide a basis for predicting changes when components of the biodiversity are altered or lost (Lamont, 1992).

There are four main kinds of functional groupings (Reich et al., 2003).

a) Qualitative properties that can be used to classify groups of plants based on certain characteristics such as life form and type of photosynthesis, among others.

b) Quantitative characteristics, such as growth rate, specific leaf area, maximum photosynthetic capacity, etc.

c) A combination of quantitative characteristics that may influence each other, such as leaves, seeds, and tree height.

d) Responses to specific environmental factors (e.g.; the C-S-R scheme of plant strategies proposed by Grime which allows species to be grouped).

2.4.3 LCCS and EODHaM

The characteristics within these four main groups are all extractable either directly or indirectly from a variety of remote sensing data. However, it is not just the characteristics but also the method by which these characteristics are extracted and used within a classification system that need to fit into remote sensing methods. A hierarchical rule based method of classification is often found to be useful particularly for classifying segmented or defined areas with hard boundaries. The Land Cover Classification System (LCCS) is such an approach and uses quantitative characteristics, qualitative characteristics and environmental factors (Figure 2.4) to classify covers of all functional

groupings suggested by Reich et al (Di Gregorio and Jansen, 2000). In short the LCCS system defines the observed biophysical cover on the earth's surface. These biophysical properties of vegetation are of particular use, with comparisons being made to spectral information obtained from satellite imagery along with structural data from sources such as LiDAR.

The LCCS classifications have been implemented within the Earth Observation Data for Habitat Monitoring (EODHaM) system and the hierarchical system of classification for the LCCS works well with the remote sensing methods. The EODHaM system is a hierarchical system for classifying vegetation. It was developed to support conservation and protected areas and surroundings by the EU-funded BIOdiversity multi-SOurce monitoring System: from Space TO Species (BIO SOS) project (Lucas et al., 2015). The EODHaM system has adopted the Food and Agriculture Organization Land Cover Classification System (LCCS) taxonomy which can be adapted or translated to other classifications. The EODHaM system uses a combination of pixel and object-based procedures with a 1st and 2nd stage which use earth observation (EO) data alone with expert knowledge to generate classes according to the LCCS taxonomy (Levels 1 to 3 and beyond) (Figure 2.4).
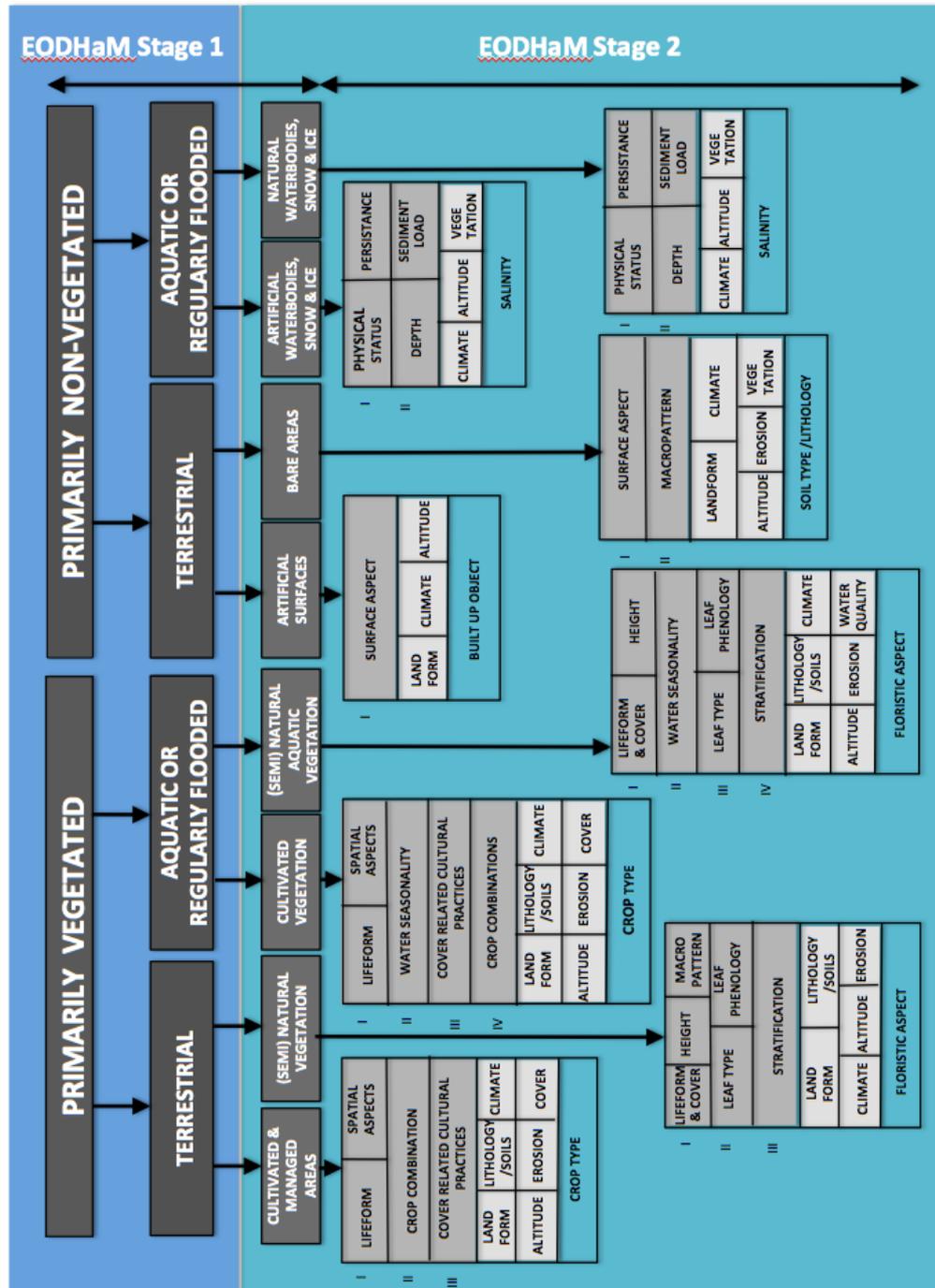
Figure 2.4: Diagram showing LCCS classification system.

The LCCS classification is arranged such that the initial steps identify areas that are either **vegetated** or **non-vegetated** (Figure 2.4), this being level 1 of the LCCS classification. This is followed by the splitting of these classes into **terrestrial vegetated**, **aquatic vegetated** and **terrestrial non-vegetated** and **aquatic non-vegetated**, forming level 2 of the LCCS (Figure 2.4). Both of these levels form the 1st stage of the EODHaM system (Figure 2.4).

Moving on to level 3 of the LCCS classification system requires splitting of level 2 classes into further categories relating to the vegetation lifeforms, such as woody trees, woody shrubs, herbaceous forbs, herbaceous graminoids, lichens and mosses. Further progress up the levels requires splitting classes into those associated with cover and height (Figure 2.5).

Many of these LCCS classes can be obtained with the aid of remote sensing data and consequently the EODHaM system has been structured to allow use of a diverse range of spaceborne and airborne remote sensing data acquired at very high resolution (VHR; e.g., Quickbird or Worldview-2) or HR, with focus on optical data but with capacity to integrate other sensor modes (e.g., LiDAR, RADAR). The EODHaM system is now undertaken using open source code.
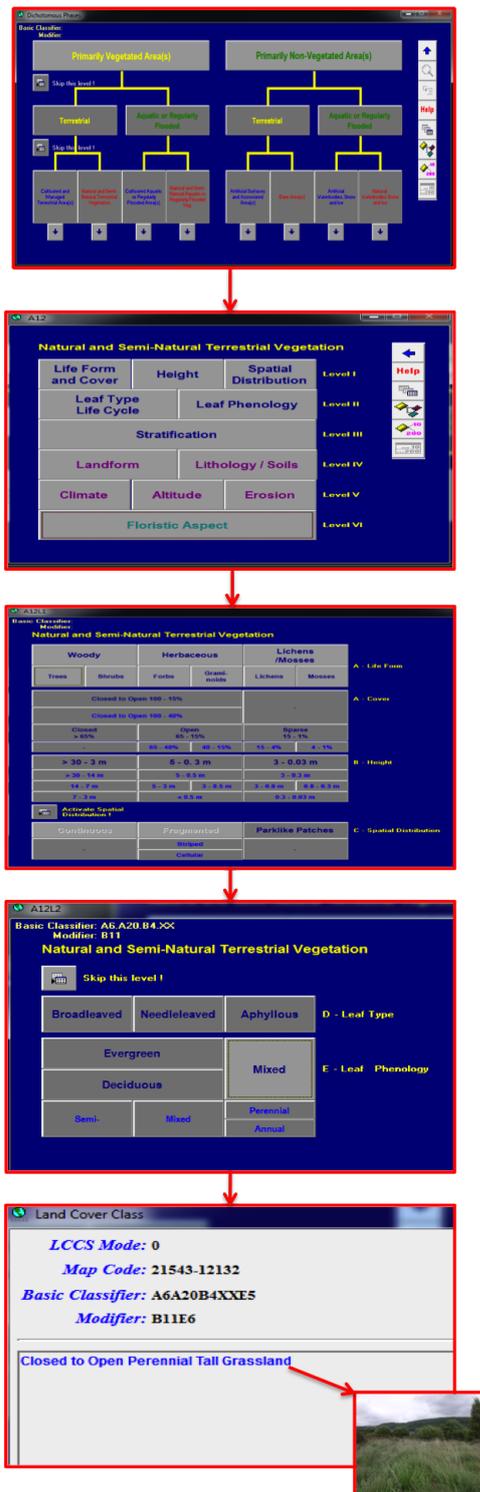
Figure 2.5: Layers within the LCCS tool indicating the pathway to obtaining the final LCCS code (in this case, semi-natural grasslands dominated by Molinia caerulea).

2.5 The use of remote sensing data to map vegetation

2.5.1 Reflective properties of vegetation

Remote sensing techniques have been developed which use measures of spectral reflectance to infer structure, composition and functioning of plant canopies. The spectral reflectance data of vegetation are used to differentiate between plant species and communities. Plant foliar chemistry, leaf structure, canopy structure and moisture content can vary greatly between species and communities. These differences produce different spectral reflectance curves (Figure 2.6) and measures derived from remote sensing data containing this information can be used to differentiate vegetation types and species. In order to help classify and identify plant species, some knowledge of how these attributes contribute to differences in spectral reflectance curves is important.

Leaf pigments, water content, carbon content, and nitrogen content are the most important components that affect spectral properties of leaves. The three main pigments in a plants' leaf are chlorophyll, caratenoids and anthocyanins. Relative concentrations of these pigments can vary significantly. These pigments serve a number of purposes and are important to the function and health of a plant. Plants that are very green tend to have high concentrations of chlorophyll. Chlorophyll is used to convert light into energy so is related to photosynthetic rates. Carotenoids (orange reflectance), xanthophylls (yellow reflectance) and anthocyanins (red reflectance) are more prevalent in plants that are either stressed or senescing and as a result, plants appear visibly yellow or shades of brown (Jones and Vaughan, 2010).
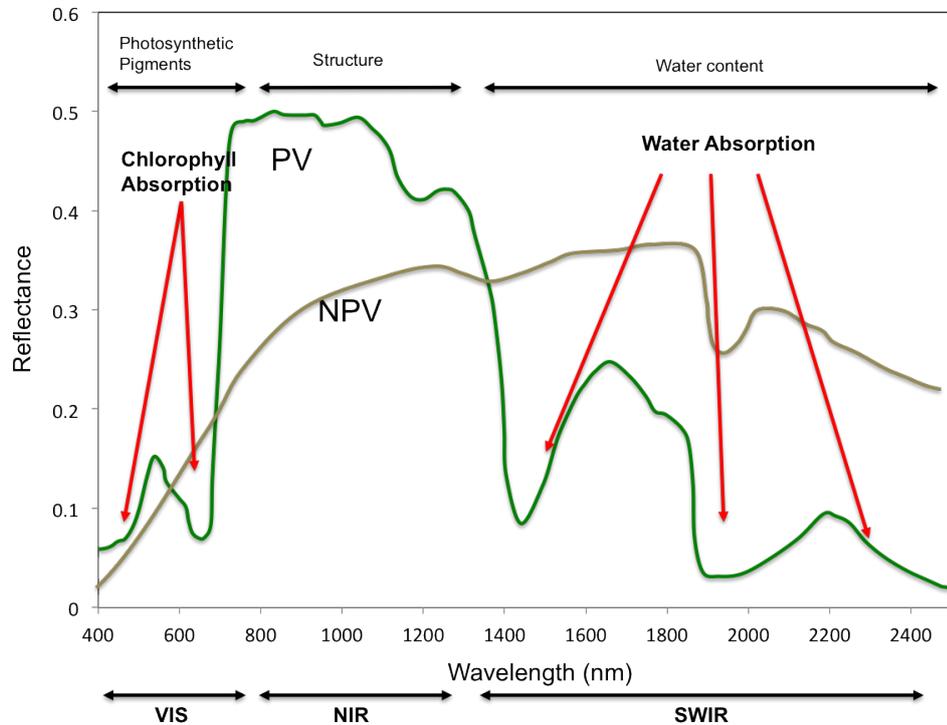
Figure 2.6: Typical spectral response characteristics for photosynthetic (green) vegetation (PV) and non photosynthetic vegetation (NPV) (adapted from Beeri et al. (2007)).

Reflectance from leaves is influenced by leaf structure. The arrangement of cells, air and water within a leaf determine the reflectance particularly in the infra-red region. Vegetation generally shows a strong reflectance within the near infra red (NIR) region. NIR is not absorbed by plant pigments. Plants that are healthy with turgid mesophyll cell walls reflect more NIR than is transmitted through. By monitoring the difference in the NIR and the visible region inferences can be made on the plants' health, productivity and senescence.

When a leaf or plant senesces it loses the pigments and moisture content, and consequently cell structure changes. The spectral curve of this is then very different to that of the spectral curve when it was a healthy or photosynthesising leaf or plant (Fig-

ure 2.6)

Plants will contain different quantities of water dependant on their leaf geometry, canopy architecture, their water requirements or as a prerequisite of their environmental conditions. For these reasons there are significant differences in water content between species, and even among plants of the same species there can be significant differences due to leaf thickness, water availability, and plant health.

Measures that relate to these attributes of a plant can often be estimated by using vegetation indices and other remote sensing indices which use two or three of the spectral bands relating to the above biophysical and biochemical attributes of vegetation.

2.5.2   Remote Sensors

Instruments which record spectral reflectance data are called optical sensors. There are many optical sensors flown either by satellite or aircraft with varying capabilities. Sensors that are suitable for conservation monitoring are dependant upon the user's needs and size of the area. The nature of vegetation classification and the scale of the study area dictate the choice of suitable spatial resolution and type of sensor required (Hengl, 206).

Both multispectral and hyperspectral imagery are used for such vegetation mapping but it is recognised that high and very high resolution imagery is underutilised in conservation research although it is more typically used to map vegetation at regional and local scales (Xie et al., 2008; Boyle et al., 2014).

Hyperspectral imagery can be suitable for providing spectral data that can be used for vegetation classifications based on vegetation types or dominant species. Having a higher level of spectral detail (large number of narrow bands) in hyperspectral images gives better capability to detect the previously unobserved. The level of spectral detail afforded by hyperspectral sensors such as EO-1 enhances vegetation characteristics that are diffi-

cult to discriminate with multi-spectral broad band satellites such as WV2 (Marshall and Thenkabail, 2015). However, there are limitations associated with spatial and temporal acquisitions as well as complexities with preprocessing (Lucas et al., 2012c). Hyperspectral imagery contains more vegetation information than multispectral imagery giving it a higher level of spectral detail which in theory should give a better capability to identify discernible differences in vegetation. However, this also adds a level of complexity and this, coupled with complex heterogeneous habitats, can lead to increased difficulties in classification. While useful for research purposes this would not be ideal for developing techniques which could be developed to form a monitoring system.

Multispectral imagery can have anywhere between 3 to 10 spectral band widths available. Whilst these provide far less spectral data than hyperspectral imagery they provide far more flexibility in terms of being able to use multi-temporal images for better species or habitat discrimination (Xie et al., 2008) as well as change analysis. The ability to monitor change within a landscape is an important conservation monitoring need.

Very high resolution (VHR) satellites such as WorldView-2 are now providing the combination of high spatial and spectral resolution in the same platform (Nagendra and Rocchini, 2008). The WorldView-2 (WV2) sensor provides highly suitable imagery for small protected site monitoring in terms of resolution and the number and type of spectral bands it provides (Table 2.1). It also provides a higher resolution than most similar multispectral satellites and records 8 closely focused bands. The bands have been chosen for their sensitivity in regions relevant to land classification (Globe, 2012).

Satellite Sensor	MS Pixel size (m)	No.of Spectral Bands	Bandwidths
EROS-C	2.8	4	Blue, green, red, NIR
GEOEYE-1	1.64	4	Blue, green, red, NIR
IKONOS	4	4	Blue, green, red, NIR
KOPMPSAT-2	4	4	Blue, green, red, NIR
Orbview 3	4	4	Blue, green, red, NIR
Quickbird	2.4	4	Blue, green, red, NIR
RapidEye	5	5	Blue, green, red, red-edge, NIR
Worldview2	2	8	Coastal, blue, green, yellow, red, red-edge, NIR1, NIR2

Table 2.1: High resolution multispectral (MS) satellite sensors available. ($\leqslant$5m resolution, at nadir)

Most other multispectral high resolution sensors record 4 bands, blue, green, red and NIR (Table 2.1). Both RapidEye and WV2 sensors record an extra band, the red-edge band which is proven to help with accuracy and sensitivity for vegetation classification. However, WV2 has a further 3 extra bands, coastal, yellow and NIR2 (Table 2.1). The 8 bands (Figure 2.2)are specifically targeted at plant identification, vegetation land cover types, with coastal and wetlands applications (Elsharkawy et al., 2012). A further panchromatic band is provided at 50cm resolution.

Sensor Band	Wavelength (nm)	Pixel size (m)
PAN	450 - 800	0.5
Multispectral Bands		
Coastal Band	400 - 450	2
Blue	450 - 510	2
Green	510 - 580	2
Yellow	580 - 620	2
Red	630 - 690	2
Red Edge	700 - 740	2
NIR 1	770 - 890	2
NIR 2	860 - 1040	2

Table 2.2: Worldview 2

Recent studies using WV2 have given promising results regarding species separation and

vegetation mapping for conservation monitoring. Cho et al. (2015) were able to use it to discriminate three dominant tree species and to identify grass and shrubby areas in canopy gaps with an overall accuracy of $\approx$89.3%. It provides promising results for vegetation mapping including heterogeneous landscapes (Rapinel et al., 2014; Nunez-Casillas et al., 2012), with derived vegetation maps found to be more detailed than existing ones (Nunez-Casillas et al., 2012).

Field spectroradiometer

In order to investigate and understand vegetation reflectance it is useful to use ground data where terrain shadows and atmospheric interference do not complicate the findings. A field spectroradiometer can measure the reflectance just as the sensor on a satellite or aircraft can and will provide in-situ calibration of surface reflectance. A field spectroradiometer can record the entire solar reflected portion of the spectrum, 350 to 2500 nm (Figure 2.6) and can be used to collate spectral libraries of vegetation species. It cannot be guaranteed that all vegetation classes or plant species will be easy to discriminate when producing a vegetation classification from satellite imagery. An initial ground assessment using a field spectroradiometer could save both time and investment.

Knowing how the spectral responses of plants and their biophysical and biochemical attributes relate to these with phenological changes can improve our abilities to discriminate species (Somers and Asner, 2012). Baldeck and Asner (2014) used non-seasonal field spectroradiometer readings to improve the accuracy of their tree crown classifications and found that they were able to use it to test separability of species as well as using the data to interpret how much training data they required. Schmidt and Skidmore (2003) collected field spectrometer readings during one summer period for 27 saltmarsh vegetation types. They proved from this data that there were significant differences in the vegetation spectra and that this therefore showed that spectral libraries created in the field could be used to identify vegetation species within hyperspectral imagery.

It is also important to assess the timing for image acquisition and so knowledge of the

temporal spectral response of the vegetation ecosystem is essential before acquiring satellite imagery (Cole et al., 2014). Cole et al. (2014) used phenological spectral responses of key vegetation (*Calluna vulgaris*) to inform on best acquisition dates but found that this was dependant upon species. Laba et al. (2005) used field spectroradiometry to assess the best time to discriminate invasive species such as *Phragmites australis* and found August to be the best period to discriminating this and other species. Comparisons of these results with satellite spectral data was not made, however, Ustin and Santos (2010) compared their ground spectral response results with hyperspectral imagery and found they showed a similar shape and magnitude but with poor agreement for aquatic species.

2.5.3 Vegetation indices

Remote sensing provides techniques to identify groups of species with functional differences by their particular biophysical properties. Using remote sensing data discrimination of vegetation types can be achieved by using biophysical attributes such as plant productivity and moisture content of vegetation (Lucas et al., 2007). Such techniques can allow for identification of biophysical and biochemical attributes, which is essential for biodiversity assessment, land cover characterization etc. (Wang et al., 2010a). They can facilitate identification of the biophysical attributes which can be used to discriminate plant functional types. Attributes such as water content, photosynthesis, specific leaf area, and chlorophyll content account for a substantial part of the functional differences observed among species from different successional stages, as well as among individuals of the same species growing in different stages. Vegetation indices and other remote sensing indices which relate to biophysical properties of vegetation such as productivity, photosynthetic, non-photosynthetic, structure, and composition can be used to assist with establishing and mapping ecosystem status. Differences in these indices between species at key times of the year can also prove to be important for discriminating species

(Castro and Sanchez-Azofeifa, 2008).

Vegetation Indices are quantitative measures derived from two or three spectral bands (Jones and Vaughan, 2010). These indices are used in order to maximise sensitivity to plant biophysical attributes and refine and enhance the precision of spectral data by minimising the effect of external (e.g. atmospheric and sun angle effects) and internal (topography and canopy background) factors on the spectral data (Baret and Guyot, 1991). Vegetation Indices have been used widely in the assessment of biomass, plant stress/health and crop production (Jackson and Huete, 1991).

Different sensors will provide information in different spectral bands so as a result there are often indices specifically developed for a sensor. Classification of vegetation using indices (Table 2.3) was one of the main methods employed within the EODHaM system for habitat and species discrimination, where WV2 was used in mapping habitats. The indices listed in Table 2.3 can all be derived from broadband multispectral data namely Worldview 2 data and provide useful information for the discrimination and mapping of different vegetation types.

Index	Bands used	Formula	Applications	References
FDI Forest Discrimination Index	NIR1, Red Edge and Coastal	$\rho MS_7 - (\rho MS_6 + \rho MS_1)$	Photosynthetic cover, phenology.	(Bunting and Lucas, 2006)
WBI Water Band Index	Blue, NIR1	$\dfrac{\rho MS_2}{\rho MS_7}$	Non-submerged aquatic vegetation, open water.	(Lucas et al, 2012b)
NDVI Normalised Difference Vegetation Index	NIR1, Red	$\dfrac{(\rho MS_7 - \rho MS_5)}{(\rho MS_7 + \rho MS_5)}$	Greenness, aboveground net primary productivity, a measure of photosynthetically active biomass.	(Rouse etal, 1973)
PSRI Plant Senescence Reflectance Index	Red, Blue, Red-Edge	$\dfrac{(\rho MS_5 - \rho MS_2)}{\rho MS_6}$	Senescent vegetation, non-submerged aquatic vegetation, NPV detection.	(Merzlyak et al, 1999)
REP Red Edge Position	Red, Red-Edge, NIR2	$\rho MS_6 - (\rho MS_8 - \rho MS_5)$	Sensitive to changes in chlorophyll concentrations, NPV detection.	(Curran et al, 1995)
NIR Diff Difference between NIR1 &NIR2	NIR1, NIR2	$\rho MS_8 - \rho MS_7$	Discriminating active bog.	(Lucas et al, 2012b)
BG Blue - Green	Blue, Green	$\dfrac{(\rho MS_2 - \rho MS_3)}{(\rho MS_2 + \rho MS3_3)}$	Chlorophyll content.	(Lucas et al, 2011a)
BR Blue - Red	Blue, Red	$\rho MS_2 - \rho MS_5$	Discriminates shrub from trees.	(Lucas et al, 2011a)
Woody	Coastal, Green	$\rho MS_1 - \rho MS_3$	Discriminates woody shrubs and trees.	(Lucas et al, 2011a)

Table 2.3: Indices that have been used in the development of the BIOSOS project for discriminating and mapping land covers and vegetation.

One of the most commonly used indices for vegetaion mapping is the normalised difference vegetation index (NDVI). This is a measure derived by dividing the difference between near-infrared and red reflectance measurements by their sum. NDVI is based on the spectral properties of green vegetation contrasting with its soil background. The index is strongly correlated with aboveground net primary productivity (NPP) and can be used as a measure of photosynthetically active biomass (Tucker and Sellers, 1986). These attributes can be used to provide an index of ecosystem function (Kerr and Ostrovsky, 2003a). The relationship between diversity and productivity has been the subject of a long standing debate in ecology. NDVI has been related to the distribution of both plant and animal species diversity (Figure 2.7).
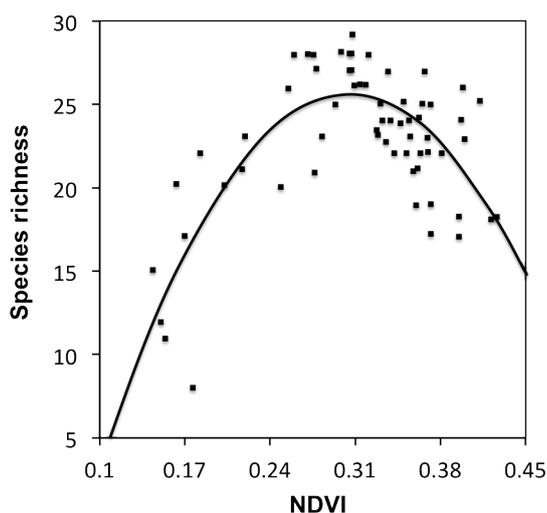
Figure 2.7: relationship between species richness and four indices of environmental productivity for 55 ungulate mammal species in East Africa (Skidmore and Oindo, 2003)

Percentage of vegetation cover can also be estimated using Normalized Difference vegetation Index (NDVI) (Table 2.8) (Purevdorj et al., 1998). These provide useful tools also for monitoring livestock production, agriculture and desertification.
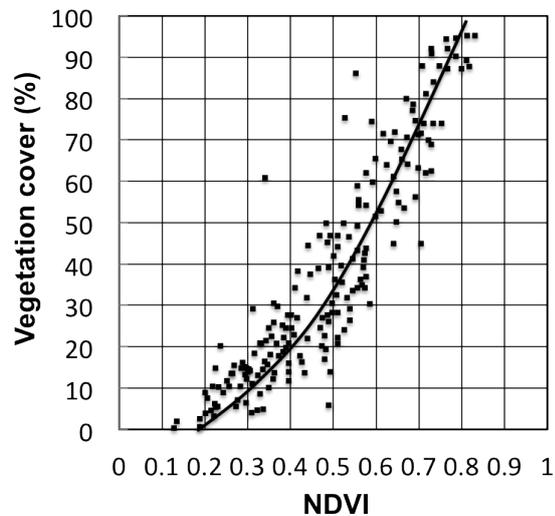
Figure 2.8: Relationships between percent vegetation cover and the vegetation indices. (Purevdorj et al., 1998)

One index that makes use of the unique red-edge band available to WV2 is the plant senescent reflectance index (PSRI) (Table 2.8), an alternative to using end-members of dead or senescent vegetation (Lucas et al., 2011b).

Information relating to the water content of vegetation normally requires the short wave infra red (SWIR) regions. WV2 does not provide spectral data in the SWIR region. Vegetation with a lower water content does however, display a higher reflectance in the NIR region. This means a water band index (WBI) such as that employed by BIOSOS used the NIR and the blue band (Lucas et al., 2011b). This proved to be more effective for use with WV2 than the more widely known WBI using the 950-970 region, which in the case of WV2 uses regions that fall within only the NIR2 band (Table 4.4) (Lucas et al., 2011b).

2.5.4 Remote sensing classification methods

Classification using an object-orientated and rule-based approach has proved advantageous when using higher spatial resolution imagery, especially when analysing for change

detection (Coppin and Bauer, 1996).

The more traditional approach to classification is based on analysis of individual pixels (Wang et al., 2004). However, when using Very High Resolution (VHR) images classification of land-covers does not require individual pixel resolution and a coarser scale is sufficient if not better in terms of accuracy (Wang et al., 2004). Using a pixel based approach for land-covers could increase the within-class spectral variance making the separation of land-cover types difficult (Shaban and Dikshit, 2001).

However, with reduced scale (i.e. small protected sites) these issues with pixel based classification are reduced. Also for discrimination of species within a heterogeneous habit patches of dominant species may be quite small and not fit within anything larger than the pixel size.

Classification systems using object based separation usually have one major drawback, that the classes created from these all have discrete boundaries separating each other. In reality many of these boundaries are gradual with graded transition zones and ecotones. Processing and classifying images in this way can therefore result in a substantial loss of information (Foody, 2000; Palmer et al., 2002). There are also issues when classifying areas of varying heterogeneity and complex patterning. It is therefore necessary to include a statistical quantification of uncertainties for these areas.

One important method of dealing with this is called spectral unmixing. This involves using end members or pure pixel/object signatures to produce a sub-pixel classification. End member extraction in the case of vegetation classification is the process of identifying areas with a pure signature from a mixture, these may include areas of a highly dominant species areas that are predominantly green or dead vegetation (Miao and Qi, 2007). Such endmembers can be defined by selecting reflectance spectra in the field using a field spectroradiometer (Abdel-Rahmana et al., 2010) or from known homogeneous areas within an image. These areas are selected and used to produce fractions of endmembers for areas of heterogeneity or mixed pixels. Once endmembers are selected spectral

unmixing techniques can be employed to derive fractions of end members (classes) from the mixed pixel or object. Linear spectral unmixing using these endmembers assigns a value to pixels which can be interpretable as a cover fraction or abundance values (Plaza et al., 2002). However this only works if all endmembers present are used within the fractioning (Adams et al., 1995).

Vegetation Heterogeneity

Although the soft classification method described above offers classifications without hard discrete boundaries, there are a number of other ways in which vegetation heterogeneity can be measured. These methods retain more information by using continuous data rather than creating abrupt patch or threshold boundaries. Spectral heterogeneity using reflectance values of pixels in remotely sensed images can be used to assess vegetation heterogeneity. There are a number of ways of looking at spectral heterogeneity. Much of this work has been carried out on a landscape scale but methods can be applied at different scales (Rocchini et al., 2010). Measures can be based on Vegetation Indices e.g. NDVI values, an individual spectral band or by using a number of spectral bands. A robust statistical method which takes spatial scales into account is based on ecological theory and is often applied to calculating species richness at different spatial scales. This powerful multiscale method is called rarefaction, and for remote sensing purposes pixel values rather than species presence are used. Another variation on this multiscale method involves using variograms or semivariograms; however Garrigues et al. (2006) found these to indicate monoculture crops to be more heterogeneous and so is not a true reflection perhaps of the heterogenity of vegeation types but more of its texture.

Vegetation Structure

One method of assessing vegetation structure is to use Light Detection And Ranging (LiDAR). This is a remote sensing system which uses a laser to send a pulse of light to

an object and uses a receiver to measure the intensity scattered back (backscattered) (Mucher et al., 2013). LiDAR sensors are able to measure heights of objects and features on the ground creating three dimensional distributions of plant canopies as well as subcanopy topography. This can provide high resolution vegetation structure maps with highly accurate estimates of vegetation canopy structure including height and cover. Vegetation density can be estimated at different heights throughout the canopy (Tan, 2008) which enables 3 dimensional profiles of vegetation structures (Figure 2.9). This demonstrates the potential for applications such as mapping emergent tree species and sub-canopy layers that are important indicators of stratification for forest bird species (Turner et al., 2003a).
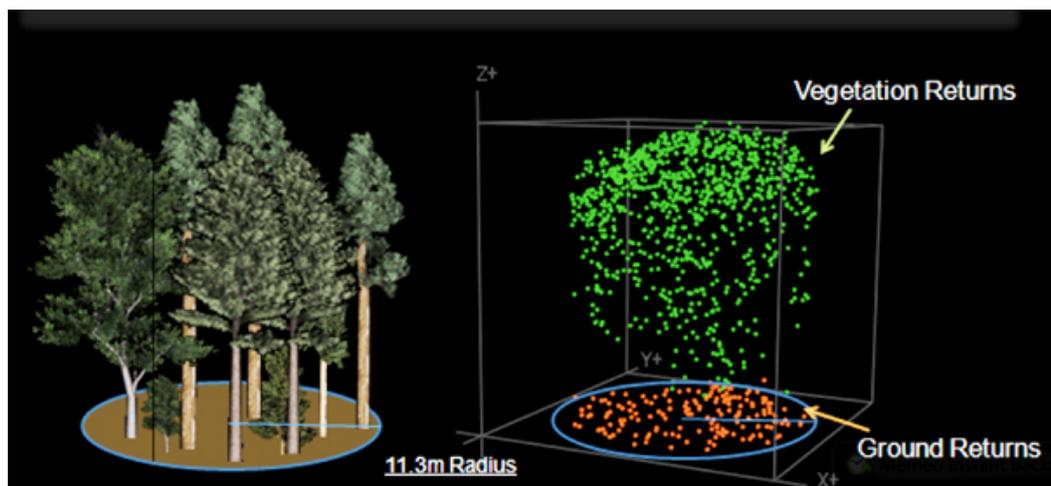
Figure 2.9: Sampled trees within an example plot. (right) LiDAR data for that plot. The green dots represent vegetation points (points where light reflected off of trees) whereas the orange dots represent the ground (Image by Leah Wasser).

Hinsley et al. (2002) used LiDAR to map forest structure and were able to find relationships between canopy heights and chick mass which in turn gave a surrogate for breeding success. This data could be used to predict habitat quality and to map species distributions as a function of habitat structure (Hill et al., 2003). For non-forest structures Davenport et al. (2000) devised a technique to measure the height of crops in farmland fields as crop height is also an important predictor of bird species population and, in

turn, can be used as a proxy for bird suitability.

The vegetation layer can be removed through modelling techniques, revealing the surface under the vegetation. This provides a much-improved perspective on landscape topography and can be used to measure topographic features otherwise concealed by vegetation (Davies and Asner, 2014).

A number of studies have incorporated high resolution multispectral images with LiDAR thereby improving their overall application in ecological monitoring of change in habitat structures and the associated effects on wildlife (Lucas et al., 2015; Leyequien et al., 2007a). Methods have been developed to fuse multispectral and LIDAR data for delineating individual tree crowns and estimating tree height (Tweddale, 2005). More recently the BIOSOS development of the EODHAM method (Lucas et al., 2015) has shown how the fusing of the two can be used successfully with classification systems where the the vegetation structure, e.g height and life-form, are required.

2.6 Identifying the relationships between species and their habitats

There are a range of different types of relationships between species and habitats and in order to make links between these it is important to understand the role of the species within the habitat. Species for purposes of monitoring are often placed into specific categories, which indicate their functional importance, habitat specialisation and dependence on environmental conditions.

Several authors highlight the use of indicator species with many well-known functional interrelationships with other species (groups), as these play an important role in the functioning of ecosystems (Ferris and Humphrey, 1999; Lindenmayer and Margules, 2000). Ecological dominance is the degree to which a taxon is more numerous than its com-

petitors in an ecological community, or makes up more of the biomass. Most ecological communities are defined by their dominant species. Dominant species are also suggested as indicators (Lindenmayer and Margules, 2000). In many ecosystems dominant species seem to drive the system and play a critical role. These species could be considered as keystone species. Studies of their ecology, spatial distribution and their relationship with other components of ecosystem are important from a functional perspective. When certain environmental conditions are designated as the indicator (e.g., soil acidity, canopy cover), a strong dependence of the indicator species on these conditions is necessary. The identification of selected keystone species or umbrella species makes conservation decisions easier.

Sometimes it is simpler to identify species that play the key role of holding together the entire biological community or ecosystem. These species are known as 'keystone species' in ecological terms (e.g. *Sphagnum* on Cors Fochno). In most of the cases, it is indeed groups of species rather than individual species that assume importance and these species groups could be referred to as the 'keystone groups' or 'functional groups'. The population dynamics of keystone species define the pattern of succession of vegetation (Khanina, 1998). The loss of a keystone species results in a range of dramatic cascading effects that alters trophic dynamics, and other food web connections, and can cause the extinction of other species (Fischer et al., 2006).

The relationships of fauna and other flora species with plant species of ecological dominance are of importance when utilising remote sensing data as these are the species that are more easily mapped through the interpretation of imagery.

2.6.1 Relationships between invertebrates and derived RS variables

It is important to be able to relate the habitat requirements of specific fauna with their habitats. Invertebrates often need different conditions at different stages of their life cycle and usually have very specific needs at small scales (micro-habitat). Microhabitats from different stages of an insect's life often need to be close together. This means that a habitat that is diverse or mosaiced at a range of scales with variations in structure and vegetation species compositions are important. There are many challenges involved in identifying invertebrate species of conservation concern. For this reason it is often more effective to focus on better-known species for example the distribution of plants (McGeoch et al., 2011b)

Remotely sensed imagery is used increasingly to detect insect habitats or the effects of insects on their environment (Leyequien et al., 2007a). Vegetation classifications can be used to provide data that can be used to correlate plant species or diversity with invertebrates. Species such as butterfly, which are often host-specific and whose diversity may correlate with underlying plant diversity have been linked to remote sensing derived habitat types (Debinski et al., 1999). Debinski et al. (1999) reported that several rare butterfly species significantly correlated with remotely sensed habitat types in the Greater Yellowstone Ecosystem. The modelling of Luoto and Heikkinen (2005) also supported the findings that specialist butterfly species distribution is closely related to remotely sensed habitat types. British ground (Coleoptera, Carabidae) and water beetle (Coleoptera spp.) species pool distribution strongly correlated with satellite-derived land cover data (Eyre et al., 2003). Woodland invertebrate distributions have been successfully associated with heterogeneity of landscape patches using satellite imagery (Chust et al., 2003).

Vegetation indices derived from multi-spectral satellite imagery, whilst usually employed

for assessing and monitoring vegetation, have been shown to act as surrogates of species richness and abundance of many fauna species. Although few studies have investigated the use of vegetation and other indices as surrogates, or as predicting habitat suitability for invertebrates, there have been a number of more recent investigations which have shown relationships between these indices and presence or abundance of various invertebrate species. Lafage et al. (2013) found that the NDVI was strongly related to activity-density and species richness for ground beetles, and had the potential as a low cost method for mapping arthropod assemblages at large spatial scales on temperate floodplains.

More research is required to relate the biophysical attributes derived from remote sensing vegetation indices to invertebrates. There are relationships and associations between invertebrates and many of these biophysical attributes that can be extracted from remote sensing data (Leyequien et al., 2007a). Moisture, plant productivity and dead litter can all be extracted from VHR satellite imagery. To illustrate this the following examples could lead to the selection of indices such as WBI to test associations between invertebrates, such as spiders, and plant moisture content. It has been recognised in ground survey experiments that both light and moisture were found to be two important biophysical attributes limiting the dominance and abundance of wolf spiders in bog habitats and Hore and Uniyal (2008) found spider species to vary with moisture levels and canopy cover.

Environmental heterogeneity is considered to be one of the main factors associated with a high degree of biological diversity, given that areas with higher environmental heterogeneity can host more species due to the greater number of available niches within them (Gaston and Blackburn, 2000). Spectral heterogeneity or spectral variability, is expected to be related to environmental heterogeneity and could therefore be used as a powerful proxy of species diversity (Rocchini et al., 2010).

Lassau et al. (2005) used NDVI and standard deviation of NIR as indicators of low

and high habitat complexity. They found a strong association between the NDVI and habitat complexity and showed that ant species differences corresponded to differences in habitat complexity. Lassau et al (2008) also showed that NDVI could be used as an habitat complexity surrogate for predicting differences in beetle compositions in open canopy forests (Lassau and Hochuli, 2007a).

Variables derived from LiDAR data have also been effective in predicting beetle assemblages (Müller and Brandl, 2009). They derived four environmental variables from LiDAR: (i) altitude, (ii) SD of the canopy height (an index for vertical variation of the canopy height, influenced by tree species combination), (iii) maximum tree height (provides information about the availability of at least one tall and old tree in a plot, which is a surrogate for habitat continuity) and (iv) penetration rate (a proxy of microclimatic conditions). Vierling et al (2011) also found they could derive spider community and species distribution information using LiDAR data. LiDAR is a viable tool to assist species-specific conservation as well as broader biodiversity planning efforts, not only for a growing list of vertebrates but for invertebrates as well (Vierling et al., 2011).

2.6.2 Remote sensing data input into habitat suitability and species distribution models

Species Distribution Models (SDMs) and Habitat Suitability Models (HSMs) can help to provide additional species information for biodiversity assessment by extrapolating species distributions in space and time. They can be used to develop spatially explicit predictions of habitat suitability or quality. SDMs and HSMs support predictions of how species distributions or location of suitable habitats might be affected by habitat management or environmental change, and to predict the impacts of land use and climate change on species distributions. They can be used to predict the impacts of invasive species, restoration and habitat management, determine suitable locations for species

reintroductions and predict the consequences of habitat loss.

Linking remote sensing to underlying ecological relationships can greatly improve species habitat distribution models (Zimmermann et al., 2007). The method showed remote sensing predictors improved the modelling of the distribution of tree species and was especially useful when modelling rare and occasional species. Remote sensing maps, when combined with species level ecological data, should give better predictions of the distribution and abundance of those species within a heterogeneous landscape (Imhoff et al., 1997).

Vegetation classification schemes can be integrated into SDMs to correlate individual species with map classes (Franklin, 2008a). However, as the overall classification of most landcover classifications are 75% to 95% accurate, this creates additional inaccuracies when inputted into SDMs. A number of studies have focused on the use of RS derived indices as input into SDMs (Zimmermann et al., 2007; Hassan and Bourque, 2009).

Plant productivity and biomass of ecosystems expressed as NDVI derived from remote sensing data is hypothesized to influence species distribution and local abundance of individuals (Seto et al., 2004; Oindo, 2002) and is often correlated to faunal species occurance and diversity. Many studies have used NDVI as input into habitat suitability models and found significant positive correlations between NDVI and mammal and bird distributions (Osborne et al., 2001; Musiega and Kazadi, 2004; Zinner et al., 2001), although very few studies have used remote sensing data in habitat suitability models for invertebrates (Leyequien et al., 2007a).

Although many of the derived indices from remote sensing data are proxies for biotic conditions that influence habitat suitability, most studies have focused on the use of NDVI. Most studies using NDVI for invertebrate species distributions have used it to locate insect attack, and subsequently linking with areas of canopy defoliation (Eklundh et al., 2009; Wang et al., 2010b).

Species assemblage data can also provide valuable information on ecological functioning of habitats and SDMs have been used to investigate these assemblages. Guisan and Rahbek (2011) state that there are two main approaches for predicting spatial patterns of species assemblages. The first approach focuses on species richness that can be directly predicted using various variables thought to control the number of species existing. The second approach applies species distribution modelling to a spatial stack of species. This uses individual species distributions usually modelled using purely abiotic variables. Guisan and Rahbek (2011) have suggested that to predict spatio-temporal species assemblages these two approaches should be compared or integrated (Figure 2.10). The properties of species assemblages can include abundance, composition, functional and structural characteristics (Guisan and Rahbek, 2011).
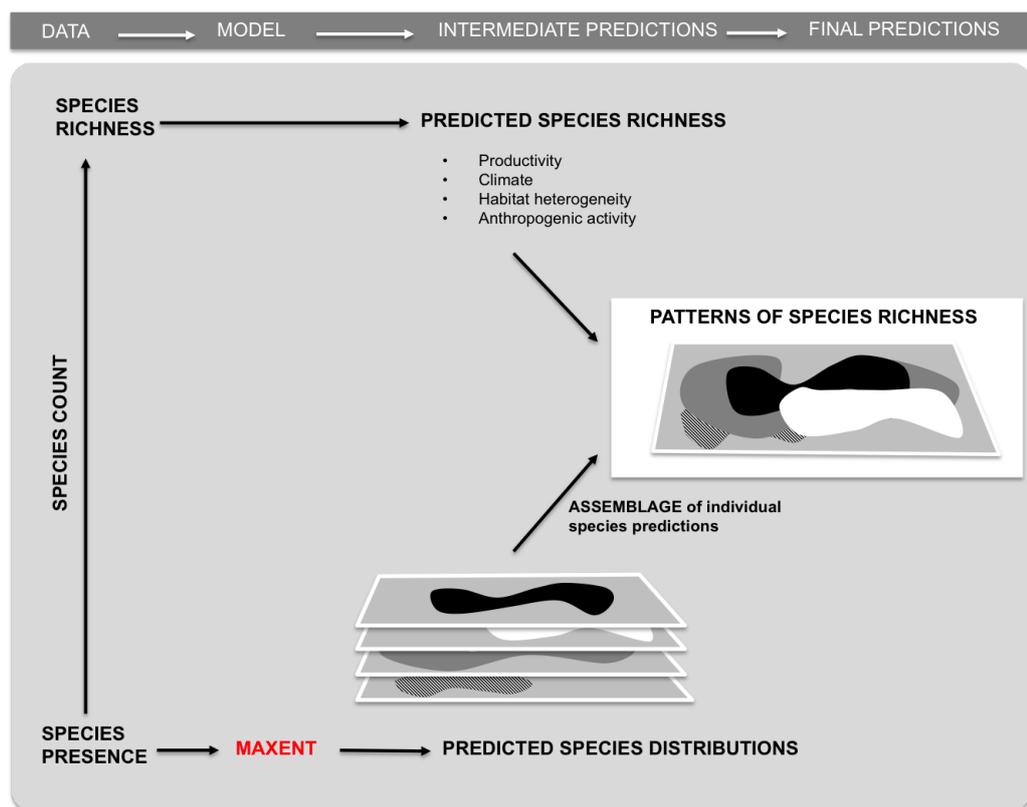
Figure 2.10: Diagram showing Species richness and SDMs used to model communities of species (adapted from Guisan and Rahbek (2011))

SDMs and HSMs are useful in predicting future scenarios as variable changes can be

entered into these models for predictive purposes. These indirect approaches using re-mote sensing to model biodiversity 'hold the promise of not only getting better estimates of species distributions and richness levels, but of also shedding light on the processes underlying them' (Turner et al., 2003b).

2.6.3 Conclusion

In order to assess and monitor ecosystems the selection and development of suitable indicators of biodiversity is required. These need to be quantifiable and capable of simplifying complex relationships (Feld et al., 2010). VHR satellite data provides spatial and temporal data which is capable of providing measures or indicators of biodiversity and biodiversity changes. Reflective properties of vegetation which relate to biophysical attributes such as productivity and moisture content (Lucas et al., 2007) of vegetation can be used indirectly as indicators of faunal species. Previous research using field data has shown that vegetation distributions, heterogeneity, structure and condition can show major associations with faunal distribution (McGeoch et al., 2011b). However, although relationships and associations between invertebrates and remote sensing data have been studied (Lafage et al. (2013); Leyequien et al. (2007a)) there has been little work to investigate the use of remote sensing these biophysical attributes especially in terms of monitoring changes across a protected site that may indicate losses or gains of biodiversity. A method is required to both identify these botanical baselines and associations with fauna that can be used to predict future and assess past events. Using biophysical attributes derived from satellite imagery in the form of spectral indices which can identify dominant species as well as indicate ecological gradients could be useful to infer associations and habitat suitability for individual and communities of invertebrates. Creating a system that as a whole could inform both spatially and temporarily on the ecosystem functioning of a protected site.

Chapter 3

Study site

3.1 Peatlands in Wales

Peatlands occur throughout Wales (Figure 3.1) and can be divided into two broad types, bogs and fens (Blackstock et al., 2010). They consist mostly of acidic peat, and rely solely on rainfall for water and nutrients (ombrotrophic). Fens tend to be richer in nutrients due to water feeding into them providing nutrients from other sources. Acid bogs occur in lowlands or uplands and are known as raised or blanket in formation. Blanket bog is usually found in the uplands and covers large expanses with a mantle of peat (a 'blanket' of peat). Lowland raised bogs are rain-fed and are usually less extensive than blanket bog and are mainly in lowland areas. Raised bogs are so called due to the formation of a raised dome of peat which has accumulated over millennia. All bogs are of acidic, nutrient poor peat and contain plants that have adapted to these conditions. The dominant species of blanket and raised bog are mostly, though not entirely the same (Tansey, 1965). Typical peatland flora consists of *Sphagnum* (bog mosses), *Calluna vulgaris* (heather) and *Eriophorum* species (cotton grass) with a number of other species such as *Drosera* (sundew) which are well adapted to the nutrient poor conditions as well as *Molinia caerulea* on upland bogs or drier areas of raised bog.

The study site for the following research was a lowland raised bog called Cors Fochno situated in the mid-West region of Wales (Figure 3.1) and is described in the following sections.
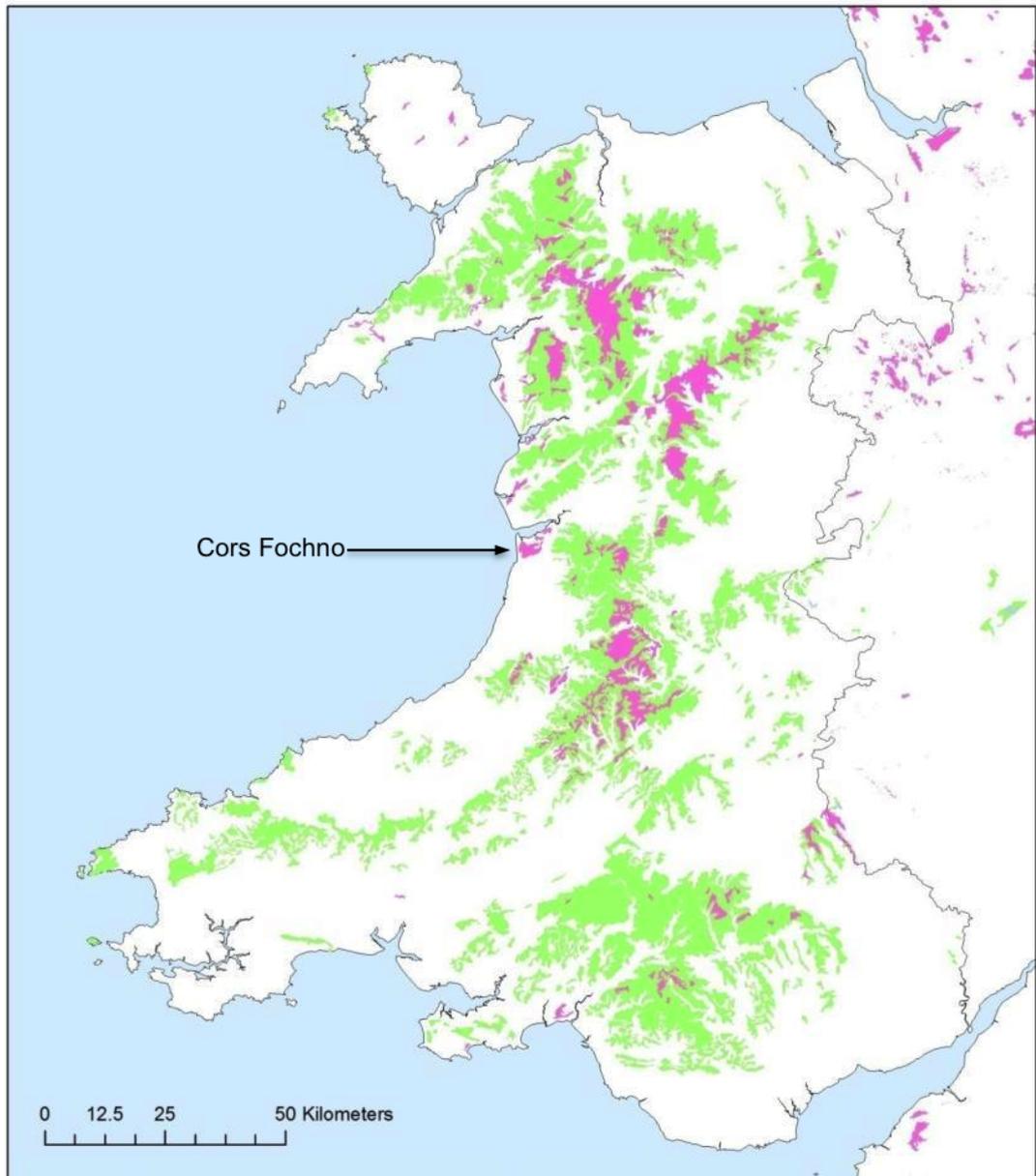
Figure 3.1: Peaty soil types in Wales.(ECOSSE project)

3.2 Cors Fochno

Figure 3.2: Aerial view of Cors Fochno bog with the Dyfi estuary to the north (Crown copyright RCAHMW, 2012).

Cors Fochno (Figure 3.1) is a rare example of an estuarine raised bog (Figure 3.2) and encompasses the largest area of intact, primary surface lowland raised bog in the UK with an active peat-forming dome of ≈ 200 ha and surrounded by approximately 450 ha of modified/secondary or degraded raised bog. Although a significant area (264 ha) of the former peatland complex was used for agriculture the primary active bog of Cors Fochno now accounts for around 4% of the total British resource of primary surface (i.e. uncut) raised mire and is one of the few sites left that represents an active northern peatland complex (Lovering, 2008). Cors Fochno is part of the Dyfi Site of Special Scientific Interest (SSSI) and National Nature Reserve (NNR) managed by Natural Resources Wales (NRW) formerly the Countryside Council for Wales (CCW) (Lovering, 2008). It is designated as a Special Area of Conservation (SAC), and is part of the Dyfi-Cors Fochno Ramsar site. The site also comprises part of the core conservation zone of the

Dyfi Biosphere Reserve and is recognised as a site of national geological importance. There are a number of special features which include both flora and fauna from which these designations were approved (Table 3.1). These are where the focus of monitoring and management of the site are placed.

	Designated Feature	Reason
	SAC features	
1	Active raised bogs	Annex 1
2	Degraded raised bogs still capable of natural regeneration	Annex 1
3	Depressions on peat substrates of the *Rhyncosporion*	Annex 1 - habitat part of 'active raised bog'
	Ramsar features	
4	Estuarine raised mire	All 3 Annex 1 SAC features
	SSSI features	
5	Raised bog ombrogenous	All 3 Annex 1 SAC features
6	Redshank *Tringa tetanus*	(<10%) of the Dyfi SSSI breeding population (the largest breeding concentration in Wales)
7	Curlew *Numenius arquata*	Entire Dyfi SSSI breeding population
8	Common snipe *Gallinago gallinago*	(c20%) of the Dyfi SSSI breeding population.
9	Otter *Lutra lutra*	Strong resident population.
10	Rosy marsh moth *Coenophila subrosea*	Largest population of few (c6) in UK.
11	Large heath butterfly *Coenonympha tullia*	Schedule 5 species. Strong population.
12	Bog bush-cricket *Metrioptera bracyptera*	Strong population at one of few sites in Wales.
13	*Heliophanus dampfi*	RDB. Only known site in Wales & England
14	Assemblage of RDB and/or Nationally scarce bryophytes	3 nationally scarce bog mosses *Sphagnum pulchrum*, *S.fuscum* and *S. austinii*; and the nationally scarce liverwort *Pallavicinia lyelli*
15	Assemblage of RDB and/or Nationally scarce vascular plants	Nationally scarce *Rhynchospora fusca*
16	Breeding bird assemblage of lowland open waters and margins	Part of Dyfi SSSI assemblage
17	Reptile assemblage	Part of Dyfi SSSI assemblage
18	Peatland invertebrate assemblage	Includes a range of RDB, nationally and locally scarce species additional to those which qualify individually.
19	Quaternary geology of Wales	Nationally important peat archive

Table 3.1: Designated special features for Cors Fochno site (adapted from Lovering (2008))

Cors Fochno bog contains a 7m archive of peat which has been developing as active bog for the last 5000 years. Prior to this it was a floodplain covered in forest c.5000BP, which later developed into fen around 4,500BP (Poucher, 2009).
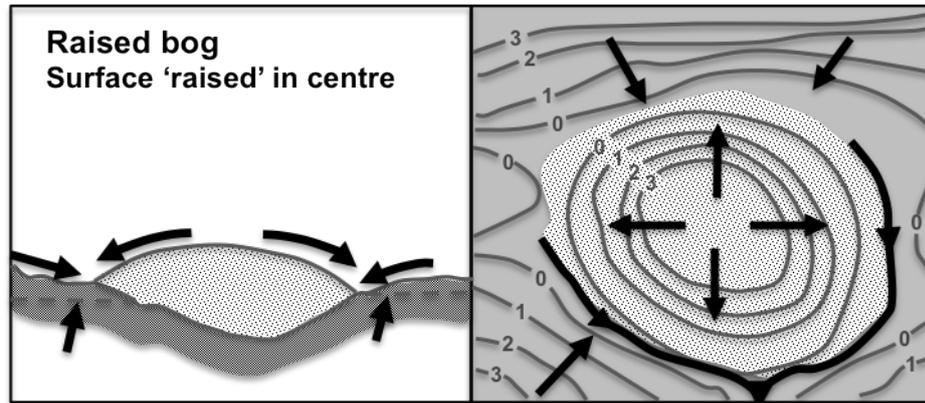
Figure 3.3: Cross section and plan view of the key hydro-morphological status of a raised bog showing the direction of flow of water in the system (adapted from source, Charman (2002)).

Cors Fochno raised bog formed due to waterlogging which provided anaerobic conditions. This slowed down dead plant material decomposition and caused an accumulation to form peat. Peat continued to form over time until the bog surface was above groundwater levels forming a dome shape. As a result of its distinct convex accumulation of peat the main water supply for the central dome area is derived solely from atmospheric inputs. Run off from streams and floods does not reach the surface of the raised dome (Blackstock et al., 2010) creating a delicate balance between precipitation, evaporation and runoff from the peat surface (Charman, 2002) (Figure 3.3).

The sloping edges of the dome appear drier than the rest of the ombrotrophic surface. The vegetation on these slopes is based on a spongy layer of Sphagnum mosses but there is a tendency for the surface to become drier with a loss of Sphagnum and an increase in ericaceous shrubs. This is called the 'rand'. Around the edges of the bog there is a minerotrophic lagg taking the form of poor fen and fen woodland. This lagg has had peripheral damage due to draining and peat cutting in previous years.

(a)

(b)

(c)

(d)
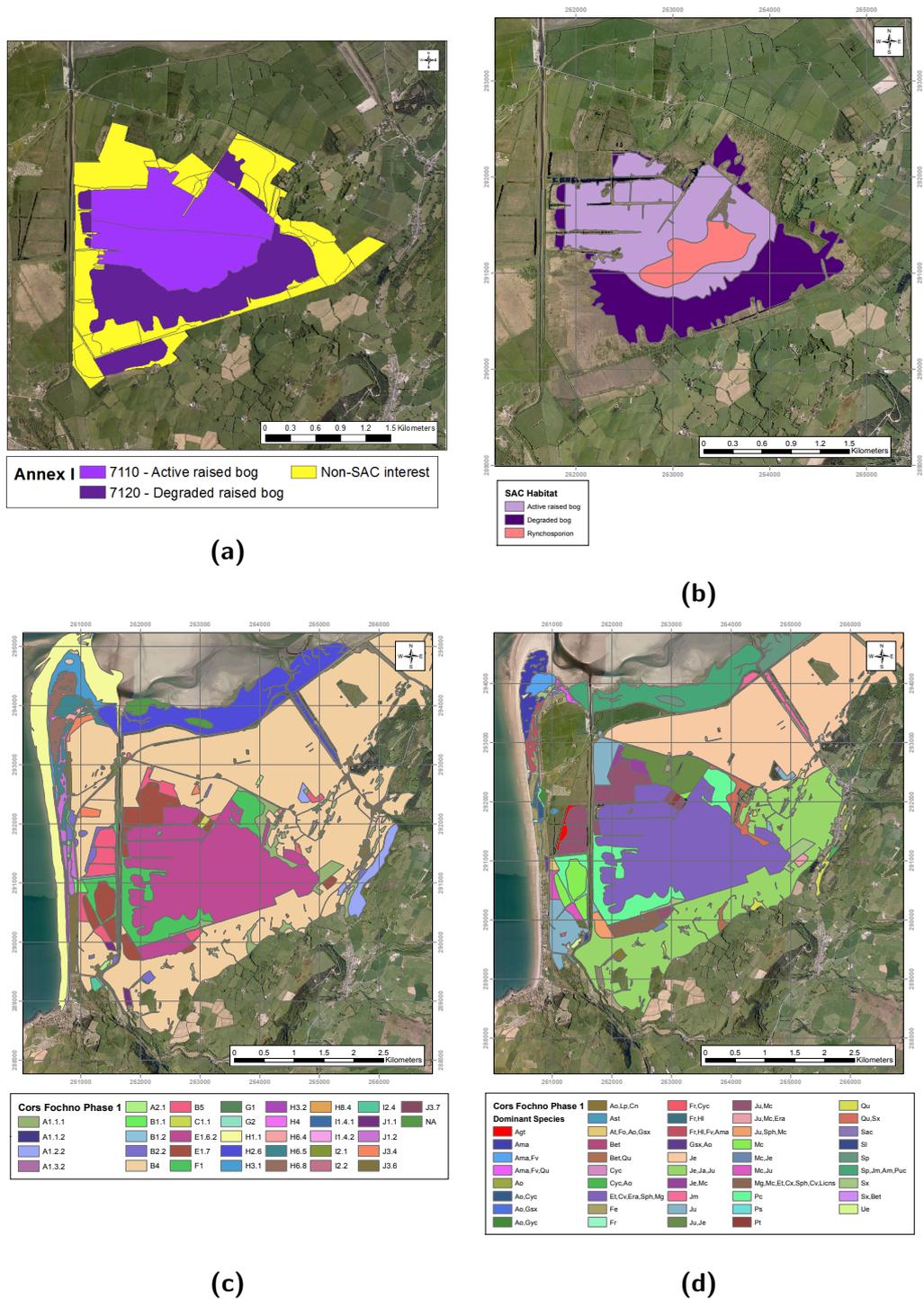
Figure 3.4: Cors Fochno bog a) Annex 1 habitats and b) SAC habitats, 2003,and Dyfi estuary c) Phase 1 habitat codes and d) dominant species, 2005 (created from data provided by NRW).

3.2.1   Habitats and flora

Being one of the largest and best quality raised bogs in Britain, Cors Fochno supports specialised ground flora. Vegetation maps of the main areas of the Dyfi reserve have been carried out in the past to record the vegetation using a number of different classifications. The SAC and Annex 1 habitats (Figure 3.4a & b) have been recorded for Cors Fochno and were last mapped in 2003. In 2005 Phase 1 habitats were mapped along with dominant species for the Dyfi estuary (Figure 3.4c & d). The SSSI and SAC area of Cors Fochno was included within this survey.

A National Vegetation Classification (NVC (Rodwell, 1991)) of the SSSI has been completed and mapped (Figure 3.5) in 2008. The main NVC communities are spatially mapped and the sub-communities are recorded as species composition for each quadrat. Some of these species recorded within the SSSI are listed in Table 3.2.
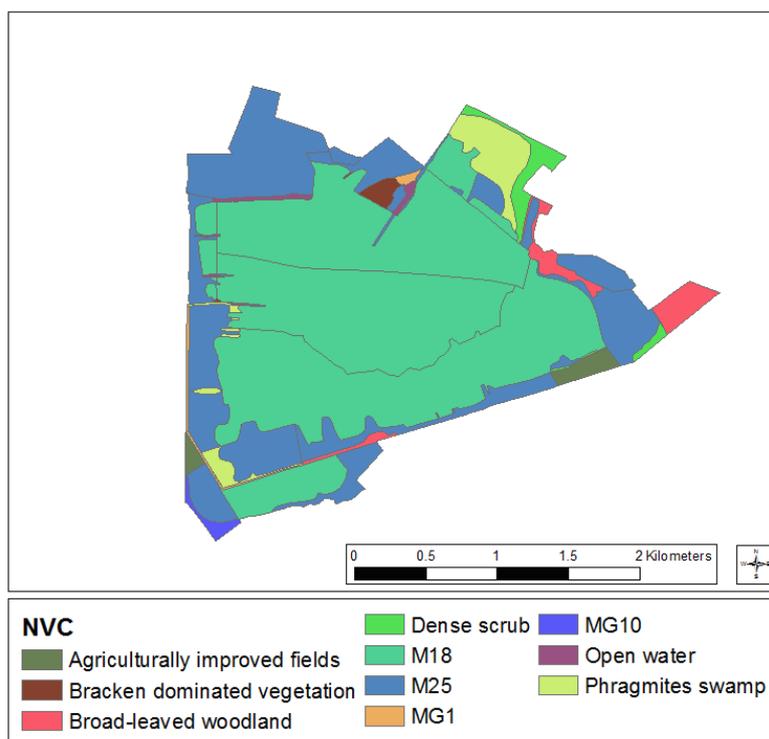
Figure 3.5: NVC Cors Fochno 2008

Species	Lifeform	On Cors Fochno found in	
		EU Habitat code	NVC
Andromeda polifolia	Shrub	7110, 7120	M18
Calluna vulgaris	Shrub	7120	M18, M25
Cladonia portentosa	Lichen	7110, 7120	M18
Drosera anglica	Forb	7110	M18
Drosera rotundifolia	Forb	7110	M18
Erica tetralix	Shrub	7110, 7120	M18
Eriophorum angustifolium	Graminoid	7110, 7120	M18
Eriophorum vaginatum	Graminoid	7110, 7120	M18
Hypnum jutlandicum	Moss	7110, 7120	M18
Juncus effusus	Graminoid	Non SAC	M25, Agriculturally improved fields
Molinia caerulea	Graminoid	Non SAC	M18, M25
Myrica gale	Shrub	7110, 7120, Non SAC	M18, M25, Phragmites swamp
Narthecium ossifragum	Graminoid	7110, 7120	M18
Phragmites australis	Graminoid	Non SAC	M18, M25
Pteridium aquilinum	Forb	Non SAC	Bracken dominated vegetation
Rhynchospora alba	Graminoid	7110	M18
Schoenus nigricans	Graminoid	7120	M18, M25
Sphagnum cuspidatum	Moss	7110, 7120	M18
Sphagnum papillosum	Moss	7110	M18
Sphagnum pulchrum	Moss	7110	M18
Trichophorum cespitosum	Graminoid	7120	M18
Betula pendula	Tree	Non SAC	Dense scrub

Table 3.2: Some of the main species recorded on the SSSI site and the areas (Annex I & NVC communities) they are found in (adapted from NRW quadrat data, 2008).

Active unmodified primary bog (EU Habitat 7110)

The active raised bog consists of a raised dome with a mosaic of hummocks, lawns and sphagnum filled hollows. Plants characteristic of the active dome include a typical range of bog moss species (*Sphagnum* spp., Figure 3.6a), *Erica tetralix* (cross leaved heath), *Andromeda polyfolia* (bog rosemary), *Eriophorum augustifolium* (common cotton grass), *Calluna vulgaris* (heather), *Drosera* spp. (sundews) and *Rhynchospora alba* (white beak-sedge). *Myrica gale* (bog myrtle), *Eriophorum vaginatum* (Hares tail cotton grass) and *Narthecium ossifragum* (Bog asphodel) are also locally abundant. Scarcer

species include *Vaccinium oxycoccus* (cranberry), *Menyanthes trifolia* (bogbean) and *Rhynchospora fusca* (brown beak sedge). Key indicators of active bog include *Sphagnum pulchrum*, *S. cuspidatum*, *S. papillosum* and *Drosera anglica* (greater sundew) (Figure 3.6b).

(a) **(b)**

Figure 3.6: a) Central bog ecotope showing a high *Sphagnum* cover. b) *Drosera anglica* is a carnivorous plant found in hollows on Cors Fochno. Plant nutrients are in short supply in bogs and trapping and digesting insects provides the plant with an alternate source. (Photos by Mike Bailey, NRW)

Modified or degraded/secondary bog (EU Habitat 7120)

The degraded bog is an area of raised bog where habitat restoration may be achievable. In these areas there is a significant reduction in the cover and diversity of *Sphagnum* spp. and other raised bog species. However, *Sphagnum* that has recovered in these areas and are hopefully capable of peat formation. *Molinia caerulea* (purple moor grass) is abundant on the more disturbed sections of the bog and *Phragmites australis* (common reed), *Juncus maritimus* (sea rush) and *Schoenus nigricans* (black bog rush) occur on areas affected by former saline incursion.

The margins of the bog (Non SAC region)

Much of the outer areas of the SSSI are areas of degraded bog which have been drained and had the top layer of peat removed through peat cutting. These are areas in which the natural formation of peat has stopped due to intensive drainage and drying out and or peat removal. Species such as *Molinia caerulea* can dominate as well as *Pteridium aquilinum* on slightly raised and sloped land which is drier. Elsewhere bog has been drained and agriculturally improved and large patches of *Juncus effusus* are often found here.

Two marginal areas which had in the past been agriculturally improved were purchased by the then CCW (currently NRW). Since purchase twenty years ago these areas are
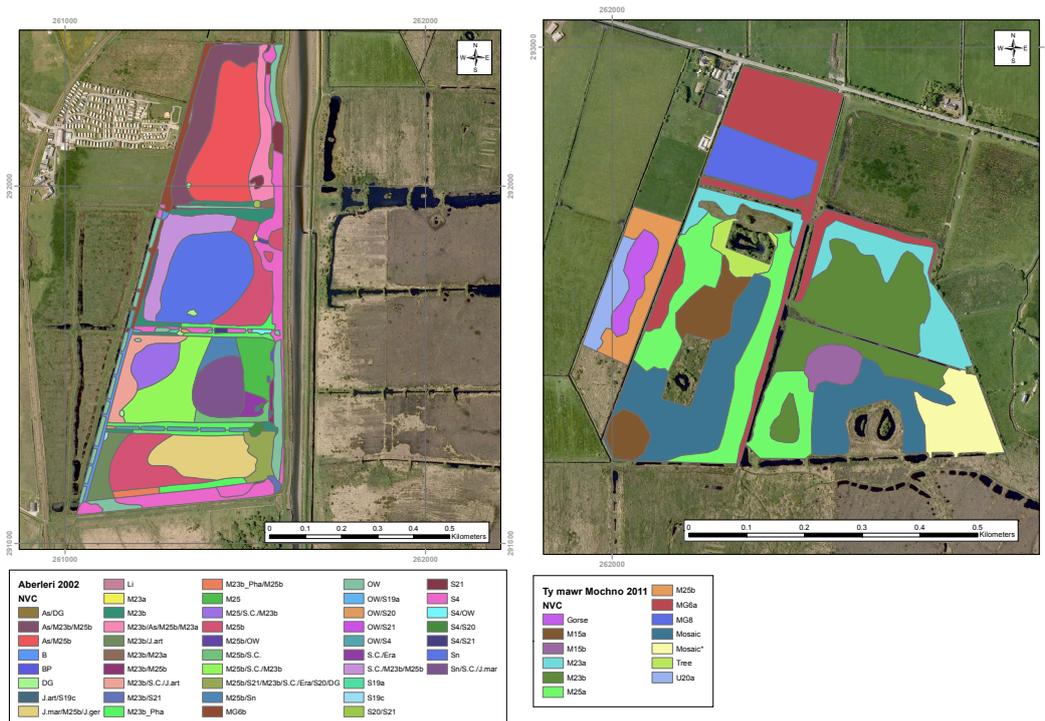
(a)   **(b)**

Figure 3.7: NVC mapped vegetation of a) Aberleri fields and b) Tymawr Mochno (created from data provided by NRW).

being re-wetted and removed from their previous agricultural regimes, with the aim of encouraging some bog species or marginal species to return to these areas that were once primary active bog. These areas have therefore been mapped in higher resolution than other areas to record any changes (Figure 3.7).

Wider landscape (Dyfi NNR)

Habitats surrounding the bog SSSI include mud and sand flats, sand dunes, saltmarshes, reed swamp, marshy grassland, wet woodland and scrub, *Juncus effusus*/ rush pasture, drier areas of acid grassland and bracken *Pteridium aquilinum*, and agricultural grasslands grazed mainly by cattle and ponies.

3.2.2   Fauna in and around Cors Fochno

For much of Cors Fochno SSSI there is poor spatial coverage for the abundance and distribution of many species due to scale and accessibility of areas. It can be seen from Figure 3.8 that many of the observations or records are from either the edge of the bog or in areas in close proximity to the boardwalk. The central areas are not void of fauna as figure 3.8 suggests, but data are absent from these and other areas as they are difficult to traverse on foot and it is easy to trample and damage the delicate and in many cases rare vegetation.

A variety of birds including waders, redshank, water rail and reed warbler breed in and around the raised bog, while hen harrier, merlin and hobby use the site to hunt prey. Other notable species which are recorded on site include otter, water vole, harvest mouse, adder, grass snake and slow worms (Lovering, 2008).
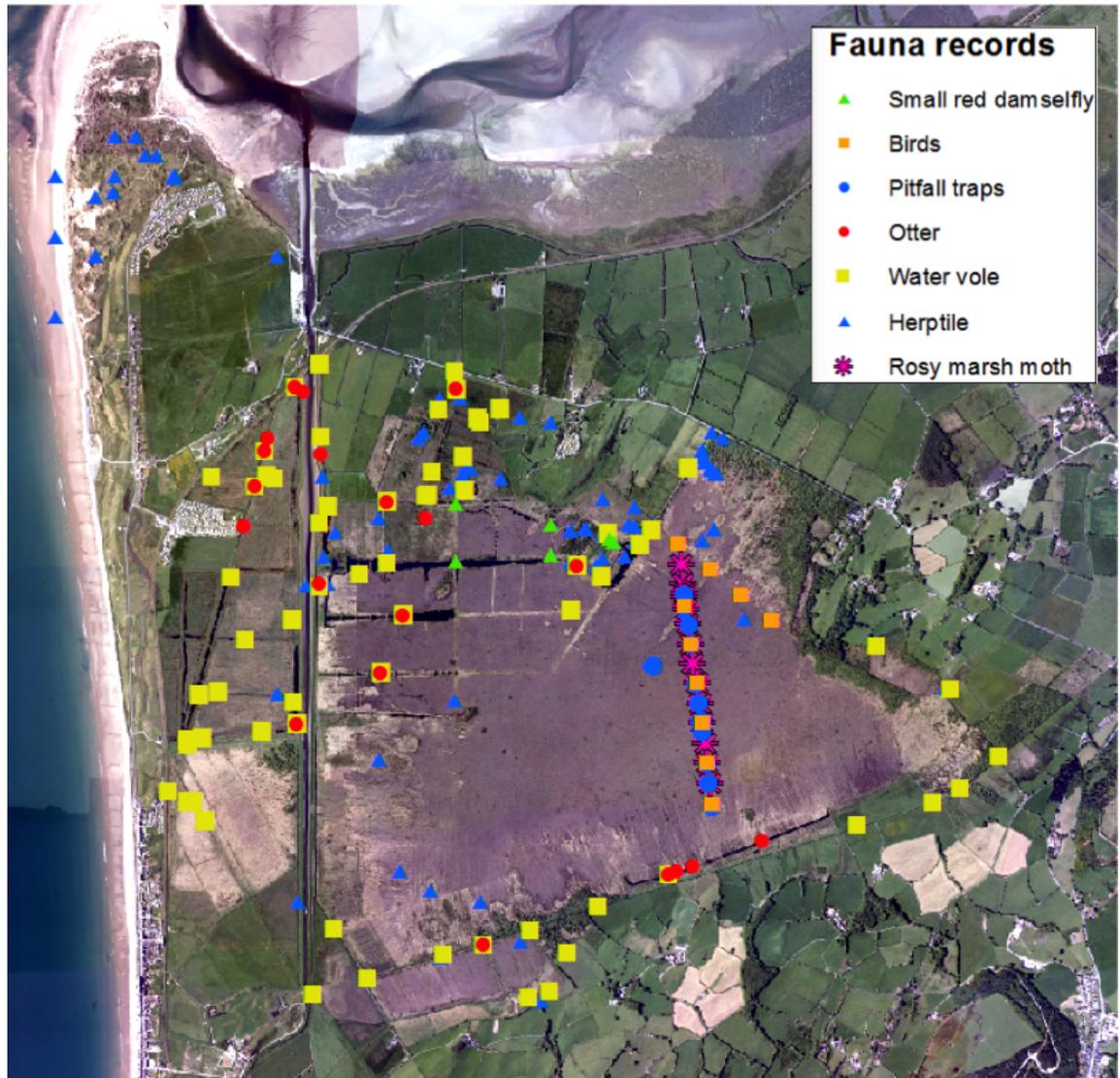
Figure 3.8: Recent (1980s to present) NRW fauna records for Cors Fochno and surrounding areas (created from data provided by NRW).

Invertebrates recorded at Cors Fochno

The invertebrate assemblages present on Cors Fochno include a wide range of nationally scarce species (Lovering, 2008). Many of these species are dependant upon vegetation types or species present or conditions provided. Some of the rare species found within the primary active bog area include the large heath butterfly *Coenonympha tullia* (Figure 3.9a), bog bush-cricket *Metrioptera bracyptera* and small red damselfly *Ceriagrion*

tenellum. The nationally rare rosy marsh moth *Eugraphe subrosea* (Figure 3.9b) only found on 5 other sites in the UK has its largest population in the UK here and is understood to require sphagnum for pupation as well as their known food plant of *Myrica gale*. Also present at its only locality in England and Wales is *Heliophanus dampfi* (Figure 3.9c), a spider found only on a small number of highest quality raised bogs in the UK.

(a)

(b)

(c)

Figure 3.9: Rare species found at Cors Fochno. a) *Coenonympha tullia* (Large heath butterfly) a rare *Lepidoptera* and b) *Eugraphe subrosea* (Rosy marsh moth) also rare which has its major British stronghold at Cors Fochno. c)*Heliophanus dampfi*, a spider found only on a small number of highest quality raised bogs in the UK.

A pitfall trapping programme as part of the Welsh Peatland survey was carried out at Cors Fochno. This traversed the primary bog area and was carried out by NRW then CCW from 1986/87 to 1996. The results were used to investigate the effects of a fire that swept across the bog in 1986 and for the period 2009 to 2010. *Formicidae, Coleoptera*, and *Arachnida* were recorded for these periods (Figures 3.10 and 3.11).
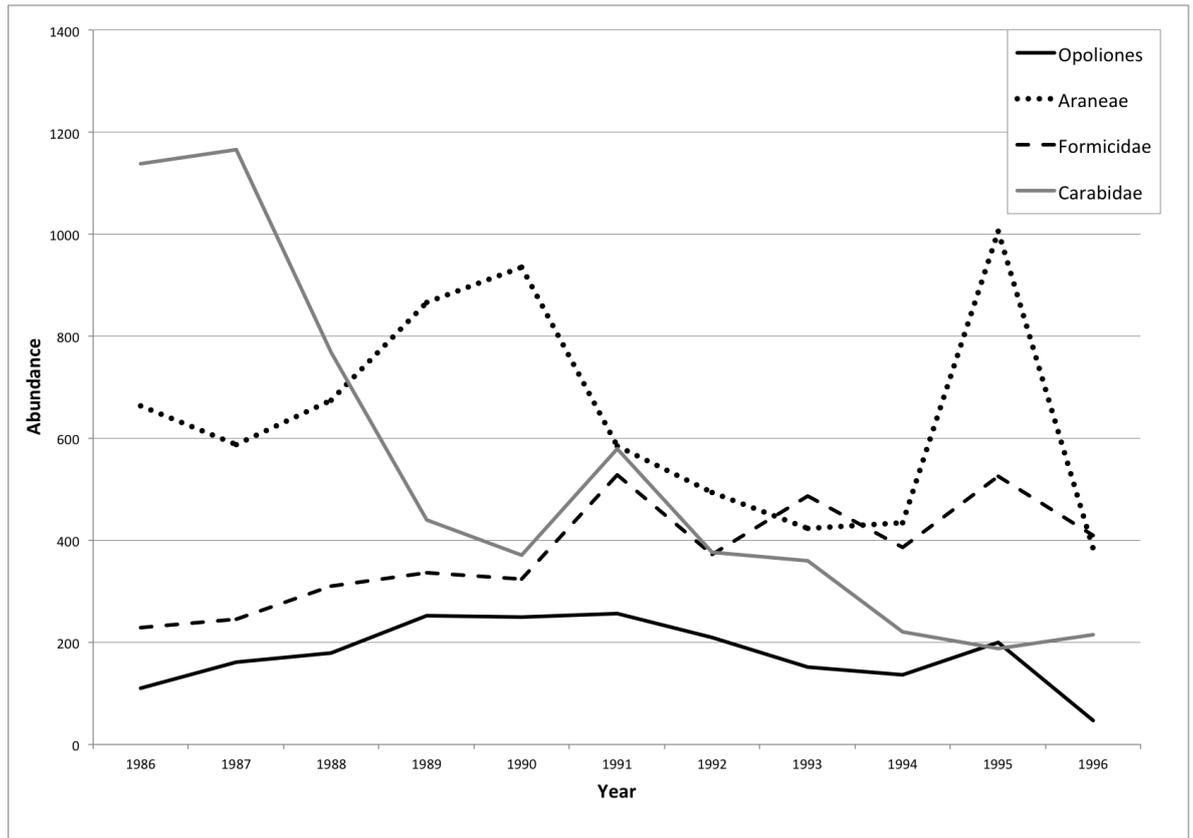
Figure 3.10: Families and order yearly abundance recorded from pitfall traps for the period 1986 until 1996.(created from data provided by NRW)

Amongst invertebrates recorded by pitfall traps on site are *Carabidae*. This family of beetles are often used as ecological indicators (Lovei and Sunderland, 1996). There are a number of species that specifically require the unique conditions present on Cors Fochno. One of the most interesting of these is *Agonum ericeti* (Figure 3.12) a species which is scarce in Britain with Cors Fochno being one of only five sites where it is found. It is only found on oligotrophic mires with active sphagnum growth but the adults have been shown to prefer warmth and dryness; it is the larvae which depend upon the permanently wet *Sphagnum* to achieve maturity (Fowles, 1997).
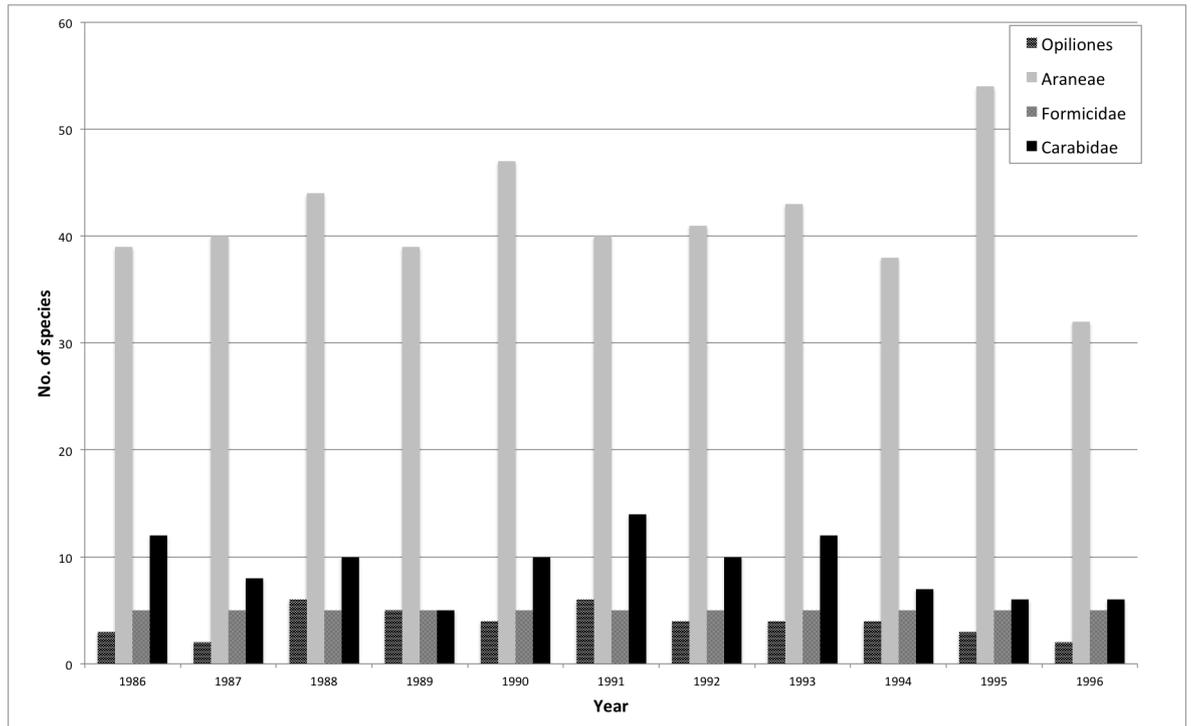
Figure 3.11: Species numbers per order or family recorded from pitfall traps for the period 1986 until 1996.(created from data provided by NRW)

Figure 3.12: *Agonum ericeti* (6.5-8.5mm), a flightless *Carabidae* species found on Cors Fochno.

Relationships between recorded species, families and orders can be inferred from the data presented in figure 3.10. This data shows that overall abundance of invertebrates trapped in pitfalls can fluctuate from year to year, and has in particular in this case, probably due to the fire. Single year data should therefore be used carefully when it comes to interpreting results. This single year data is useful for showing the best times to trap and collect data.
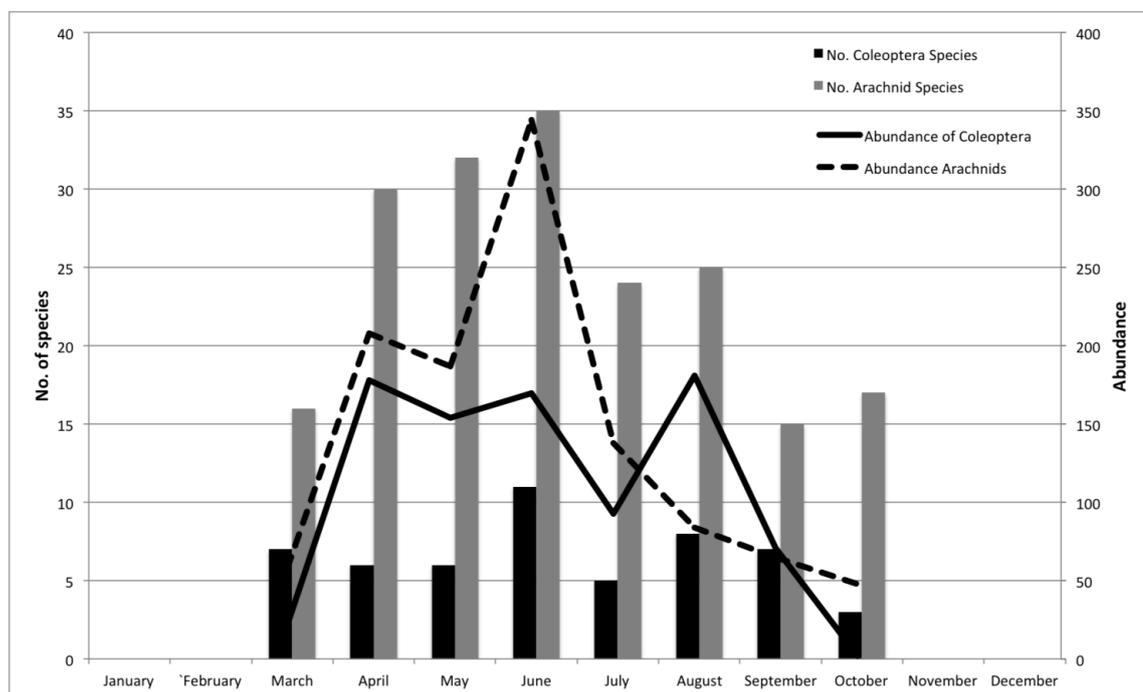
Figure 3.13: Seasonal pitfall data from 2009.(created from data provided by NRW)

Collation of historic data can provide valuable information for interpretation of biodiversity data. When using data from short periods of survey collection there are a number of issues that one needs to be aware of. For example unusual seasonal weather could skew the results. Historic data can help to provide a comparison that can be used to help interpret current survey data and avoid inaccurate assumptions.

3.2.3 Pressures and threats

Drainage reclamation (Figure 3.14a) and hand peat cutting (Figure 3.14b) were extensively carried out during the late 18th, 19th and early 20th century, and this activity, together with the canalization and diversion of the River Leri through the bog (Figure 3.15), have led to habitat loss and fragmentation around the bog margins.
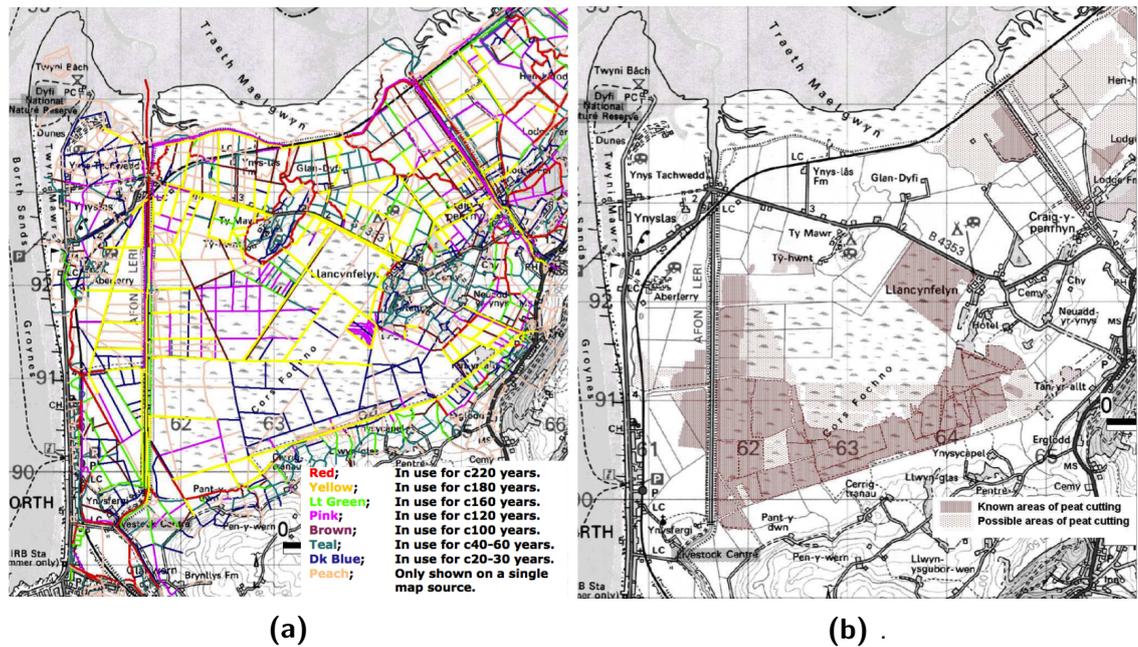
Figure 3.14: Some past causes of bog degradation. a)Drainage and b)peat cuttings (Poucher, 2009)

Many areas drained were improved for agriculture and the transitions between the estuarine environment in the north and the shingle and dune ridge to the west was severed by the road and rail networks and the canalization of the River Leri. These impacts took place in the first half of the 19th Century.

Figure 3.15: Canalisation and diversion of the River Leri. (Photo by P. Laverty)

The drainage has led to shrinkage and subsidence of the peat, which has impacted on the vegetation species composition and dynamics, particularly in the margins and partly because of increased burning under drier conditions. Vegetation dominated by *Molinea caerulea*, scrub and wet woodland has replaced open bog in some marginal areas (Figure 3.16). The future of the bog is under threat from sea level rise and climate change, which are compounded by past and continuing flood defence and agricultural land drainage management.

Figure 3.16: Encroachment of purple moor-grass and woody vegetation in old peat cuttings. (Photo by Mike Bailey, CCW)

In 1986 an accidental fire caused a large swathe of the central bog area to be burnt causing damge although apparently not permanent or longlasting to a section of the central dome area.

3.2.4 Management

The main objectives for management at Cors Fochno are to:

- Restore active peat forming conditions, maximising peat growth and elevation

- Prevent deterioration of the peat archive (through drying and oxidation) and loss of carbon to the atmosphere.

- Restore areas of degraded mire by hydrological controls (Figure 3.17) and appropriate vegetation management.

- Maintain or increase all rare and notable species populations.

- Enhance the landscape quality of the bog and surrounding ecosystems.

- Monitor important conservation features and environmental influences (e.g. aerial deposition).

- Maximise scientific research, education and access as far as compatible with the scientific features.

Figure 3.17: An aerial view of a section of Cors Fochno showing hydrological controls (damming of drains) to stabilize a high water-table and reduce surface runoff, highlighted by winter frost (Crown Copyright RCAHMW, 2012).

3.2.5   Areas of change

Cors Fochno and the surrounding areas have been subject to constant change over centuries (Figure 3.18) either through anthropogenic or natural occurance.

Figure 3.18: Historic maps illustrating change over the recent centuries, showing the disappearance of large waterbodies and the appearance of large tracts of ditches and drainage on the bog between 1875 and 1922 (Copyright Reserved)

This study focuses on investigating the areas of change, caused by drying out either through anthropogenic or climatic influences. For Cors Fochno many areas drained and used for peat cutting are the areas most affected by change and so focus is placed

on comparing areas inundated by *Molinia caerulea* and *Phragmites caerulea* with areas that have had less immediate anthropogenic influence and consequently less dramatic long-term changes.

Focus needs to be concentrated on areas of change in order to try and quantify and predict possible outcomes of changes in biodiversity of those regions. i.e. around the bog margins. Areas of change can be clearly seen when looking at and comparing vertical aerial images (1948) with recent satellite and aerial imagery (Figure 3.19).

The main areas that have encroached since 1948 on the bog area are broad-leaved woodland, marshy grassland (*Molinia* & *Molinia/Phragmites* mix) and some areas of bracken (*Pteridium aquilinum*) on drier rises. Areas which saw anthropogenic activity such as peat cutting and ditching prior to 1948 are now classed as secondary bog, which is also an area of change.

Figure 3.19: Llancynfelin 1948 and 2012

3.2.6 The main management questions to be answered are:

1. Is the site deteriorating. Is the raised dome drying out (e.g.less *Sphagnum* pools) and is the *Molinia* area encroaching?

2. What are the distributions and populations of rare and notable species? Are these increasing or decreasing? Can these be maintained or increased?

3. What would be the effects on biodiversity of restoring areas of degraded mire?

4. Are surrounding landscapes changing and if so does this effect the site?

Chapter 4

Species discrimination using field spec-troradiometer data

4.1 Introduction

Successful classification of vegetation from satellite imagery depends on vegetation or species spectral separability. To assess this separability and the most appropriate times for satellite imagery to be acquired for optimising separability, field spectrometers were used to collect ground based data. A field spectrometer records the spectral reflectance of whatever surface it is aimed at and is useful for recording spectral reflectance of vegetation in the same way in which a satellite would, albeit at a far smaller scale. Many studies of species discrimination have been undertaken from one single time period. However, very few have investigated the seasonal implications on species' reflectance spectra or indeed how these differences between seasons. Baldeck and Asner (2014) used field spectroradiometer readings to improve the accuracy of their tree crown classifications and found that they were able to use it to evaluate the separability of species, as well as to interpret how much training data they required. Schmidt and Skidmore (2003) collected field spectrometer readings during one summer period for 27 saltmarsh vegetation types. They proved from these data that there were significant differences in the vegetation spectra and showed that the spectral libraries created in the field could be used to identify vegetation species within hyperspectral imagery. Reflectance spectra of different species were found to have either visually different reflectance shapes or statis-

tical quantified differences (Vogelmann and Moss, 1993; Schmidt and Skidmore, 2001). Where discrimination of species is less apparent from single data observations, phenological differences can be considered. Vegetation phenology represents a potentially significant source of information to aid land cover classification. Multiseasonal imagery that captures the phenology have been used in land cover classification with some success (Simonetti et al., 2014; Goetz et al., 2004). Many researchers have found that using phenological data improved their species classifications (Elatawneh et al., 2013). Seasonal change such as leaf-flush or senescence can be captured by satellite and it is these changes that have previously been used with multi-seasonal data to improve forest classifications (Jensen, 2000) as well as their under-story composition (Schaepman-Strub et al., 2009). Phenological data are also valuable as a tool for documenting trends over time. The phenological events are sensitive to environmental and climate variations and can be used to detect and assess the impacts of such variations. Field spectrometers can provide full spectral reflectance data often within the spectral ranges of 300nm and 2500nm. However, when using this data to produce species or habitat classifications on protected sites, high resolution data are required to provide more detailed information. A number of very high resolution satellites and hyperspectral imagery can be employed. The hyperspectral data is capable of producing spectral reflectance data within the field spectroradiometer range (300nm and 2500nm); however, processing and using hyperspectral data is often more costly, and the processing and atmospheric correction is more difficult (Borengasser et al., 2008). There is also a danger of having too much data/information which becomes difficult to decipher. Vegetation indices are useful parameters which can considerably reduce the data volumes for processing and analysis (Coppin Correspond et al., 2004) and are also valuable for maximising sensitivity to biophysical parameters (Charan Sahu, 2008).

Spectral vegetation indices have been used since the 1960s and are continuously evolving to suite their uses (Bradley and Fleishman, 2008b). Both the use of phenological information in satellite imagery and the use of vegetation indices are known to independently

improve vegetation classifications (Dymond, 2002). Combinations of vegetation indices with multiseasonal imagery that captures phenology has produced successful vegetation classifications (Hill et al., 2010; Lucas et al., 2011a). However, most methods have not used the combination of ground data and vegetation indices to analyse the effects of phenology and the selection of suitable indices. This information will provide valuable information for appropriate satellite, image selection and synchronisation of this within a complete flora and fauna monitoring system. This chapter focuses on how these phenological phases can be used in combination with vegetation indices which are suitable for focusing on a number of biophysical attributes relevant to the species present in healthy active bog as well as degraded bog and surrounding areas. The main aim of this approach is to minimise the number of images required for separation of a number of species within a relatively small site and to produce evidence of the most suitable indices for use in classification. This chapter focuses on the vegetation indices selected, developed and used within the BIOSOS programme.

Aims:

This study aims to use field spectro-radiometer data to develop a method for identifying optimum months of the year and best indices for species discrimination on Cors Fochno protected site, that can later be used within a system for accurate classification of species.

Objectives:

1. Using ground collated spectral reflectance data for dominant species assess and analyse the separability /similarity of species spectral data throughout the year (April to November).

2. Apply the same assessment and analysis as in objective 1 to resampled spectral reflectance data to correspond with the reflectance measurements from WV2 data.

3. Using results from objective 2 evaluate the best times for acquisition of WV2 satellite data.

All with a view to using the developed method for actual WV2 data within Chapter 5.

Hypothesis:

The ANOVA F-ratio method provides a successful method to statistically show that distinctive phenological differences of key lowland plant species on a lowland raised bog are important for selecting the best months and best spectral indices for species discrimination and can be used to select optimum WV2 imagery acquisitions for a more successful species classification.

4.2 Methods

4.2.1 Collection and processing of field spectro-radiometer readings

Field samples were recorded once in the first week of each month throughout 2013 from the very beginning of April through to November, between the hours of 11.00am and 14.00pm under sunny, mostly cloudless conditions. 20 field spectrometer readings were taken at random for each species at approximately 1m above the vegetation to ensure a 50cm radius recording of the vegetation. An Analytical Spectral Devices (ASD) spectro-radiometer was used to measure the in-situ reflectance. This was fitted with a pistol grip with scrambler to homogenize the optical radiation and was specifically used in this case for reflectance measurements. This spectrometer measured up to 2500 bands between 350nm and 2500nm and a white spectrolon panel was used to calibrate to absolute reflectance. A photo of each vegetation species of that target location was also collected to give a photographic representation to compare with the field spectrometer. A differential GPS reading was taken from the centre of the target locations to help relocate for monthly sampling and also to help locate it within satellite imagery. The

fieldspectrometer data was collected and processed using the RS3 software provided. This data was transformed afterwards using the ViewSpec programme also provided to give a reflectance value for each recorded wavelength.

4.2.2 Spectral reflectance

The mean spectral reflectance for each species was graphically represented using R Stats and visually compared with the photographic data (Figure 4.2) to give an indication of the relevance of any seasonal changes seen within species' spectral signatures. The average reflectance spectra were graphically represented and all 20 readings for each species were used for comparisons in analysis. Spectral angle analysis (within ENVI) was also performed to assess if the spectral reflectance was significantly different to allow discrimination of different species and also to assess what months were the best for discrimination. The Spectral Angle Mapper (SAM) algorithm was used in the Spectral Analyst within the program ENVI to compute the "spectral angle" between the species spectrum. Smaller angles represent closer matches to the reference spectra. The result indicates the radian of the spectral angle computed using the following equation (Equation 4.1)(Wen and Yang, 2012).

$$\alpha = cos^{-1}\left[\frac{\sum_{i=1}^{m} t_i r_i}{\left[\sum_{i-1}^{m} t_i^2\right]^{\frac{1}{2}} \left[\sum_{i=1}^{m} r_i^2\right]^{\frac{1}{2}}}\right] \tag{4.1}$$

Where

$m =$ the number of bands.

$t_i =$ pixel spectrum.

$r_i =$ reference spectrum.

$\alpha =$ radian of the spectral angle

Values produced by the spectral analyst for SAM indicate the similarity of the spectra and is measured in radians. To extract this value a minimum and maximum angle size can be set, in this case angle sizes were set to a minimum of 0 and a maximum of 0.25 radians. Petropoulos et al. (2010) showed that mapping accuracy became optimum between spectral angles of 0.2 and 0.3 when classifying burnt areas using Landsat imagery. A lower spectral angle value could have been used to provide a more definite similarity/dissimilarity, but on testing a smaller spectral angle it was noticed that the higher angle size would provide more information for interpretation of spectra differences. As this method was not the final method for discrimination, and was used merely to help investigate differences the spectral angle size, it was not investigated further. Where values were less than or equal to the minimum of 0 indicate a perfect match was indicated and a score of 1 assigned. Values greater than or equal to the maximum of 0.25 radians received a score of 0. To summarise, a score of 1 indicated the spectra are a perfect match and the two spectra being compared are the same species. A score of 0 indicated that the spectra are from separable and that species are different and highly distinguishable.

Spectral reflectance analysis was carried out on field spectrometer data collated for each of the ten species recorded. The first step to determine whether using these different wavelength ranges had an effect on the separability with respect to using the field spectrometer data. Consideration was also given to when these were translated to corresponding WV2 bands to determine whether the separation of species was affected by using a shorter range and to see if reducing to the 8 wavelengths used in WV2 also had a further effect on the separability. For each pair of species the correlation between the spectral curves were calculated.

The 3 different sets of wavelength values analysed were:

a. The reflectance values for wavelengths between 300 and 2500 nanometres recorded

for each species by the field spectrometer at 1 nanometre intervals.

b. The reflectance values for wavelengths between 300 and 1000 nanometres to fall within the wavelength range recorded by the WV2 satellite but at 1 nanometre intervals.

c. The reflectance values for the 8 wavelength values only, these being the same wavelengths recorded by WV2 satellite at 429, 480, 548, 608, 659, 723, 825, 915 nanometres.

Between and within species variance was calculated and seasonal graphical representations made. Combining bothe between and within species data the F-ratio method as described in section 4.2.4. was used to demonstrate the optimum period for species separation.

4.2.3   Indices calculations

A number of indices which can be used to derive vegetation biophysical properties were calculated from the spectral data. Indices which were used within the BIOSOS project for vegetation discrimination were investigated in the same way as the spectral reflectance data. Using these indices gives more precision to the spectral data and enables comparisons to be made with satellite data (Baret and Guyot, 1991).

Indices are incorporated within the EODHaM system. Indices that give relevant indirect emphasis on certain selected biophysical properties were selected. Analysis of the field spectroradiometer data in the World View 2 8 band format were carried out, following on from the spectral angle analysis to investigate whether using the indices altered the separability of species and best seasonal separability period/s in any way.

Wavelength (nm)	Band name	Band symbol
429	Coastal	ρMS_1
480	Blue	ρMS_2
548	Green	ρMS_3
608	Yellow	ρMS_4
659	Red	ρMS_5
723	Red Edge	ρMS_6
825	NIR1	ρMS_7
915	NIR2	ρMS_8

Table 4.1: Worlview 2 bands showing wavelength values and codes for indices formulas.

NDVI

The Normalised Difference Vegetation Index (NDVI) highlights areas of high plant productivity (Rouse et al., 1973) (Figure 4.1a & b). It has become one of the most extensively used vegetation indices in ecological remote sensing (Miller and Rogan, 2007; Pettorelli et al., 2005) The value of this index ranges from -1 to 1. The common range for green vegetation is 0.2 to 0.8.

$$NDVI = \frac{\rho 825 - \rho 659}{\rho 825 + \rho 659} \tag{4.2}$$

PSRI

The Plant Senescence Reflectance Index (PSRI) highlights areas of dead and senescent material (Figure 4.1c & d) was developed by Merzlyak et al. (1999) This index has been used as a quantitative measure of leaf sensence and fruit ripening (Merzlyak et al., 1999) and is sensitive to the caratinoid /chlorophyll ratio.

$$PSRI = \frac{(\rho 659 - \rho 480)}{\rho 723} \tag{4.3}$$

WBI

The Water Band Index (WBI) is useful for identifying areas of water or gives information on moisture content of vegetation (Figure 4.1e & f). WBI highlights non-submerged aquatic vegetation and open water and was developed for use in the BIOSOS project (Lucas et al., 2011b).

$$WBI = \frac{\rho480}{\rho825} \qquad (4.4)$$

FDI

The Forest Discrimination Index (FDI) is useful for discriminating photosynthetic cover and phenological differences (Bunting and Lucas, 2006). This was used within the BIOSOS project to discriminate areas within specific vegetation categories (e.g. trees).

$$FDI = \rho825 - (\rho723 + \rho429) \qquad (4.5)$$

REP

Red Edge Position (REP) is used to derive foliar chlorophyll concentrations and was used within the BIOSOS project to discriminate areas of non-photosynthetic vegetation (Curran et al., 1995). This particular formulation has also been used by the BIOSOS project (Lucas et al., 2012b).

$$REP = \rho723 - (\rho915 - \rho659) \qquad (4.6)$$
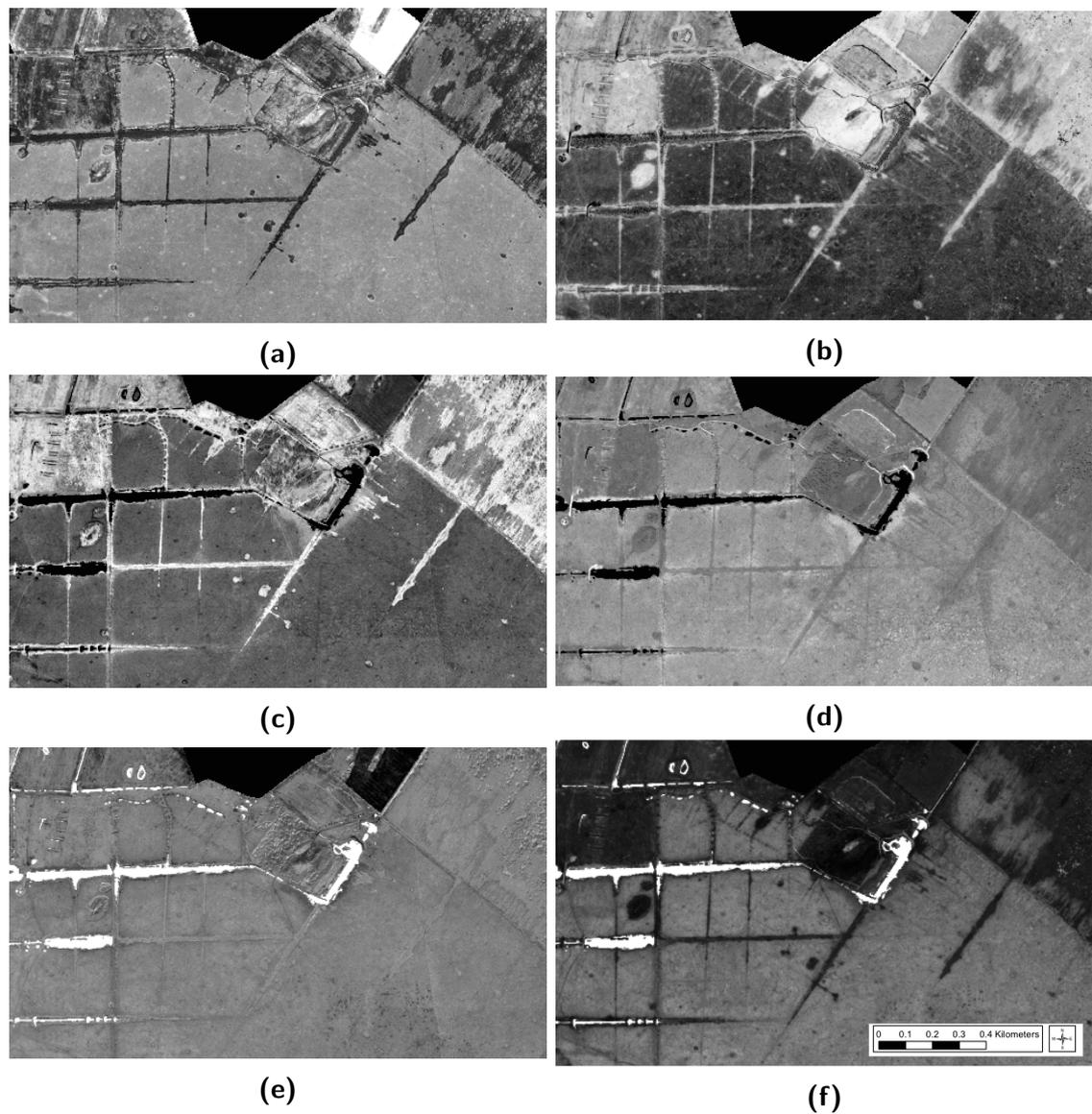
Figure 4.1: Examples of some indices a) preNDVI, b) peakNDVI, c) preP-SRI, d) peakPSRI, e) preWBI and f) peakWBI to demonstrate areas that they highlight. Light to dark indicates high to low indices values. Light areas in a) and b) are highlighing areas of productive green vegetation, in c) and d) are highlighting dead vegetation and in e) and f) are highlighting waterbodies and ditches.

NIR Diff

The difference between the NIR1 and NIR2 (NIR Diff) gives a value for the region NIR1 to NIR2 and was specifically selected for use in the BIOSOS project for discriminating the active bog area of Cors Fochno from the surrounding landscape (Lucas et al., 2012b, 2011b).

$$NIR_{Diff} = \rho 915 - \rho 825 \tag{4.7}$$

BG The Blue green difference (BG) is used to calculate the height of the green peak in spectral data and is useful for assessing chlorophyll content. This was developed and used within BIOSOS (Lucas et al., 2011b).

$$BG = \frac{(\rho 480 - \rho 548)}{(\rho 480 + \rho 548)} \tag{4.8}$$

Woody The Woody index was created and used within BIOSOS to discriminate trees and shrubs from other vegetation (Lucas et al., 2011b).

$$Woody = \rho 429 - \rho 659 \tag{4.9}$$

BR The Blue Red difference index (BR) is the difference between the blue and the red wavelengths. It was used in BIOSOS project to discriminate areas of shrub from trees where LiDAR data is not present or good enough (Lucas et al., 2011b).

$$BR = \rho 480 - \rho 659 \tag{4.10}$$

These indices were used within the BIOSOS project as they were selected using ecological knowledge and trial and error to discriminate surfaces within the LCCS categories of

classification (further explanation in Chapter 5). Their use within this project was to test their suitability for discriminating to the plant species level. Other indices are available but were not investigated as the aim was to investigate the method of selection and not to test all other available indices for suitability.

4.2.4 Species separation analysis

As there are single values for indices rather than a series of 8 spectral reflectance values, a different analysis method was required to test separability of the species data using indices. As indices use different equations with different bands, the values of these varied. This meant there were multiple variables with different scales which. For this reason all index data was standardised first in R using Equation 4.11 before further analysis was carried out in R (see scripts in appendix) to calculate variables (indices) with the greatest separations between the species.

$$x_{i,1\sigma} = \frac{x_i - \bar{x}_s}{\sigma_{x_1 s}} \tag{4.11}$$

To calculate the separations achieved by all of the variables in the multivariate data set a separation index otherwise known as the ANOVA coefficient or F-ratio (F) was calculated. The F-ratio is an extension of Fisher's discriminant (for use between only two classes) which provides a measure of separability between multiple classes (Nicholson et al., 1997). This method was used on each standardised index set. The analysis of variance for between group (Equation 4.12) and analysis of variance for within group (Equation 4.13) were calculated (Weinberg and Abramowitz, 2008). To achieve a separation index for each index variable the between group variance was divided by it's within group variance (Equation 4.14) thus giving a separation value which indicates greater or lesser separation when compared with other variable separation values. This value is known as the F-ratio or F. The larger the value of F, the more likely it is that the null

hypothesis of no differences between the group means is false (Anderson, 2001).

Between group variance:

$$V_b = \frac{\sum \text{n}(\text{x} - \bar{\text{x}})^2}{\text{p} - 1} \qquad (4.12)$$

V_b = Sum of squares between species

p = Total number of species

n = Total number of samples.

Within group was calulated as so:

$$V_w = \frac{\sum (\text{n} - 1)S^2}{\text{N} - \text{p}} \qquad (4.13)$$

V_w = Sum of squares within species

S = Standard deviation for each species

N = Total number of observations.

$$F = \frac{V_b}{V_w} \qquad (4.14)$$

This method is suitable for the data collated as although the F-ratio from an ANOVA test is recommended for Gaussian data there is a general rule that when used on non-normal data there is little effect on the F-ratio values (Tiku, 1971).

Although most of the data analysed is more or less normal some samples have slightly skewed distributions. Scatter plots of best and least effective indices for separating species were used to demonstrate whether this method is still effective at selecting the most suitable indices.

4.3 Results

4.3.1 Visual differences of species

The ten plant species selected for this analysis vary greatly in their seasonal growth patterns and habits. These differences can be observed in Figure 4.2.

Evergreen species such as *Calluna vulgaris* stay green throughout the year but due to a slow down of growth have a considerably larger quantity of dead leaf and dead flower in the winter months (Figure 4.2). In July the plant clearly shows an increase in growth and green leaf. In September there is a flush of pink flowers remaining and fading until November.

Graminoid species such as *Eriophorum angustifolium, Eriophorum vaginatum, Molinia caerulea* and *Phragmites australis* all have lush green growth from July, fading in October and showing a mass of dead litter from November through to July again. For the lower growing graminoids such as *Eriophorum vaginatum* emergent green vegetation is more visible from above in June. The taller graminoids having dead vegetation that obscures the initial emerging green vegetation in June. Eriophorum angustifolium is different in that it has more dead litter visible all year long and less coverage of green productive material in the July to October period than other graminoids. Its leaves have a noticeable red anthrocyanin shade in November as it goes through autumnal senescence. Flowers for *Phragmites australis* are a dark purple shade and the vegetation appears to take on a more glaucous hue in August. By November the flowers have gone to seed and produce large plumes of fluffy white seed heads as can still be seen in April (Figure 4.2) *Juncus effusus* continues to have green material present although largely dead in winter months. As with other graminoids there is a flush of green vegetation in July with live green flowers appearing at the same time. Flowers mature by August turning a brown shade.

Myrica gale a deciduous shrub, has an orange flush of flowers in May with no leaf cover at this time. By June green leaves have emerged with these increasing to their full potential by July. Leaves remained green in early November unlike many of the other deciduous plants.

Pteridium aquilinum, as with *Molinia caerulea*, is a plant that gives complete ground coverage of dead litter in the winter months. It remains this way until a sudden emergence of fast growing green vegetation in July with complete green coverage from then until October when it starts to senesce with yellow and brown shades. By November it was back to complete ground coverage with dead material and no green leaf at all. This appeared to happen much faster for *Pteridium aquilinum* than for other species sampled.

Both *Sphagnum* spp. sampled change very little in appearance throughout the year. They are very different in colour with *Sphagnum cuspidatum* being a lime green and *Sphagnum pulchrum* an amber shade. Both kept these colourings with a slight increase in intensity of colour from July and decreasing again as autumn approaches. A tinge of lime green in fresh growth appeared for *Sphagnum pulchrum* in July until September.

It can be seen too that for the autumnal months (November) there appears to be more shading in the vegetation. This is a major consideration for gathering spectral information. For species such as *Myrica gale* there were noticeable differences within photography. The photograph of *Myrica gale* for November contained a large range of contrast with dark shade, green vegetation and very light bright areas. The photo from the July period had less contrast with few large areas of shading or bright patches.
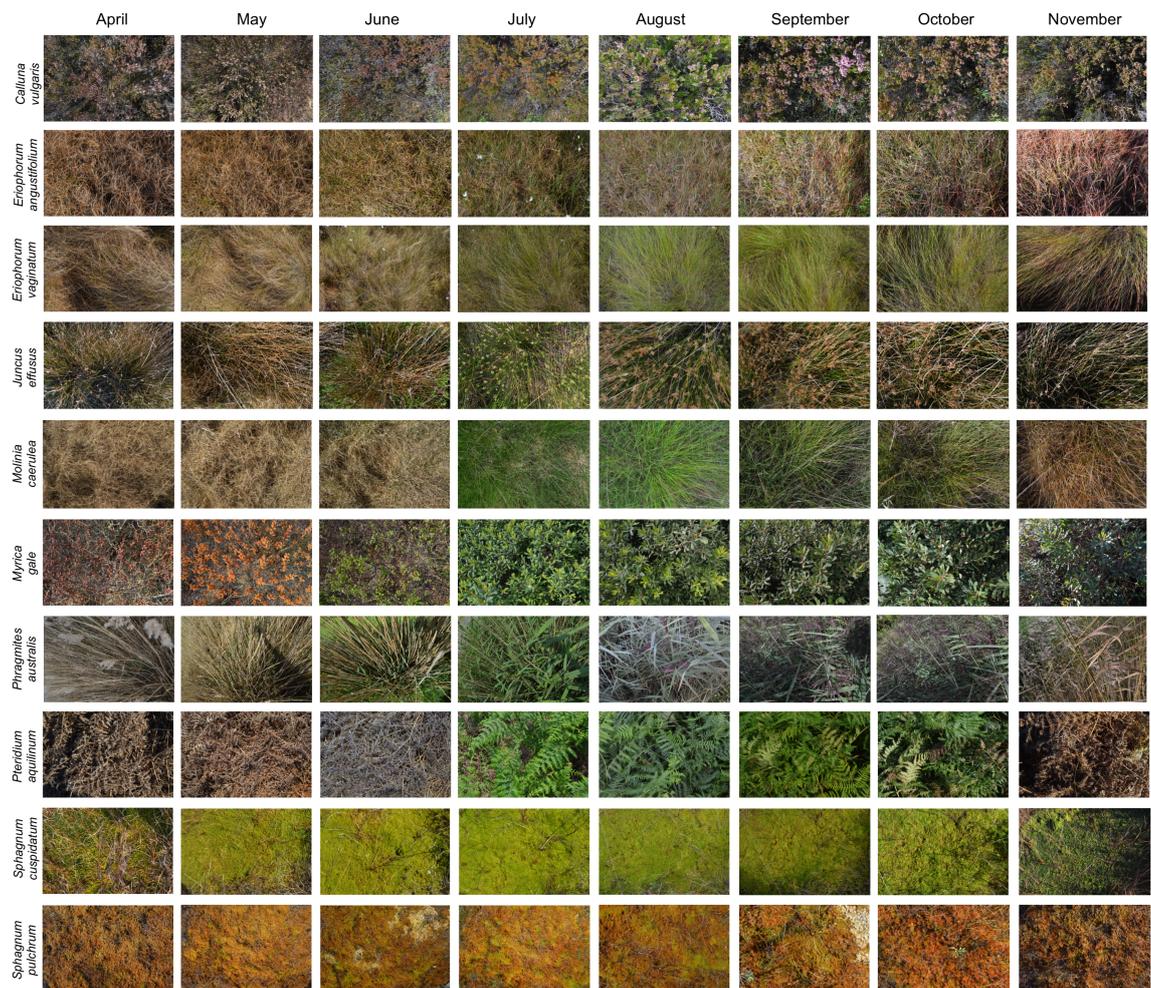
Figure 4.2: Photos of 10 plant species taken at the same time each month from April through until November.

4.3.2 Spectral differences of species

Between species spectral reflectance

Differences in the mean spectral reflectance curves between species may be observed in plots of wavelength versus reflectance (Figure 4.3).

Calluna vulgaris has low green reflectance values throughout the year despite being an evergreen shrub *Calluna vulgaris* as it contains a large amount of dead material throughout the year. There is a noticeable rise in reflectance in the red edge region in

September which is reflected in the photography (Figure 4.2) where the plant is flowering. These observations can also be made in the WV2 reflectance graphs (Figure 4.4). There is also a slight increase in September in the blue region.

Five species with complete dead material/senescent material coverage in April, *Eriophorum angustifolium*, *Eriophorum, vaginatum*, *Molinia caerulea*, *Phragmites australis* and *Pteridium aquilinum* showed a distinctive spectral graph which is typical of dead vegetation. These species become active after the winter months over different time periods and this is reflected within the spectral graphs. Species such as *Pteridium aquilinum* and *Molinia caerulea* are the slowest to green up. This is shown in the reflectance graphs were *Molinia caerulea* starts to green in June as seen in the June spectral graph where the dead material slope is starting to decrease with a decrease in reflectance of the red edge region. *Pteridium aquilinum* does not show a typical green vegetation spectrum until July.

Eriophorum angustifolium has a large amount of dead senescent material present throughout the year with very little green vegetation present in the peak growing period, possibly due to it having very thin upright leaves (synonymous with its latin name angustifolium meaning 'narrow leaves') which from above are not so obvious amongst the dead material when upright. However, when dead and collapsed the leaves lie horizontal. The reflectance spectrum shows the green reflectance is low and does not indicate a significant peak in green wavelength (Figure 4.4). This corroborates the lack of a flush of green material at the peak time as with other graminoids. There is a distinct red hue to its autumnal senescence in November (Figure 4.2) although this does not appear to be reflected in the November spectrum.

As an observer on the ground June and July flowering/seed head periods of *Eriophorum vaginatum* shows as large clouds of white fluffy seed-heads. However, from above, and as shown in the photo (Figure 4.2) seed heads are not visually predominant. There are also no visible changes in the spectrum for the period where they are present.
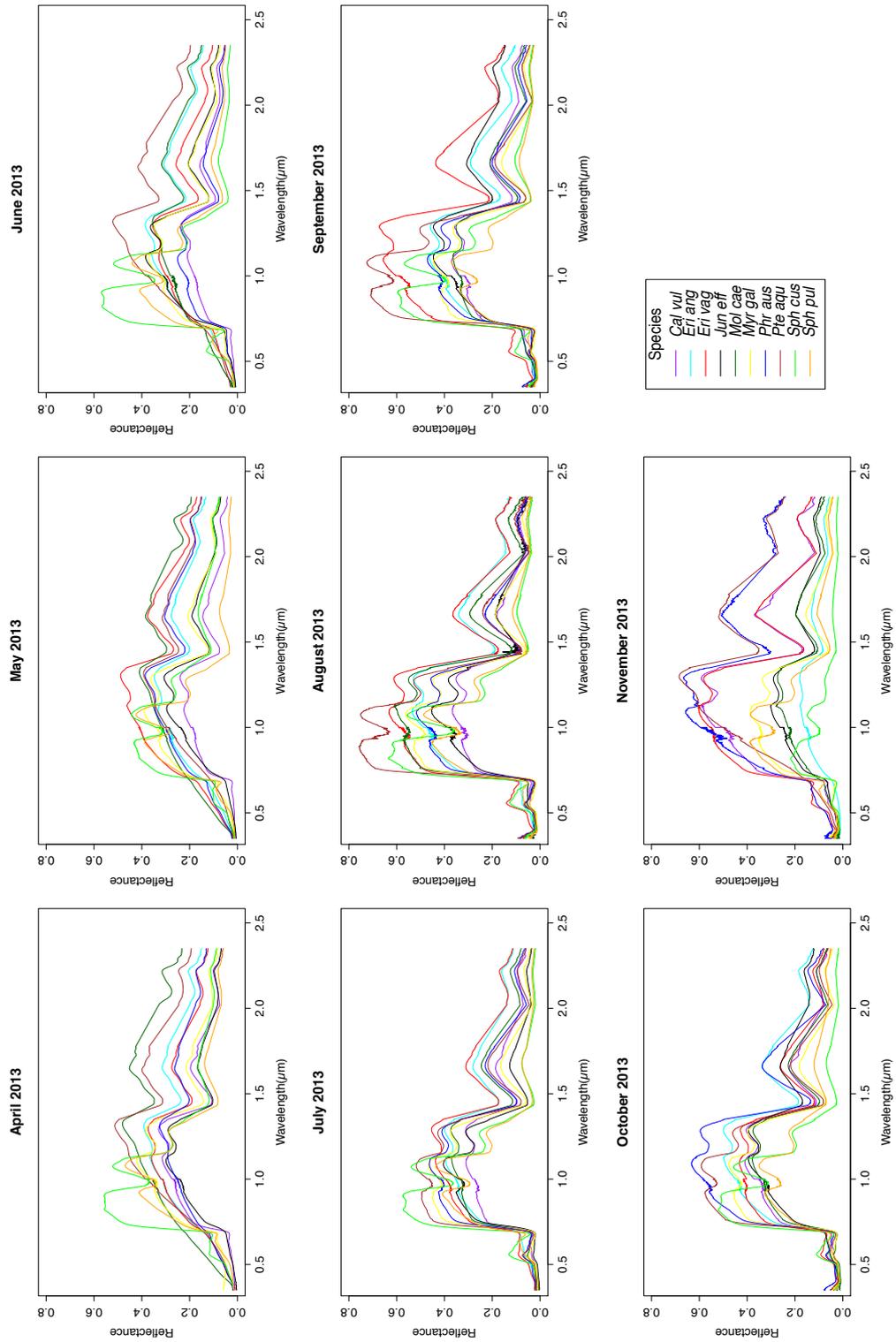
Figure 4.3: Mean spectral reflectance of each species for each month showing differences between species.
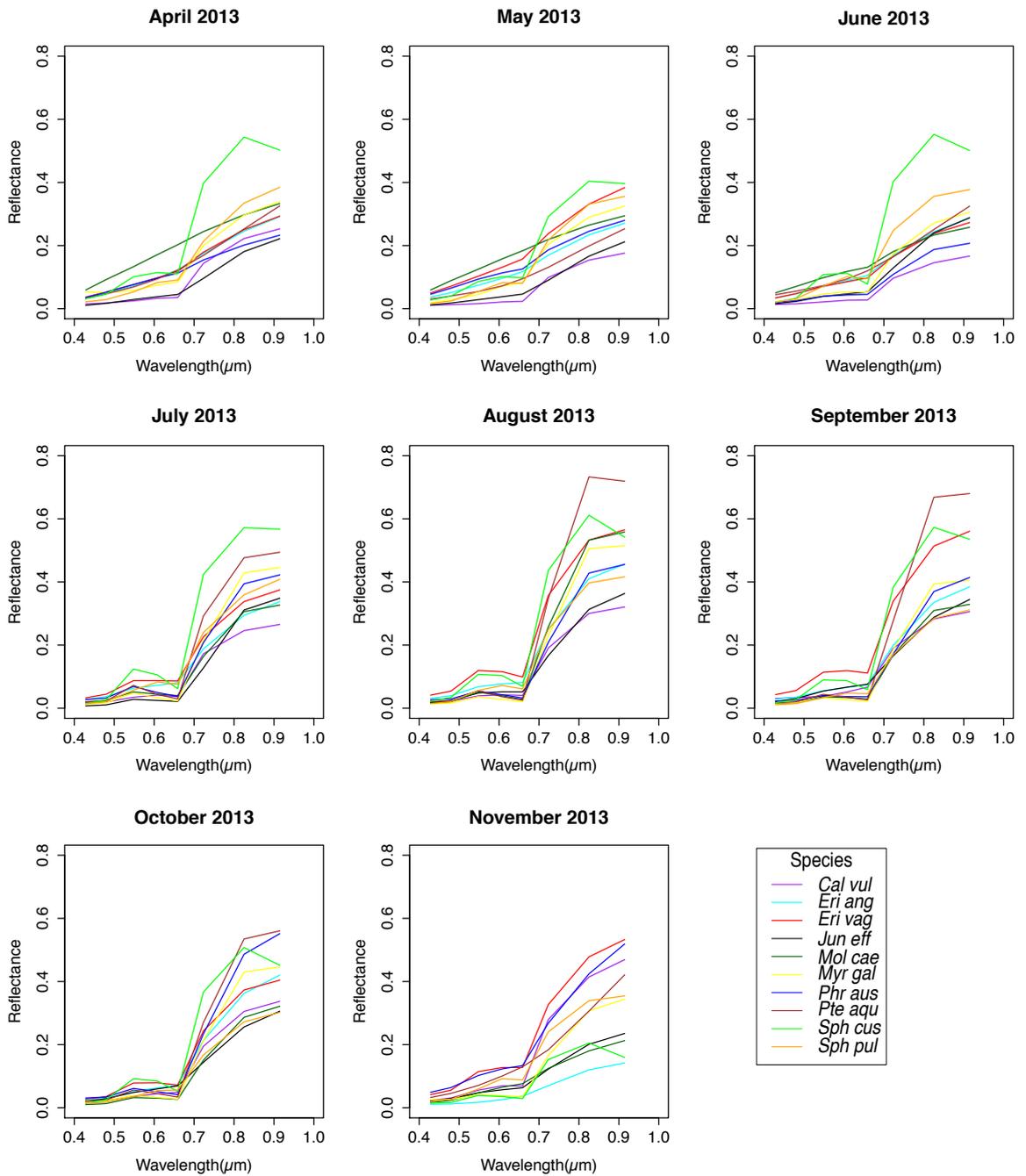
Figure 4.4: Mean spectral reflectance of each species for each month translated to WV2 bands.

Both *Molinia caerulea* and *Pteridium aquilinum* have very distinct periods of dead litter/ senescent material and very lush green growth. There appears to be only 4 months (July - October) of this lush green growth and for the rest of the year they are large

mats of impenetrable dead litter. Differences in growth in these seasonal periods is clearly seen in spectral data (Figures 4.3 & 4.4). Spectral reflectance graphs show a large increase in reflectance in the NIR region for *Pteridium aquilinum* in August and September. Measurements of stacks of leaves, which increases total optical thickness, show increases in near infrared reflectance (Blackburn, 1999).

Compared with other species *Myrica gale* has higher reflectance in the coastal band region. *Myrica gale* shows distinct orange flowering in May (Figure 4.2) although this is not distinguishable in the spectral data (Figures 4.3 & 4.4).

Throughout the year both *Sphagnum* species show a very distinct difference on the shape of their spectral reflectance graphs with a very pronounced dip in the NIR region of the spectrum compared to other species. *Sphagnum cuspidatum* has a reflectance value peak in the green wavelength region throughout the year. *Sphagnum pulchrum* appears unchanged all year but it was noticed however that although there was no apparent senescence the areas of *Sphagnum cuspidatum* were much tighter and more compact with less shading in summer months than in senescent periods (autumn and spring). April and November photos showed looser less compact habit. One of the most noticeable differences between *Sphagnum cuspidatum* and *Sphagnum pulchrum* is the orange colouration of *Sphagnum pulchrum* compared with the almost lime green of *Sphagnum cuspidatum*. These differences in colouration remain throughout the year with slight greening of *Sphagnum pulchrum* occurring in the summer months. These year round differences are visible in the green reflectance region with *Sphagnum cuspidatum* showing very high reflectance values in the green wavelength compared to *Sphagnum pulchrum*. *Sphagnum* has very large cell size compared to other plant species and the dip in the NIR region could be as a result of this structural difference. Both *Sphagnum* species have low reflectance in the SWIR region possibly due to having a large water content and also the effects of growing in water-filled pools or ditches (therefore some backgound effects from water also).

Within species spectral reflectance

The spectral curves of 20 samples of each species were compared within each species. Selected months for visual comparison were to typify the pre, peak and post growing seasons so April, July and November field spectroradiometer readings were used.

Variation in spectral reflectance curves throughout all months is low up to $0.6/0.7nm$(Figure 4.5. 4.6, 4.7 & 4.8). For wavelengths $>0.7nm$ the variation increases and is more pronounced in the NIR and SWIR regions. In comparison with other months April shows a more noticable increase in variation of spectral curves within species for all species (Figure 4.5. 4.6, 4.7 & 4.8). In July the spectral curve of the 20 within species samples for most species is visibly less varied. Spectral curves within species generally shows less variation in November (Figure 4.5. 4.6, 4.7 & 4.8). Species such as *Eriophorum vaginatum* (Figure 4.5), *Pteridium aquilinum* (Figure 4.7) and the *Sphagnums* (Figure 4.7 & 4.8) show least variation in November whilst other species such as *Phragmites australis* (Figure 4.7) are shown to have more variation within species spectral curves in November.

This spectral information shows that discrimination of one species from another may also be dependant not only upon between species differences but also within species similarities.
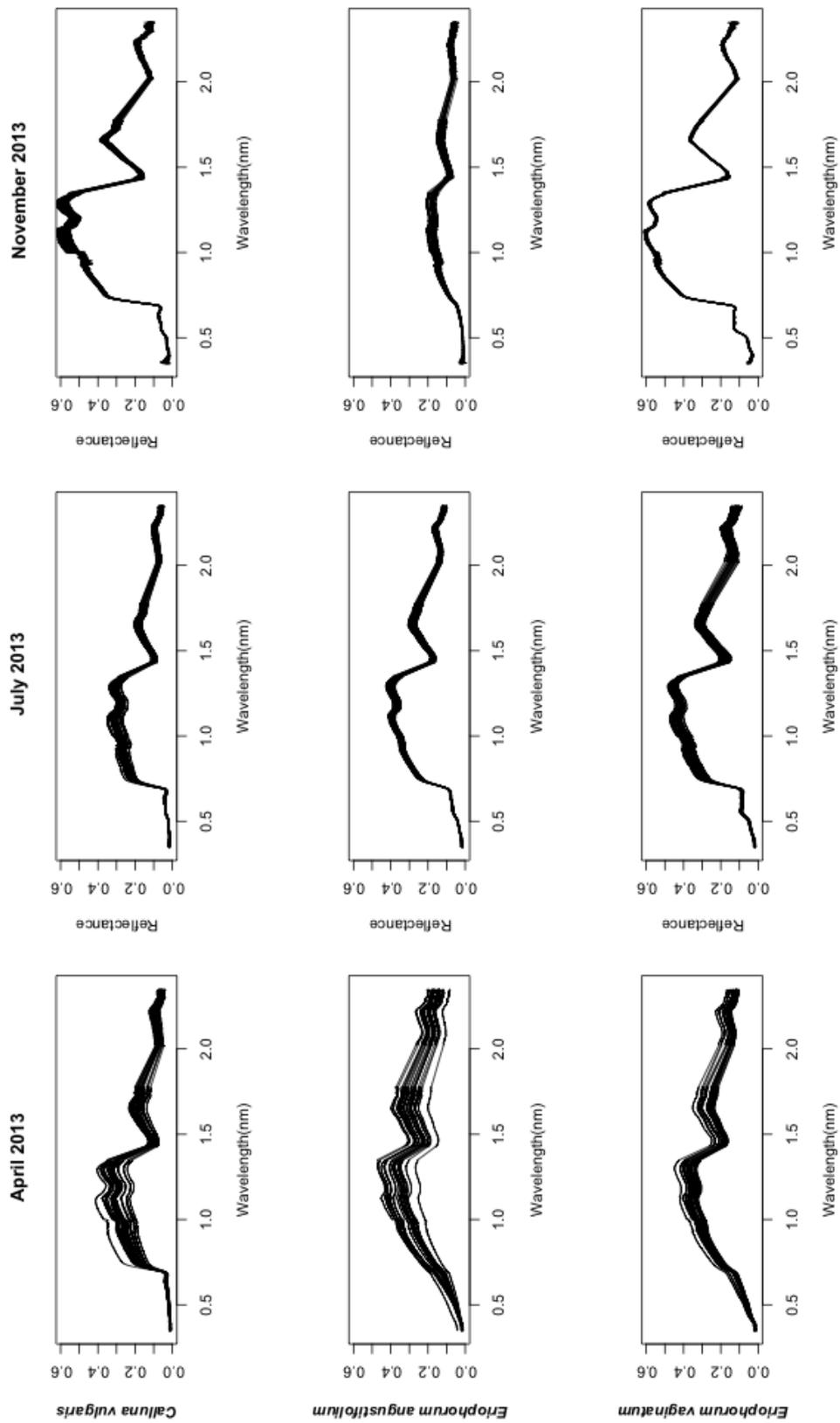
Figure 4.5: Spectral reflectance of each species for April, July and November showing the within species variation in spectral curves.
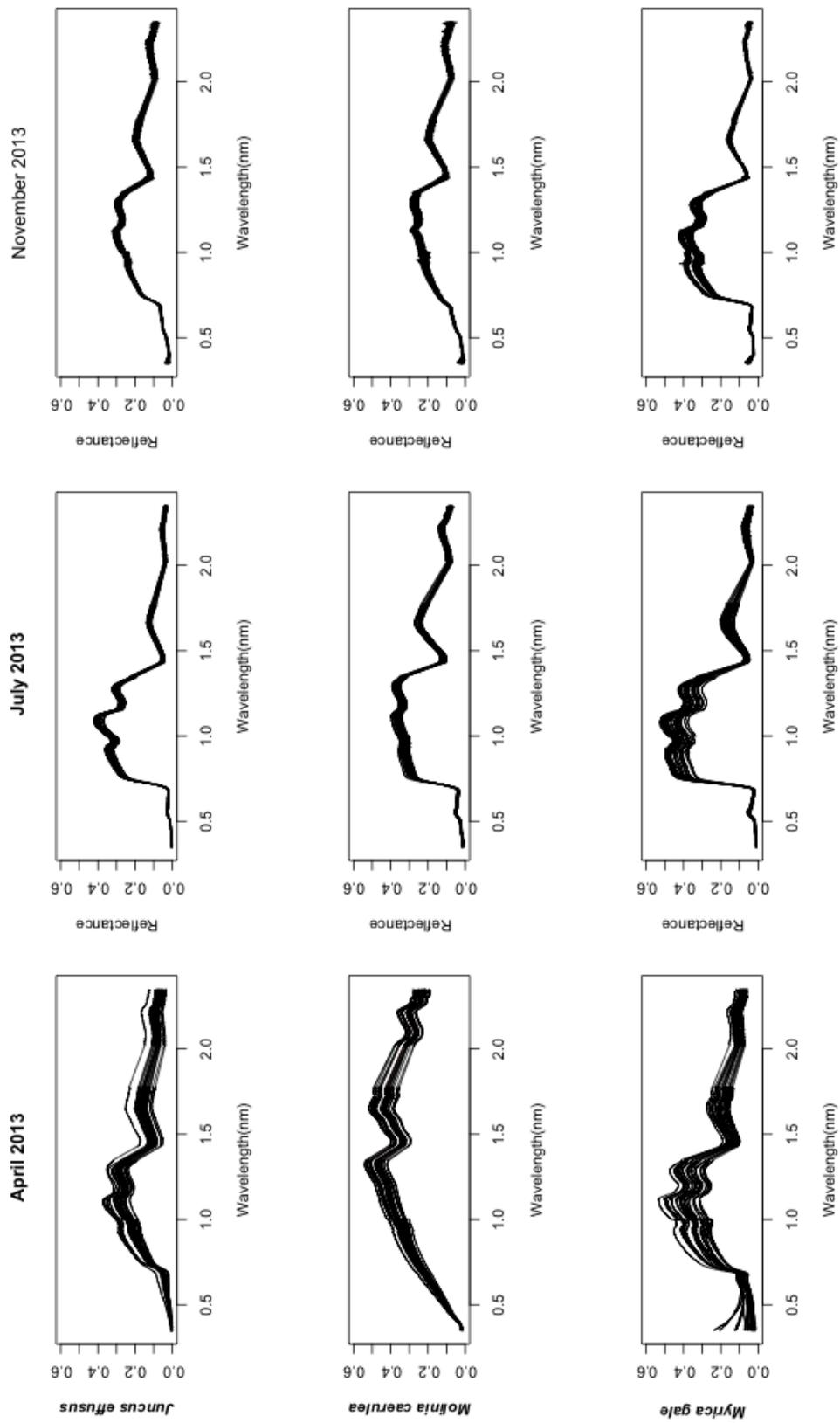
Figure 4.6: Spectral reflectance of each species for April, July and November showing the within species variation in spectral curves.
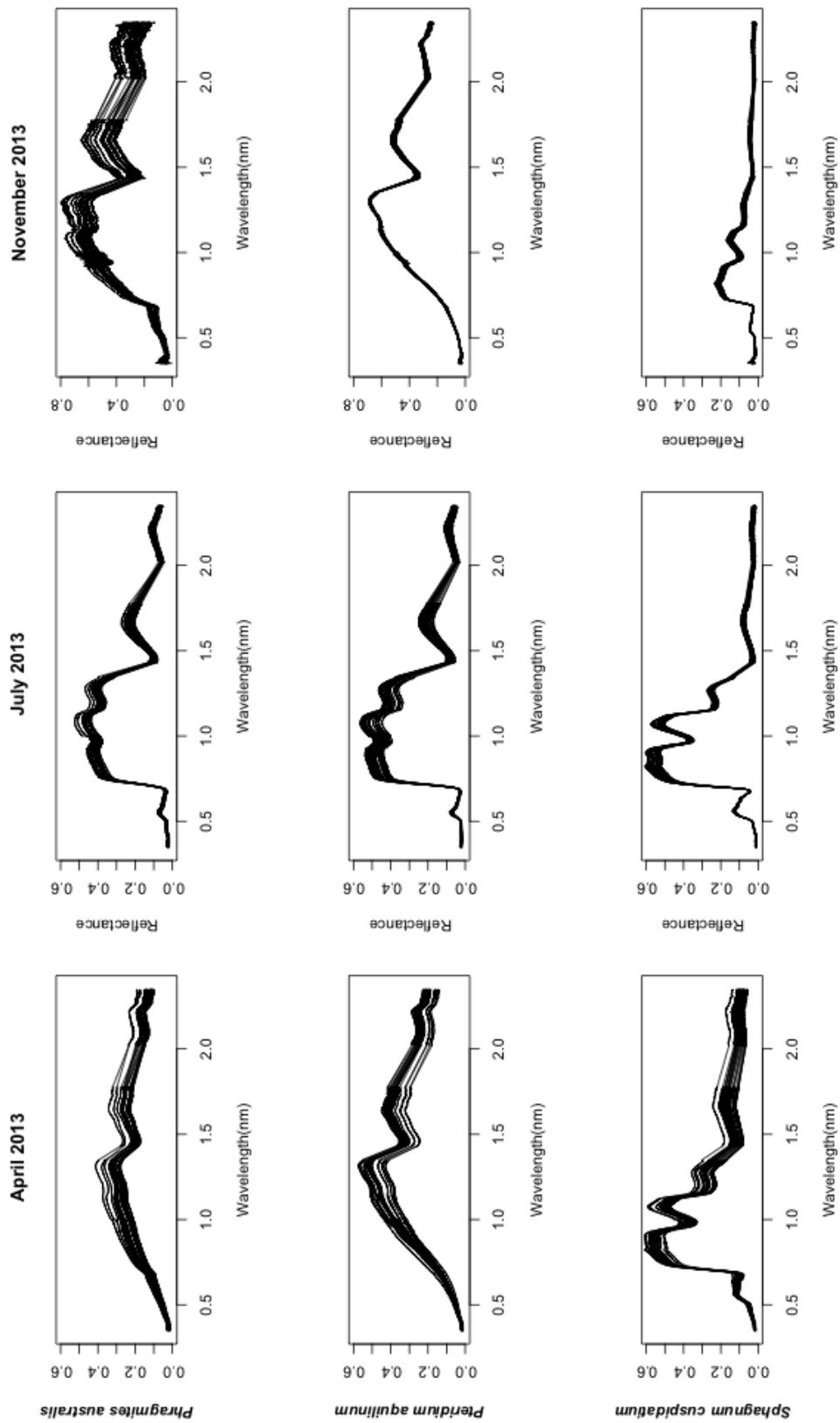
Figure 4.7: Spectral reflectance of each species for April, July and November showing the within species variation in spectral curves.

Figure 4.8: Spectral reflectance of each species for April, July and November showing the within species variation in spectral curves.

4.3.3   Spectral angle analysis

Between species spectral reflectance

For the full recorded spectrum where the total number of species comparisons with scores for 0.00 in the spectral angle analysis, April is shown to be one of the best months for species separability with an overall total of 52 equal to 0.00 scores (Table 4.2). November and June also gave higher scores of 46 and 44 (Table 4.2). The month with the least separability was August with 30 equal to 0.00. These results can also be seen using the variance of spectral angle values for between species analysis (Figure 4.9) showing this to be greatest in April for most species.

For the spectrum range between 300 and 1000nm range using the total number of scores of 0.00, again April is one of the best months for species separability with an overall total of 18 (Table 4.3). Again June and November months were better at providing reflectance data with better discrimination of species with 16 0.00 scores. The month with the least separability was September as there were no 0.00 scores.

For the spectrum converted to WV2 bands only, using the total number of scores of 0.00 April was again shown to be one of the best months for species separability with an overall total of 17 equal to 0.00 scores (Table 4.4). Months from July until October gave no equal to 0.00 scores at all proving to be months that provide the least separability if using the WV2 bands.

Despite the decrease in spectral angle scores of 0.0 as the number of wavelengths are reduced these results still show the same outcome with April being the best across all the scales of wavelengths.

	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Total
April	6	4	2	4	5	6	5	4	8	8	52
May	4	2	2	3	5	4	3	3	7	8	41
June	2	2	2	4	5	4	4	5	8	8	44
July	2	5	5	3	3	4	2	4	8	6	42
August	2	4	3	1	1	2	1	3	8	3	28
September	3	4	4	5	3	4	2	5	7	5	42
October	1	4	1	4	1	3	3	3	9	3	32
November	3	3	3	3	3	6	3	5	9	8	46
Total	23	28	22	27	26	33	23	32	64	49	

Table 4.2: Table showing number of spectral angle scores with values of 0.00. using reflectance values for **full spectrum** available from field spectroradiometer of range 300um to 2500um i.e. the number of occasions (out of a total of 90 possibles for each month) were there is a highly significant separability score.

	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Total
April	2	1	0	2	4	0	2	1	5	1	18
May	2	0	0	1	5	1	1	0	1	1	12
June	1	1	1	2	4	1	0	1	5	0	16
July	0	0	0	0	0	0	0	0	0	0	0
August	0	0	0	1	0	0	0	0	1	0	2
September	0	0	0	0	0	0	0	0	0	0	0
October	0	0	0	1	0	0	1	0	3	0	5
November	1	1	1	1	1	1	1	1	8	0	16
Total	6	3	2	8	14	3	5	3	23	2	

Table 4.3: Table showing number of spectral angle scores with values of 0.00. using reflectance values for the spectrum of range **300um to 1000um** to reflect WV2 range i.e. the number of occasions (out of a total of 90 possibles for each month) were there is a highly significant separability score.

	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Total
April	4	1	1	2	5	1	3	0	2	1	20
May	3	1	0	2	5	1	2	0	1	1	16
June	1	0	0	0	6	1	1	1	2	1	13
July	0	0	0	0	0	0	0	0	0	0	0
August	0	0	0	0	0	0	0	0	0	0	0
September	0	0	0	0	0	0	0	0	0	0	0
October	0	0	0	0	0	0	0	0	0	0	0
November	0	1	0	1	1	1	1	1	6	0	12
Total	5	3	0	5	15	3	6	3	14	3	

Table 4.4: Table showing number of spectral angle scores with values of 0.00 using reflectance values significant to the **8 WV2 bands**, 429, 480, 548, 608, 659, 723, 825, 915 nanometers i.e. the number of occasions (out of a total of 90 possibles for each month) were there is a highly significant separability score .

The results of the spectral analysis shows that differences between mean reflectance spectra of vegetation types are statistically significant for different vegetation types. April is the best period for discrimination of species based on the spectral angle analysis of the mean spectral reflectance values.

Sphagnum mosses are more highly separable from all other species throughout most of the year. *Sphagnum* reflectance values for the full 300 to 2500nm range gave the best separability. However, this decreased more for *Sphagnum pulchrum* when less of the spectrum was used. There are, as previously described, significant dips in the NIR region for *Sphagnum*. This dip occurs at a slightly higher wavelength for *Sphagnum pulchrum* so that reflectance measured below 1000nm misses this significant feature. Anomalies like this are useful for species seperation. However, this anomaly is unfortunately not recognised with WV2 reflectance values. It may be however that another very high resolution sensor (e.g.hyperspectral imagery) (Harris et al., 2015) which focuses on the relevant wavelength range, would be better to use if this species was of particular focus.

Eriophorum vaginatum gave the lowest scores for separability for all 3 reflectance testing regions with expected decreases in separability as less of the spectrum is used. Where only WV2 bands were used *Molinia caerulea* and *Sphagnum cuspidatum* had the best separability scores (Table 4.4).
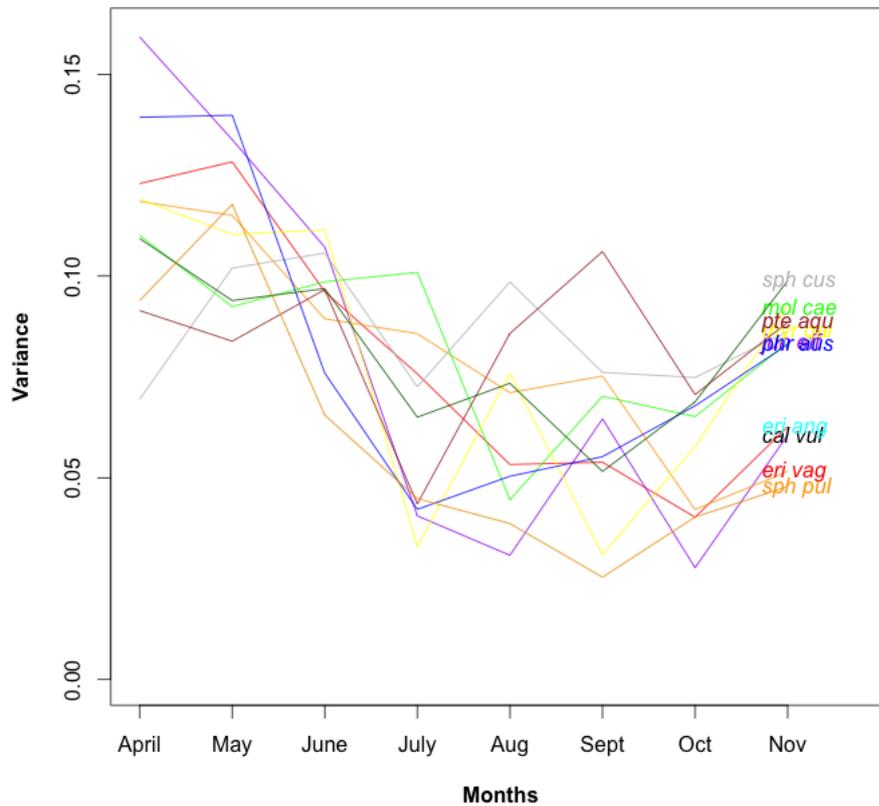
Figure 4.9: Variance of spectral angle values between species for each month from April to November.

Within species spectral reflectance

It is shown and acknowledged from previous spectral curve data (Figure 4.5. 4.6, 4.7 & 4.8) in the previous section that within species spectral differences could be significant at different times of year and these variations within the species may have an influence on the between species discrimination. To investigate this visual appearance the variance of spectral angle values from within species spectral angle analysis was calculated.

	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Total
April	10	4	2	0	18	0	5	15	7	13	74
May	13	9	8	0	19	5	13	16	6	10	99
June	11	17	14	14	6	13	3	19	18	17	132
July	2	17	4	0	1	0	1	0	0	0	25
August	20	5	13	4	20	12	11	20	20	20	145
September	20	20	19	16	20	17	11	19	20	19	181
October	20	20	20	1	20	20	14	18	20	20	173
November	20	19	20	20	20	20	0	15	19	20	173
Total	116	111	100	55	124	87	58	122	110	119	

Table 4.5: Table showing number of spectral angle scores with values above 0.95 using reflectance values significant to the **8 WV2 bands**, 429, 480, 548, 608, 659, 723, 825, 915 *nm* i.e. the number of occasions (out of a total of 200 possibles for each month) were the separability score is 0.95 and above demonstrating the greater similarity of spectral data within a species (opposite way round to the between data to illustrate best times for acquisition being when within species are most similar).

The number of occasions where the spectral angle was ≥ 0.95 was highest in September to November, much lower in April and the lowest being July (Table 4.5). This shows that spectral variation within species was less in November and greatest in July with April also being a month of greater variation in spectral data within species. The data here also shows that species such as *Juncus effusus, Myrica gale*, and *Phragmites australis* have more variability in their spectral data. Using Table 4.5 it can be seen that the month where species have less variation in their spectral values is in September with the most variation in July. This is not necessarily the best month for species taken individually but the best for looking at the species if there were only one period available for species discrimination.

It can be seen in (Figure 4.10) that the variance of the spectral angle values is generally greater in April for within species comparisons. This variance is greatly reduced for most species in the July and August months (Figure 4.10). Species such as *Molinia caerulea* and *Phragmites australis* have an increase in October and November when they have died back and remain as dead litter (Figure 4.10). All other species show far less spectral angle variance for the autumnal October and November periods (Figure 4.10).
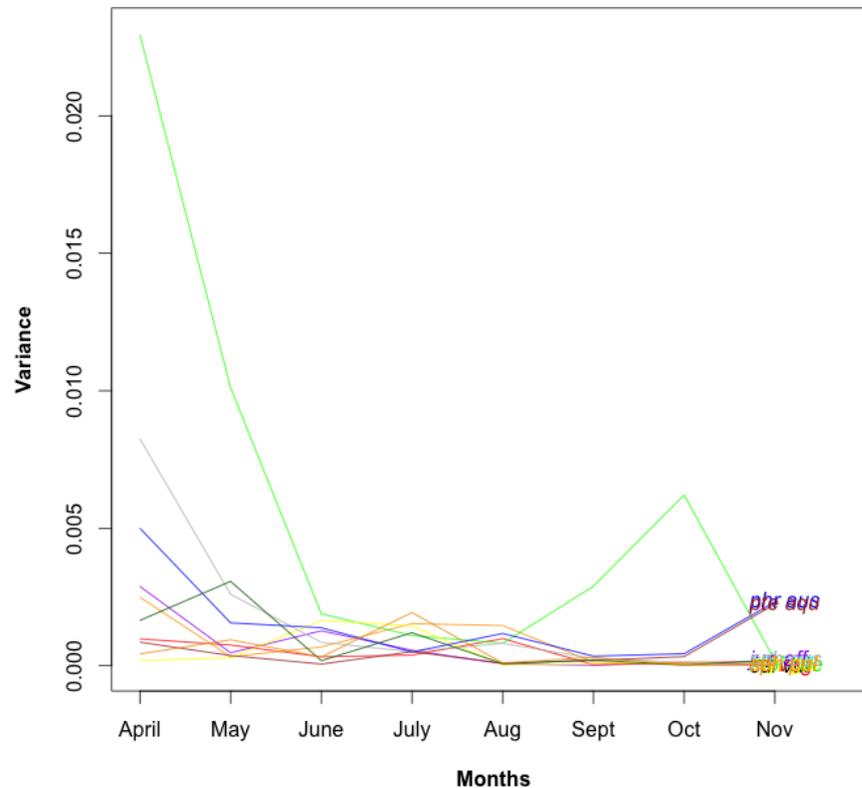
Figure 4.10: Variance of spectral angle values within each species for each month from April to November.

4.3.4 Species discrimination using spectral indices

Visual Differences

Flowering of *Calluna vulgaris* is reflected in the NDVI curves with a dip in the September flowering period (Figure 4.11). *Molinia caerulea* has a very steep increase in NDVI compared with many other species in peak growth periods (Figure 4.11). Phenological occurrences like these have the potential within a site to be used to help discriminate from other species. BG indices also showed significant changes in this flowering period (Figure 4.12). Sphagnum pulchrum has a relatively constant NDVI throughout the year

whilst *Sphagnum cuspidatum* gave much lower BG and NIR diff values compared to other species throughout the year (Figure 4.12). The August and September period show a much higher FDI value for *Pteridium aquilinum* than for other species.
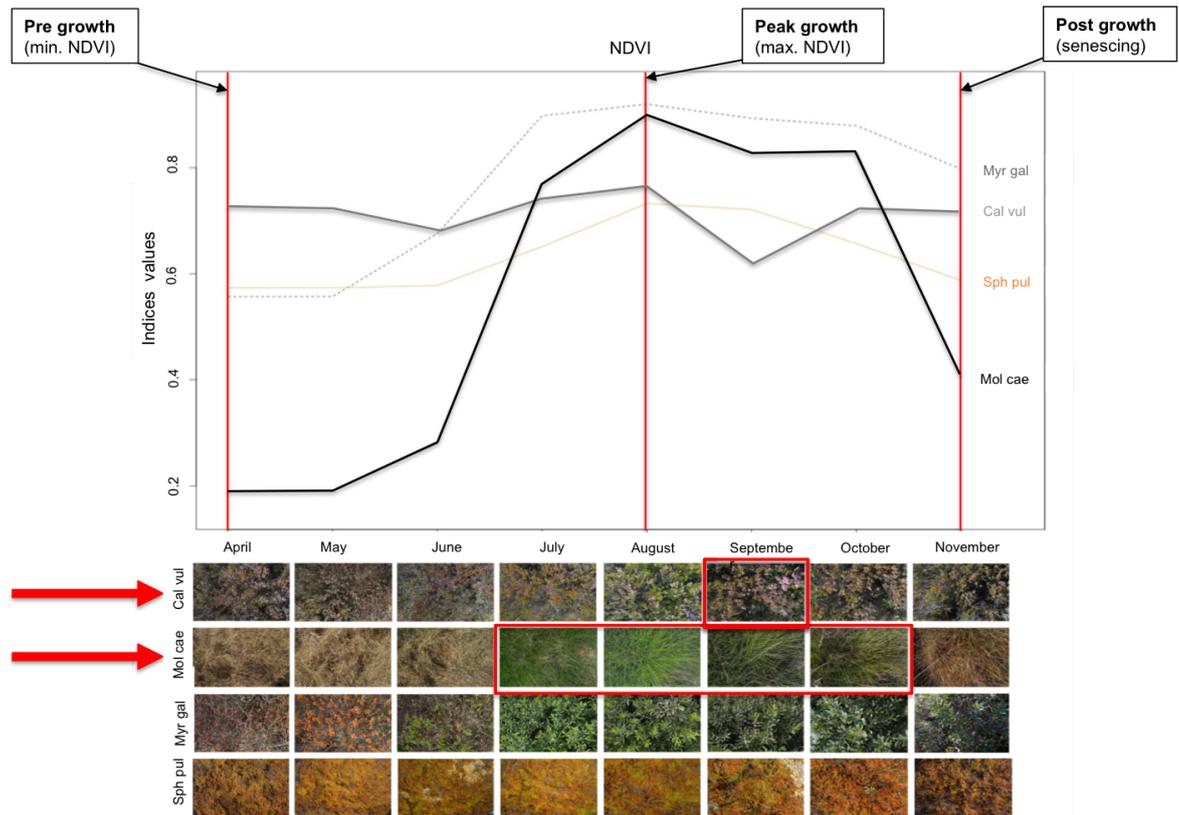
Figure 4.11: NDVI seasonal Curve for four selected species.

Species Separation Analysis

ANOVA analysis using separation values gave high F-ratio (separation) values for a number of indices. The F-ratio values were very variable with a large scale from 85888.25 down to 90.09 (Table 4.6). These values indicated that the species were highly separable. The best separation was achieved using the September BG followed by September PSRI and September NDVI. The period giving least separation are the majority of April indices which give the lowest separation was April, with all indices (and particularly the FDI) performing poorly.
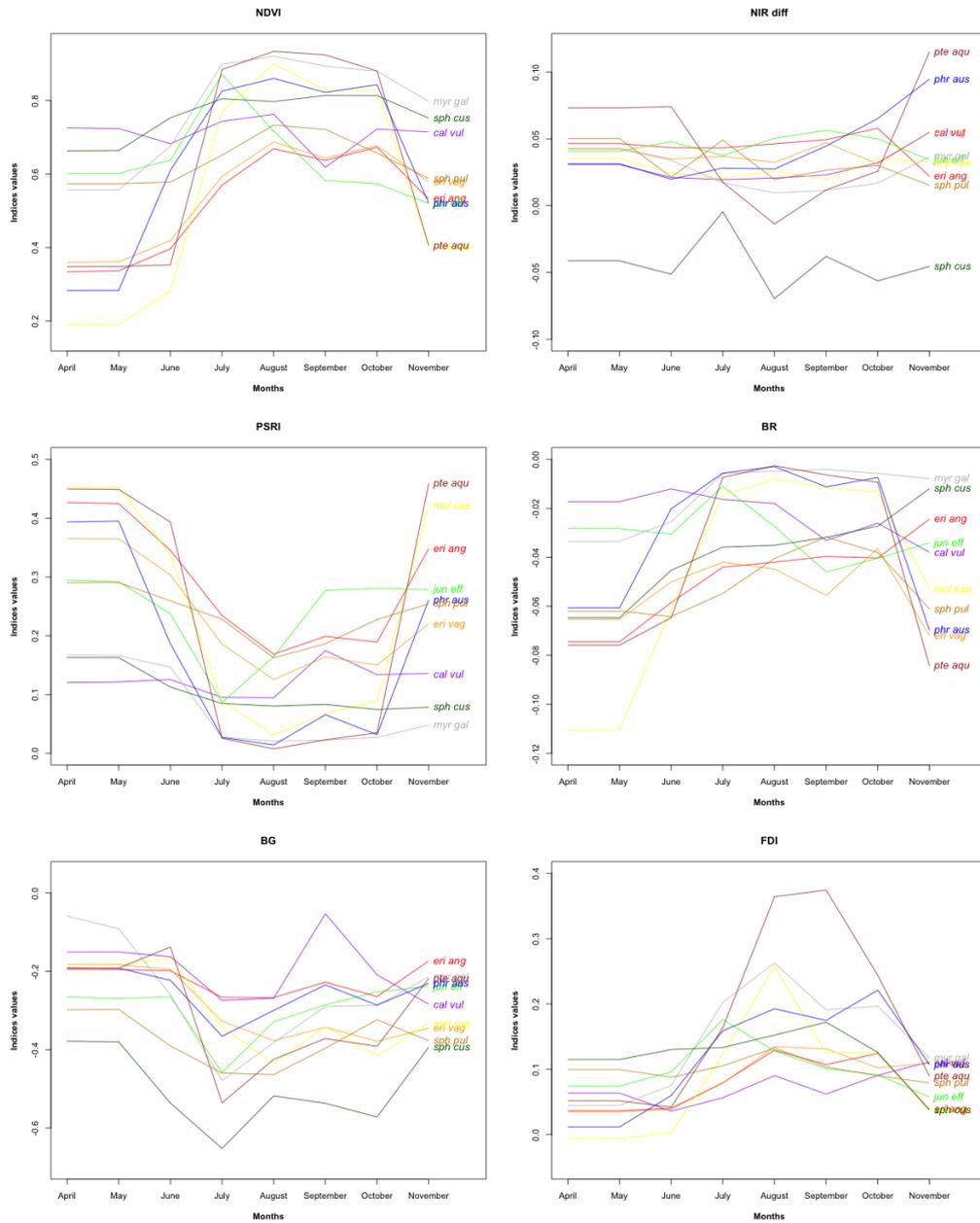
Figure 4.12: Monthly indices of species based on mean data.

The best 5 indices were September BG, September PSRI, September NDVI, October, PSRI, and November NIR diff. These indices give the best separation as they have the lowest within specie variance and the highest between species variance. Once the best 5 indices were selected a pair plot (Figure 4.13) demonstrated the separability of species using these.

A pair plot of five of the least useful indices for separating species were compared with the best/most effective indices to demonstrate the methods' success (Figure 4.14). The pair plots of the least effective indices showed a greater spread of points with some species merging with others thereby proving. This is due to there being a greater within species variance in April. These plots showed that the selection process for best indices for species separation worked. Table 4.6 shows how the variance within each species generally increases from best to least effective indices for discrimination. The order of variance increase is not necessarily the same when species are sampled individually as a group (Table 4.7).

As an example, in the pair plots it is apparent that *Calluna vulgaris* is easily separable using the September BG index (Figure 4.13). This result is shown in the BG index where a peak for *Calluna vulgaris* in the flowering period is visible (Figure 4.12). This peak shows the BG value to be much higher than that of the other species giving it a distinction from these.

Species	Sept BG	Sept PSRI	Sept NDVI	Oct PSRI	Nov NIR diff		April PSRI	April BR	April BG	April WBI	April FDI
Cal vul	0.00036	0.00081	0.00034	0.00221	0.00193		0.01035	0.00906	0.05690	0.04270	0.10577
Eri ang	0.00114	0.00048	0.00127	0.00401	0.00248		0.20774	0.28439	0.04492	0.08674	0.05989
Eri vag	0.00042	0.00005	0.00010	0.00206	0.00051		0.09258	0.07206	0.01184	0.04692	0.03293
Jun eff	0.00032	0.00527	0.00251	0.03149	0.00068		0.06182	0.08430	0.13979	0.11391	0.29616
Mol cae	0.00916	0.00075	0.00328	0.00266	0.00116		0.14497	0.14474	0.00224	0.00417	0.00419
Myr gal	0.00101	0.00443	0.01033	0.00304	0.00313		0.33950	0.57047	1.12027	1.52171	1.35365
Phr aus	0.00311	0.00684	0.01571	0.01978	0.06419		0.13679	0.10800	0.02718	0.05383	0.02016
Pte aqu	0.00121	0.00709	0.01177	0.01057	0.00336		0.04965	0.09944	0.00982	0.01691	0.02225
Sph cus	0.00094	0.00039	0.00238	0.00038	0.00036		0.04787	0.11955	0.08963	0.01078	0.04701
Sph pul	0.00802	0.01016	0.00718	0.00041	0.00188		0.02589	0.04958	0.05207	0.00447	0.04632
					Best	$\Rightarrow$	**Least**				

Table 4.7: Variance for each species of indices used for best and least discrimination of species.

The pair plots (Figure 4.13) show September BG and November NIR Diff indices are effective at discriminating *Sphagnum cuspidatum* from other species as also indicated by the BG and NIR Diff indices graphs (Figure 4.12). *Phragmites australis* shows more variability within the species in the best indices pair plot (more scattered points) (Figure 4.13).

Variable	Vw	Vb	F-ratio	Variable	Vw	Vb	F-ratio
Sept BG	0.00	22.06	8588.25	June REP	0.02	21.60	893.06
Sept PSRI	0.00	22.03	6075.12	Sept REP	0.02	21.59	871.46
Sept NDVI	0.01	22.00	4008.26	Sept FDI	0.03	21.57	839.39
Oct PSRI	0.01	21.95	2865.30	July NIR diff	0.03	21.54	802.33
Nov NIR diff	0.01	21.94	2753.24	Nov WBI	0.03	21.54	790.78
Nov PSRI	0.01	21.94	2719.24	Oct Woody	0.03	21.53	786.37
July BR	0.01	21.92	2410.47	June PSRI	0.03	21.53	777.18
Nov BG	0.01	21.92	2388.27	Oct BR	0.03	21.51	756.89
Sept BR	0.01	21.91	2325.28	Nov BR	0.03	21.46	690.58
Oct NIR diff	0.01	21.91	2280.66	July NDVI	0.03	21.44	677.75
Sept WBI	0.01	21.91	2261.39	Aug REP	0.03	21.42	650.79
Nov NDVI	0.01	21.91	2247.40	May REP	0.03	21.41	645.36
June BG	0.01	21.88	1996.44	Oct FDI	0.03	21.41	641.57
Aug NIR diff	0.01	21.88	1994.23	May BG	0.03	21.40	634.70
Aug BR	0.01	21.87	1925.49	July REP	0.04	21.31	565.02
Nov REP	0.01	21.85	1757.42	Aug FDI	0.04	21.29	550.68
June NIR diff	0.01	21.82	1585.00	April NIR diff	0.04	21.29	549.27
Aug Woody	0.01	21.82	1581.93	May FDI	0.04	21.21	498.30
Oct BG	0.01	21.82	1575.03	May PSRI	0.05	21.15	463.20
Sept NIR diff	0.01	21.81	1509.37	April Woody	0.05	21.10	440.38
Sept Woody	0.01	21.80	1503.03	April NDVI	0.05	21.05	420.59
May WBI	0.02	21.78	1398.69	July FDI	0.05	20.99	395.75
June WBI	0.02	21.75	1255.68	July WBI	0.05	20.98	390.54
April REP	0.02	21.72	1172.77	June BR	0.06	20.93	375.43
Oct REP	0.02	21.71	1138.92	Aug WBI	0.06	20.93	374.17
May NDVI	0.02	21.70	1112.50	July BG	0.06	20.80	333.76
July Woody	0.02	21.69	1092.11	Aug BG	0.07	20.73	316.67
July PSRI	0.02	21.69	1085.19	May Woody	0.07	20.63	294.43
Nov Woody	0.02	21.69	1078.59	May NIR diff	0.07	20.58	284.49
Oct NDVI	0.02	21.66	1010.19	Oct WBI	0.09	20.24	227.84
June NDVI	0.02	21.66	1006.12	May BR	0.09	20.17	219.77
June Woody	0.02	21.65	989.75	April PSRI	0.10	20.05	205.27
Aug PSRI	0.02	21.65	987.94	April BR	0.15	18.86	122.32
Aug NDVI	0.02	21.63	943.69	April BG	0.16	18.83	121.11
Nov FDI	0.02	21.62	925.66	April WBI	0.19	18.10	95.13
June FDI	0.02	21.62	925.65	April FDI	0.20	17.91	90.09

Table 4.6: Separations between species. Larger F-ratio values indicating better separation of all species using the specified indices for all months. Vw= Variance within species, Vb= Variance between species
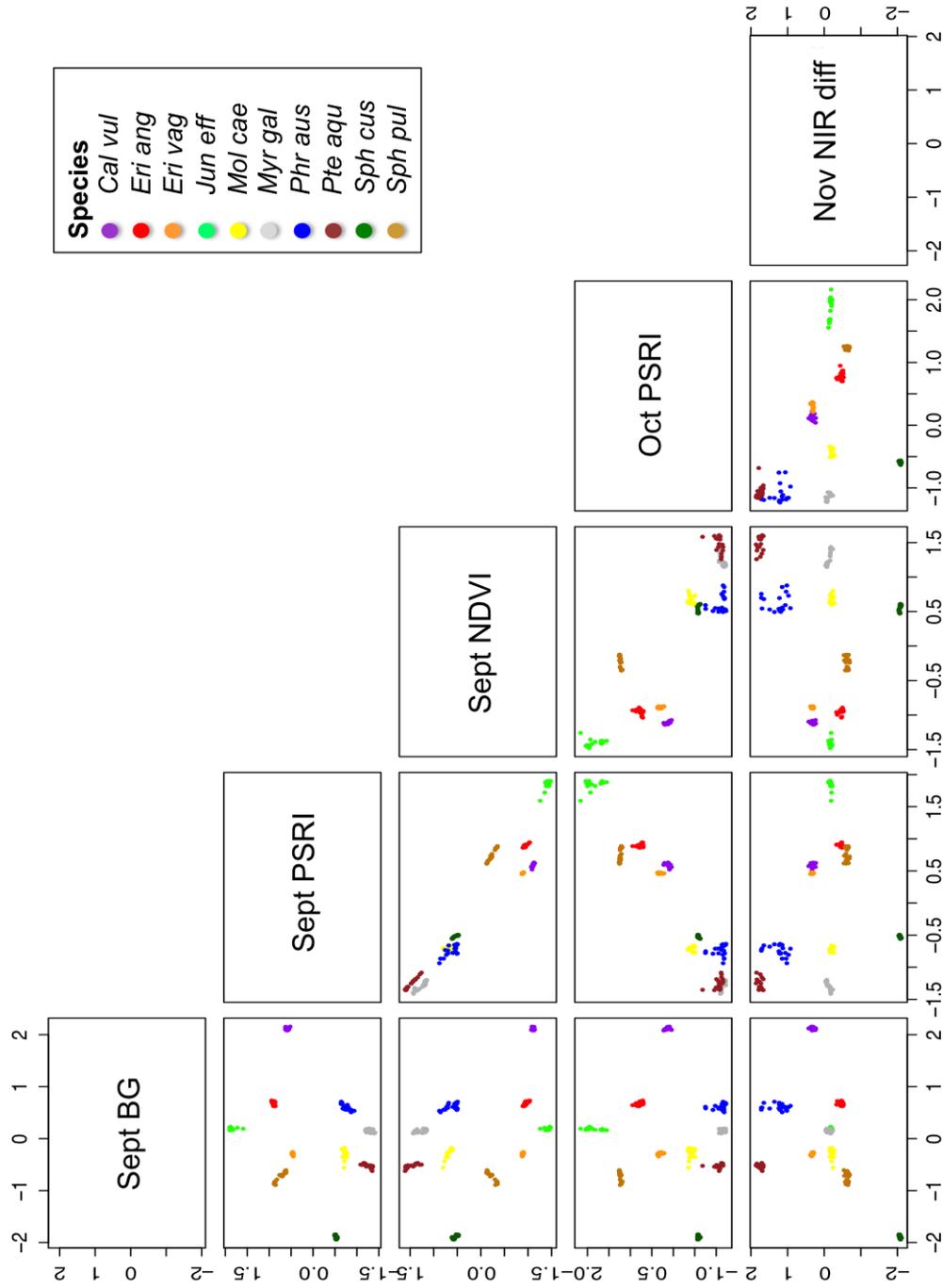
Figure 4.13: Pairplots of species indices values using the best 5 indices for species separation using the F-ratio values 4.7, demonstrating definite separation of species using pairs of the 5 most effective indices.
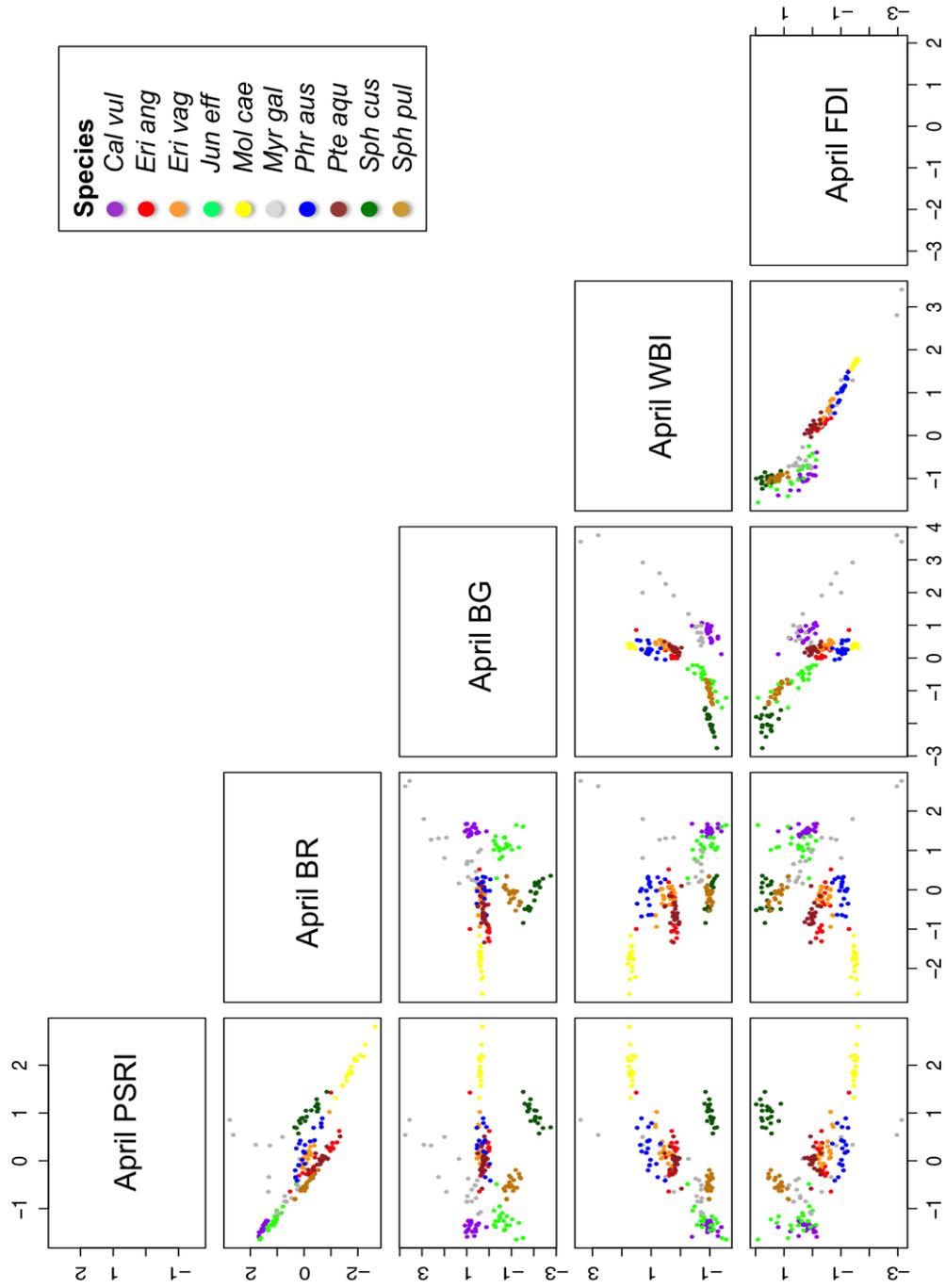
Figure 4.14: Pairplots of species indices values using the least effective 5 indices for species separation using the F-ratio values 4.7, demonstrating difficulty of separation of species using pairs of the 5 least effective indices.

4.3.5   Species discrimination from multiple dates

Combining between and within species variance of spectral angle scores an F-ratio for each month and species was calculated. The results of this analysis shows that the best time for discrimination of each species is dependant upon which species is to be discriminated. When trying to discriminate a larger number of species (in this case 10) multidate imagery would be advantageous providing more accurate species discrimination. In an ideal world an image for each suitable period for each species would be selected. If costs were excessive a smaller selection would be appropriate. Using the F-ratio of the spectral angles (Table 4.8) the obvious selection would be September and November with June, August and October showing equal potential for the third choice. When using results from the indices F-ratios (Table 4.6) it can be seen that these results are in agreement. The first five best indices selected using the F-ratio method were from the September, October and November periods. These results, however, do not take into account the usefulness of differences in growth between pre and peak periods that can also be used to improve species discrimination. For this reason it may also be useful to use a pre and peak period image.

	April	May	June	July	August	September	October	November
cal vul	55.23	283.75	84.37	72.08	444.80	3693.01	242.54	2203.48
eri ang	125.76	170.37	296.52	196.40	54.04	1343.10	362.21	403.97
eri vag	47.59	354.76	130.62	56.01	48.71	564.07	1665.39	3150.17
jun eff	4.80	9.14	52.22	91.89	54.55	24.31	10.49	415.01
mol cae	633.18	384.69	67.58	22.69	2782.13	397.51	469.39	1149.37
myr gal	8.41	39.24	124.29	141.91	120.76	290.98	574.05	1147.47
phr aus	27.87	89.69	54.95	84.32	42.95	158.06	155.97	35.78
pte aqu	106.63	226.84	1620.26	85.32	943.87	538.59	213.41	39.56
sph cus	66.30	30.61	527.81	54.15	972.78	253.50	2681.54	464.21
sph pul	219.28	124.68	206.07	23.17	388.20	84.17	1343.80	3106.84

Table 4.8: F-ratio values for the variance of between and within species spectral angle values for 8 WV2 bands.High values as indicated by values in blue show best separability due to low within species variance and high between species variance. Low values as indicated by values in red show high within species variance as well as low between species variance.

These results (Table 4.8) show that the best month for discrimination using the WV2 spectral data for the species are as follows with decreasing discrimination shown from F-ratio values:

Species	Month	F-ratio
Pte aqu	June	1620.26
Mol cae	August	2782.13
Cal vul	September	3693.01
Eri ang	September	1343.10
Phr aus	September	158.06
Sph cus	October	2681.54
Eri vag	November	3150.17
Jun eff	November	415.01
Myr gal	November	1147.47
Sph pul	November	3106.84

Table 4.9: Best months for discrimination of each species.

These data (Table 4.9) also show that although a particular month was selected as best for a species F-ratio values of the spectral analysis variance were low for some such as *Phragmites australis* and *Juncus effusus*. For these species, data acquired from two dates may be better for discrimination as their phenology could be used to benefit this. For example *Phragmites australis* is very lush growth in summer and has expanses of dead litter in winter. *Juncus effusus* is a darker shade of green in the summer and is still quite green in the winter with no large expanses of flattened dead litter. Species such as *Pteridium aquilinum* and *Molinia caerulea* have very lush green growth in the summer months are also better discriminated in those months (June and August). This indicates that although September and November are overall the best months for discrimination of most species a summer month may also be useful for better discrimination of all these species.

4.4 Discussion

4.4.1 Seasonal separability

Using spectral analysis the vegetation spectrum shows the best separation using the whole spectrum is in April. This result is reproduced with all 3 selected sections of the spectrum. Reducing the wavelengths for analysis, as one would expect, lessens the separability, however these results show that discrimination of species still occurs when WV2 wavelengths are used proving that it may be possible with the correct acquisition timings to separate some species. These results used the mean spectral values for each species and although this between species spectral analysis suggests that April is the best month to provide data for the best species discrimination the within species analysis (using a sample of 20 per species) show April as being the month where there is most variation in spectral data within species. F-ratio analysis of the spectral angle data which takes into consideration both the between and within species variance show (Table 4.8) that April is not the best month for species discrimination.

Results have shown that species discrimination is somewhat dependant upon what species or how many are to be isolated. For example if only *Calluna vulgaris* was to be separated from others using WV2 spectral data the results (Table 4.4) indicate that April and May gave the best separation for this species and therefore were the best month to have an image acquired. Results show that choosing the dates for satellite acquisition that are preferable for species discrimination is very dependant upon which satellite data is being used. A satellite using the SWIR region also may have more separability in the month of April than the WV2 image (Figure 4.3).

It was more difficult to take readings in constant light conditions with fluctuations in intensity in November. It may be best to use November readings for an indication of (spectral graph shape changes) increases or decreases of reflectance at wavelengths but

species discrimination, particularly using indices that use the red edge and NIR regions of the spectrum, in this month may be partly due to this so should perhaps be viewed with caution. The photographic representations corroborate this (Figure 4.2).

As not all species are easily separable with a limited number of wavelengths available for analysis, other methods such as phenological comparisons and vegetation indices can be employed to increase their separability. The pair plots (Figure 4.13) show that using indices at a particular period in time can discriminate species. Using these results along with phenological information (e.g. flowering periods or senescence versus lush growth) (Figures 4.12 and 4.11) improve this discrimination further.

Using the spectral analysis results (Tables 4.3, 4.4 and 4.6) it can be seen that there are months that are more useful for the separability of a group of species (Figures 4.11 and 4.15). It would be useful to use an image that is suitable for discrimination of each species. However, due to cost and weather conditions, this is not a possibility so it is important to investigate the periods that are showing the largest differences in species separability. From both the spectral angle analysis of reflectance values and the F-ratio analysis of the indices values it can be seen that there are at least 3 main periods that are most effective for species separation. These can be divided into peak-flush (June to August), September and post-flush (October, November; as shown in Figure 4.11). Using only between species mean spectral data the pre-flush (April) period was the most effective at discrimination so may also despite the increase in within species variation be a month worth considering for species discrimination. If a species such as *Phragmites australis* which is not so easily discriminated but has better far better discrimination from all species using only between analysis in April then it may be worth using a pre-flush image to assist with the discrimination. This may provide a more definite discrimination for the species data that is most similar to the mean and leave out other areas of *Phragmites australis* that are not so similar. However, this provide a more accurate representation of definite *Phragmites australis* but of course will have

missed other areas. It was also shown that one of the periods with least variation within species was the July and August period (Figure 4.10). This is also worth noting when selecting months for species discrimination. Results would therefore suggest a pre-flush, peak-flush, September and a post-flush period are best for discrimination of the selected species.

Hill et al. (2010) also found similar periods most effective for discrimination of tree species. They tested images that provided green-up, full-leaf phase and an autumnal senescence period equating to the Pre, Peak and Post periods with the most effective months for his classification being, March, July and October. Lucas et al. (2011a) also used phenological data from spring and summer to improve classification of habitat. Where species such as *Pteridium aquilinum* or *Calluna vulgaris* were classified, a spring and summer photosynthetic vegetation (PV) difference was used. However this was on larger scales and dates and indices were chosen using ecological knowledge rather than statistical analysis.

4.4.2   Species separability

Jones and Vaughan (2010) has shown that differences in pigment composition can be used as a tool for species discrimination on the basis of leaf or flower colour and has been demonstrated here in indices graphs (Figure 4.12).This was demonstrated with flowering in *Calluna vulgaris* where pink flowers contain pigments such as anthocyanin. This showed on the spectral graphs as an increase in the red and decrease in the green wavelengths in September (Figure 4.3). For vegetation that moves dramatically from dead to lush green growth in a short periods (e.g. *Molinia caerulea*), the increase in chlorophyll content is very apparent and can be clearly seen in the change of spectral shape for the peak growth periods (Figure 4.15).

The spectral angle analysis of between species for the full spectrum showed a large

proportion of spectral angle values of zero (Table 4.2) showing there to be a reasonable separation of species, however this separation lessened as the spectral data was reduced (Tables 4.3). Using only WV2 wavelengths separation was far less successful (Figure 4.4). Using indices appears to improve this as shown by the high F-ratio values (Table 4.6). Scatter/pair plots also indicate the distinct separation of all species using the specific best (highest F-ratio values) to do so and in particular in the September, October, November period (senescent periods). There appeared to be far more variation within species which gave indices in this period a low F-ratio in the April periods which was visible in scatter plots. Spectral angle analysis also indicates that a summer period would be useful for discrimination of species such *Molinia caerulea* and *Pteridium aquilinum*.

Hill et al. (2010); Wolter et al. (1995); Lucas and Centeno (2008) have all acknowledged that spectral variation within species is typically greater than between them making it difficult to discriminate. The results here show that the spectral variation within a species can be taken into account when selecting the best months to acquire imagery. Using differences in spectral data between Pre, Peak and Post periods could also be very useful in separation of species with very different seasonal growth habits. The differences in growth habits between species such as *Sphagnum pulchrum* and *Molinia caerulea* are significant enough to help with separation (Figure 4.15), however their indices differences at times such as June and October are not so different (Figure 4.11). This shows the importance of using both knowledge of the ecology of a species as well as the appropriate seasonal indices to help with separation of species.

Asner (1998) found that variability in surface reflectance was dominated by presence of standing litter in the canopy. This was recognised as correlating with standing litter within imagery (Breyer, 2010) and could be the same source of variability being found within the field spectrometer species data for the senescent periods. Dead litter can vary according to moisture, decay, temperature, etc. and are perhaps more likely to show greater variation within a species than live material.
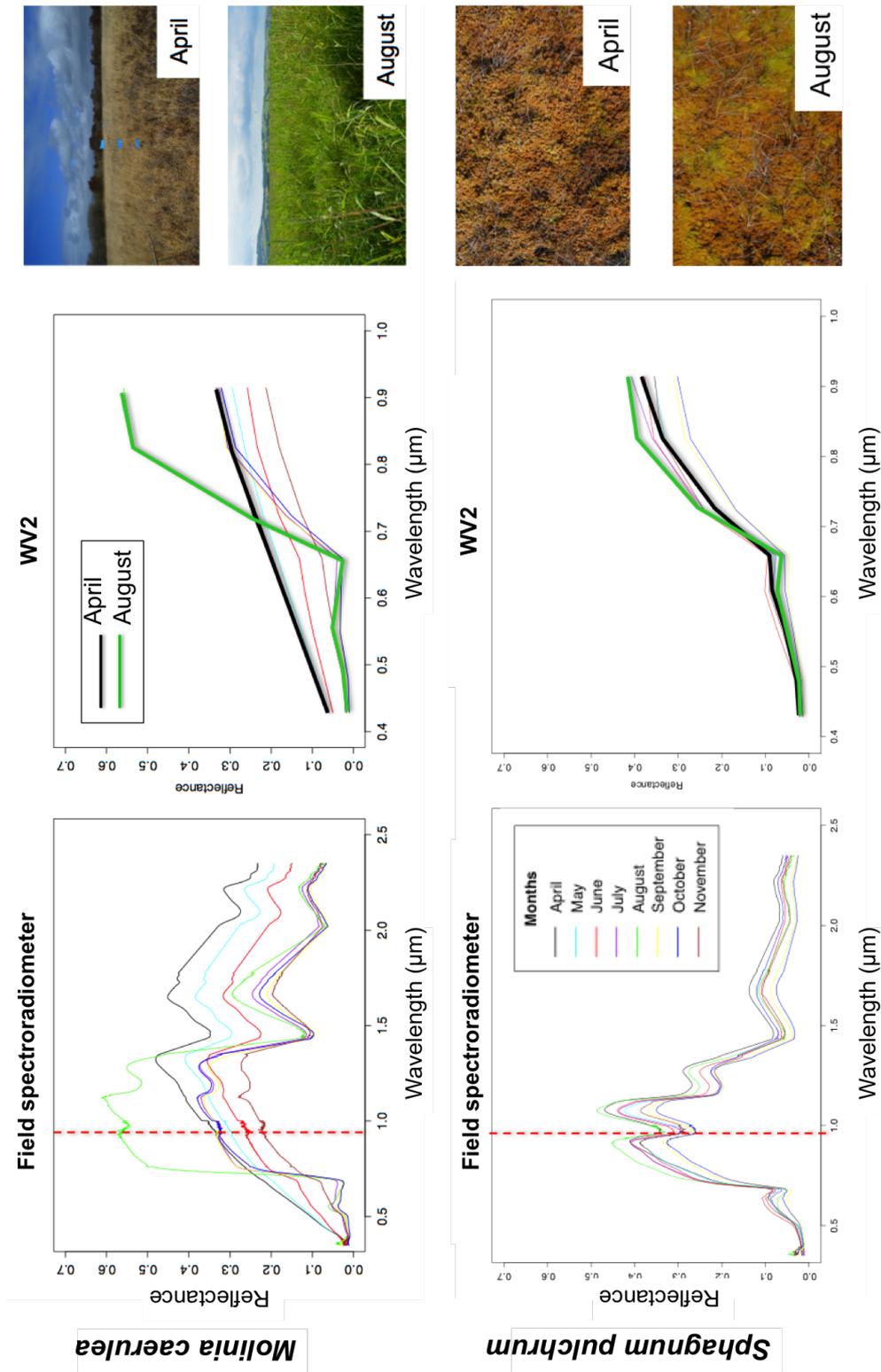
Figure 4.15: Seasonal differences of *Molinia caerulea* and *Sphagnum pulchrum*.

This could explain why April was one of the months that showed much more variation within species. Areas of primary bog have larger quantities of dead material present all year round due to the nature of the habitat. The possible influence of this could in part cause difficulties in separation of spectral data giving greater variation within a species. Other variables such as shading (e.g. low sun-angles) will also influence the spectral variability within-species with some species such as *Myrica gale* having more issues with this than other species (e.g. *Sphagnum* spp.) (Figure 4.2). Hill et al. (2010) and Jackson and Huete (1991) found that factors influencing and increasing within-species spectral variation in a remotely sensed optical image included all aspects that can be affected by seasonal conditions; these include illumination and view angle differences, natural variability in canopy structure and openness and shadowing effects. All of these effects may become more pronounced when focusing sample sizes on a larger scale (e.g. using imagery such as WV2 with 2x2m pixel size).

4.4.3   Methodology

The spectral angle analysis for between species gave opposing results to the F-ratio of indices initially but once within species spectral angle analysis was included in analysis results gave very similar results to the indices ANOVA F-ratio separation results. This shows that the ANOVA F-ratio separation analysis which used all the data and calculated the separation values using both the variance within the species group and between species groups is a suitable method for selecting the best indices to discriminate species.

Although many hyperspectral or multispectral separations use linear discriminant analysis (LDA) (Lucas and Bunting, 2006) or further use of ANOVA analysis methods (Petropoulos et al., 2010) this F-ratio method has been used due to its ease and success in results. F-ratio has been used in other areas such as in the wine industry to find chemical components that separate grape varieties (Coghlan, 2014) and for medical methods of

analysis, for example separation of speech elements (Nicholson et al., 1997). This F-ratio otherwise called a separation index provides a simple method for an analysis of the effectiveness of indices for comparison with each other.

4.5 Summary conclusions

1. UK flora has huge variations in seasonal attributes with massive variations both between years and seasons. These variations can affect any data that a satellite image may record and therefore timing of the acquisition of imagery is vitally important to its identification and recorded condition. An understanding of just how these vary throughout the year is therefore critical.

2. Using a protected site with areas of natural vegetation as well as areas of degradation a suite of 10 species common to each of these zones was compiled. These were limited to the species that would be most likely to be identified within satellite imagery by their coverage and dominance.

3. Field spectroradiometer readings as well as corresponding photography were compiled for each species on a monthly basis to record seasonal changes. Spectral data was analysed to assess between and within species seasonal separability using spectral angle analysis. Indices relevant to WV2 satellite acquisition data were analysed using a multivariate analysis of variance to asses both seasonal species separation and the suitability of indices.These two methods gave almost identical results in terms of best seasonal timings for discrimination of species.

4. Using spectral angle analysis it was found that some species were far easier to separate than others and that the timing of satellite acquisition should be dependent upon what species are present. Using spectral angle analysis it was shown that within species variation had an effect on species discrimination with the greatest variation within

species being in April.

5. An ANOVA method giving F-ratios was used effectively to select the indices most likely to be successful at discriminating species and this information also provided information on the best periods for satellite acquisition.

6. Phenological occurrences such as the flowering of *Calluna vulgaris* in September have the potential within a site to be used to help discriminate from other species. However, to be discriminated from other species an image from the flowering period and a pre flowering period would be required to establish this difference.

7. This data shows that the best 2 periods for discrimination of species is September and November but a summer month to include some of the lush competitive species would improve discrimination for all species. To improve the separability of a number of phenologically differing species the optimum timings for acquiring satellite imagery corresponds with both a Pre flush period (when deciduous vegetation is senescent), a Peak flush period (when all vegetation is usually at its most productive) and a Post flush period (autumnal senescence).

8. These results also show that for separation of species the best months to get the most significant separation are dependant on a number of variables. These being:
a) what satellites are used,
b) what species are to be separated or selected,
c)both between and within variation must be considered in analysis.

This study highlights two important phenomena; i)within-species spectral variability affects the discrimination of species and ii)the within species variability is possibly due to seasonal effects. This study further highlights the importance of selecting satellite imagery to suit the species present or those to be investigated.

Chapter 5

Vegetation classification

5.1 Introduction

Peatlands or acid bogs are one of the most difficult ecosystems to classify with remote sensing data (Ozesmi and Bauer, 2002). Lowland raised bogs contain very specialized and highly distinctive assemblages of plant species (Moore (2002), Anderson et al. (2011)). Many of these species present at Cors Fochno, as outlined in chapter 4, can also be highly distinctive when it comes to spectral signatures. Dominance of particular plant species and their patterns of growth can also reflect the ecological gradients present. This chapter focuses on the classification of species likely to form larger patches and that are indicative of the ecological gradients present in this habitat. Now with the advent of satellites such as WV2 providing high resolution imagery it is becoming easier to classify small patches (pixel size) of dominant species.

A system for selecting suitable indices for separation of the species spectral and indices data was developed within chapter 4; however, until it is used within the classification of an area its practical use and accuracy is unknown. This chapter applies the methods developed in chapter 4 to a modified EODHaM system (Lucas et al., 2015) classification of Cors Fochno SSSI and surrounding landscape. The system was then adapted and modified within this chapter where necessary. The EODHaM system incorporates levels 1 to 3 of the Food and Agriculture Organisation (FAO) Land Cover Classification System (LCCS) (Di Gregorio and Jansen, 2000). The LCCS is a hierarchical system involving

several levels which are utilised throughout the classification process (Figure 2.4). This method allows the combination of LiDAR and spectral data to provide information for classification.

The success of using spectral data from high resolution imagery for peatland classification has been demonstrated by others (Middleton et al., 2012; Harris et al., 2015). Hyperspectral data has been largely employed for peatland classification due to the often heterogeneous nature of these habitats (Harris et al., 2015), however, hyperspectral data can be both difficult and costly to obtain and process. VHR multispectral datasets often lack a short-wave infrared band (Nagendra et al., 2013) which can present challenges for classification. Many that have used other very high resolution multispectral imagery have used a fusion of a single multispectral image and LiDAR (Anderson et al., 2010; Borka and Sub, 2007). Combining vegetation height and spectral data is known to improve vegetation classifications (Lucas et al., 2012b; Mucher et al., 2010), using regression analysis between field measurements and LiDAR, concluded that LiDAR could provide accurate height measurements on shrubs and trees even when no leaves were present although this was not found to be possible for the whole range of plant life forms. A number of studies (Adam et al., 2010; Klemas, 2013) have demonstrated that a combination of LiDAR, plant classification, and vegetation index data can improve species-level classifications and estimation of biophysical variables. Combining structural data from LiDAR with multispectral data has been shown to improve accuracy of classification (Gilmore et al., 2008; Hill and Thomson, 2005) and has specifically been shown to improve the distinction of peatland types within a habitat (Anderson et al., 2010).

In addition to this, many studies (Cole et al., 2014; Gilmore et al., 2008; Jabloun et al., 2009; Cho et al., 2008) have found the use of spectral indices can improve separability and considerably reduce the data volumes for processing and analysis. The limitations of using an optical remote sensing approach with purely spectral-based index classifiers

are evident in studies of wetland species classification (Milton et al., 2005). However, using more than one image to provide seasonal information to improve vegetation discrimination has not been used for peatland classifications other than with the EODHaM system (Lucas et al., 2015) and is more usually employed in woodland/forestry tree classifications (Hill et al., 2010). The EODHaM system incorporates two or more images to provide seasonal information along with LiDAR and a number of thematic layers (urban & cadastral), and found these extra layers improved the classification including for life-form and species classifications.

In addition to these emerging practises of improving classifications with additional height and seasonal data, this chapter draws on the field information (chapter 4) by using it to identify the most appropriate imagery acquisition periods to provide the best seasonal data to assist with species discrimination. The method used in chapter 4 were again used for indices selection and threshold identification. In addition to this, ecological information gathered from the field work and expert knowledge is used and implemented in the seasonal aspects of the classification, in the hierarchical rule based classification system. Unlike the previous EODHaM system study (Lucas et al., 2015), imagery was atmospherically corrected to provide data that should be comparable with the field spectroradiometer data.

Aims:

This study aims to assess the use of methods and ecological information developed in Chapter 4 for use with WV2 data acquired over 3 time periods (March, July and November) and to produce a multiscale classification of Cors Fochno SSSI and it's surrounding landscape suitable for use within a monitoring system.

Objectives:

1. Assess the correspondence of atmospherically corrected WV2 data and field spectroradiometer data.

2. Use the methods developed in Chapter 4 to select the best indices for dominant species discrimination from the 3 WV2 data sets.

3. Develop a classification process adapting the EODHaM system methods in order to integrate both the results of the indices selection process in objective 2 and ecological information gathered in field work, as well as expert knowledge.

4. Classify the protected site and surrounding landscape to Level 2 of the Landcover Classification System (LCCS) and the dominant species present within the Cors Fochno protected site.

5. Assess the accuracy of the process using field data and UAV data and demonstrate the effectiveness of the process developed for monitoring purposes.

Hypothesis:

Classification of varying scales, from landscape to species level, can be carried out effectively with good accuracy results within one classification process, using an F-ratio method for best indices and image time selection, and ecological information gathered in field surveys to produce a system that is repeatable for improved monitoring purposes.

5.2 Methods

5.2.1 Classification process utilising the EODHaM system

For Cors Fochno, WV2 imagery were acquired during the pre (24/3/12), peak (27/7/11 and post (15/11/11) flush periods with this selection confirmed through reference to the spectral reflectance data in chapter 4 acquired for the main species groups. These were classified using an adaptation of the Earth Observation Dynamic Habitat Mapping (EODHAM) system (Figure 5.1). The EODHaM system is based on the Food and Agricultural Organisation (FAO) Land Cover Classification System (LCCS) (Figure 2.4)

and is divided into corresponding stages.

The classifications were carried out using atmospherically corrected imagery. Two separate classifications were carried out; a landscape classification to map the landscape surrounding the SSSI study site and a second classification to map the smaller scale site level of the SSSI. LiDAR data was also downloaded from Geomatics to create a Canopy Height Model for integration into the system.

The classification process comprised of:

(a) preparation and pre-processing (orthorectification, radiometric, atmospheric and/or topographic correction),

(b) segmentation in eCognition,

(c) extraction and analysis of indices for input into the classification

(d) classification to LCCS Level 2 (EODHaM 1st stage) and

(e) classification to species (adaptation of EODHaM 2nd stage), with this involving expert knowledge and index threshold values derived from statistical analysis of extracted imagery data.

(f) Accuracy assessment

For steps (c) and (f) ground, aerial and UAV data was required to collate training and accuracy data. This was used to compare the WV2 data with the field spectroradiometer data and to create thresholds for classification input and for use in an accuracy assessment.

The classification was processed using the Remote Sensing and GIS Library (RSGISLib) software (Bunting et al., 2014), the Geospatial Data Abstraction Library (GDAL), with XML and PYTHON scripting. The classification system also made use of the KEA image file format (Bunting and Gillingham, 2013), which allowed for processing within a raster attribute table (RAT).
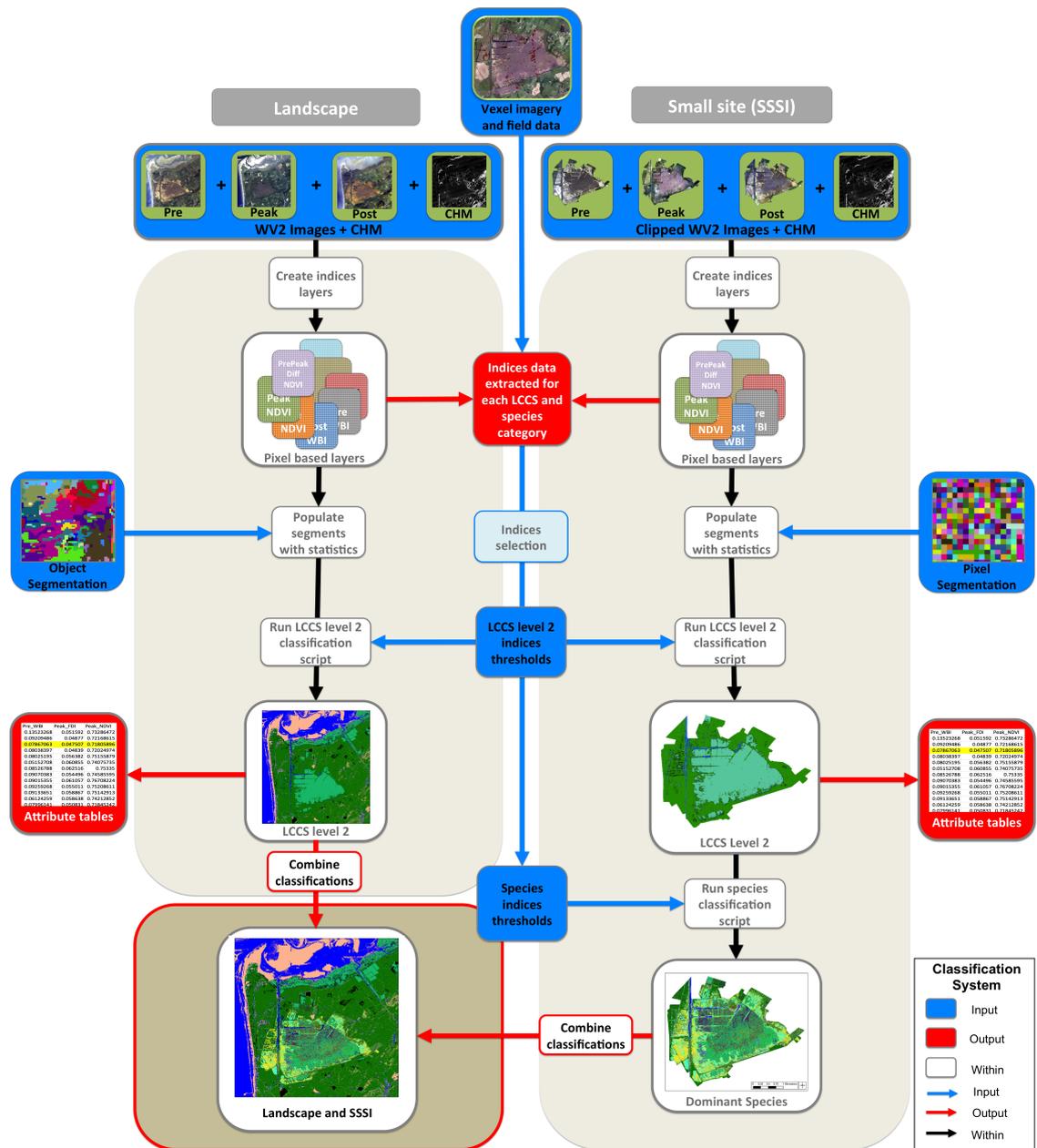
Figure 5.1: Classification process using an adaptation of the EODHaM system incorporating a threshold selection method developed in chapter 4.

Within the RAT, which has been developed such that large datasets can be efficiently analyzed (Clewley et al., 2014), for the object segmentation all pixels of the same object shared the same ID. This table was first populated with image data and derived products (e.g., vegetation indices) and class codes and species names were added progressively as

the classification proceeded, with the final attribution being the LCCS code, and species names. All RAT attributes from training pixels were imported into R (Team, 2012) and used in analysis for assessment of indices and category suitability. This data was then used for development of thresholds for input in the classification system.

5.2.2   Collation of field and vegetation data

Two levels of classification were used, one to classify the landscape surrounding the SSSI site and the other to classify in more detail the Cors Fochno SSSI protected site. Two sampling methods were therefore employed to take into account differences in scale.

Sampling land-cover in the wider landscape.

To provide sample data for LCCS level 2 categories in the wider landscape aerial photography was used to distinguish areas up to LCCS Level 2. The classes for LCCS level 2 were Aquatic Non Vegetated (ANV), Aquatic Vegetated (AV), Terrestrial Non, Vegetated (TNV) and Terrestrial Vegetated (TV) (Table 5.1). It was decided a tree class would be added for additional information (Table 5.1).

	Class	**Samples for threshold**	**Samples for accuracy**
1	Aquatic Non Vegetated (ANV)	25	50
2	Aquatic Vegetated (AV)	25	50
3	Terrestrial Non Vegetated (TNV)	25	50
4	Terrestrial Vegetated (TV)	25	50
5	Trees (T)	25	50
	Total	125	250

Table 5.1: Classes sampled for use in landscape classification and accuracy testing.

A total of 75 data points were selected for each of the above LCCS categories giving a total of 375 data points. These were spread as evenly as possible across the whole of

the 10×10km area. The sample points were randomly split into two groups for training and accuracy testing. 25 points per class were allocated to training by using them to identify thresholds and 50 points were used for accuracy testing (Table 5.1).

Sampling the SSSI

The same selection of plant species were used for classification (Table 5.2) as were used in chapter 4. Previous field sample points used for the field spectroradiometer data collation in chapter 4 were utilised. In chapter 4 there were 20 dominant patches for each of the 10 species with a differential Global Positioning System (dGPS) used to record the exact positions for each.

	Species (Dominant)	**Samples for threshold**	**Samples for accuracy (Ground)**	**Samples for accuracy (UAV)**
1	*Calluna vulgaris*	25	26	50
2	*Eriophorum angustifolium*	25	16	50
3	*Eriophorum vaginatum*	25	11	50
4	*Juncus effusus*	25	12	50
5	*Molinia caerulea*	25	31	50
6	*Myrica gale*	25	19	50
7	*Phragmites australis*	25	18	50
8	*Pteridium aquilinum*	25	11	50
9	*Sphagnum cuspidatum*	25	7	50
10	*Sphagnum pulchrum*	25	18	50
	Other areas (mixed species, water & bare ground)			
1	Aquatic Non Vegetated (ANV)	25	23	50
2	Aquatic Vegetated (AV)	25	12	50
3	Terrestrial Non Vegetated (TNV)	25	25	50
4	Terrestrial Vegetated (TV)	25	9	50
5	Trees (T)	25	22	50
	Total	375	260	750

Table 5.2: Species sampled for use in SSSI classification and accuracy testing. Other areas are areas that are either mixed, water or trees.

In addition to this over 300 point quadrats and areal quadrats of 2×2m were sampled in 2011-13 (Figure 5.2). Areas of primary active bog, degenerated (secondary) bog as well as surrounding habitats were selected for field sampling with the main focus being areas where particular species dominated. In central active bog areas with typical

hummock and hollow stucture, vegetations in each were sampled to distinguish between them. Areas with dominant species (or as dominant as possible) were selected to aid classification of species in images. As well as recording the dominant species, areas representative of homogeneous patches within the range of habitats were selected and sampled in the same way. Quadrats were placed within the selected areas avoiding the edge. A differential Global Positioning System (dGPS) was used to record their exact position. A detailed assessment of species composition within each of these quadrats based on percentage cover from an areal viewpoint (100%) were recorded. Each quadrat was photographed to record a visual coverage for reference.
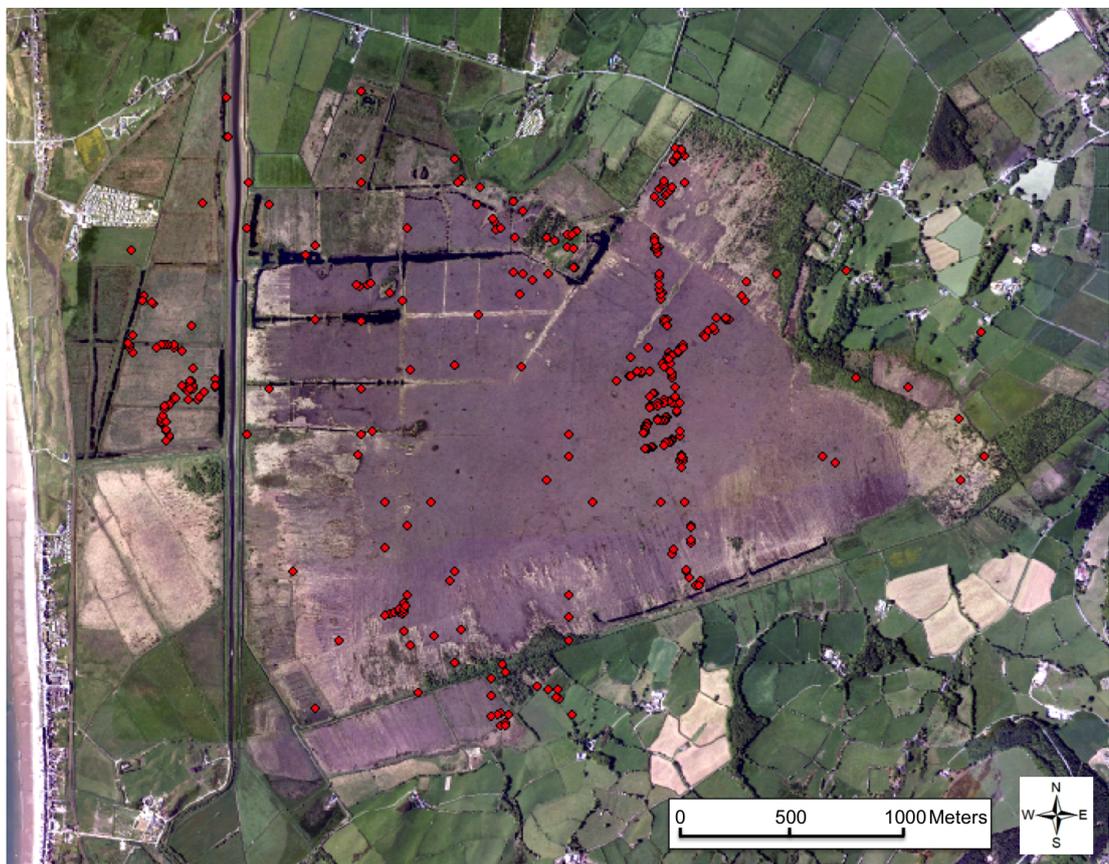
Figure 5.2: The SSSI sample points which include both threshold and accuracy sample points..

The EODHaM system also provides the ability to translate a classification from the LCCS to the General Habitat Category (GHC). This is known to cause issues regarding

translation to multiple GHC categories from a single LCCS category or even from species to GHC (Adamo et al., 2014). For example on the bog *Myrica gale* in particular grows to different heights according to the conditions so is very short ($\leq$50cm) within the wetter, more acidic, very low nutrients regions but is much taller ($>$50cm, $<$200cm) in the outer regions of the bog where more nutrients are available. Classification of *Myrica gale* using GHC categories could on translation create at least three options (Shrubby Chaemophytes (SCH), Low Phanerophytes (LPH), Mid Phanerophytes (MPH). Non shrub plants for example graminoids are all classified as Caespitose Hemicriptophytes (CHE) despite height differences, e.g. *Molinia caerulea* which can be $>$100cm tall or more and some *Carex* spp. present on the verges of the bog which can be as low as 10cm.

Lifeforms within the LCCS system (Table 5.3) were translated from the field data as an additional layer which can be included in the 2nd stage of the EODHaM system.

No.	Lifeform category	Lifeform
1	Woody	Trees
2	Woody	Shrubs
3	Herbaceous	Forbs
4	Herbaceous	Graminoids
5	Lichen/Moss	Lichen
6	Lichen/Moss	Moss

Table 5.3: LCCS Lifeform categories.

Sample points were split into two groups, one for training and one for accuracy testing (Table 5.2). 25 points per dominant species were used for threshold identification. The remainder of field sample points were used for accuracy assessment. In total there were 260 points remaining. Due to the heterogeneous nature of the habitats present all quadrats with a species composition where one species accounts for 70% or above were used as a dominant species point. Those quadrats with very mixed vegetation were noted instead as categories of LCCS level 2 and were used for accuracy assessment. Any quadrats with trees were used for accuracy assessment of tree classification. There was

not an equal number of each category or species due to the difficulty in finding patches of dominant species large enough and due to difficulty in traversing the site.

Two high resolution (3cm) UAV images made available were used to provide data for further accuracy assessment using only the UAV sample points. These were flown in March 2012 and September 2012. The UAV imagery from the two time periods was sufficient to ascertain patches of relevant dominant species. For each species 50 points were selected within this imagery as well as a further 50 for each LCCS category and 50 for areas of trees. A total of 750 points where selected.

5.2.3 Preparation and pre-processing of remote sensing data

By assessing the data collated and analysed in the field spectroradiometer studies in the previous chapter 4, three image periods were selected. The periods selected were from the Pre, Peak and Post time periods. These were found to be the periods providing the most information for separation of species with the least number of images. Exact times could not be selected due to the use of either previous acquisitions or due to cloud cover and conditions being unsuitable, therefore, dates of imagery used were in the end (March 2012, July 2011 and November 2011), as close as possible to the suggested Pre, Peak and Post periods.

World View 2

The relevant months of WV2 satellite imagery were selected from pre requisitioned images. The best months to provide suitable data for input into the classification system were selected using field spectroradiometer data (see below). The three Worldview 2 images acquired for this classification work were 24th March 2012, 27th July 2011 and 15th November 2011. Each image covered the same window area of 10×10km.

All imagery required orthorectification and the ERDAS program was used for this. The

method of orthorectification used within ERDAS requires both the image and the Rational Polynomial Coefficient (RPC) files which are provided with this. RPCs are simple empirical mathematical models relating image space (line and column position) to latitude, longitude, and surface elevation. A Digital Elevation Model (DEM) was also required in order to orthorectify WV2 satellite images. The relevant area was selected and the latest 1m Digital Terrain Model (DTM) (in this case 2013) was ordered from Geomatics. Finally synchronisation was carried out within ERDAS by selecting tie-points (83 selected) across the whole image. Once these were selected the images were re-sampled to a common projection, co-ordinate system and pixel grid.

Once orthorectified, the images required atmospheric correction. Atmospheric correction was necessary to provide surface reflectance data that could be compared with the field spectroradiometer data in the previous chapter. It is also known that atmospheric correction has been shown to significantly improve the accuracy of image classification. When using vegetation indices the effects of atmosphere can lead to major discrepancies and atmospheric correction is especially important in cases where multi-temporal images are used and analyzed (Hadjimitsis et al., 2010).

Images were first converted from Digital Number (DN) to radiance (Wm-2 sr-1Âţm -1) and then to surface reflectance (unit of reflectance being a value from 0 to 100 signifying % of reflectivity) using Atmospheric and Radiometric Correction of Satellite Imagery (ARCSI) software which is built on the 6s atmospheric model. ARCSI software provides a tool for the correction of satellite imagery (Bunting and Lucas, 2014). ARCSI retrieves the atmospheric correction parameters from the image data and uses them for input into the 6s model. ARCSI multiples the output pixels by 1000 and integerises the values to provide reflectance as a percentage to 1 decimal place.

Canopy Height Model

LiDAR data for the Cors Fochno and surrounding area was downloaded in the form of a Digital Terrain Model (DTM) and Digital Surface Model (DSM) from the Geomatics Group of the Environment Agency at 1m resolution. This data was flown in January 2013. Both the DTM and DSM which provided mean height values per cell were clipped to the 10×10km area. To obtain a Canopy Height Model (CHM) an image was created by subtracting the DTM from the DSM using a RSGISlib script. This CHM image was to be used within the classifications to provide vegetation height data. The DTM was also used to investigate the position of the raised bog central dome with a view to this being used to assist in assessing the condition of this area.

UAV

High resolution (3cm), low cost, aerial imagery (using UAV) was used in the development of thresholds for the classification of satellite imagery. Two images had been acquired for two periods, March 2012 and September 2012. The UAV imagery was used to identify dominant stands of vegetation (Figure 5.3) for extracting satellite spectral data for species indices and threshold selection data. It was also used to provide data for the final accuracy assessment.
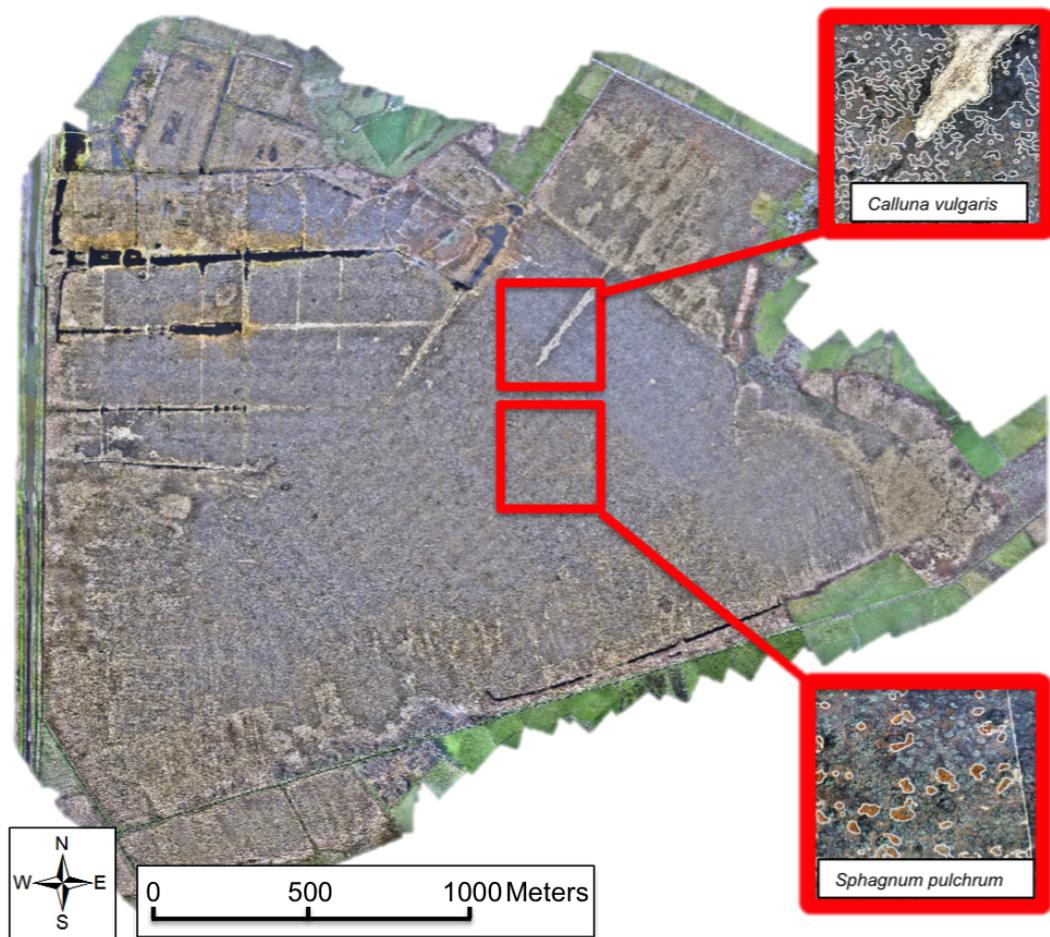
Figure 5.3: March 2012 UAV image of CorsFochno SSSI showing species identified within the imagery.

Preparing corrected WV2 imagery for 2 scales of classification input

Once imagery was rectified and corrected two scales of classification imagery were created. The full 10×10km was used for the landscape classification to Level 2 LCCS. To carry out a landscape classification to level 2 of the whole 10×10km image an object based segmentation was required for input. This was performed within eCognition using a multi-spectral difference segmentation with the spectral difference set at 3 with all 8 bands used to calculate the difference.

For the species classification of the SSSI area each 10×10km image was clipped to the SSSI recorded shape-file. For use within the classification it was more useful to use the smallest segmentation possible (2×2m) due to the small size of patches of species. The clipped SSSI area was segmented to a one pixel resolution (2×2m) chessboard within eCognition.

5.2.4 Segmentation

The 10×10km landscape was classified to LCCS level 2 using the EODHaM stage 1 process using an object based segmentation whilst the SSSI site was classified to species using a pixel based segmentation for input into the EODHaM stage 1 and a stage 2 adaptation. A pixel based segmentation of the SSSI was used due to the small size of patches of dominant species. This was carried out in eCognition using a chessboard segmentation. The object size that defined the size of the square grid in pixels was that of the pixel size of the image e.g. 2×2m. This was used to create square image objects which could be used within the EODHaM system classification. An object based segmentation was carried out for the 10×10km landscape area. This was done using a spectral difference segmentation which was created within eCognition. Within the spectral difference segmentation, neighbouring pixels were merged if the difference between their mean spectral values were below a value of 3. All 8 bands were used and evenly weighted.

5.2.5 Extraction and analysis of indices for input into the classification

In order to classify categories or species within the EODHaM system thresholds are applied to selected index for each. This uses ecological knowledge and personal input for indices threshold values however, unless very experienced this is open to errors or a

lengthy process of trial and error. In order to try and overcome these issues the following process of index threshold calculations was used after investigation in chapter 4 found this method to be effective. Indices (Figure 5.4) to select Level 2 LCCS categories, Lifeform and species were assessed.

Index	Bands used	Formula	Applications	References
FDI Forest Discrimination Index	NIR1, Red Edge and Coastal	$\rho MS_7 - (\rho MS_6 + \rho MS_1)$	Photosynthetic cover, phenology.	(Bunting and Lucas, 2006)
WBI Water Band Index	Blue, NIR1	$\dfrac{\rho MS_2}{\rho MS_7}$	Non-submerged aquatic vegetation, open water.	(Lucas et al, 2012b)
NDVI Normalised Difference Vegetation Index	NIR1, Red	$\dfrac{(\rho MS_7 - \rho MS_5)}{(\rho MS_7 + \rho MS_5)}$	Greenness, aboveground net primary productivity, a measure of photosynthetically active biomass.	(Rouse etal, 1973)
PSRI Plant Senescence Reflectance Index	Red, Blue, Red-Edge	$\dfrac{(\rho MS_5 - \rho MS_2)}{\rho MS_6}$	Senescent vegetation, non-submerged aquatic vegetation, NPV detection.	(Merzlyak et al, 1999)
REP Red Edge Position	Red, Red-Edge, NIR2	$\rho MS_6 - (\rho MS_8 - \rho MS_5)$	Sensitive to changes in chlorophyll concentrations, NPV detection.	(Curran et al, 1995)
NIR Diff Difference between NIR1 &NIR2	NIR1, NIR2	$\rho MS_8 - \rho MS_7$	Discriminating active bog.	(Lucas et al, 2012b)
BG Blue - Green	Blue, Green	$\dfrac{(\rho MS_2 - \rho MS_3)}{(\rho MS_2 + \rho MS3_3)}$	Chlorophyll content.	(Lucas et al, 2011a)
BR Blue - Red	Blue, Red	$\rho MS_2 - \rho MS_5$	Discriminates shrub from trees.	(Lucas et al, 2011a)
Woody	Coastal, Green	$\rho MS_1 - \rho MS_3$	Discriminates woody shrubs and trees.	(Lucas et al, 2011a)

Table 5.4: Indices used showing which bands are used for calculations. These indices were used due to their input into the original EODHaM classifications within the BIOSOS project. Thresholds and indices were selected for this using ecological knowledge and through trial.

As part of the EODHaM system indices layers are created in the initial steps of the classification from the image spectral data. Once the imagery had been corrected and rectified and clipped, the initial steps in the classification were processed to produce these pixel based index layers. Using the shape-files of LCCS points and species points developed from the ground data previously mentioned, 25 samples of each classification category were used in analysis (Table 5.2). The index value for each LCCS category sample point and each species sample point to be used for threshold creation was then extracted from these layers to form a set of data for use in the following analysis. Focus was placed on using the same indices which were used in chapter 4 and which were used

previously within the EODHaM system for vegetation discrimination by the BIOSOS project. (Table 5.4). These indices were selected using ecological knowledge and trial and error to discriminate surfaces within the LCCS categories of classification (further explanation in Chapter 4).

Comparison of field spectroradiometer and satellite data

A comparison of field spectroradiometer indices values and WV2 indices values was carried out to assess whether the field data could be used to select suitable indices and to create thresholds for input into the EODHaM system. July field spectroradiometer spectral measurements were re-sampled to the WV2 response function for each wavelength. These were compared with the July acquired satellite spectral data indices to check correspondence. A linear regression was carried out to assess whether field spectroradiometer data would be sufficient to be used to calculate thresholds for classification input.

Spectral discrimination of LCCS categories and species

As with chapter 4 a spectral angle analysis (within ENVI) was performed using the spectral data extracted for the species from the WV2 satellite data. This was used to establish whether the spectral reflectance for each species was significantly different enough to differentiate between them. As before the Spectral Angle Mapper (SAM) algorithm was used in the Spectral Analyst within the program ENVI to compute the 'spectral angle' between the species spectrum. Pre, peak and post images were used for this. Results greater than or equal to the maximum of 0.25 radians receives a score of 0. To summarise, a score of 1 indicates that the spectra are a perfect match and the two spectra being compared are the same species. A score of 0 indicates that the spectra are completely separable and that species are different and highly distinguishable.

Discrimination of species and LCCS classes

Species and LCCS classes were classified using thresholds on derived indices.. To select thresholds for use in the classification a number of methods were used:

1) Use the top indices from the ANOVA analysis (i.e. those with the highest F-ratio values).

2) Assess indices with pair plots to a) assure indices not selected as a best index is not better for an individual species, and b) to assess best combinations of indices.

3) Produce box-plots to illustrate separations.

4) Test indices within TuiView to check index and threshold selections.

Indices with the greatest F-ratio scores for each level of classification were used to calculate threshold values for input into the classification. Maximum and minimum values were calculated from the 25 field samples of each category and species. Box plots were used to illustrate LCCS categories and species separability using specific indices. These boxplots gave further indications of the best indices to use from the selected indices for individual species discrimination. Using the maximum and minimum values of an index for a species or class the values were entered into a query within TuiView to test representation of areas. Small adjustments to these thresholds were made to improve the performance of the classification according to areas visible in a high resolution UAV image.

1) ANOVA analysis for selection of best indices

All indices data was standardised first before a multivariate analysis was carried out in R to calculate variables (indices) with the greatest separations between the LCCS level 2, life-form and plant species.

A method of ANOVA was used creating separation values from analysis of variance for between-group and analysis of variance for within-group otherwise known as the ANOVA

coefficient (F). This is known as an index of separation or F-ratio (F) and is based on the ratio of between and within-group variance (Weinberg and Abramowitz, 2008). To calculate the separation achieved by each index variable the between-group variance was divided by it's within-group variance thus giving a separation value which indicates greater or lesser separation when compared with other variable separation values. Larger F-ratio values are due to a larger between-group variance and smaller within-group variances and signify indices that are better for separation of the vegetation groups.

2) Pair plots

Pair plots (Figure 5.10) were used to illustrate the effectiveness of separation F-ratio scores and give a visual representation to guide the selection of pairs of indices combinations. The combination of pairs of individual variables gave a greater separation of LCCS level 2, life-form or species in some cases than using an individual variable. Further discrimination with pairs of best indices shown by pair plots were used to select suitable indices combinations. Pair plots of the best selected indices were used to showing the best combination of indices for discrimination of a species or class. Pairs of indices selected for each class or species were derived from best visible separations in these pair plots.

3) Box-plots

Box plots (Figure 5.17) were used purely as a visual aid to assess separation of classes and species and also as with pair plots to indicate whether one or a combination of index thresholds were required for separation.

4) TuiView

TuiView is an open source freely available remote sensing image viewer. Threshold values were inputted to test classification. This was done with each class and species with occasional small adjustments made to the thresholds. Using ecological knowledge with the threshold values within TuiView determined the order of classification and assisted in the non-threshold rule set (e.g. classifying trees first to remove taller vegetation from

classification of shrub species).

5.2.6 Classification to LCCS Level 2 (EODHaM 1st stage)

The EODHaM 1st stage involved classification at the pixel and small object level. This utilized a sequence of decision rules (Figure 5.4), with these minimised to include only a narrow range of spectral indices that allowed discrimination of LCCS Level 1 and Level 2 categories (i.e. vegetated and not vegetated terrestrial and aquatic). The thresholds applied to the sequence of rules and data layers were derived in the previously mentioned statistical analysis process. At the pixel level, simple binary masks representing, for example, the extent of vegetation cover are generated ((Clewley et al., 2014)). However, at the small object level, the raster attribute table (RAT) associated with the KEA format is accessed for classification (Bunting and Gillingham, 2013). Within the RAT, each small object has a unique ID with all pixels associated with each object having the same characteristics. Each object within the RAT was then progressively attributed with the means of reflectance data and derived indices calculated from the pixels contained, binary mask information (e.g., water, not water) and ultimately the class assigned (e.g., vegetated, non-vegetated).

Classification at the pixel level was undertaken to generate binary masks of the extent of different vegetative states (terrestrial vegetated and aquatic vegetated), open water and bare ground using the indices (Table 5.4) calculated. Thresholds from 3 indices only were selected using the analysis previously described to discriminate these. Initially all vegetated states were merged into a vegetated category and remaining pixels associated with a non-vegetated category.

At the small object level, non-vegetated areas were associated with open water and urban infrastructure, classified using the selected indices. A second component then identified aquatic surfaces, with these including the open water areas used for the classification of

non-vegetation but also submerged and non-submerged aquatic vegetation.
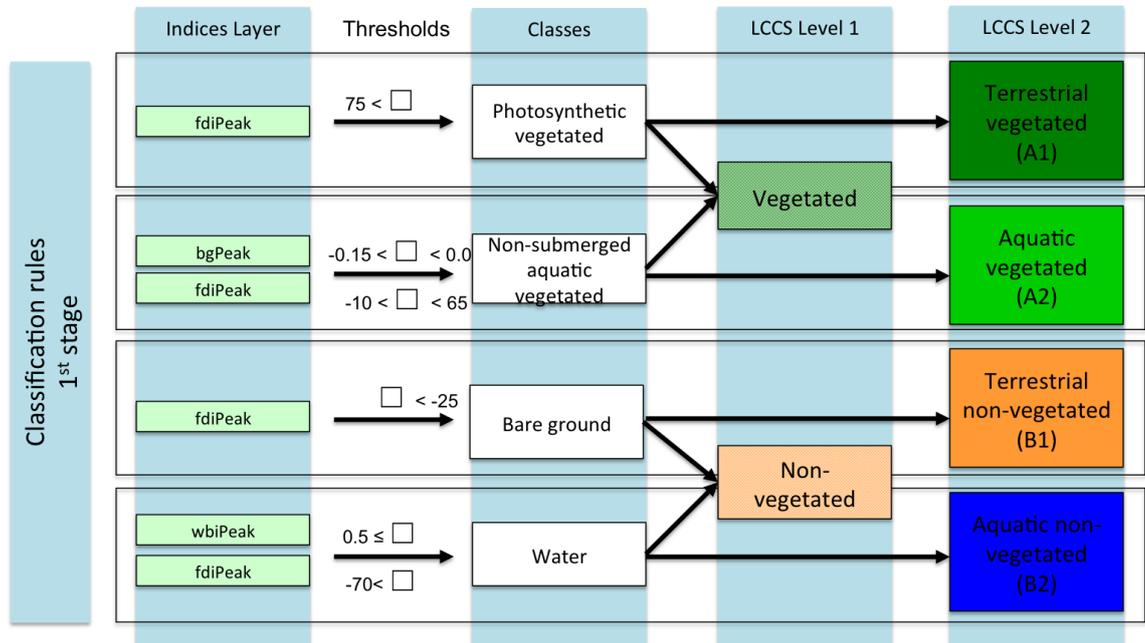
Figure 5.4: 1st stage landscape classification rules which incorporate the 1st stage of the EODHaM system.

Once defined as aquatic, all remaining objects are assigned as terrestrial using an inverse rule. The classification at LCCS Level 2 (i.e., vegetated or non-vegetated terrestrial or aquatic) is then achieved through cross tabulation of the areas of vegetation and non-vegetation with those that are aquatic and terrestrial.

5.2.7 Classification to species level (adaptation of EODHaM 2nd stage)

The EODHaM 2nd stage has two main components focusing on classification to LCCS Level 3 and, subsequently, Level 4, however, as this stage was only being performed on a non-cultivated SSSI there was little reason to classify to Level 3. Analysis of life-form data suggested discrimination of life-forms were not possible (Figures 5.12) so further progression from the LCCS first stage EODHaM system through the LCCS classification

system to the second stage was not carried out.

Figure 5.5: 2nd stage species classification rules which incorporate an adaptation of the EODHaM system. ■ = Pre image, ■ = Peak image, ■ = Pre peak image difference, □ = Pixel thresholds.

As the system is a hierarchical classification each stage carries an inaccuracy which can increase the possibility of inaccuracy in the following stages. If accuracies are not good for each layer the final outcome will be very poor. The life-form category was left out and classification progressed straight from first stage EODHaM classification to a species classification. The species classification again utilized user-defined thresholds as calculated through previous selection and threshold analysis of derived indices. A Canopy

Height Model derived from a DTM and DSM was integrated into the RAT.

Classification of Trees

For the classification of trees the CHM layer was used. A threshold value of >1m was used for this. All areas that were not classified as vegetated within the EODHaM stage 1 were excluded so avoiding the classification of tall objects such as buildings and caravans as trees.

Classification of Species

For a species classification just the SSSI area was used. First the EODHaM system 1st stage was run with the same script with the same indices and threshold values as for the landscape classification. Species classification followed this using a rule set developed through the above methods (Figure 5.5) with the specified selection of terrestrial vegetated (TV), aquatic vegetated (AV) and the exclusion of areas already classified as aquatic non vegetated (ANV), terrestrial non vegetated (TNV) and tree (T) layers to decrease further confusion and improve accuracy. Subsequent species classification divided species into areas where they were expected to be found (e.g. in AV or TV or both) and used the threshold values as selected through analysis as input.

The order in which the rules are applied to the image for classification is a key parameter for the classification. In this case species that were 'easier' to classify or known to prefer drier environments were classified first. Species such as *Pteridium aquilinum* which prefer drier ground were only classified within the terrestrial vegetated category but excluding the Tree category in order to narrow areas for its classification (Figure 5.5). This allows for the input of ecological knowledge to improve the spectral indices classification.

Areas with no species classification but classified as Aquatic Vegetated can be assumed to be highly mosaicked vegetation as these areas do not fall within the species categories defined in this classification. Most dominant species that will give large enough patches

of a species dense enough to be classified using the WV2 imagery were recorded within this SSSI area for classification.

5.2.8 Accuracy assessment

Accuracy assessment based on a standard confusion matrix was carried out on the two scales. For the landscape classification an assessment of the Level 2 categories was carried out using aerial photography as described in section 5.3.2. For the SSSI accuracy assessment of species classification two assessments were used; one using the UAV collated data and the other using the ground collated data. A producer's, user's and overall accuracy was calculated for all (Congalton and Green, 1999). The 'users' accuracy refers to the probability that a pixel labelled as a certain class on the map is actually that class on the ground (or in the UAV image). The 'producers' accuracy refers to the probability that a land cover or species on the ground is classified as such on the map. Each assessment utilised the available ground or UAV based data. By calculating the kappa coefficient (Equation 5.2.8), the effect of random distributions was removed and determined whether the results in the error matrix were significantly better than random or chance classification. Landis and Koch (1977) characterised the kappa values into three agreement categories: >0.8 - strong agreement, 0.4-0.8 - moderate agreement, <0.4 - poor agreement.

$$KappaCoefficient = \frac{N \sum_{c=1}^{r} x_{cc} - \sum_{c=1}^{r} x_{c+} x_{+c}}{N^2 - \sum_{c=1}^{r} x_{c+} x_{+c}}$$

where:

r = number of rows in the error matrix

cc = number of observations in row c column c (i.e. diagonal line)

$c+$ = total of observations in row c (shown as marginal total on the right)

$+c$ = total of observations in the column c (shown as marginal total at bottom of matrix)

N = total number of observations in the matrix

5.2.9   Potential for further use of the classification system

The central dome area is a natural feature of raised bogs (Figure 3.3). The preservation and morphology of this central dome area dictates the type and condition of vegetation growing there. An important consideration for indicating the health of the delicately balanced hydrology of the bog is to monitor and map the *Sphagna* within the central dome area. A number of attributes are used to quantify the condition of active raised bog. One method is to assess coverage of pool forming Sphagna e.g.*Sphagnum pulchrum* and *Sphagnum cuspidatum* (Robinson, 2010). A coverage of >20% of *Sphagnum pulchrum* and *Sphagnum cuspidatum* denotes active bog in good condition, <20% indicates active bog in poor condition. A DTM was used to map the terrain of the SSSI and surrounding area. The central dome area was located and a 5m contour created to delineate an area of active bog in the central dome area. This area was then used to select a set area to analyse percentage coverage of *Sphagnum pulchrum* and *Sphagnum cuspidatum* high-

lighted using the species classification. Using the set contour level denoting the central dome area ensured that the same area can be measured again in time to assess the condition of the bog and to give an indication of whether there is any drying out occurring. Once the area of *Sphagna* was clipped within ArcMap to this area the percentage coverage was calculated by total using counting the number of pixels of *Sphagnum pulchrum* and the number of *Sphagnum cuspidatum* number coverage. This was then divided by the total number of pixels within the 5m contour area and multiplied by 100 to give a percentage coverage.

5.3 Results

5.3.1 Relationship of field spectrometer readings to WV2 imagery

Linear regression of WV2 Peak (July) indices and field spectroradiometer July indices showed poor linear relationships for most of the indices to be used in the classification (Figure 5.6 and 5.7). The REP ($r^2 = 0.804$) and BR ($r^2 = 0.740$) indices for this period show the best correspondence. The Woody ($r^2 = 0.136$) and BG ($r^2 = 0.116$) indices had a group of points that appeared to be the reason for low r^2 values. When investigated these points were from *Sphagnum cuspidatum* readings.
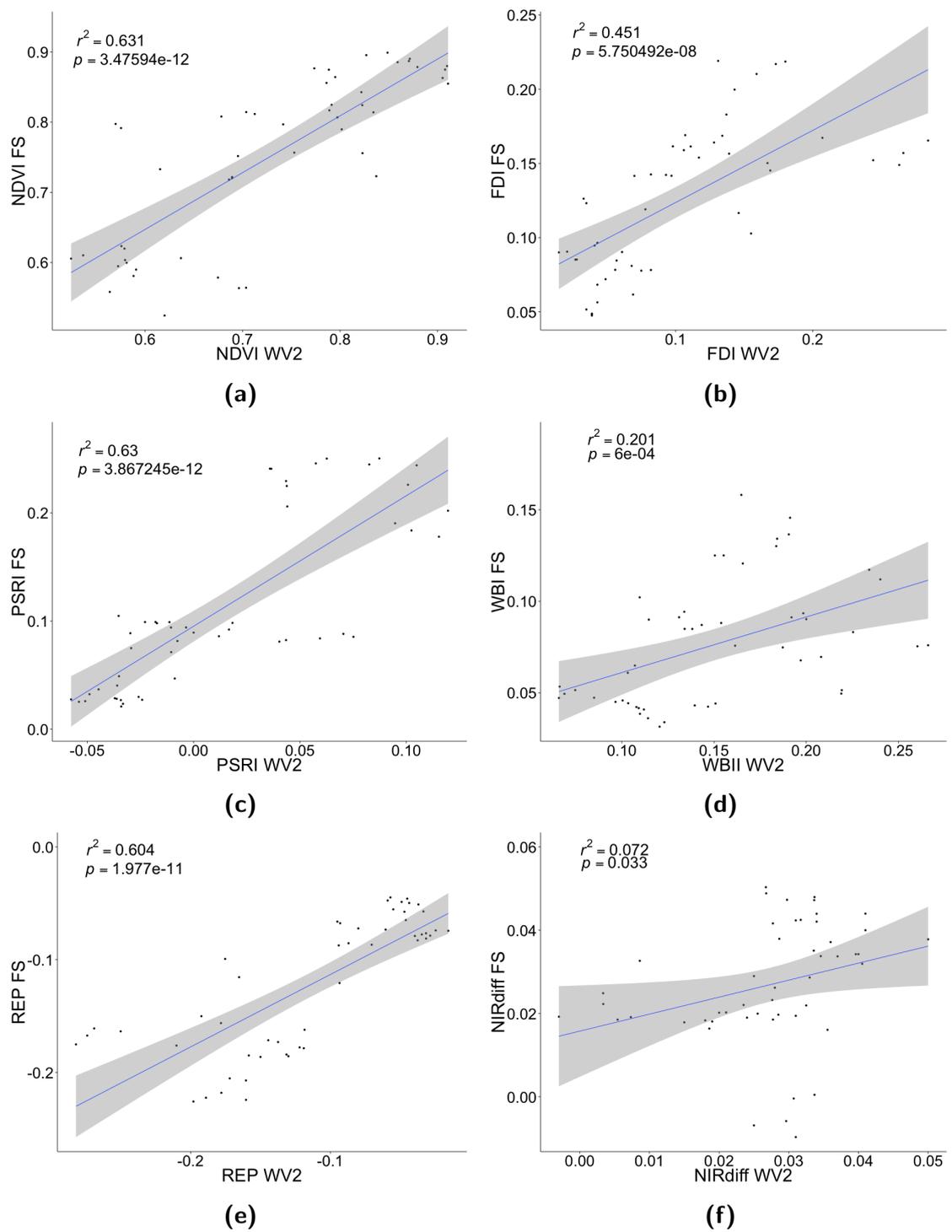
Figure 5.6: Linear regression of indices derived from field spectroradiometer (FS) and WV2 derived indices
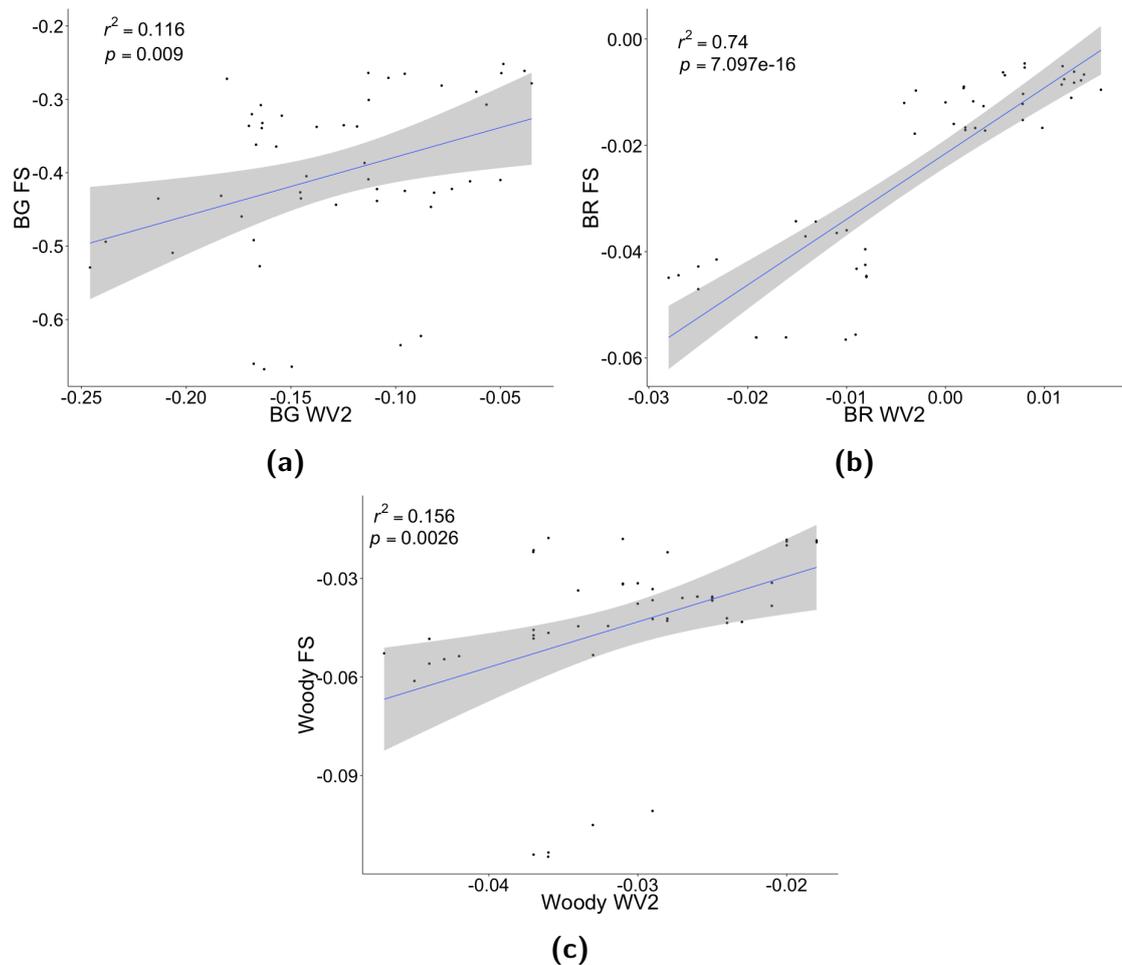
Figure 5.7: Linear regression of indices derived from field spectroradiometer (FS) and WV2 derived indices

Using a graphical comparison of spectral curve data for atmospheric corrected and field data (Figure 5.9a) it could be seen that for *Sphagnum cuspidatum* the green band (λ 0.548μm) has poor correspondence with the field spectroradiometer. For field spectroradiometer readings the green band was much greater than for the WV2 green band readings. Both of these indices Woody and BG use the green band for calculations. Other species such as *Calluna vulgaris* and *Phragmites australis* gave much better correspondence between field spectroradiometer and WV2 spectral curves (Figures 5.9b and c).
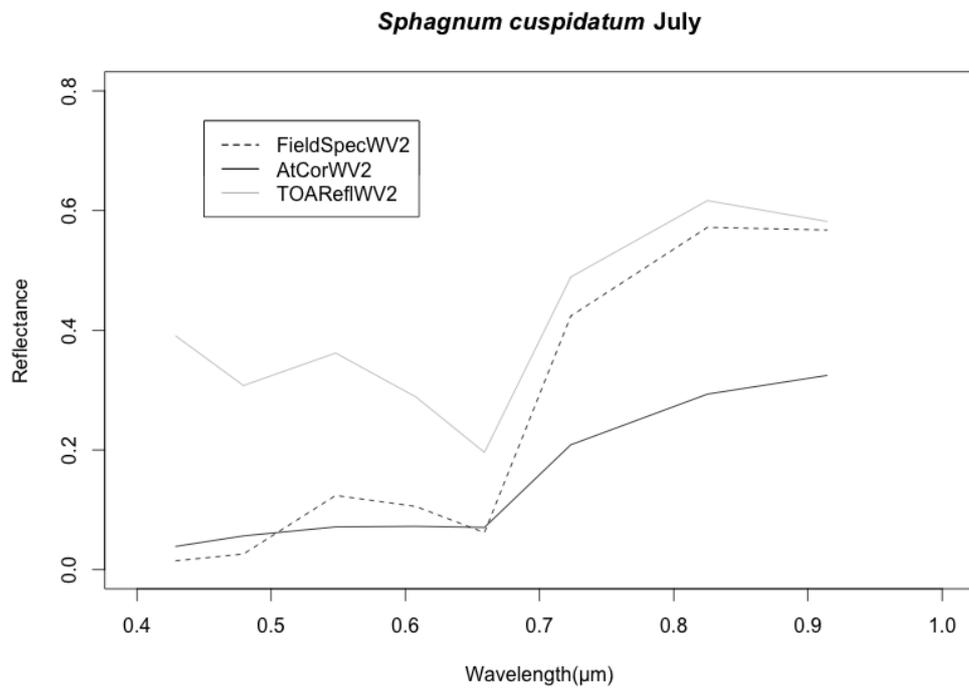
(a)
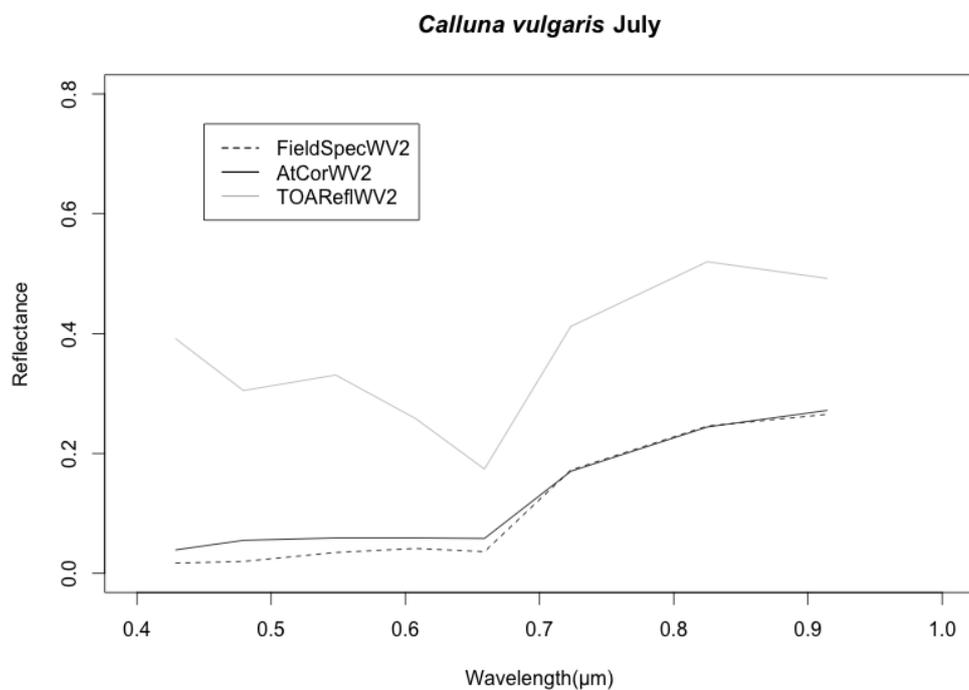
(b)

Figure 5.8: Spectral graphs for species a) *Sphagnum cuspidatum* and b) *Calluna vulgaris* in July showing the Top of Atmosphere reflectance versus the Atmospherically corrected and the field spectroradiometer data.
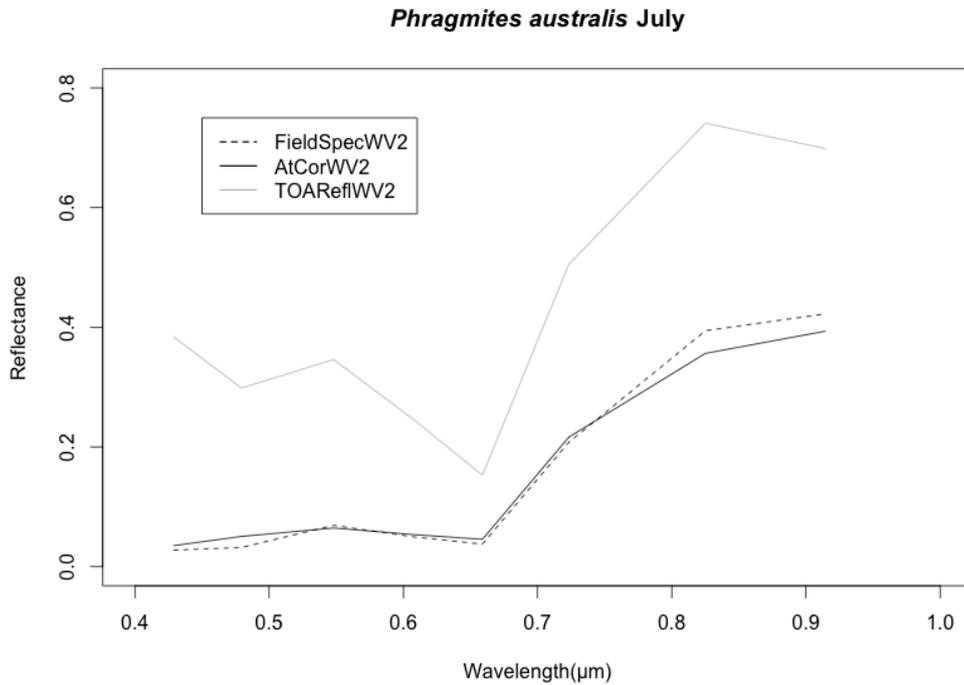
(a)

Figure 5.9: Spectral graph for species *Phragmites australis* in July showing the Top of Atmosphere reflectance versus the Atmospherically corrected and the field spectroradiometer data.

5.3.2 Spectral discrimination of species with extracted WV2 data

Field spectrometer data in chapter 4 was assessed according to the number of scores of 0, however, in this chapter as the WV2 data only contains 8 wavelength values the spectral separation is not as pronounced so spectral angle scores that were less than 0.5 were counted instead. Although species spectral data are showing some separability (Table 5.8), results showed separation was not as statistically significant as the comparable field spectroradiometer data using only the WV2 related spectral bands (Table 4.4).

The results of the spectral analysis shows that differences between reflectance spectra

of vegetation types are statistically significant for different vegetation types.

According to the < 0.5 results (Table 5.8), *Juncus effusus* is more separable from all other species with this more pronounced in the pre and post periods (Tables 5.5, 5.7). Table 5.8 suggests that all 3 acquisitions are of equal importance for spectral discrimination.

Eriophorum angustifolium and *Sphagnum cuspidatum* gave the lowest scores for separability (Table 5.8).

Pre	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Cal vul	1.000	0.609	0.791	0.458	0.344	0.880	0.463	0.578	0.652	0.895
Eri ang	0.609	1.000	0.769	0.108	0.729	0.659	0.793	0.891	0.914	0.629
Eri vag	0.791	0.769	1.000	0.336	0.506	0.876	0.577	0.721	0.825	0.848
Jun eff	0.458	0.108	0.336	1.000	0.000	0.437	0.000	0.083	0.165	0.470
Mol cae	0.344	0.729	0.506	0.000	1.000	0.394	0.804	0.705	0.676	0.364
Myr gal	0.880	0.659	0.876	0.437	0.394	1.000	0.482	0.623	0.713	0.961
Phr aus	0.463	0.793	0.577	0.000	0.804	0.482	1.000	0.786	0.724	0.455
Pte aqu	0.578	0.891	0.721	0.083	0.705	0.623	0.786	1.000	0.818	0.590
Sph cus	0.652	0.914	0.825	0.165	0.676	0.713	0.724	0.818	1.000	0.684
Sph pul	0.895	0.629	0.848	0.470	0.364	0.961	0.455	0.590	0.684	1.000

Table 5.5: Table showing spectral angle scores using Pre WV2 spectral data. Mean spectral values for each species were used.

Peak	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Cal vul	1.000	0.910	0.766	0.559	0.556	0.440	0.680	0.318	0.892	0.765
Eri ang	0.910	1.000	0.803	0.610	0.563	0.446	0.687	0.318	0.934	0.795
Eri vag	0.766	0.803	1.000	0.442	0.392	0.274	0.513	0.156	0.818	0.902
Jun eff	0.559	0.610	0.442	1.000	0.931	0.823	0.903	0.688	0.615	0.411
Mol cae	0.556	0.563	0.392	0.931	1.000	0.876	0.862	0.748	0.569	0.362
Myr gal	0.440	0.446	0.274	0.823	0.876	1.000	0.746	0.840	0.449	0.247
Phr aus	0.680	0.687	0.513	0.903	0.862	0.746	1.000	0.615	0.689	0.485
Pte aqu	0.318	0.318	0.156	0.688	0.748	0.840	0.615	1.000	0.331	0.121
Sph cus	0.892	0.934	0.818	0.615	0.569	0.449	0.689	0.331	1.000	0.781
Sph pul	0.765	0.795	0.902	0.411	0.362	0.247	0.485	0.121	0.781	1.000

Table 5.6: Table showing spectral angle scores using Peak WV2 spectral data. Mean spectral values for each species were used.

Post	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Cal vul	1.000	0.656	0.888	0.602	0.369	0.777	0.230	0.543	0.642	0.785
Eri ang	0.656	1.000	0.685	0.290	0.697	0.569	0.521	0.719	0.922	0.805
Eri vag	0.888	0.685	1.000	0.588	0.395	0.752	0.243	0.552	0.683	0.820
Jun eff	0.602	0.290	0.588	1.000	0.000	0.656	0.000	0.265	0.279	0.415
Mol cae	0.369	0.697	0.395	0.000	1.000	0.275	0.748	0.552	0.703	0.549
Myr gal	0.777	0.569	0.752	0.656	0.275	1.000	0.112	0.599	0.538	0.617
Phr aus	0.230	0.521	0.243	0.000	0.748	0.112	1.000	0.359	0.514	0.411
Pte aqu	0.543	0.719	0.552	0.265	0.552	0.599	0.359	1.000	0.670	0.576
Sph cus	0.642	0.922	0.683	0.279	0.703	0.538	0.514	0.670	1.000	0.818
Sph pul	0.785	0.805	0.820	0.415	0.549	0.617	0.411	0.576	0.818	1.000

Table 5.7: Table showing spectral angle scores using Post WV2 spectral data. Mean spectral values for each species were used.

<0.5	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Total
Pre	3	1	1	9	4	3	4	1	1	3	30
Peak	2	2	4	2	2	5	0	5	2	5	29
Post	2	1	2	6	4	2	6	2	1	2	28
Total	7	4	7	17	10	10	10	8	4	10	

Table 5.8: Table showing number of spectral angle scores with values less than 0.5 using reflectance values for WV2 spectral data.

5.3.3 Selection of best spectral indices for discrimination of species and LCCS categories

Analysis of indices was performed for all scales, LCCS level 2, Life-form and species. Separation using this method performed better for some categories than others with the scale and hierarchical level being of influence on the effectiveness of these methods. The combination of pairs of individual variables gave a greater separation of LCCS level 2, Life-form or species in some cases than using an individual variable. Further discrimination with pairs of best indices shown by pair plots were used to show suitable index combinations.

Landscape - LCCS Level 2

Analysis of LCCS level 2 categories using separation values gave high F-ratio (separation) values particularly for peak FDI and peak BG. The F-ratio values varied from 106.79 to 5.16 (Table 5.9). These values indicated that the best indices for LCCS Level 2 category separation were peak FDI and peak BG. Post NIR and NDVIDiffPrePeak indices were the poorest indices at LCCS Level 2 category separation.

Pair plots (Figures 5.10 and 5.11) help to illustrate the effectiveness of selection of best indices using F-ratios. It can be seen in Figure 5.11 that indices with the smallest F-ratios (Table 5.9) provide the least separation. Care needs to be taken as all indices with low F-ratios are not necessarily the worst separators for individual categories. This can be seen in Figure 5.11 were the ANV category (water) appears to be relatively well separated from other categories as would be expected of this index.

SSSI - Lifeform

Categories used in the indices selection process were forb, graminoid, moss and woody. The woody could not be subdivided into woody shrubs and woody trees without using a CHM so for the indices selection process they were treated as one category - woody (see Figure 5.3). Lichens were present on the site but were present in patches that were not large enough to dominate a pixel and were often under a canopy (e.g. beneath *Calluna*) so these were omitted.

Both F-ratio results (Table 5.10) and the pair plots (Figures 5.12 & 5.13) showed that separations of life-form was not effective for this particular habitat (Cors Fochno SSSI). Variance within life-form categories was high and there was too much overlap of life-form categories using these indices (Figures 5.12 & 5.13). For this reason the 2nd stage of the EODHaM system classification was not performed due to the likely introduction of inaccuracies at this stage causing further inaccuracies at species level classification.

Variable	Vw	Vb	F-ratio
Peak FDI	0.21	22.14	106.79
Peak BG	0.24	21.20	87.50
Post FDI	0.30	19.70	65.90
NDVI Diff PeakPost	0.31	19.52	63.85
Post BG	0.32	19.18	60.31
Peak REP	0.32	19.08	59.24
Post NDVI	0.33	18.96	58.12
Pre NDVI	0.38	17.56	46.34
Pre FDI	0.39	17.20	43.81
Pre PSRI	0.41	16.62	40.11
Post REP	0.43	16.07	36.94
Pre WBI	0.44	15.82	35.59
Pre REP	0.46	15.51	34.05
Post PSRI	0.48	14.94	31.29
Post WBI	0.51	14.07	27.58
Peak Woody	0.51	14.06	27.55
Pre BG	0.54	13.32	24.75
Peak PSRI	0.55	13.04	23.76
Peak NDVI	0.57	12.53	22.08
Pre NIR diff	0.57	12.48	21.90
Peak BR	0.68	9.63	14.25
Pre Woody	0.68	9.44	13.82
Pre BR	0.76	7.47	9.86
Peak WBI	0.76	7.42	9.78
Post Woody	0.77	7.01	9.06
Peak NIR diff	0.83	5.68	6.89
Post BR	0.83	5.44	6.53
NDVI Diff PeakPre	0.87	4.52	5.21
Post NIR diff	0.87	4.49	5.16

Table 5.9: Separations between Level 2 of LCCS (WV2). Larger F-ratio values indicating better separation of all lifeforms using the specified indices. Vw = Variance within Level 2, Vb = Variance between Level 2
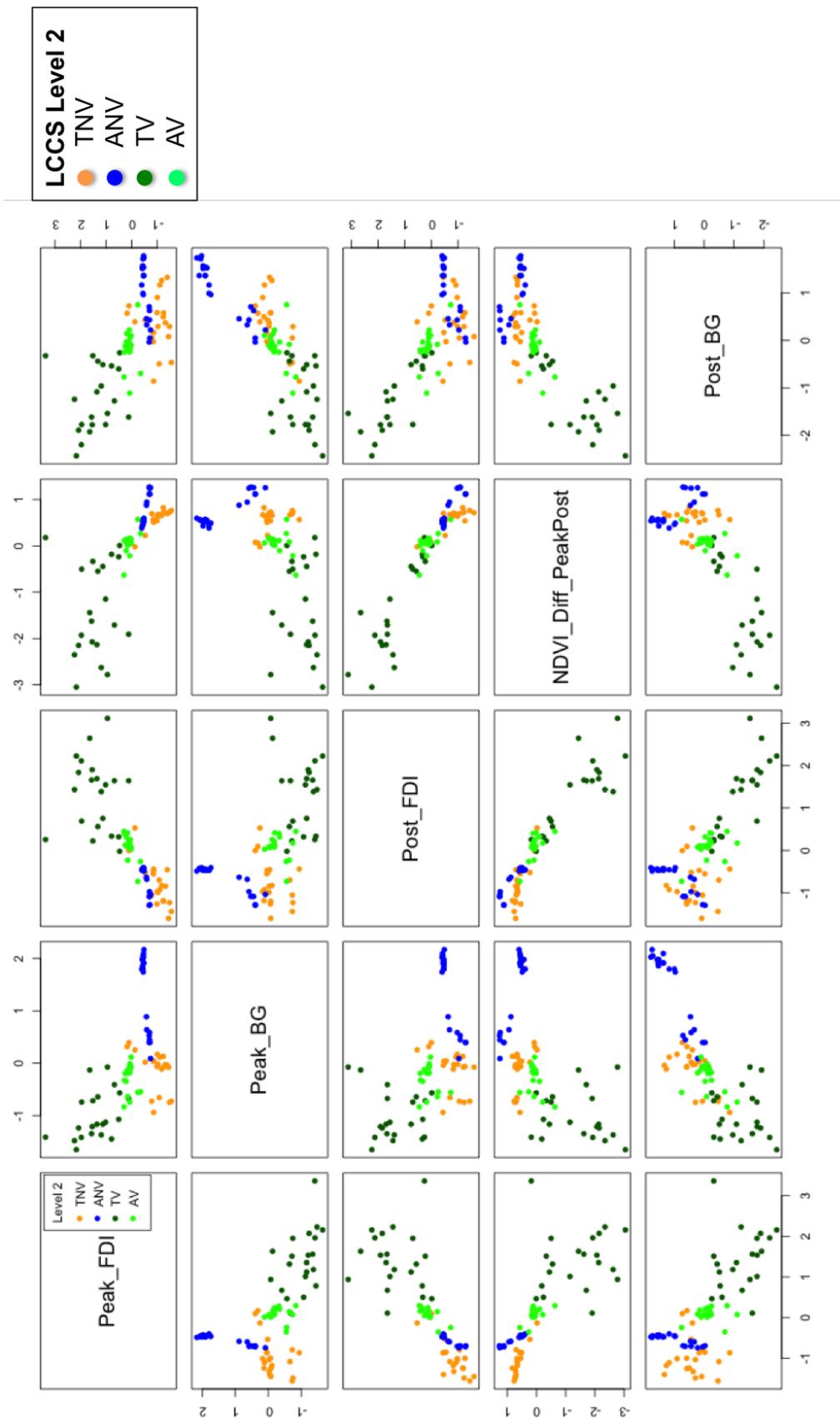
Figure 5.10: Best separations for LCCS Level 2 demonstrating effective separation of categories.
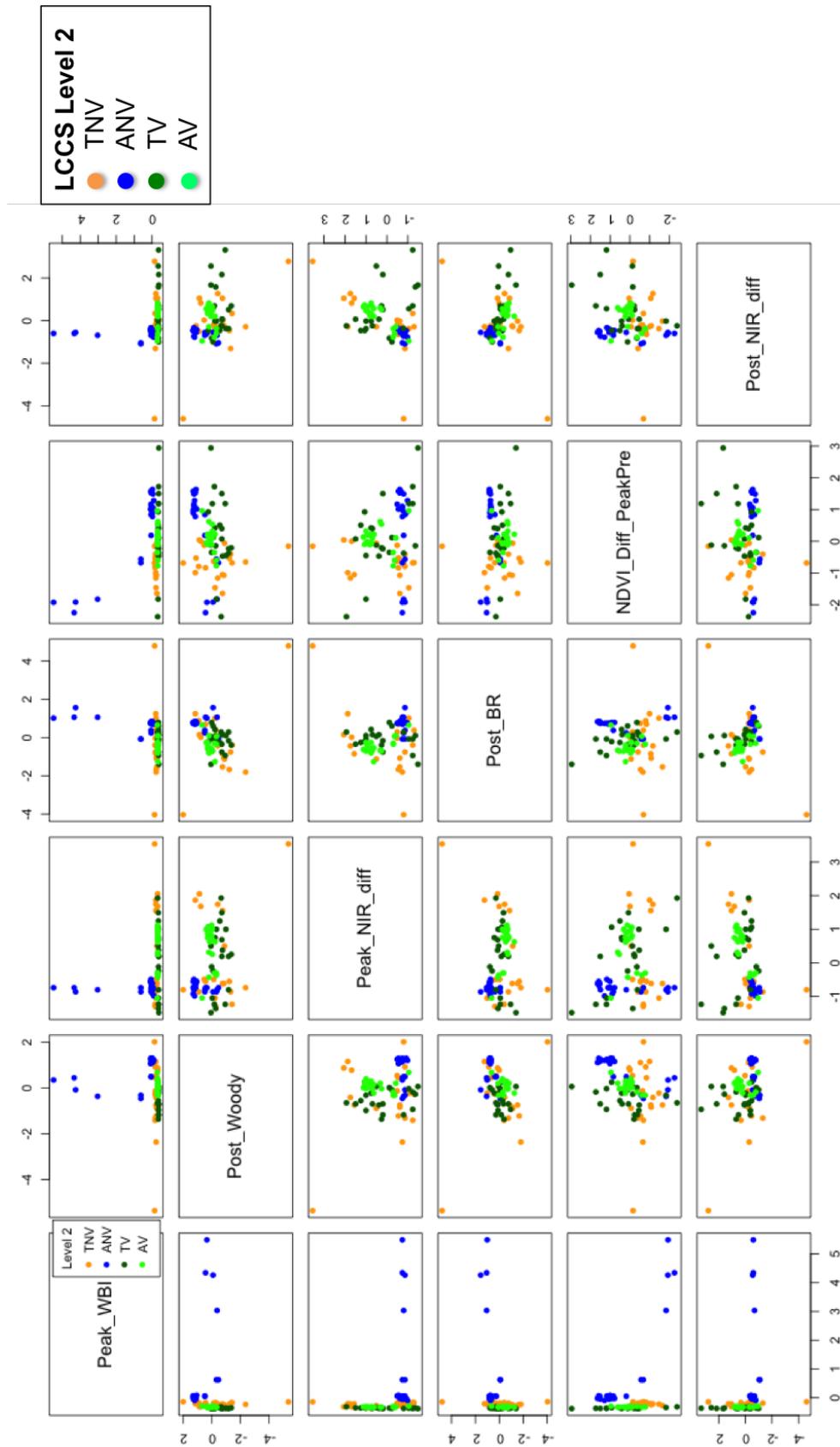
Figure 5.11: Least separations for LCCS Level 2 demonstrating poor separation of categories.

Variable	Vw	Vb	F-ratio
Peak NIR diff	0.32	11.50	36.44
Peak_FDI	0.40	10.14	25.14
Peak_REP	0.47	9.08	19.20
Peak_BG	0.51	8.55	16.83
Peak_Woody	0.56	7.70	13.67
Peak_NDVI	0.58	7.47	12.93
Peak_BR	0.59	7.35	12.55
Peak_PSRI	0.59	7.34	12.50
Post_Woody	0.62	6.87	11.12
Peak_WBI	0.64	6.45	10.00
Pre_BG	0.70	5.66	8.14
Post_NIR_diff	0.70	5.60	8.00
NDVI_Diff_PeakPre	0.70	5.59	7.97
Post_PSRI	0.72	5.29	7.34
Post_BG	0.75	4.82	6.42
NDVI_Diff_PeakPost	0.76	4.68	6.15
Pre_Woody	0.79	4.15	5.22
Post_BR	0.81	3.92	4.84
Pre_PSRI	0.82	3.72	4.53
Post_NDVI	0.89	2.74	3.09
Pre_BR	0.89	2.66	2.99
Pre_NIR_diff	0.90	2.61	2.91
Pre_NDVI	0.91	2.34	2.57
Post_REP	0.92	2.26	2.47
Pre_WBI	0.98	1.26	1.28
Pre_REP	1.03	0.58	0.56
Post_WBI	1.03	0.53	0.51
Pre_FDI	1.04	0.43	0.42
Post_FDI	1.06	0.07	0.06

Table 5.10: Separations between life-form (WV2). Larger F-ratio values indicating better separation of all life-forms using the specified indices.Vw= Variance within life-form, Vb= Variance between life-form
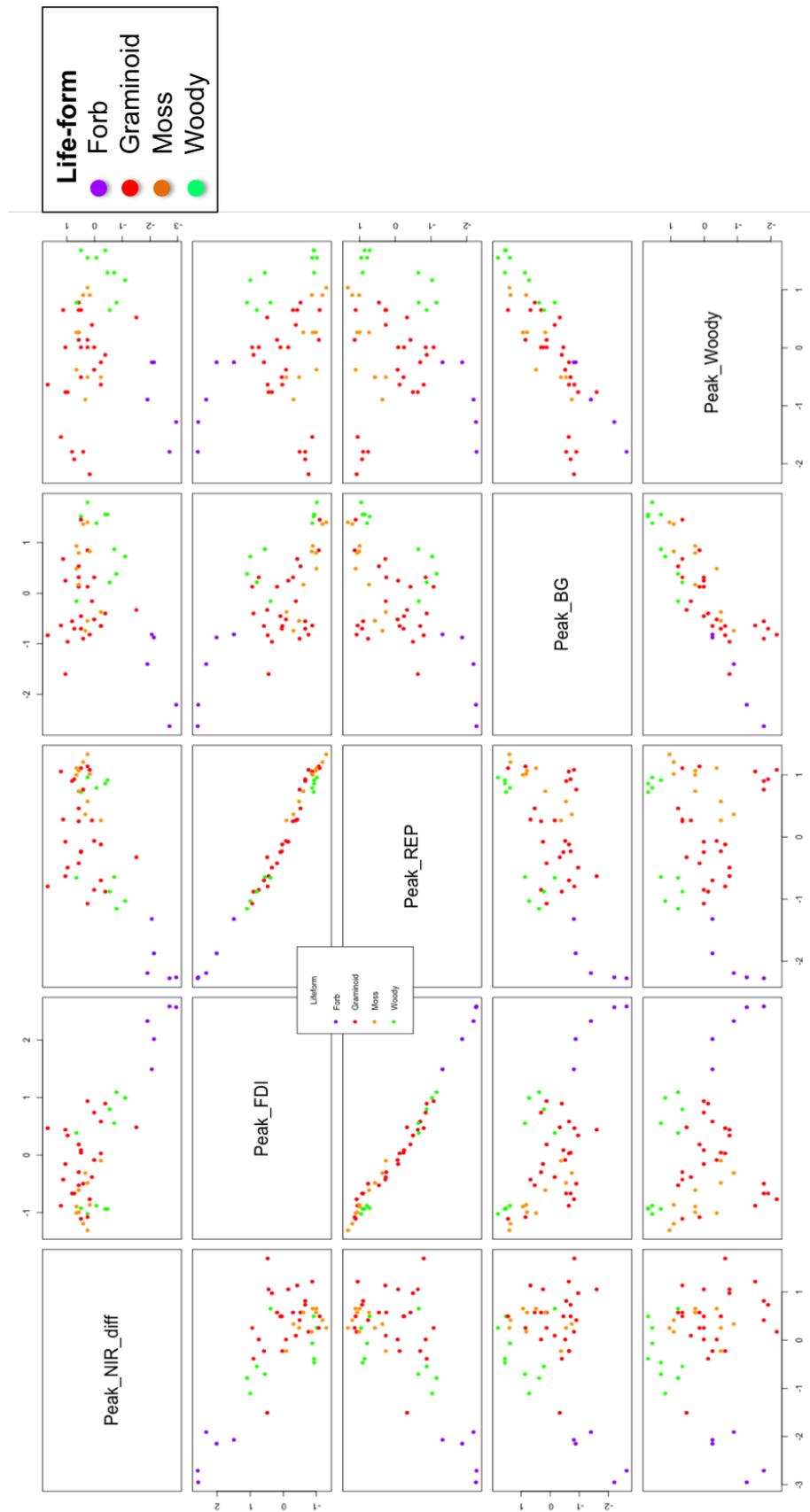
Figure 5.12: Best separations for life-form demonstrating effective separation of life-form.
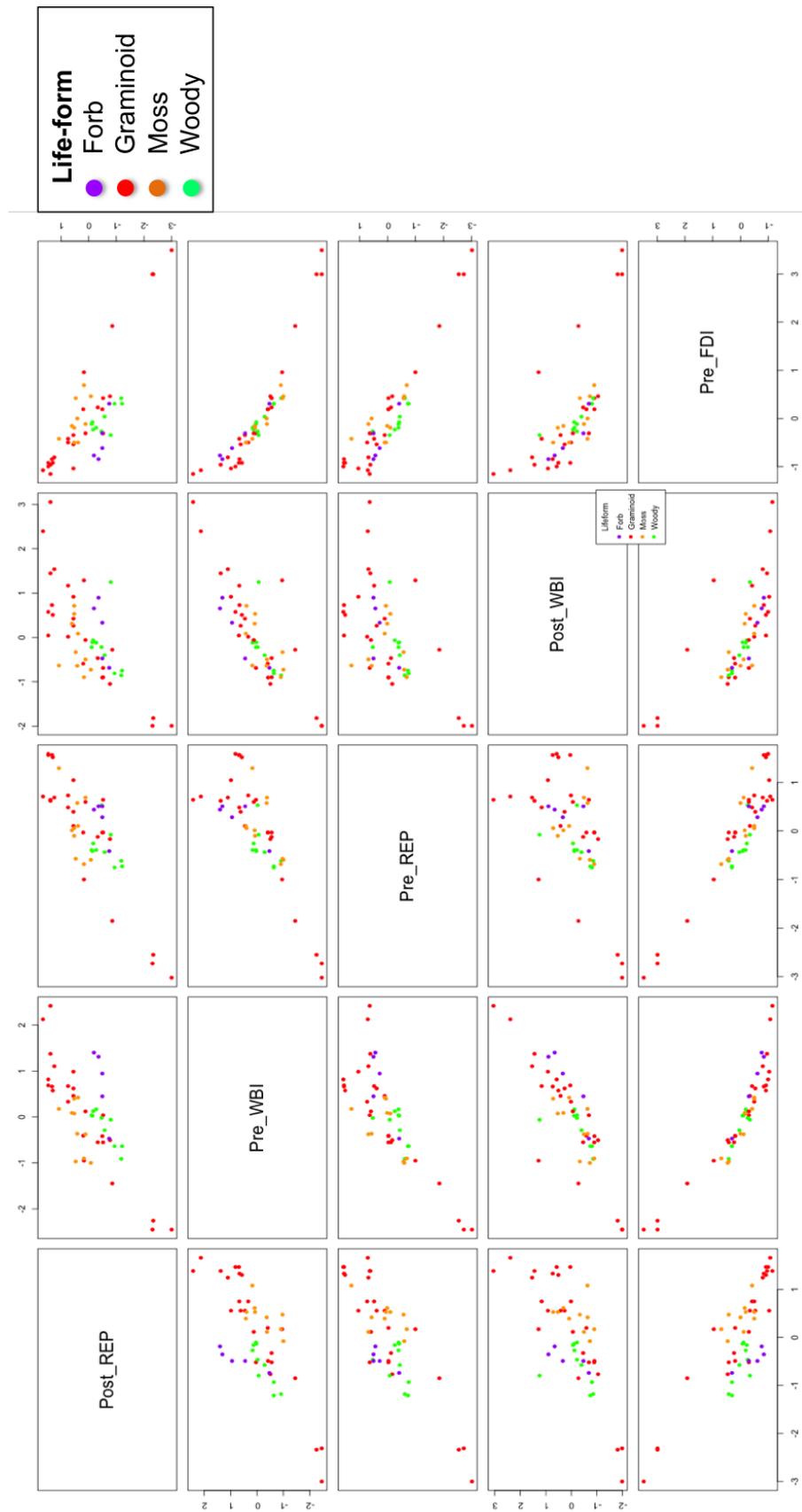
Figure 5.13: Least separations for life-form demonstrating poor separation of life-form.

SSSI - Species

F-ratio results for dominant species (Table 5.11) and as illustrated by pair-plots (Figures 5.14 and 5.15) where much better than for life-form. These results however, were not as high as the results obtained with field spectroradiometer data (Table 4.6) in chapter 4. This demonstrates that actual satellite imagery dominant species patches are more difficult to separate than the dominant patches sampled in the field spectroradiometer data. Pair plots (Figure 5.14) of indices with the highest F-ratios show that those with highest values were better at separating species and that a combination of two of these best indices provided better separation than one index. The best indices were from the peak (July) image. PeakBR, peakPSRI, peakREP, peakFDI and peakNDVI along with the seasonal difference indices NDVIDiffpeakpre (Figure 5.14) were the best indices for species separation. Whilst postWBI, postFDI, postNIRdiff and postBG indices gave the least discrimination.

Variable	Vw	Vb	F-ratio
Peak_BR	0.06	5.18	87.06
Peak_PSRI	0.07	5.14	75.96
Peak_REP	0.10	5.00	50.52
Peak_FDI	0.10	4.98	47.68
Peak_NDVI	0.11	4.96	45.81
NDVI_Diff_PeakPre	0.12	4.92	41.26
Pre_NDVI	0.13	4.89	38.81
Peak_Woody	0.15	4.78	32.23
NDVI_Diff_PeakPost	0.16	4.75	30.42
Pre_REP	0.16	4.72	29.00
Pre_FDI	0.18	4.64	25.46
Post_PSRI	0.21	4.51	21.57
Post_NDVI	0.23	4.43	19.34
Pre_PSRI	0.23	4.40	18.76
Peak_BG	0.24	4.40	18.67
Peak_WBI	0.24	4.39	18.52
Pre_WBI	0.24	4.37	18.18
Post_REP	0.27	4.25	15.77
Post_Woody	0.27	4.22	15.39
Pre_BR	0.30	4.12	13.83
Pre_Woody	0.30	4.09	13.43
Peak_NIR_diff	0.31	4.08	13.30
Post_BR	0.31	4.06	13.04
Pre_BG	0.42	3.58	8.56
Pre_NIR_diff	0.46	3.42	7.51
Post_WBI	0.51	3.19	6.29
Post_FDI	0.52	3.11	5.94
Post_NIR_diff	0.55	3.01	5.51
Post_BG	0.55	3.00	5.47

Table 5.11: Separations between species (WV2). Larger F-ratio values indicating better separation of all species using the specified indices.Vw= Variance within species, Vb= Variance between species
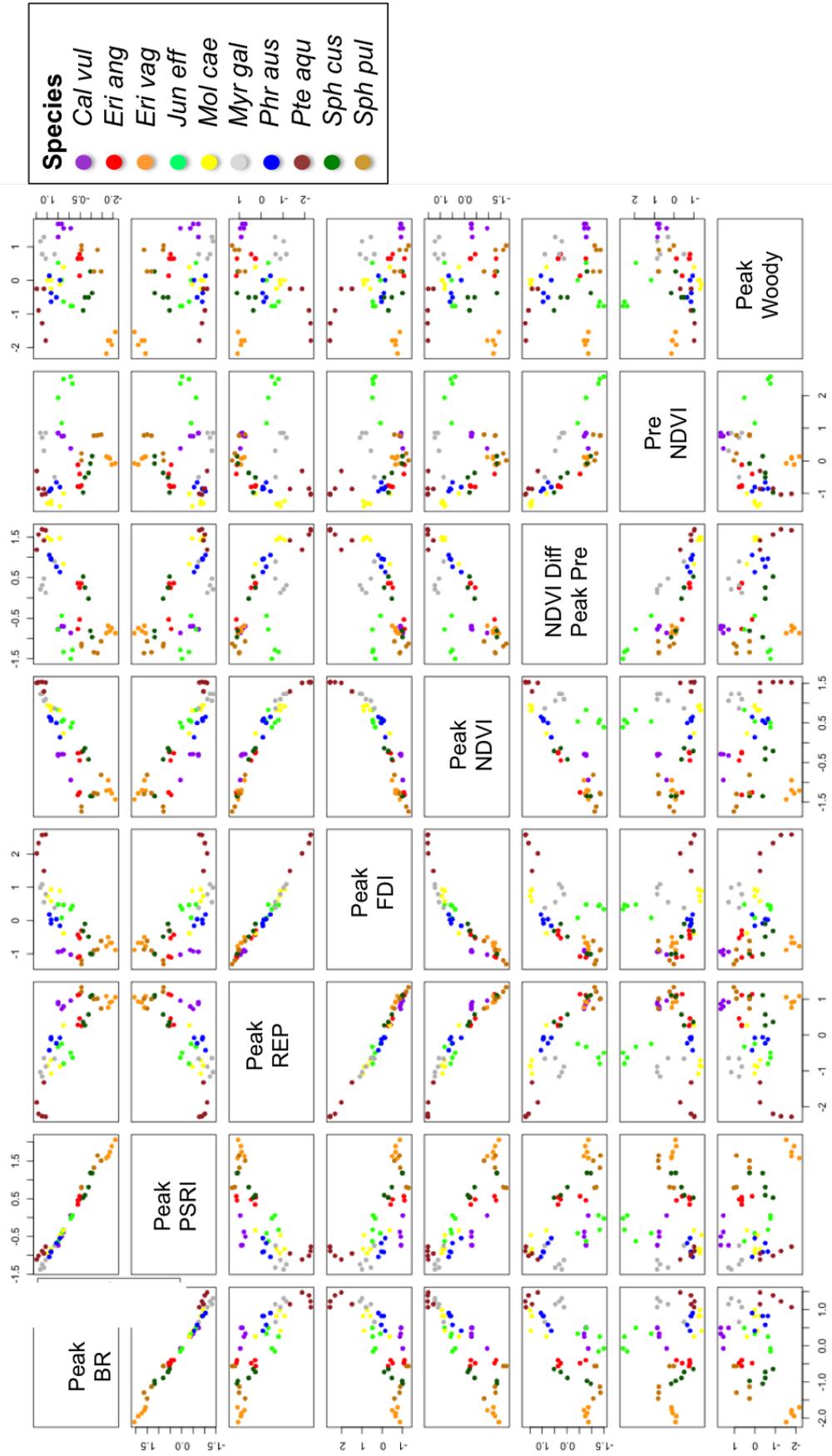
Figure 5.14: Best separations for species demonstrating effective separation of species.
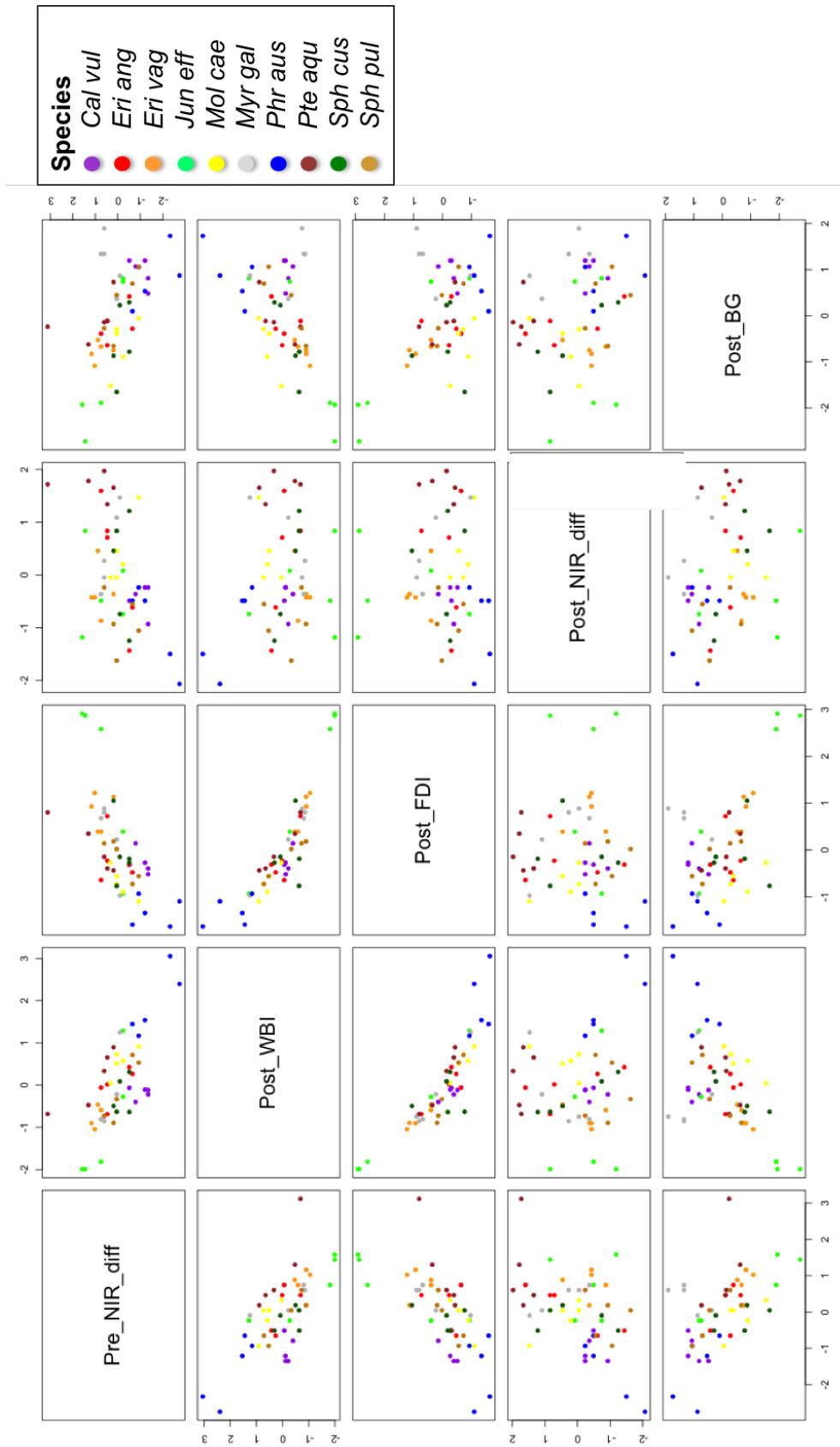
Figure 5.15: Least separations for species demonstrating poor separation of species.

Canopy Height Model

Canopy height was to be used as part of LCCS classification for use with determining shrub and tree heights. However, the canopy height model (CHM) heights did not correspond well with actual quadrat recorded vegetation heights with an r^2 value of 0.307 (Figure 5.16). For this reason the CHM was not used in the classification process. This reduced the LCCS categories classified (e.g. Woody shrub, Woody trees, shrub heights). However, areas of trees could be successfully classified by using >1m as a threshold value of the CHM. This value was selected through trial and error using Tuiview and the attributes table produced from the pixel layers of the EODHaM system, one of which was a CHM layer with values to correspond to each 2×2m pixel for each pixel. Field hedgerows and wooded areas were classified using this method. Poor correspondence of low vegetation height (e.g.<1m) ($r^2 = 0.307$) meant it was not suitable for use in anything lower than 1m (Figure 5.16).
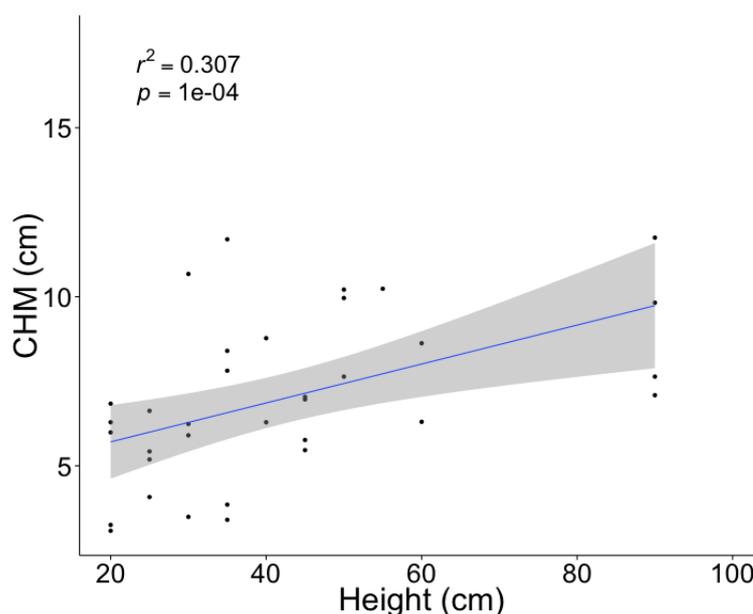
Figure 5.16: Linear regression of field height data and the CHM height data for the vegetation shorter than 1m

5.3.4 Landscape classification

The landscape scale classification within the EODHaM system focused on the four classes with an extra layer to show trees . This area had coastal, river, ditches and ponds/small lake water features all classed as aquatic non vegetated (ANV). Areas of terrestrial non vegetated (TNV) were urban areas, buildings, roads and bare ground. Aquatic vegetated (AV) areas consisted of areas of saltmarsh and raised bog habitats. The terrestrial vegetated (TV) class consisted of all areas that were vegetated but not regularly waterlogged.

Thresholds were developed from only a small number of selected spectral indices (Figure 5.17) for LCCS level 2 classification. For LCCS level 2 category classification (4 categories, ANV, TNV, AV and TV) only three indices were used for threshold input with only one image required for this from the Peak period (July). The two indices with the highest F-ratios peakFDI and peakBG were selected for threshold calculations. However on examination of the pair plots (Figure 5.11) it could be seen that peakWBI was a good separator of ANV (water) from all other categories (Figure 5.17) so was incorporated in the threshold input.

(a)

(b)

(c)
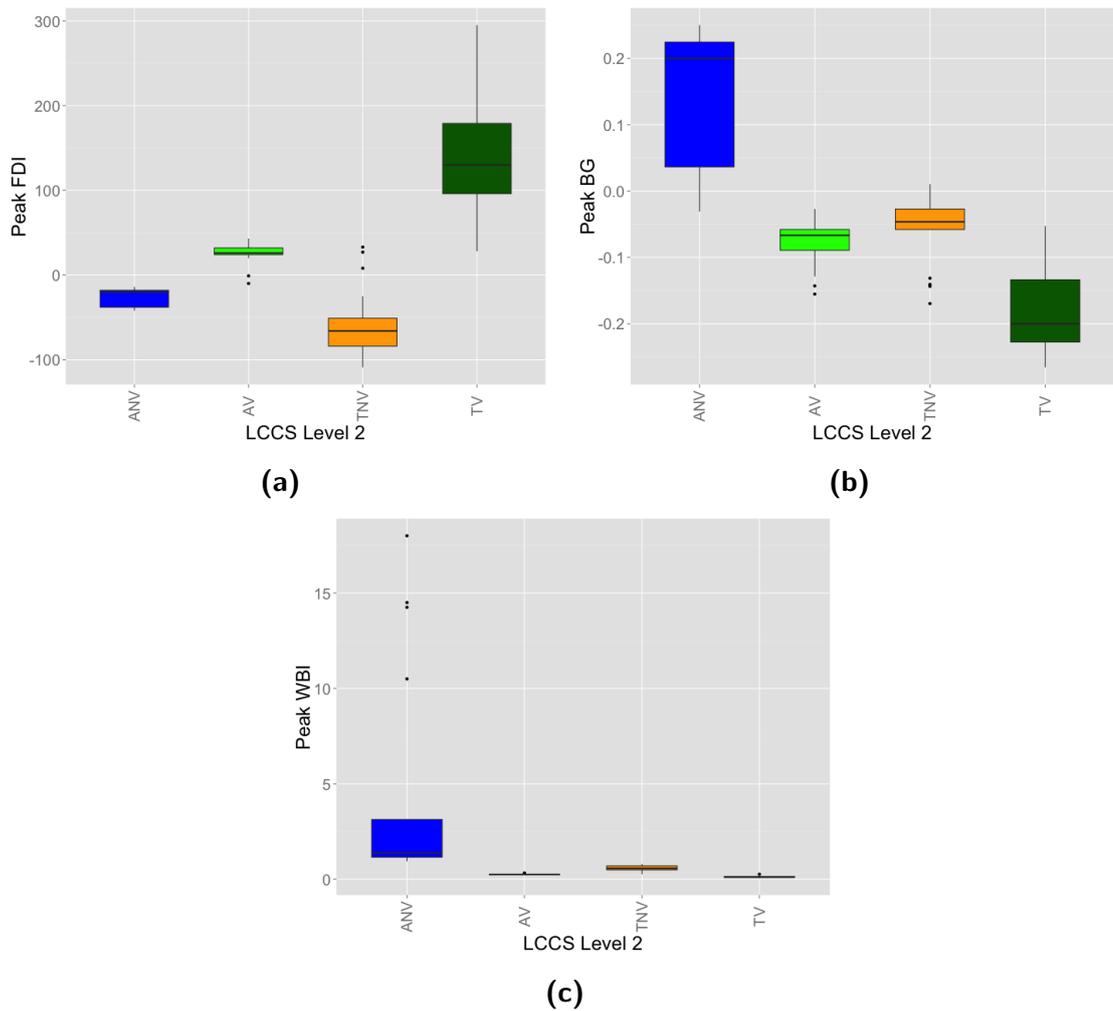
Figure 5.17: Boxplots showing peak FDI, peak BG and peak WBI indices (best selected) range of values for each LCCS level 2 class. These also illustate how thresholds using the maxium and minimum values can be used to separate these classes.

This was also an index used within EODHaM for classification of water (Lucas et al., 2011b). Each category used more than one index threshold (Figure 5.4). Minimum and maximum values were selected for each category. These were entered into the classification Python script. Assessment within TuiView decided whether to use both greater than and less than values for input or a singular greater or less than value (Figure 5.4).

Accuracy for the landscape scale classification of LCCS Level 2 categories and Trees

using a standard confusion matrix (Table 5.12) provided an overall accuracy of 84.4% with a kappa value of 0.805. Aquatic non vegetated (ANV) (water) gave the best results with user accuracies between 72 and 78%. These categories brought the overall accuracy down and the poor CHM is partly responsible for the lower 78% user accuracy.

Classified data	Reference (UAV)						User's Accuracy (%)
	ANV	AV	T	TNV	TV	Sum	
ANV	49	0	0	1	0	50	98
AV	0	36	0	6	8	50	72
T	1	2	39	5	3	50	78
TNV	8	2	0	39	1	50	78
TV	0	2	0	0	48	50	96
Sum	58	42	39	51	60	250	
Producer's Accuracy (%)	84.5	85.7	100.0	76.5	80.0		

Table 5.12: Confusion matrix for the landscape scale classification of LCCS level 2 and Trees. Overall accuracy = 84.4%, Kappa value = 0.805

There was some confusion in areas between the terrestrial non vegetated (TNV) category and the aquatic non vegetated (ANV) (Figure 5.18). Threshold values can be seen to overlap between these classes (Figure 5.18) for all indices used. When investigated it appeared that incorrect classification seemed mostly to be on roads or roofs (Figure 5.18) and it can be seen that cars parked on a sandy beach were classified as aquatic vegetated (Figure 5.18). Despite these issues TNV was classified to an accuracy of 78% and ANV to an accuracy of 98% (Table 5.12).

In addition to the 4 LCCS level 2 classes a further Tree layer was added using the CHM (Figure 5.20). This was successful at classifying trees to an accuracy of 78% (Table 5.12) especially those that were coniferous and hedgerows that appeared to be >1m especially those that were coniferous and hedgerows that appeared to be > 1m. (Figures 5.19).
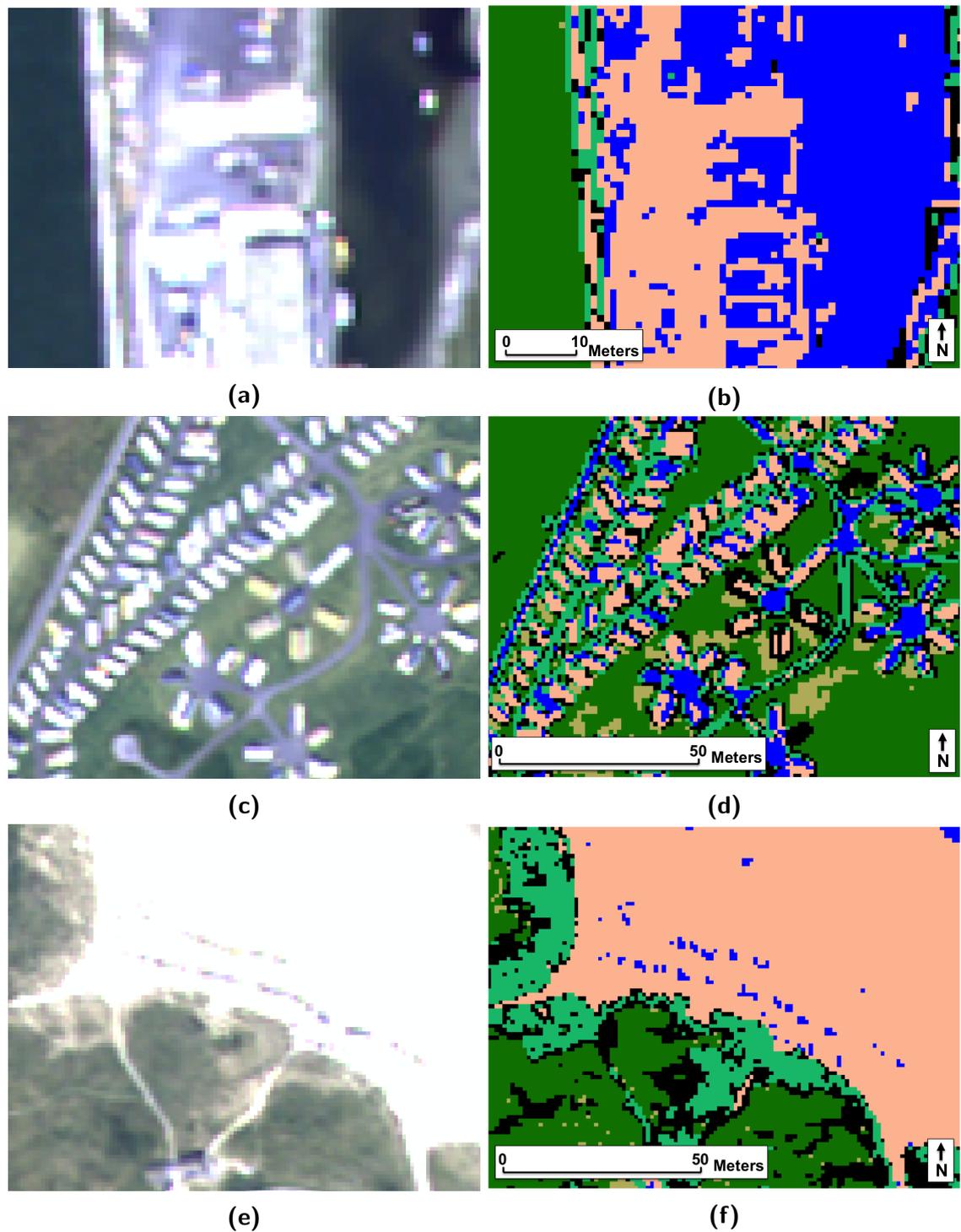
Figure 5.18: Images showing classification of LCCS level 2 with the corresponding section in WV2 imagery. a)&b) boat yard near the estuary, c)&d)caravan park, e)&f) Ynyslas visitor centre with cars parked on the beach. ■ = AV, ■ = ANV, ■ = TV, ■ = TNV, ■ = Trees(>1m)
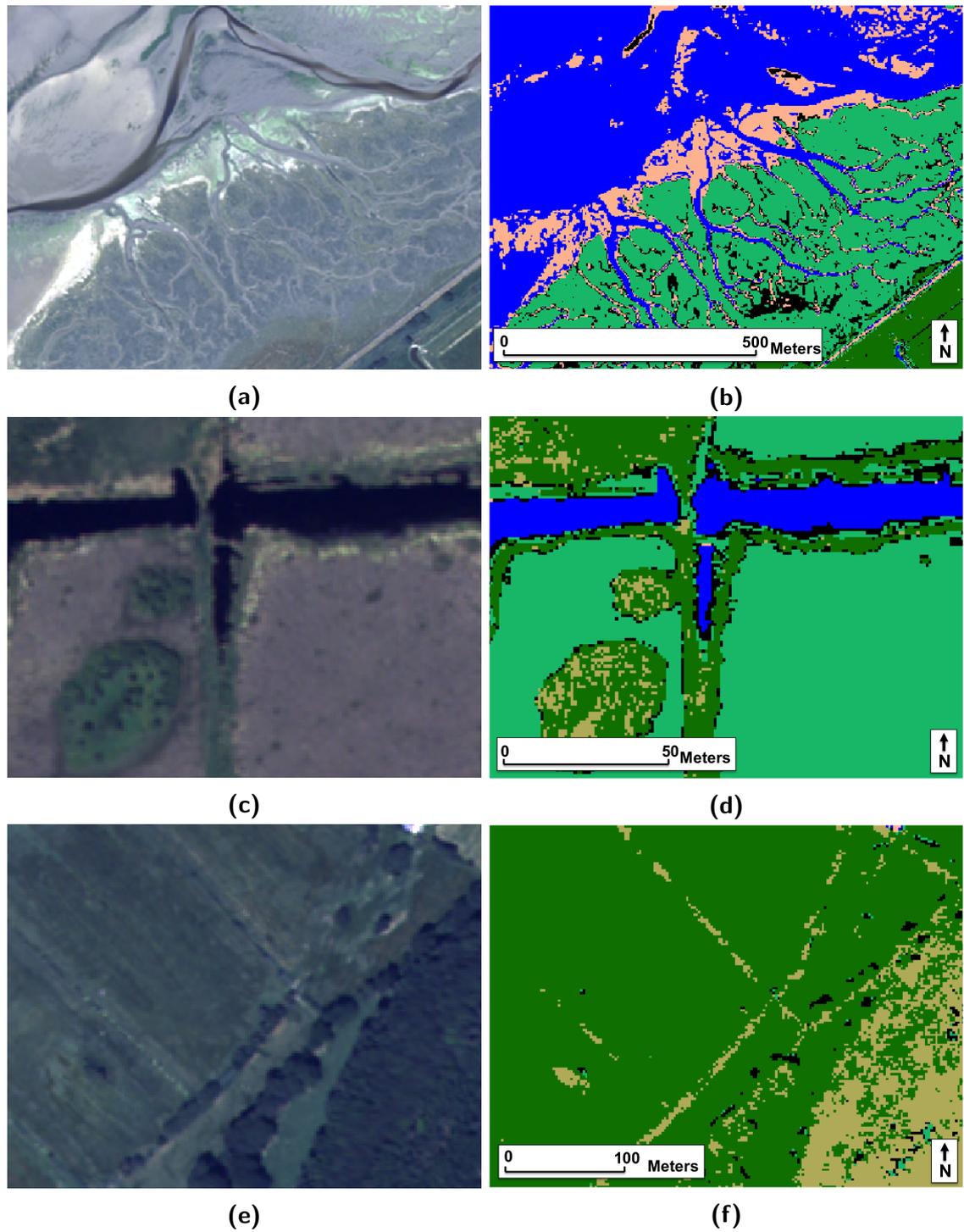
Figure 5.19: Images showing classification of LCCS level 2 with the corresponding section in WV2 imagery. a)&b) saltmarsh, c)&d) ditched and small raised stoney island within SSSI, and e)&f) hedge line and coniferous woodland in landscape. ■ = AV, ■ = ANV, ■ = TV, ■ = TNV, ■ = Trees(>1m)

Figure 5.20: Classification to LCCS Level 2 & trees of whole landscape with overall accuracy of 84.4%.

5.3.5   SSSI classification

It was found that species classification worked most reliably using 9 indices which were identified as the top indices for separation along with an index that shows seasonal changes (Figure 5.14). In the end no Post indices were used as the majority of these gave low-F-ratio values (Figure 5.11).

All indices selected for discrimination of species were selected using methods described, however the reasoning here explains why they work well and supports the methods accuracy. Trees are found in both aquatic vegetated and terrestrial vegetated areas. Most vegetation over 1m in height for this region are trees. *Pteridium aquilinum* is found only in drier areas bounding the bog. Vegetation is rarely over 1m in height in these areas and so the tree classification layer is removed from this classification in order to avoid any potential confusion with trees growing in and around the *Pteridium aquilinum*. ndviPeakPreDiff layer works well due to *Pteridium aquilinum* having very lush growth in summer (Peak) but a monoculture of dead litter in the winter providing a large value for ndviPeakPreDiff compared with other species. *Juncus effusus* is found mostly in fields or areas of degraded SSSI surrounding the wetter bog (i.e. drier less waterlogged) and does not die back like *Pteridium aquilinum*, although it does senesce a little. A small value in the ndviPeakPreDiff can therefore be used to differentiate *Juncus effusus* from species such as *Pteridium aquilinum*. *Calluna vulgaris* is found in drier peaty areas such as heaths but also in hummock areas of the bog so both terrestrial vegetated and aquatic vegetated were selected. Due to its woody branches all pixels associated with trees were excluded from classification. woodyPeak index is specifically for discriminating woody shrubs etc. ndviPeakPreDiff values are small compared with other non-evergreen species.
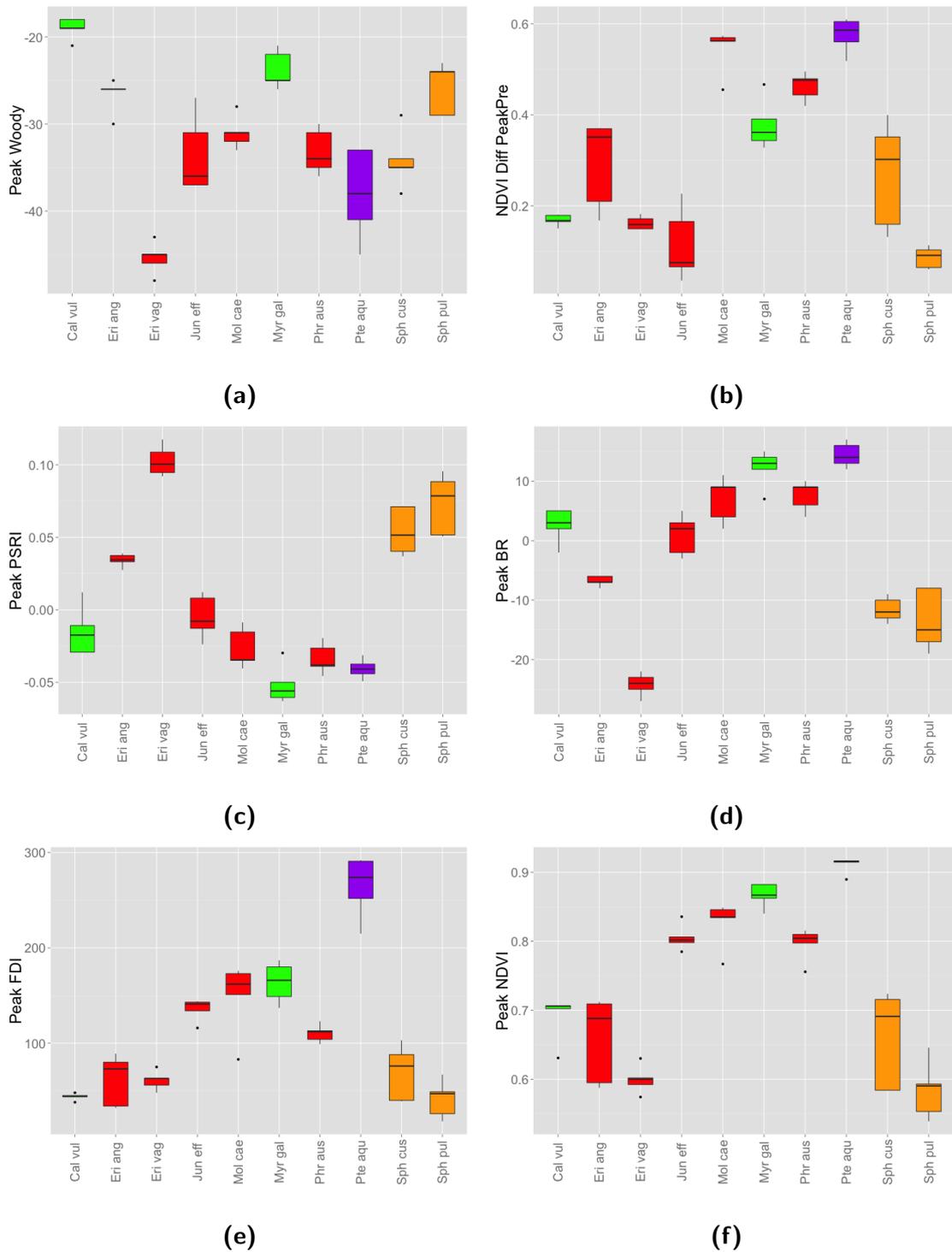
Figure 5.21: Boxplots showing the range of values for species of the indices identified as the top indices for separation of species, a) peak Woody, b) NDVIDiffpeakpre (seasonal difference in NDVI), c) peak PSRI, d) peak BR, e) peak FDI and f) peak NDVI. Life-form categories are highlighted in colours to highlight difficulty in separation. ■ = forb, ■ = graminoid, ■ = moss, ■ = woody

(a)   **(b)**
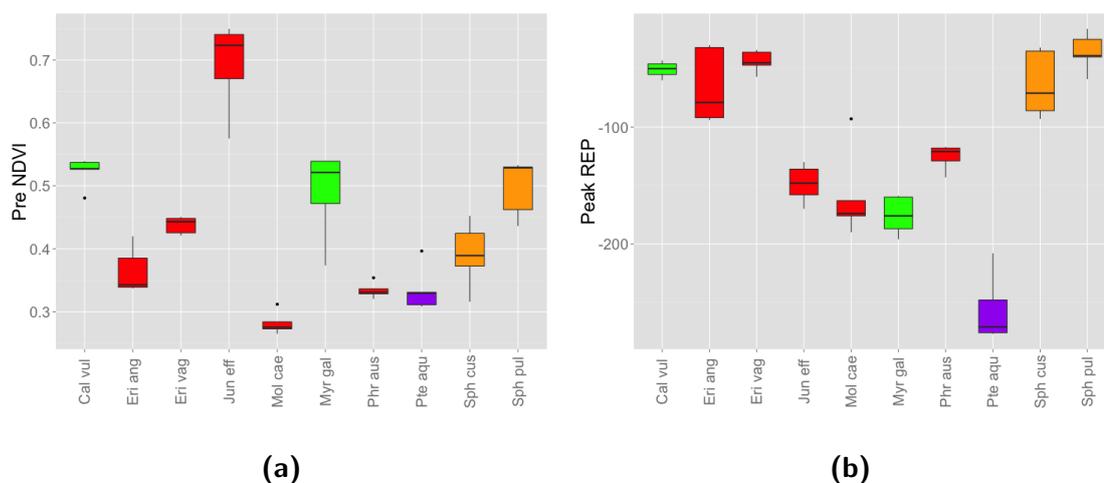
Figure 5.22: Boxplots showing the range of values for species of the indices identified as the top indices for separation, a) pre NDVI and b) peak REP. Life-form categories are highlighted in colours to highlight difficulty in separation. ■ = forb, ■ = graminoid, ■ = moss, ■ = woody

Although *Calluna vulgaris* is evergreen there does appear to be significant die back in the winter. *Myrica gale* is found in both bog and surrounding drier areas so both terrestrial and aquatic vegetated areas were selected. As this species is a woody shrub to help with discriminating this species and reduce confusion with Tree species the Tree classified pixels were excluded from classification. Woody Peak is used for discrimination of woody shrubs. *Eriophorum vaginatum, Sphagnum pulchrum, Eriophorum angustifolium, Sphagnum cuspidatum* and *Phragmites australis* are only found in the wet bog areas and so only the aquatic vegetated layer is used for classification. woodyPeak index is used to help distinguish *Eriophorum vaginatum, Eriophorum angustifolium* from the woody shrubs which grow in the same areas. The values for these non-woody plants are much lower. *Sphagnum pulchrum* used ndviPeakPreDiff as there was very little change in colouration or structure between summer and winter months with it remaining an orange colour throughout the year. The brpeak shows the difference between the blue and red wavelength which may be useful in discriminating vegetation such as this with an orange hue. *Eriophorum angustifolium* has a lot of dead litter surrounding its green photosynthetic leaves and therefore has a higher psriPeak value in summer than other

species within the aquatic vegetated areas. It was initially difficult in some areas to separate *Phragmites australis* from *Molinia caearulea* as they are both lush growth in summer and an expanse of dead litter in the winter and tend to both occupy the degenerated outer fringes of the bog. Expanses of *Phragmites australis* were classified first as this was restricted to only the aquatic vegetated layer. This species is found usually in wet ditches or very wet regions of the outer bog. ndviPre was used for both species as they create a blanket of dead litter in the winter which is a distinct feature of these species in the winter months. Once *Phragmites australis* was succesfully discriminated and classified the remainding deadlitter in the aquatic and terrestrial vegetated areas was most likely to be *Molinia caerulea* so classification of this was carried out on pixels excluding the *Phragmites australis* classified pixels.

Classified data	Reference (UAV)																User's
	AV	ANV	TV	TNV	T	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Sum	Accuracy (%)
AV	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	100
ANV	0	47	0	3	0	0	0	0	0	0	0	0	0	0	0	50	94
TV	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	50	100
TNV	0	4	0	46	0	0	0	0	0	0	0	0	0	0	0	50	92
T	3	0	1	0	46	0	0	0	0	0	0	0	0	0	0	50	92
Cal vul	5	0	0	0	0	42	0	0	0	3	0	0	0	0	0	50	84
Eri ang	2	0	0	0	0	0	33	2	0	13	0	0	0	0	0	50	66
Eri vag	1	0	0	0	0	1	2	43	0	3	0	0	0	0	0	50	86
Jun eff	0	0	8	0	1	0	0	0	40	1	0	0	0	0	0	50	80
Mol cae	0	0	0	0	0	0	0	0	0	45	0	5	0	0	0	50	90
Myr gal	12	0	6	0	4	0	0	0	0	0	28	0	0	0	0	50	56
Phr aus	0	0	0	0	0	0	0	0	0	10	0	40	0	0	0	50	80
Pte aqu	0	0	0	0	0	0	0	0	0	0	0	3	47	0	0	50	94
Sph cus	16	0	0	0	0	0	0	0	0	0	0	0	0	34	0	50	68
Sph pul	12	0	0	0	0	0	0	0	0	0	0	0	0	0	38	50	76
Sum	101	51	65	49	51	43	35	45	40	75	28	48	47	34	38	750	
Producer's Accuracy (%)	49.5	92.2	76.9	93.9	90.2	97.7	94.3	95.6	100	60	100	83.3	100	100	100		

Table 5.13: Confusion matrix for the SSSI scale classification of LCCS level 2, trees and species using UAV data. Overall accuracy = 83.9%, Kappa value = 0.827

| Classified data | Reference (Ground plots) | | | | | | | | | | | | | | | | User's |
	AV	ANV	TV	TNV	T	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul	Sum	Accuracy (%)
AV	18	1	1	0	0	0	3	0	0	0	0	0	0	0	0	23	78.3
ANV	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	12	100
TV	0	0	22	0	0	0	0	0	0	3	0	0	0	0	0	25	88
TNV	0	0	3	6	0	0	0	0	0	0	0	0	0	0	0	9	66.7
Trees	0	0	4	0	18	0	0	0	0	0	0	0	0	0	0	22	81.8
Cal vul	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	26	100
Eri ang	2	0	0	0	0	0	8	2	0	4	0	0	0	0	0	16	50
Eri vag	0	0	0	0	0	0	2	8	0	1	0	0	0	0	0	11	72.7
Jun eff	0	0	4	0	0	0	0	0	8	0	0	0	0	0	0	12	66.7
Mol cae	2	0	1	0	0	0	0	0	0	28	0	0	0	0	0	31	90.3
Myr gal	3	0	4	0	0	0	0	0	0	0	12	0	0	0	0	19	63.2
Phr aus	2	0	0	0	0	0	0	0	0	0	0	16	0	0	0	18	88.9
Pte aqu	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	11	100
Sph cus	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	7	100
Sph pul	1	0	0	0	2	0	0	0	0	0	0	0	0	3	12	18	66.7
Sum	28	13	39	6	20	26	13	10	8	36	12	16	11	10	12	260	
Producer's Accuracy (%)	64.3	92.3	56.4	100	90	100	100	80	100	77.8	100	100	100	70	100		

Table 5.14: Confusion matrix for the SSSI scale classification of LCCS level 2, trees and species using ground data. Overall accuracy = 81.5%, Kappa value = 0.799

Accuracy of the SSSI classification was high for both assessment methods. Overall accuracy of the SSSI classification using UAV imagery for accuracy assessment was 83% with a Kappa value of 0.827, whilst the accuracy test using ground plots gave 81.5% (Kapp = 0.799). LCCS level 2 categories had higher user accuracy when smaller (SSSI as opposed to landscape) areas were classified. As with the landscape aquatic non vegetated (ANV) and terrestrial vegetated were more accurately classified with user accuracies between 88 and 100%. Both terrestrial vegetated (TV) and aquatic vegetated (AV) both had a user accuracy of 100%. This was an improvement on the accuracy for the wider landscape due to it being done on a smaller area. As the accuracy was so high the subsequent classification of species which used these two LCCS level2 classes in its rule set was not affected by the hierarchical system of LCCS classification and EODHaM system.

Myrica gale proved to be harder to classify correctly with user accuracies (UAV derived) of 56% and 63.2% (Tables 5.13 and 5.14). *Myrica gale* was similarly the species most dif-

ficult to discriminate using field spectrometer data (Chapter 4). *Sphagnum cuspidatum* also had a low user accuracy (UAV derived) of 68%.

Active raised bogs have characteristic 'microtopes' within the central dome area which consist of hummocks and hollows (Lindsay, 1995). *Calluna vulgaris* usually dominates hummocks and in the case of Cors Fochno *Sphagnum pulchrum* or *Sphagnum cuspidatum* dominates the hollows. These hummocks and hollows tend to be larger than the pixel size (2×2m)(Figure 5.24). Both of these species have been discriminated with accuracies of 76 and 84% . Species such as *Juncus effusus* which proved to be difficult to distinguish in the EODHaM project (Lucas et al., 2011b) proved to be successfully identified using this method (Figure 5.25).
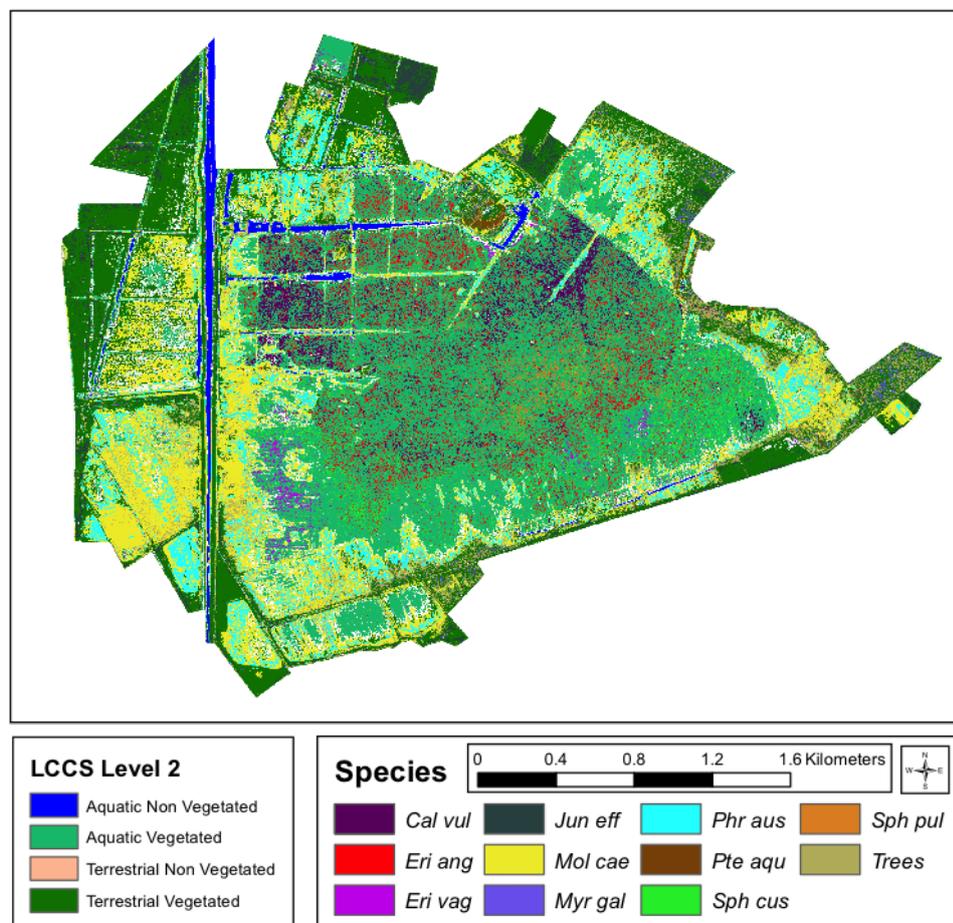
Figure 5.23: Dominant species classification of Cors Fochno SSSI with underlying LCCS level 2 classification.

(a) **(b)**

(c) **(d)**

(e) **(f)**
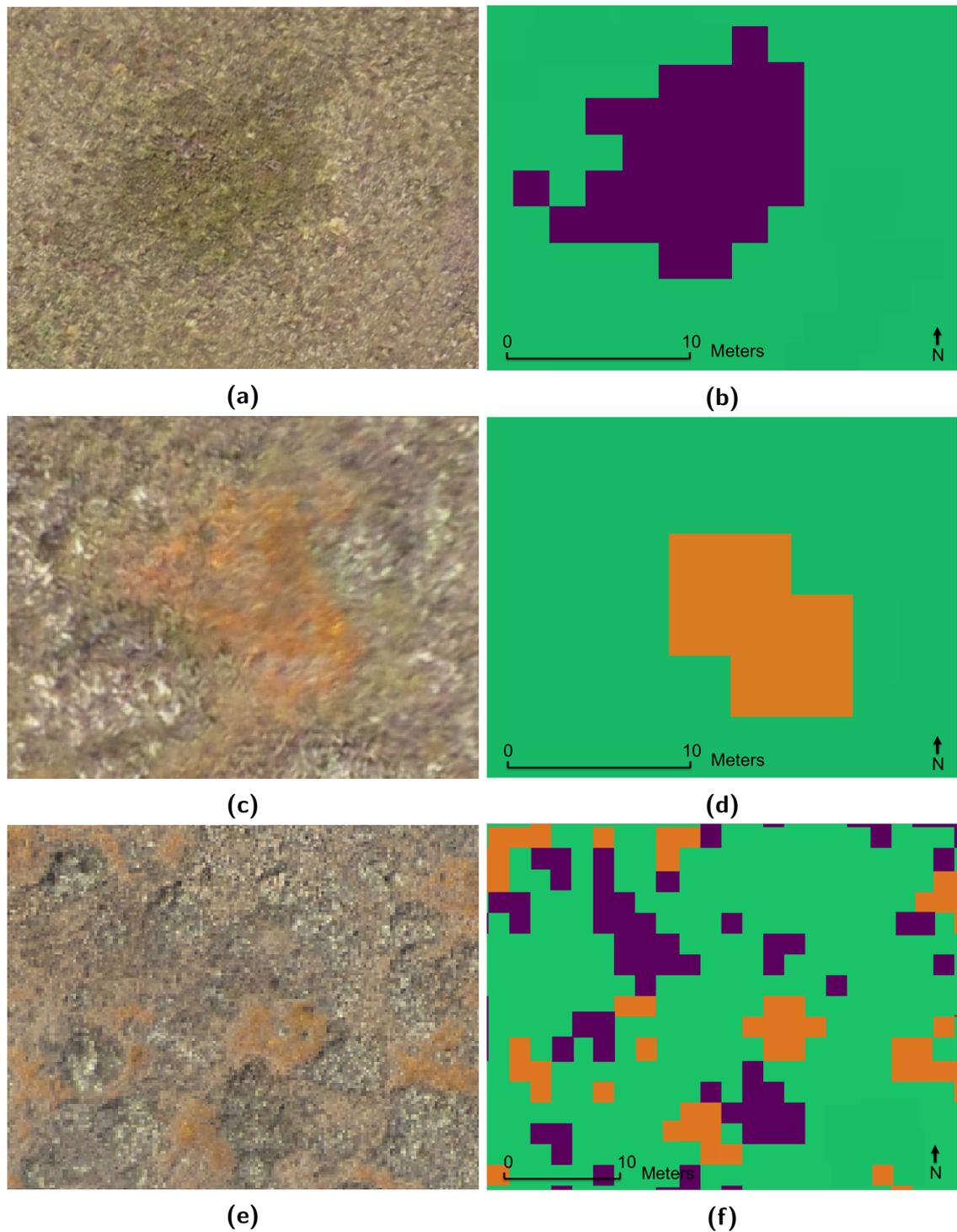
Figure 5.24: Species classification with corresponding UAV imagery for a section of the central dome area, a) and b) *Calluna vulgaris* hummock, c) and d) *Sphagnum pulchrum* hollow, e) and f) hummock and hollow 'microtope'.
■ = AV, ■ = *Calluna vulgaris*, ■ = *Sphagnum pulchrum*
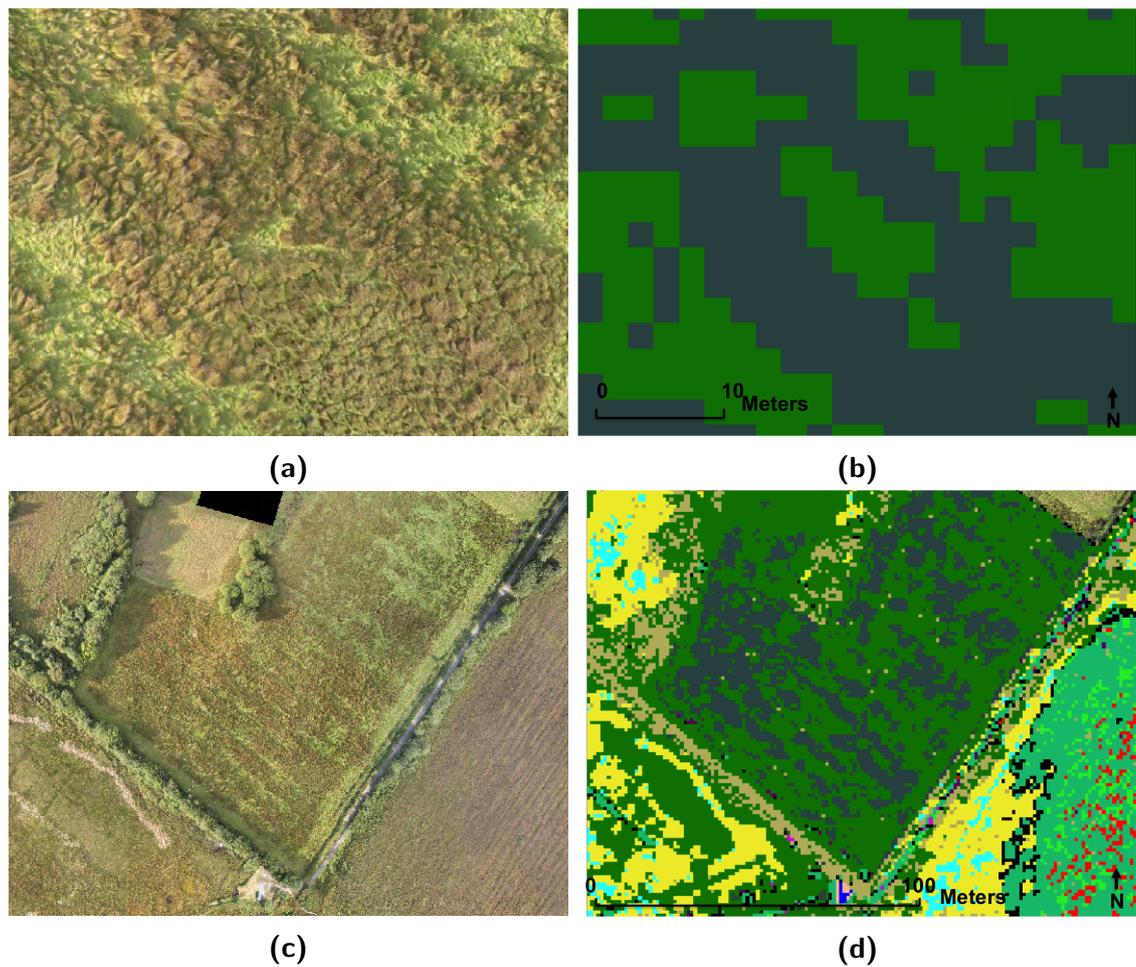
Figure 5.25: Species classification with corresponding UAV imagery showing *Juncus effusus* classification, a) and b) close up, c) and d) same field with obvious stripes of *Juncus effusus* most likely following the ploughing pattern from some time before. ■ = AV, ■ = ANV, ■ = TV, ■ = TNV, ■ = Trees(>1m), ■ = *Calluna vulgaris*, ■ = *Eriophorum angustifolium*, ■ = *Eriophorum vaginatum*, ■ = *Juncus effusus*, ■ = *Molinia caerulea*, ■ = *Myrica gale*, ■ = *Phragmites australis*, ■ = *Sphagnum cuspidatum*, ■ = *Sphagnum pulchrum*, ■ = Unclassified.

(a)

(b)

(c)

(d)

(e)

(f)
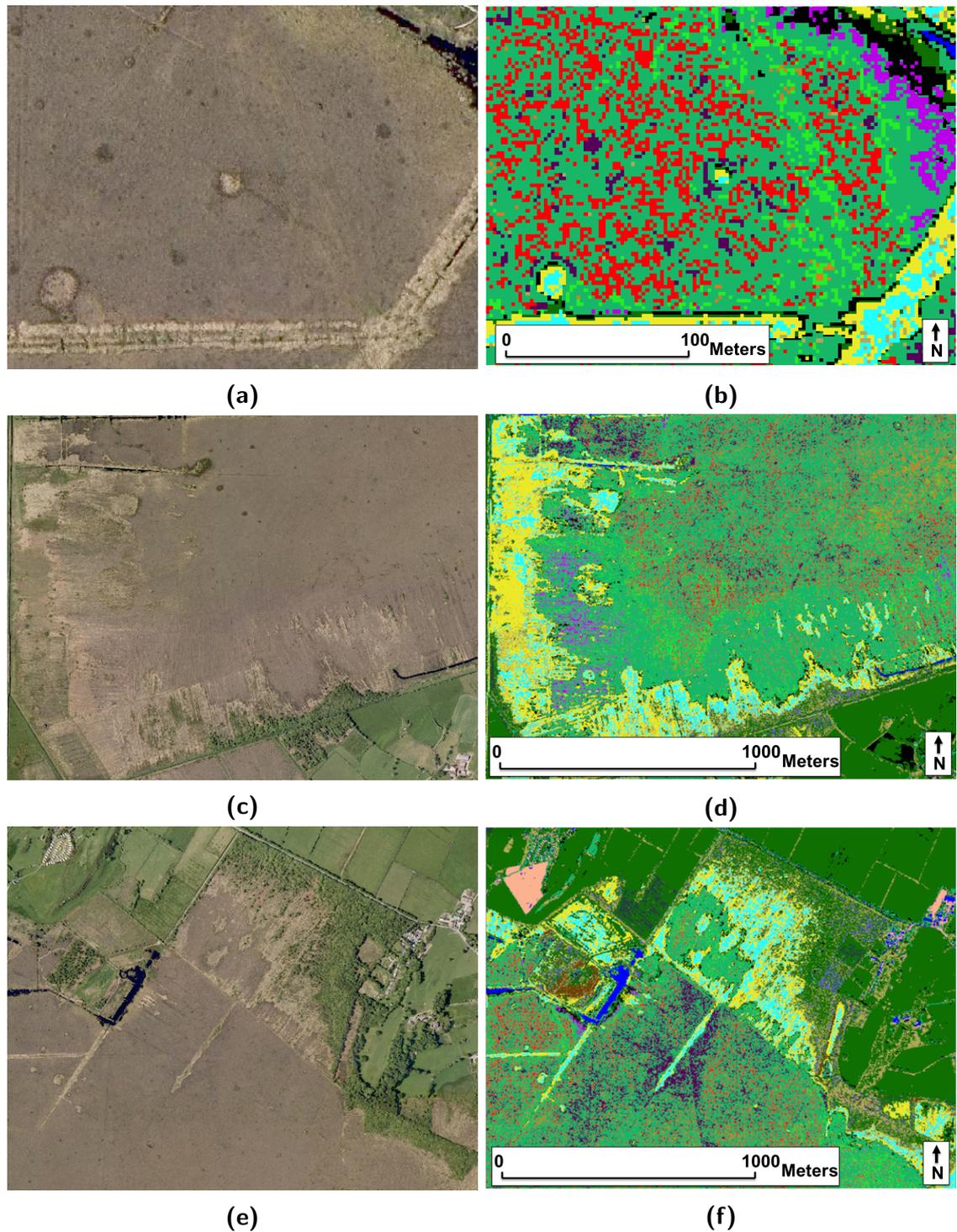
Figure 5.26: a) and b) northern section, c) and d) south west section, e) and f) north east section of Cors Fochno SSSI showing classification of species with corresponding Vexel imagery. ■ = AV, ■ = ANV, ■ = TV, ■ = TNV, ■ = Trees(>1m), ■ = *Calluna vulgaris*, ■ = *Eriophorum angustifolium*, ■ = *Eriophorum vaginatum*, ■ = *Juncus effusus*, ■ = *Molinia caerulea*, ■ = *Myrica gale*, ■ = *Phragmites australis*, ■ = *Sphagnum cuspidatum*, ■ = *Sphagnum pulchrum*, ■ = Unclassified.

The two classifications were merged by overlaying the SSSI species classification on the landscape LCCS level 2 classification (Figure 5.27).
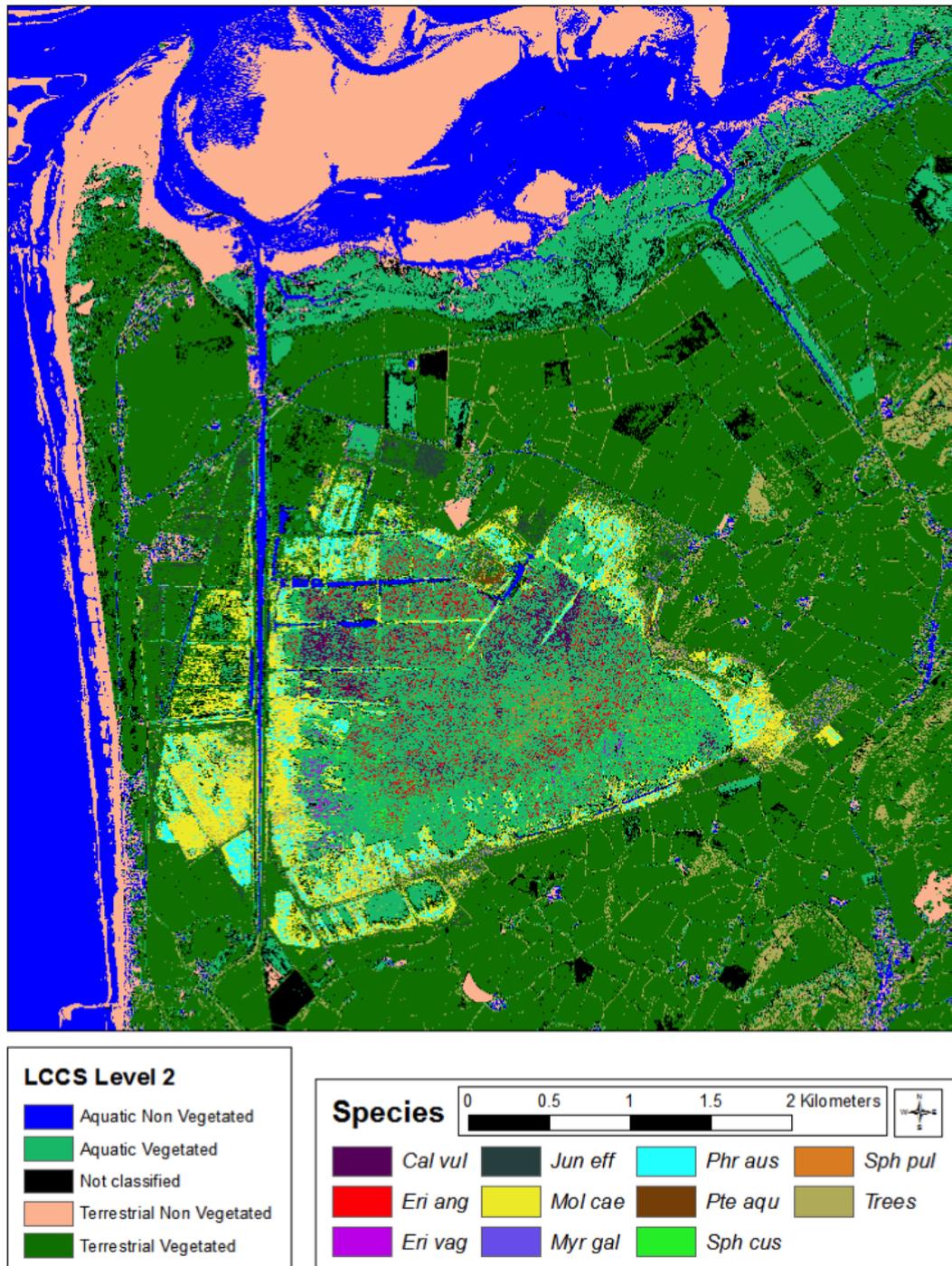
Figure 5.27: The landscape LCCS level 2 classification with the SSSI species classification overlaid.

5.3.6 Uses of the classification system

Using the vegetation classification produced and combining with the DTM of the central dome area condition statistics for the central bog and active bog area were calculated. An area shown to be 5m and above in the central dome was used (Figure 5.28) and the percentage coverage for these calculated within ArcMap was shown to be 10.36%, half the recommended coverage for a healthy raised bog.

At Cors Fochno the central dome is still well preserved and can be clearly shown by using the DTM from LiDAR data to show the convex shape (Figure 5.29).
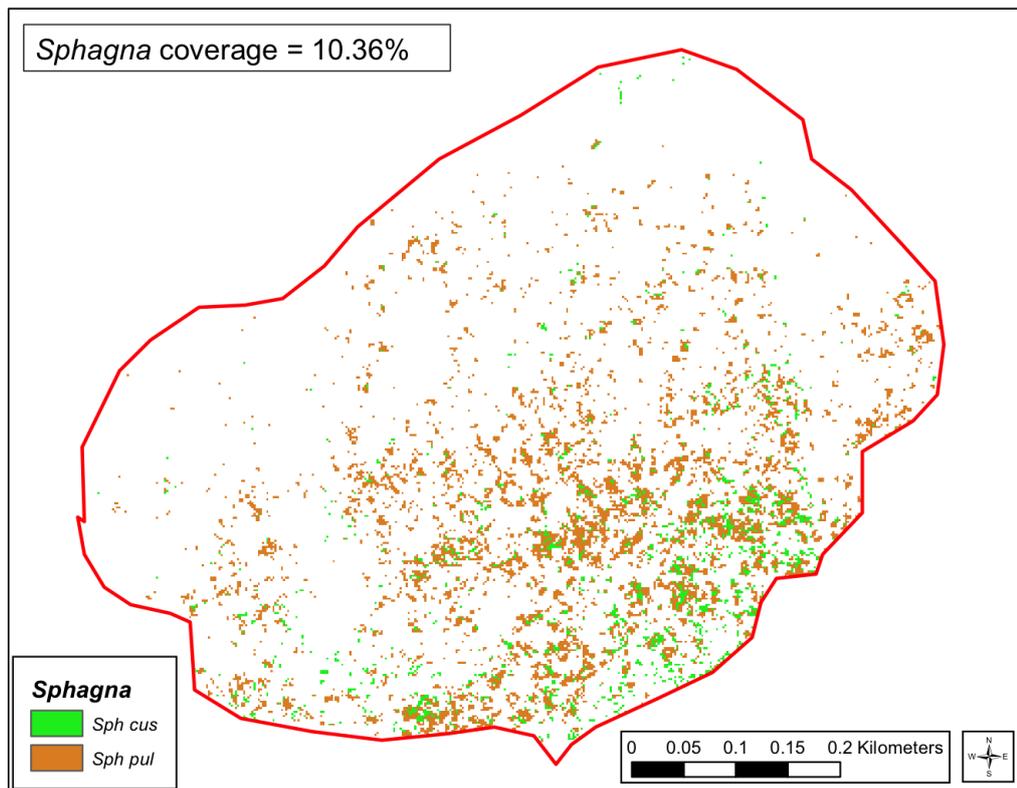
Figure 5.28: *Sphagnum* pools in the central dome area. The contour line is 5m above sea level. *Sph cus = Sphagnum cuspidatum, Sph pul = Sphagnum pulchrum.*

Cors Fochno: Central raised dome, created by a convex accumulation of peat, shaded to show topography in 10cm increments from 4m to 6m above sea level.

Height above Sea level (m)

0 - 1	3 - 4	6 - 7	9 - 10	12 - 13
1 - 2	4 - 5	7 - 8	10 - 11	13 - 14
2 - 3	5 - 6	8 - 9	11 - 12	14 +
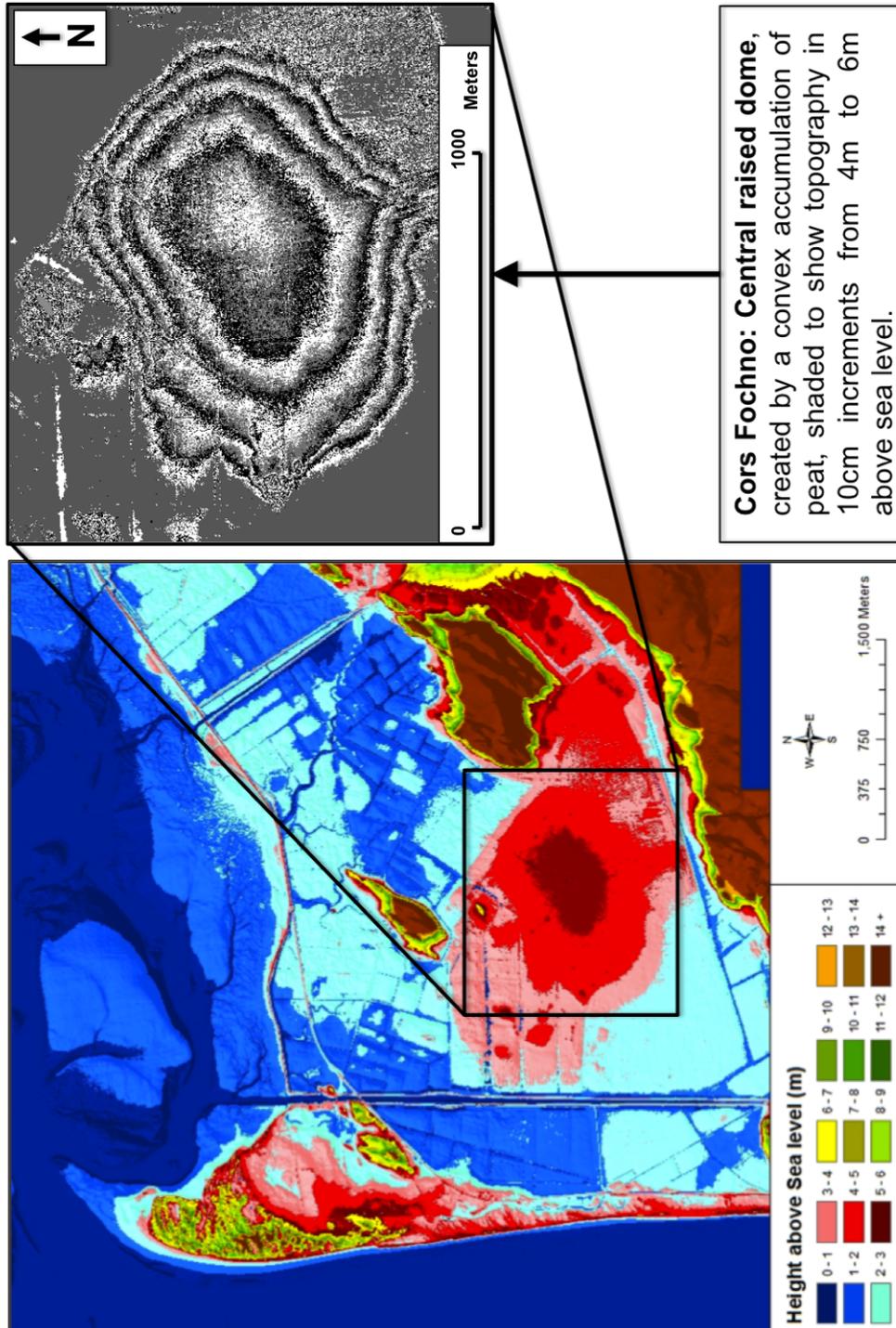
Figure 5.29: Images developed from the LiDAR DTM showing the concentric central dome of Cors Fochno raised bog, beleived to be the first time the Cors Fochno dome has been clearly mapped and illustrated using a DTM.

5.4 Discussion

5.4.1 Correction of imagery

Remote sensing data is severely influenced by the atmosphere and atmospheric correction of optical remote sensing data has been shown by others to be a challenging task (Ben-Dor et al., 2005). Results here show that although atmospheric correction improved greatly the similarity of field collated species spectral reflectance data with satellite spectral reflectance data (Figure 5.9), there was a poor linear relationship between the ground data and the satellite data for spectral indices (Figures 5.6 and 5.7). Field spectroradiometer data thresholds and indices selections could not be used as input into the classification of species. It may also be that bogs are particularly susceptible to inaccuracies of atmospheric correction due to their physical state. They are sites which hold and soak up vast quantities of water but they also heat up and release moisture into the air much more so than many other habitats (Lindsay, 1995). This and the coastal sea evaporation would most likely affect the atmospheric moisture content. Damaged and drained bogs are also known to release gases such as methane (CH_4) carbon dioxide (CO_2) and nitrous oxide (N_2O) (Couwenburg, 2009). The use of a general atmospheric correction for coastal and wetland habitats may introduce some inaccuracies if this consideration is not being taken into account. Using field spectrometer data from the same day as the image acquisition may have given far better results and provided correspondence of field collated spectral data and satellite spectral data.

5.4.2 Indices selection

Multivariate techniques, such as Canonical Correspondence Analysis (CCA) or redundancy analysis (RDA) and ANOVA analysis that test relationships between for example species composition and spectral information have previously been used (**?**, Brook and

Kenkel (2002)). Although ANOVA techniques are well known methods of analysing hyperspectral data, the use of the F-ratio to select suitable indices for species separation has not previously been employed to choose the best indices to separate plant species. Previous usage of this method has involved speech recognition where it was used to analyse similarities/dissimilarities of the sound spectrum of letters in the English language (Nicholson et al., 1997). Other uses have been to show differences in chemical composition of wines with varying grape variety in the wine industry (Coghlan, 2014).

Although statistical analysis (F-ratio) showed and resulted in pre and peak only indices being used, it can be seen from the spectral analysis that some species would be better separated using images from different seasonal periods, e.g. *Juncus effusus* in the Pre period (Table 5.8). The spectral analysis, however, only accounted for the periods of acquisition (pre, peak and post) and it was not possible to use this to select indices but to highlight the best periods for a species discrimination using all 8 spectral bands. For this reason the F-ratio method of index selection performed better by not only providing the best indices but also the best period for the use of the particular indices. It could be seen that the species (e.g. *Juncus effusus*) where discrimination was best in pre or post periods using the spectral analysis were actually better discriminated using a pre and peak indices difference (ndviPeakPreDiff) as thresholds (Figure 5.5). This means the spectral analysis and indices selection methods both gave the same results for acquisition periods for each species. These results demonstrate how important seasonal imagery is for the discrimination of species.

Post imagery indices were not used as these were shown to give small F-ratios. This seemed likely to be due to high within species variation due to varying degrees of senescence within a species in their autumnal die back. There is also a reduction in the between species variance possibly due to similarities between certain species (e.g. *Eriophorum, Molinia*) however, this was not found to be the case with FS data.

Milton et al. (2005) chose an autumnal acquisition for a similar but upland raised bog (Cors Caron) classification. This used CASI imagery which had 288 spectral bands, providing more information than the WV2 8 band imagery, to highlight regions that capture autumnal senescence which may have less within species variance and indeed more between species variance. The downside with this though is that airborne scanner data can contain more geometric distortions and is more difficult to acquire than satellite based measurements (Milton et al., 2005).

5.4.3 Species discrimination

The ability to discriminate species spectral data using satellite data was greatly reduced when compared with field spectroradiometer data. Again this may be partly due to atmospheric influence despite the corrections but there are also other anomalies such as shade and pixel noise which can effect this as well.

Spectral mixing may be occurring within what is thought to be a patch in which a species is dominant due to pixels containing several species when thought to contain only one. Not all edges of patches or distinct lines fit within pixel areas, so smaller patches of species become problematic and those that are selected for data extraction and analysis unless the centre of a large patch may sometimes contain noise from other species. The type of species creating the noise may have bearing on the amount of influence a neighbouring species may be creating, e.g. a tall shrub next to a *Sphagnum* patch may create shade as well as its own spectral signature influence.

Species which are usually found in large dominant patches such as *Pteridium aquilinum* and *Molinia caerulea* were easy to pick out with this system as it was less likely to be mixed and usually in large dominant patches. Extraction of the spectral data for analysis was therefore very accurate. Definition of the thresholds and indices used required no alteration when using TuiView to test their application. For this reason these areas

carried the highest accuracies (Tables 5.13 and 5.14).

For the converse of this where a species tends to be found in smaller patches and is surrounded by other species (e.g. *Sphagnums*) there may be underestimation of the species due to the patch edges falling within and not bounded by pixels or as spectral mixing is occurring due to other species being within a pixel. *Sphagnum cuspidatum* showed different green band readings for field spectroradiometer and WV2 (Figure 5.9). This species was found mostly in deep water logged ditches or pools that were not much more than 2 metres wide. Vegetation found on the edges of these ditches may be causing pixel contamination as well as noise from the water filled ditches surrounding the *Sphagnum*.

Eriophorum vaginatum is very similar to *Schoenus nigricans* in leaf structure, plant structure and senescence (Figure 5.30). As a result the area in the south west of the SSSI where *Schoenus nigricans* is present has been classified as *Eriophorum vaginatum*. *Schoenus nigricans* has not been recorded for this classification as it is only present within this south west region of the SSSI. This highlights some issues that unknown presence of species could cause to the accuracy of the classification. The mis-classification was realised when maps generated by NRW were used to perform a check on the suspicions that this was a very large and therefore unlikely patch. Further work to separate these could involve recording the spectral signature using a field spectroradiometer and also using any differences in flowering/ seed heads produced to seek differences in the spectral data. The other point worth bearing in mind though is that this plant is not expected to be in most of this SSSI. It is present due to conditions that favour it. These conditions have been caused by both the presence of peat cuttings and recent incursion of salt water, not usual in other areas of the SSSI.

(a) *Eriophorum vaginatum.* **(b)** *Schoenus nigricans.*

Figure 5.30: Two species providing some inaccuracies in classification.

For some species it was difficult to get a good classification, for example *Myrica gale*. There was some overlap in the spectral signatures of *Myrica* and that of many tree species. This discrimination between tree and *Myrica* may have been improved with a better canopy height model, however, *Myrica* is present in a more mixed habitat in areas where *Calluna* also tends to dominate and taller plants in areas of trees. Its representation within this classification is merely of dominant patches of 2×2m stands or more. There were not many patches of this size or greater. Ecological gradients were still recognised from those species that were accurately classified (i.e. *Sphagnum pulchrum, Calluna vulgaris, Molinia caerulea*). It may have been useful to classify this site using methods such as fuzzy classifications (Stankiewicz et al., 2002), linear spectral unmixing (Shanmugam et al., 2006), and direct subpixel techniques (Ozesmi and Bauer, 2002) in order to provide information such as a *Myrica gale* probability or percentage classification that may be important for identifying suitable habitat for rare species such as the Rosy Marsh moth (*Coenophila subrosea*) that feed on *Myrica gale*. Spectral unmixing was not actually possible for species level due to the total number of species present within many of the pixels amounting to many more than there were bands available for analysis. Cors Fochno had many more species present than those classified. For this method to work an alternative imagery, e.g. hyperspectral, may be required as illustrated by Harris et al. (2015).

5.4.4 Spectral

The multispectral imagery of the WV2 satellite is of particular interest for wetland mapping because, in addition to the typical spectral bands (i.e., visible blue, green, red, and near-infrared), WV2 also provides four extra spectral bands (coastal, yellow, red-edge, and near-infrared 2) from parts of the spectrum not typically covered by satellite sensors. These bands have been designed to better discriminate vegetation properties and penetrate water features (Globe, 2012) although have not yet been used extensively for this. The usefulness of having eight spectral bands in this work was demonstrated. Of the eight spectral bands five were used in the initial landscape classification. Seven bands (excluding Yellow) where deployed in the species classification.Others have shown that the accuracy associated with certain classes increased markedly with the increase in the number of spectral bands (Lane et al., 2014).

Using indices of the spectral data helped to provide metrics that can relate to some of the species structure and phenology and it was of particular interest to see that the selection method carried out separately to any ecological knowledge corresponded in the final rule set to suitable ecological assessment of this. It was discovered through Chapter 4 that both Sphagnum species had a very significant dip in reflectance in the NIR region however, this did not translate to the WV2 data and this significant phenomenon was not able to be made use of with WV2 data. Hyperspectral imagery would be better employed to do this (Harris et al., 2015). Overall species spectral differences were less pronounced with satellite acquired data than with ground based field spectroradiometer data.

5.4.5 Phenology

The phenology of species has also been helpful in identifying vegetation species in re-motely sensed imagery even with relatively spatially coarse MODIS data (Zhou et al.,

2013). Imagery providing phenological data (i.e. 2 from different seasons) improves species discrimination (Hill et al., 2010; Somers and Asner, 2012). Whilst it is not necessarily novel to use phenology to help map species it was found to be particularly useful using multi-temporal images to separate areas that had significant degradation due to competitive species presence (e.g. *Molinia caerulea*) having large differences in indices such as NDVI. Multi-temporal images, however, showed little change in NDVI throughout seasons for the central dome area. The result, while not unexpected, occurred due to the mix of dead and green material and the evergreen *Calluna vulgaris* within this area.

5.4.6 Indices

Amongst spectral indices used the normalized difference vegetation index (NDVI) has become a standard remote sensing product for ecological applications (Pettorelli et al., 2005) and it has been widely applied for discriminating and interpreting mapped vegetation units (Rahman and Gamon, 2004). Studies using coarser multispectral satellite data Lucas et al. (2010) or hyperspectral imagery (Pu et al., 2015; Cho et al., 2008) incorporated other spectral indices for vegetation mapping but few have used with a view to further using these for fauna monitoring.

5.4.7 Mapping at different classification levels and scales

Classifications are often completed all to one scale. This method provides a simple way to combine both landcape and species level scales. On a larger scale it would be more difficult to carry out species mapping due to the fact that a larger area inevitably contains more species and overlaps in spectral and indices threshold values would be increasingly likely. Restricting to a smaller SSSI site from the landscape followed by the classification within terrestrial or aquatic vegetated areas and then removal of definite dominant areas

helps to decrease the size of the area to classify. This helps to lessen the effect of the threshold overlap thereby improving the overall accuracy.

The practical benefits of standardised classifications for survey and conservation assessments are considerable but one needs to be aware that the characteristics of plant assemblages vary as do the opinions of their classifiers (JNCC, Joint Nature Conservation Committee, Version February 2004). The characteristics of an assemblage can vary within site and between sites. It is therefore perhaps more appropriate on occasions to classify relevant species. Systems that can be followed and adapted such as the LCCS and its implementation within the EODHaM system give flexibility to adjust a known system to specific sites.

The EODHaM system can be altered and developed to meet these scale considerations. Previous complications where more than one species had similar indices values were improved by:

1) reducing the area classified (sub-setting to SSSI)

2) selecting indices that are best for separation of species as a whole rather than selecting as the best for an individual species

3) using the classification script to further reduce the area classified by the threshold rule.

5.4.8   Pixel and object based classification

The general consensus is that object based classifications prove more effective than pixel based (Petrou et al., 2015). This may be due largely to spectral variability within habitats (Zohmann et al., 2013; Kobler et al., 2006). Larger areas (e.g. water bodies and buildings etc. with a greater spectral variability) are better classified using object based methods. However, with sites such as Cors Fochno patches of species occur in quantities and sizes that befit WV2 pixel size and not object classifications. A pixel

classification was used due to the size of the patches of single species generally being less than 10m^2.

Very few studies exist where one can classify an image using both pixel and object classifications to produce one classification in the same process with the same imagery. The landscape classification is required to provide context of what is happening to the landscape surrounding the protected site that may have an external influence, however, this is not necessary to species level, whereas the protected site management usually requires species level information. This method uses both pixel and object in order to compile a map of the whole protected site along with the surrounding landscape at differing scales but at scales which are of use to conservation management of the protected site.

Combining pixel and object classification has also been shown to increase mapping accuracies (Rapinel et al., 2014). Rapinel et al. (2014) also compared the hybrid approach against stand alone pixel-based methods and found that difficulties spectrally separating natural vs. non-natural vegetation classes was reduced in the object-based approach. Object based classification of the LCCS level 2 showed this to be the case and the use of this in the hierarchical system of classification made use of this. Often pixel based methods can be computationally demanding (Lui and Coomes, 2015), however, this method for relatively large areas was carried out often within seconds. This method therefore has even more potential as satellite resolution increases or on UAV data with very high resolutions.

5.4.9   Rule based

The use of a rule base system also gives flexibility. Contextual knowledge (e.g. Pteridium aquilinum found on higher drier land around the bog and not within) can be incorporated to separate from any similar spectral thresholds for different species. It allows for

the combination of the knowledge of landscape ecology, plant species and vegetation reflectance.

5.4.10 Supervised

Supervised classification, using pre-selected reference areas as spectral training sites, has long been used in studies seeking to discriminate vegetation types (Lewis, 1998; Nagendra and Gadgil, 1999; Sesnie et al., 2010). These image analyses lend themselves well to homogeneous vegetation stands, although they perform less well in classifying mixed vegetation stands (Teillet et al., 1997). Dominant species that are relevant to the conditions of an ecological gradient and large enough (over 2m+) to be contained within a pixel were selected with gps readings made within the centreof a homogenous patch. Reinke and Jones (2006) highlight the importance of plot location within homogenous patches to avoid the effect of mixed pixels.

5.4.11 Sub-pixel classifcation

Where there are heterogeneous patches techniques such as fuzzy classification and spectral unmixing have been recognized as a suitable tools to map (semi-) natural vegetation units because they allow a soft overlap of several hard classes (Foody et al., 1992). In order to provide a species classification these methods would require a complete set of species for the whole of the protected site. However, the bog and particularly the more intact and less degraded areas have too many species to analyse using spectral unmixing due to only 8 bands being available. This would also be too complex for a fuzzy classification given the number of species in total.

5.4.12 Data fusion

Fusion of imagery and LiDAR improved species discrimination further, however, a better vertical discrimination is required. Using a combination of multi-temporal data and the classification system developed has improved the accuracy. Also of importance to the accuracy of the classification of species is the input of ecological knowledge, that ecological knowledge being specific to each site or habitats. The indices threshold selection process did not on its own give the best classification and required the input of ecological knowledge and UAV imagery to improve its accuracy. Combining both the ecological knowledge and statistical methodology improved classification accuracy. In this case the systematic reduction of areas using the rule set to classify in a hierarchical method has helped to increase overall accuracy by reducing the size of the area to be classified.A zooming in approach and the ability within the scripting system to reduce the area in which to discriminate a species increased accuracy. The use of the LCCS within this provides a globally recognised land cover classification whereby the 1st stage can be used to narrow the areas where species are discriminated. This helps improve accuracy.

5.4.13 Peatlands and wetlands

Despite the heterogeneous nature of lowland raised bog systems such as Cors Fochno high resolution imagery such as WV2 provides a sufficient resolution to identify the main patches of species that can be identified as ecological indicators of the gradients of moisture and degradation. Lowland bogs and other wetland systems are the most difficult systems to inventory (Lane et al., 2014) and in the situations present at Cors Fochno remote sensing data has helped to provide an informative baseline which would not otherwise have been possible. The species selected are those that over time could be informative to the overall condition of the bog and inform sustainable management

of this important ecological system. Any changes or shifts in the coverage of these particular species could provide significant information to drive management and inform on other flora and fauna species conditions.

So far few have used WV2 to study freshwater wetlands and aquatic habitats. Lantz and Wang (2013) used it with success in their research of the distribution of the species Phragmites australis, however the lack of globally consistent mapping of peatlands is a major source of uncertainty in assessing their current role in the global carbon and water cycle and projecting their future change (Frey and Smith, 2007; Beilmann et al., 2008). Mansour et al. (2012) suggested that more research is required to improve accuracy of the classification of species indicating ecological gradients in particular using WV2 to investigate biophysical parameters. Using the methods presented in this research and the selection of species for mapping of dominant species as indicators of ecological gradients this was successful and provided useful information on the condition end extent of the health of the lowland raised bog, in particular by showing ranges of the dominant patches and by providing a more accurate method to assess Sphagnum % coverage. In particular temporal mapping of these indicator species for identifying degradation or ecological gradients would be specifically useful for monitoring degradation or restoration of wetland/bog sites. Classification of protected conservation sites often focuses on habitat or species classification. Few studies have looked at classifying specifically the species that can provide information on the ecological gradients of an entire site. These are particularly important to assess for change over time to feed valuable information to site management.

5.4.14 Accuracy

When comparing overall accuracy and Kappa values it can be seen that 1st stage EOD-HaM classification accuracy did not affect the smaller SSSI area species classification produced in this hierarchical method. It could be assumed that accuracy at the first

level could affect the next layer of classification, however, the 1st stage accuracy was high and did not seem to affect the species classification but actually helped to narrow areas down for subsequent classification.

Accuracy results can be affected according to what source of data is used for assessment. A comparison of the ground data accuracy assessment and the UAV accuracy assessment showed there are some issues of testing accuracy especially with ground data. This is possibly due to the registration of GPS points on the ground with image pixels. This may have be avoided with an object segmentation but only if the vegetation patches had been larger. Other possibilities for differences are the differences in sample times versus imagery data (Congalton and Green, 2009).

Another reason for differences in accuracy assessment results between the UAV data and ground data could be accounted for by two reasons. a) The GPS readings from the ground plots may have been subject to some inaccuracies and may not have mapped exactly to the WV2 imagery and subsequently classification and b) there were equal numbers of test points for each species using the UAV data but not for the ground data due to difficulties in accessing an equal number on the ground for each species.

Noticeably those species (e.g. *Myrica gale* and *Sphagnum cuspidatum*) which had poor accuracies in the UAV confusion matrix had much better accuracy using the ground data confusion matrix. This may have been due to the low number of samples used in the ground data for these particular species.

5.4.15 Outcomes for the classification method used for raised bog condition analysis.

This method was used to classify areas of Sphagnum in the central dome area which when combined with the DTM to locate the central dome area was employed to calculate the % coverage of Sphagnum for the central dome area. This is a measure calculated

by eye usually due to the difficulty of the spatial mapping and calculation of % coverage from in this case the boardwalk area in order to assess the condition of the raised bog. This is a method that could be repeatable and provide far more accurate and valuable data on any changes (increase and decrease in Sphagnum) that could indicate changes in hydrology than are currently in use

5.4.16 Further investigations

Further work could be done using this method to assess a whole suite of indices more recently derived for WV2 (Pu and Landry (2012) & DigitalGlobe (2009)). This method could also be tested on other similar peatland sites with the same species present. It would be useful to see how indices and thresholds selected may differ for the same species on a different site or indeed differ with imagery from different satellite types. The application of this method to other very different habitats would also be useful to assess its application for use within a protected sites monitoring system.

5.4.17 Further uses

1. As has been demonstrated in this chapter the health of raised bog can be partially assessed by focusing on the central dome and assessing the percentage coverage of sphagnum (as demonstrated in this chapter). This method could also be used on subsequent imagery to assess any change over time and is a far more accurate method than ground based estimations.

2. A more detailed assessment of ground data to show ecological gradients would be useful to have more cohesion with the species mapping as indicators of gradients of moisture and degradation.

3. The indices layers and maps produced can provide valuable spatial data for input into the next chapter 6. They can be assessed for their use as invertebrate biodiversity

indicators and as well as other faunal biodiversity indicators.

4. These same layers can also be used to create habitat suitability models.

5. As the indices threshold method provides better accuracy for species likely to occupy larger areas in a monoculture, this method would be particularly suitable for monitoring invasive species. This could then be developed to provide assessment of change for invasive species.

5.5   Conclusions

1. Correspondence of atmospherically corrected WV2 data and field spectroradiometer data was not sufficient to use the field spectrometer data as input for indices and threshold selection. Data for input into the classification had to be collated from the actual WV2 imagery.

2. The F-ratio method was successful at selecting the best indices for overall species discrimination from all three images used giving results which showed the two best time periods (July and March) for use in the classification. This provides a much simpler and more user friendly statistical method for conservation managers than other more lengthy methods such as CCA and RDA.

3. Both a landscape and a species classification using both pixel and object classification methods were performed and combined to produce a single multi-scale classification output. The hierarchical system using LCCS was important for achieving this combination.

4. Classifying dominant species has provided valuable information on the ecological gradients and condition of the raised bog, which have provided valuable information on the condition of the site which relate in particular to its hydrology and degradation. With further temporal analysis this system would provide a valuable management tool.

5. Accuracies of this method where high overall ($>81\%$) and showed the importance of taking GPS readings within the centre of a homogeneous patch larger than 2m.

6. The final outcome of this research has produced a classification process that can carry out classification of varying scales from landscape to species level as one overall classification in a system that captures the ecological gradients to provide information on condition and hydrology and is repeatable for monitoring purposes.

7. This method is designed so that with further scripting work an additional input and scripting layer for fauna suitability and distribution modeling could be added to provide a complete monitoring package for the reserve manager.

Chapter 6

Evaluation of remotely sensed attributes of habitat as indicators of invertebrate biodiversity.

6.1 Introduction

Although invertebrates comprise of at least 80% (Collen et al., 2012) of the world's known species, they are a hugely understudied component of the worlds' ecosystems. Many vertebrates depend on invertebrates for food and many are instrumental in the reproduction of plant life. Any changes in numbers, distribution or losses of these can cause a large impact in functional diversity and provision of ecosystem services (Cardoso et al., 2011). Their distribution and density is therefore of vital importance to conservation and can contribute to the understanding of the overall health of protected sites.

Whilst plant mapping and associations can be produced through direct methods, faunal data requires approaches based on proxies or surrogates (Leyequien et al., 2007b). Improving methods used in biodiversity assessment by improved sampling and analytical methods to give better information is an important priority for insect conservation and diversity (Didham et al., 2010). The use of remote sensing data can help in providing better spatial information and assist in providing a better understanding of ecosystem

functioning (Cabello et al., 2012). There are numerous studies where remote sensing variables have been tested and used in species distribution modelling (Hill and Hinsley, 2015; Pettorelli et al., 2011; Wilson et al., 2013; Cord and Raudder, 2011) however, the use of remote sensing in the mapping and prediction of occurrence of invertebrate species is poorly investigated (Leyequien et al., 2007a). The main emphasis of studies has generally concentrated on those that are considered to be pests and focus on crop or forest infestations (Huang et al., 2008; Thomas et al., 2013; Eklundh et al., 2009). This chapter therefore investigates the use of remote sensing derived attributes as indicators of invertebrate species and community associations and distributions. It will draw on the data and mapping produced in the previous 2 chapters using the species classification (Figure 5.23) and the indices layers produced using the EODHaM system classification.

The invertebrates selected for analysis of attribute associations were Araneae, Coleoptera and Diptera. Vegetation type, structure and diversity is of major importance to many invertebrates (Harvey et al., 2002). Cole et al. (2005) discovered a relationship between dominant vegetation type and invertebrates across upland sites. Spider communities, however, are highly sensitive to habitat structure (Marc et al., 1999) and the architecture of component plant species dictates which species are present according to their web building techniques (Robinson, 1981). The most important factors affecting Carabidae (Coleoptera), ground beetles, and many other Coleoptera species are moisture gradients separating dry habitats from wet habitats (Eyre et al., 1996; Uvei, 1996), as well as vegetation, both dead and living (Halme and Nielme, 1993). Diptera are known to frequent a large number of ecological niches of which many can be defined using remote sensing data. Some of these specific habitats consist of soil, decaying vegetation (deadlitter), mosses and other live vegetation (Smith, 1989).

Many dominant species can reflect ecosystem gradients. Transient or subordinate species can drive ecosystem functioning by influencing recruitment of these dominant species

(Grime, 1998). Therefore vegetation classifications such as that produced in chapter 5 can provide a map of dominant species which can inform on the ecological gradients and subsequently inform on the ecosystem functioning of habitats present. The dominant species on Cors Fochno represent a gradient of disturbance, moisture and nutrients. The dominant species recorded that represent the ecosystem gradients exhibit a continuum of functional traits in response to these gradients. Plant functional traits particularly those that respond to disturbance and fertility can determine invertebrate distributions (Lovering, 2008; Storkey et al., 2013) Dominant vegetation types can, as illustrated in the previous chapter, be identified in the raised bog habitat of Cors Fochno. A selected number of vegetation types present and classified relate to conditions present. For example areas with high *Sphagnum pulchrum* coverage indicate wetter areas, whilst more heather can indicate drier conditions. The change from *Sphagnum*-dominated to *Calluna*-dominated to *Molinia*-dominated areas can be considered to follow a soil moisture gradient. Areas with *Calluna* or *Molinia* provide different structures for web building. Although all areas have dead litter present, *Molinia caerulea* is indicative of large expanses of dead and rotting litter.

Although image spectral values and vegetation indices derived from remote sensing data have seldom been used as predictor variables for invertebrate distribution models (Miller and Rogan, 2007), many other studies have used indices of vegetation (Pettorelli et al., 2011; Lafage et al., 2013) for other taxa. This has provided a greater range of continuous data than vegetation classifications alone and it is believed this approach could lead to improved models of species distributions. (Bradley and Fleishman, 2008b). Remote sensing indices which correlate with greenness/plant productivity, senescence and wetness of vegetation cover are easily derived from the WV2 satellite data and indices can be essential as key indicators for the assessment of ecosystem function. Senescent vegetation can be recognized as litter, dead leaves, dead branches etc., whilst greenness is shown by the visibly green photosynthetic vegetation and can be used as an indication of plant productivity. These RS indices can be used as indicators for a number of ecosys-

tem functions which are known to effect invertebrate distributions. Spatial heterogeneity of plant productivity has been shown to influence faunal species distributions (Leyequien et al., 2007a). Typical measures of spectral heterogeneity focus on indices such as the NDVI, with the simplest measures being the standard deviation or coefficient of variance of pixels within a sampling region (Rocchini et al., 2010). Vegetation phenology has also been used as a predictor in animal habitat suitability (Osborne et al., 2001; Pettorelli et al., 2011) Seasonal attributes of vegetation are also important in invertebrate life cycles, and vegetation phenology has been shown to be correlated with mosquito life cycles and outbreaks of malaria (Rogers, 2002).

Changes over time in these properties of ground cover could indicate biodiversity and productivity loss. This provides a valuable tool to quantify the effects of drivers of change and provides insight into management and planning actions for areas vulnerable to change. In order to turn any valuable information on associations between species and environment/vegetation variables into useful conservation management tools, maps of the probability of occurance generated by species distribution models (SDMs) and habitat suitability models (HSMs) can be created using the remote sensing data. One of the most useful estimates of faunal distributions can be made using remote sensing data to identify and map animal habitat suitability (Leyequien et al., 2007a) which can be used for planning and management of habitat. These models can also be seen as a way of reducing bias from the availability of only a few scattered points (Diniz-Filho et al., 2010) and can be used to help predict the effect of scenarios of change on those species. Further interpretation of habitat suitability can be used to improve species density estimates and provide species survival estimates. One of the most popular methods in creating SDMs is to model distributions of individual species. This does not take into account the fact that species do not respond solely to environmental interactions and also interact and respond to other taxa. The distribution of a species is defined by both its environment and its interaction with other species (Hutchinson, 1957). Community-level modelling may be more beneficial, especially at finer scales and where a large number of species

are rare within these areas (Bonthoux et al., 2013).

Aims:

This study aims to use WV2 satellite derived parameters that relate to environmental variables relevant to invertebrate habitat suitability and invertebrate plant food sources (vegetation species composition maps and the indices data relating to abiotic factors and structural heterogeneity produced in Chapter 5) to assess their associations with selected invertebrate species and assemblages.

Objectives:

1. Identify the most suitable satellite derived parameters (e.g. plant species, abiotic factors and structural heterogeneity) for use as ecosystem indicators, which also relate to both invertebrate microhabitats and invertebrate plant food sources.

2. Using *Araneae* assemblages, *Coleoptera* assemblages and *Diptera* suborders, analyse associations with WV2 derived environmental variables as identified in objective 1.

3. Evaluate associations between a rare *Coleoptera* species (*Agonum ericeti*) and WV2 derived environmental variables as identified in objective 1 and create a habitat suitability model suitable for a reserve manager to extract further information about this rare species in order to improve monitoring techniques.

Hypothesis:

WV2 satellite derived spectral indices and WV2 satellite derived dominant plant species can be used together as invertebrate diversity and distribution indicators.

6.2   Methods

This section describes the selection of the sampling areas as well as the methods involved to compile both the field data and satellite data required for analysis. Field data collected include, vegetation data and invertebrate data. Satellite data prepared in the classification process within chapter 5 was used as input into the associations analysed and models produced. A number of statistical analysis methods used on the data are described.

6.2.1   Description of sampling areas

The sampling areas were selected from a gradient of habitat condition ranging from intact primary lowland raised bog through to degraded secondary lowland raised bog. These areas also represent moisture gradients, with intact primary lowland raised bog being the wetter habitat and degraded secondary lowland raised bog the drier habitat. The priority for sampling was to select environmental gradients across these characteristic features, as well as providing data useful for management that could quantify and estimate the influence of changes on the biodiversity of this ecosystem.

The transects traversed areas of intact primary lowland raised bog with little anthropogenic activity and into areas where anthropogenic activity had degraded the bog after historic drainage and removal of peat layers from peat cuttings. Much of the anthropogenic activity has not been recent and stopped in the early 20th century. Sampling across these gradients provides material to quantify and predict biodiversity losses and gains with future work. Changes resulting from these activities can be seen in the vegetation especially around the peripheries of the bog area (Figure 6.1,6.2).

(a) Cors Fochno 1948

(b) Cors Fochno 2012

Figure 6.1: RAF reconnaissance aerial photo (a) and WV2 satellite image (b) of Cors Fochno showing changes in vegetation and use over 64 years

The central dome is an area of intact primary raised bog with classic hummock and hollow vegetation of *Sphagnum* and *Calluna*. Although fire accidently swept across a

section of this in 1987 the affected area has more or less returned to its original state and the biodiversity of the central bog remains unchanged.

Areas of peat cutting, especially Llancynfelin area (Figure 6.2), have changed dramatically. These areas changed after the top layer of peat was removed and the remaining peat layers later dried out and shrank. This in turn caused vegetation to alter from open raised bog vegetation (e.g. M18) towards a greater dominance of graminoid and shrub/tree species characteristic of degraded and drained bog. There are also other changes around marginal areas of the bog with *Molinia, Phragmites*, shrub and tree encroachment.

Figure 6.2: Llancynfelin 1948 and 2012 showing the encroachment of tree species and *Molinia* during this period.

6.2.2 Habitat and plant species within sample area

Often the same vegetation species exist in degraded secondary lowland raised bog (where removal of the surface layer and drainage has occurred) as in intact primary bog but the composition and heterogeneity of vegetation can vary greatly. There were four main areas of significance in terms of recognising areas with differing vegetation synonymous

with gradings from wet to dry and healthy to degraded within the raised bog system (Figure 6.3). These areas of change reflected Annex 1 habitats (Figure 6.3) and were used as a focus of this study in order to provide information that could be used to further quantify and estimate the influence of these changes on the biodiversity of this ecosystem.

These areas (reflecting Annex1 habitats) were:

- **A** - the wet central dome area of active primary bog.

- **B** the drier edge of the central dome area of active primary bog

- **C** an area where transition species (*Molinia caerulea*) are encroaching into active secondary bog areas.

- **D** areas of *Molinia caerulea* dominant swards/tussocks - degraded inactive secondary bog (where peat formation is unlikely due to absence of peat forming *Sphagnums*).

Only 6 species which dominate within the areas that span from inactive degraded secondary bog through to areas of active primary bog were recorded and are as follows in table 6.1:

No.	Species	Found in Area*
1	*Calluna vulgaris*	A, **B**, C
2	*Eriophorum angustifolium*	A, **B**, C
3	*Molinia caerulea*	C, **D**
4	*Phragmites australis*	**D**
5	*Sphagnum cuspidatum*	A, B, C
6	*Sphagnum pulchrum*	**A**

Table 6.1: Species recorded as dominant patches within sampling areas. * Areas in bold are where the species are most dominant.
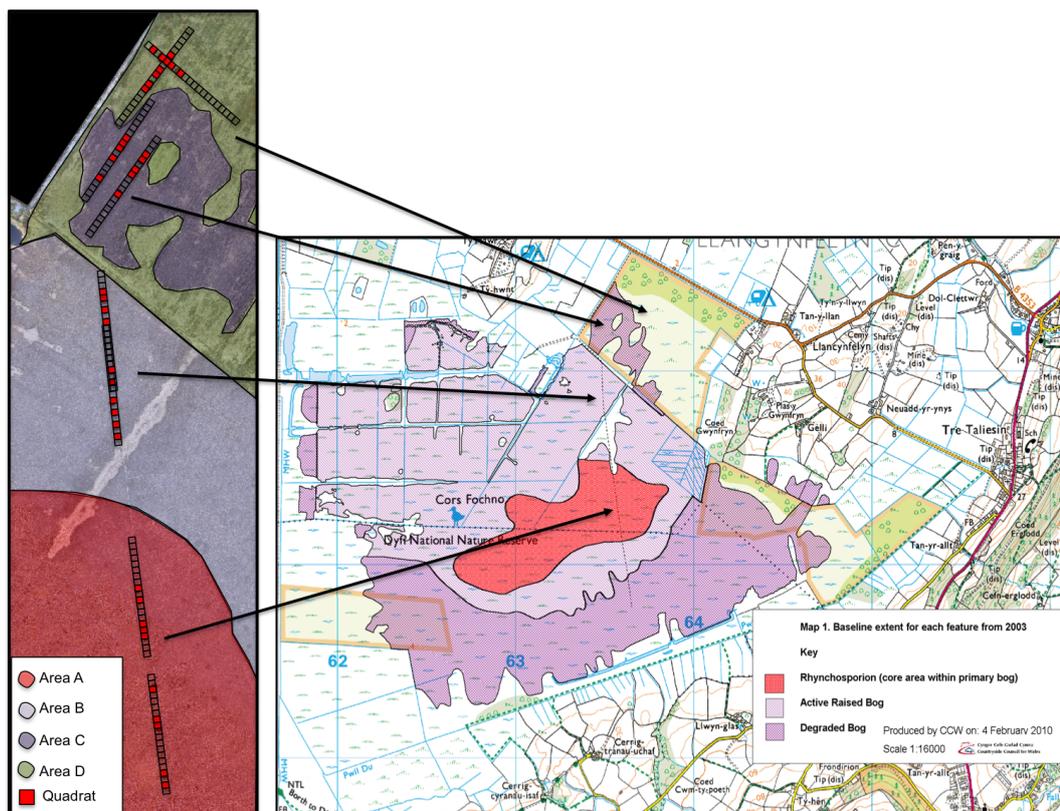
Figure 6.3: Cors Fochno areas for selected for faunal sampling (adapted from CCW,2010)

An initial ground survey across similar transects for a previous project, for July and August of 2012, and using satellite imagery (WV2 and Landsat7) showed there to be significant differences in vegetation (Figure 6.4) and invertebrate diversity across transition area ecotones around the edge of Cors Fochno bog (Undertaken with support from postgraduate students, 2012). From this correlations were observed between satellite derived indices as indicators (Figure 6.5) and traditional indicators of change such as Ellenberg and CSR (Figure 6.4).
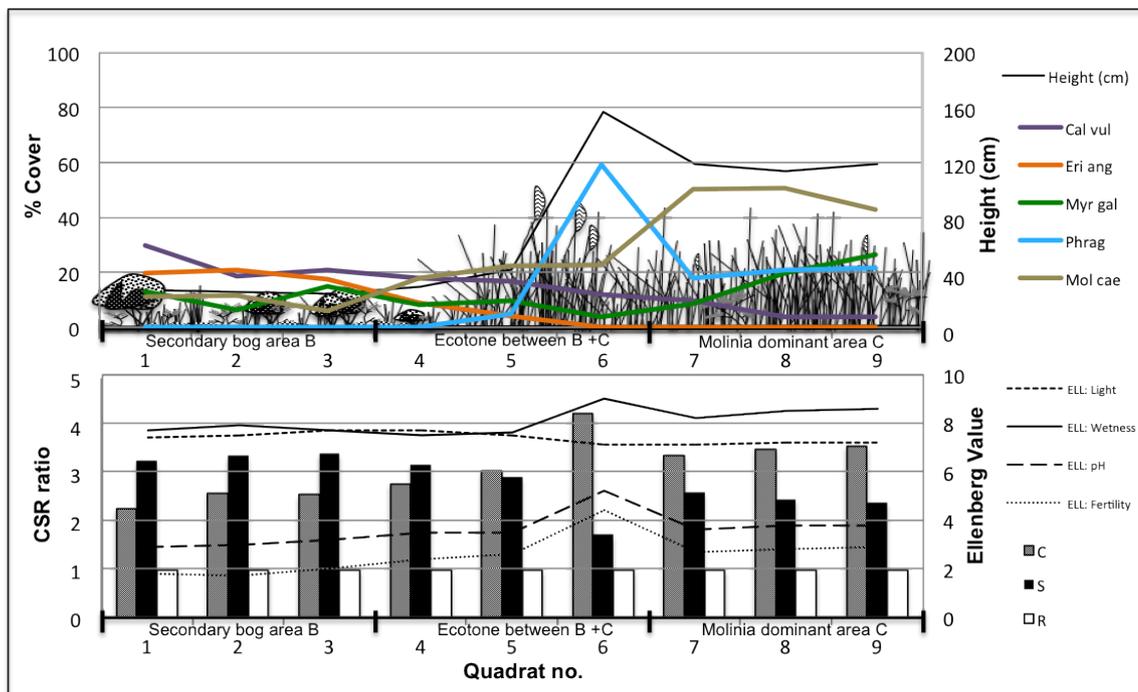
Figure 6.4: Transect with 9 quadrats across a transition area of Cors Fochno in 2012. a)% cover of main species along transect, b)traditional methods of condition evaluation (CSR and ellenberg).
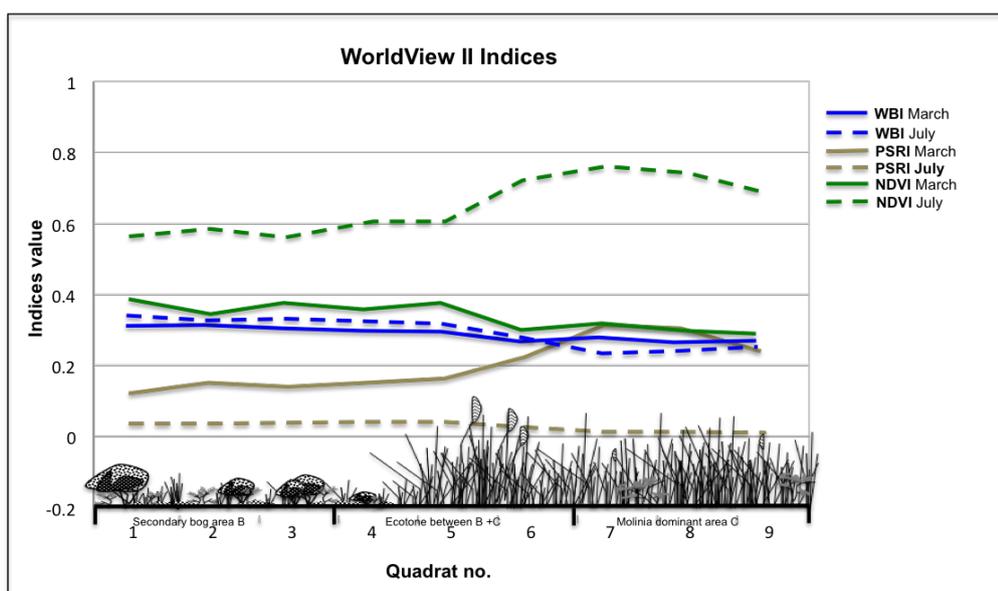
Figure 6.5: WorldView II band indices for transect across transition area of Cors Fochno (2012)

6.2.3   Sampling method

For Cors Fochno there are a number of issues that create constraints on typical methods used for creating species distribution models. To accurately calibrate a species distribution model the ideal scenario would be to ensure no major extrapolation in the model by using a gridded system of evenly spread sample points (Franklin, 2008a). However, access on foot to the majority of Cors Fochno remains difficult if not impossible in places due to the highly sensitive nature of the habitat and the fact that consistent trampling of areas is strictly prohibited. The main access to the most sensitive areas is via a wooden boardwalk that traverses the central dome area. Regular access on foot beyond this boardwalk is not permitted; therefore a sampling design based on easy access, causing least direct damage is essential in this protected landscape.

In areas where systematic sampling is required to investigate differences between habitat/vegetation types it is recognised that transects are a suitable method to use. Oline and Grant (2002) proved that transects were the best method for exploring differences in process and pattern over multiple scales. Many biodiversity monitoring protocols suggest transect sampling for multiple species sampling. Bennie et al. (2010) used it to measure biodiversity across spatial scales on a raised bog although this was only vegetation based surveying. Gadjo and Toft (2000) used transects to look at changes in spider fauna along a heathland-marsh transect. The BTO and butterfly conservation groups recommend transect methods for monitoring birds and butterflies. A similar method of a randomly placed fixed transect (40 traps) over a site with arbitrarily placed traps (60-116 traps) in two other sites was employed by Wells et al. (2007), who investigated the effect of anthropogenic activity on species richness and species assemblage composition of mammals.

For this study, transects (Figure 6.6) were placed across the selected sample areas (Figure 6.3). Two transects per area were positioned so that although constrained by the

previously described restrictions would cover an area extensively enough to include heterogeneity that may occur in certain conditions/habitat areas (e.g the hummock and hollow type habitat of the central dome area). Each transect was 200m long and quadrats were used to sample along this. For each transect 5 quadrats each 10×10m were selected randomly for sampling (Figure 6.6). Each area therefore had a total of 10 sampling quadrats. The 10×10m quadrat area was deamed to correspond with recommendations of a reasonable area of sample for invertebrates such as surface active carabids (Greenslade, 1964).

The central primary bog was selected as area A (Figure 6.3). This is the area of the site that is closer to the original state of the protected habitat and with no *Molinia* present. In this central area of primary bog two transects (Figure 6.3) were placed across the bog pool and hummock system (dryer and wetter areas) to encompass the heterogeneous nature of this area. The second sampling area, area B (Figure 6.3) was placed on the drier edge of the central dome area of active primary bog. Again the transects had to be placed a short distance from the boardwalk which created a slight overlap of transects, although this did not cause an overlap in randomly selected sample quadrats. The third area C (Figure 6.3) to sample was an area where *Molinia* has started to encroach but was not the dominant species present. The area selected was classed as secondary bog where peat cutting had removed the surface layer of peat causing a system of wet troughs and drier ridges within the habitat. The areas sampled in Area C were on the drier ridges due to the difficulty of placing traps and access to the trough/ditch areas. However, the troughs/ditches are of very close proximity so traps are in the near vicinity of both areas of vegetation. The fourth area D was an area D (Figure 6.3) degraded area where invasive vegetation has encroached and is now almost completely dominated by *Molinia caerulea* and *Phragmites australis*.

For areas such as the central dome with hummocks and hollows the transects were large enough to span the heterogeneous nature of this area. This ensured that no bias was
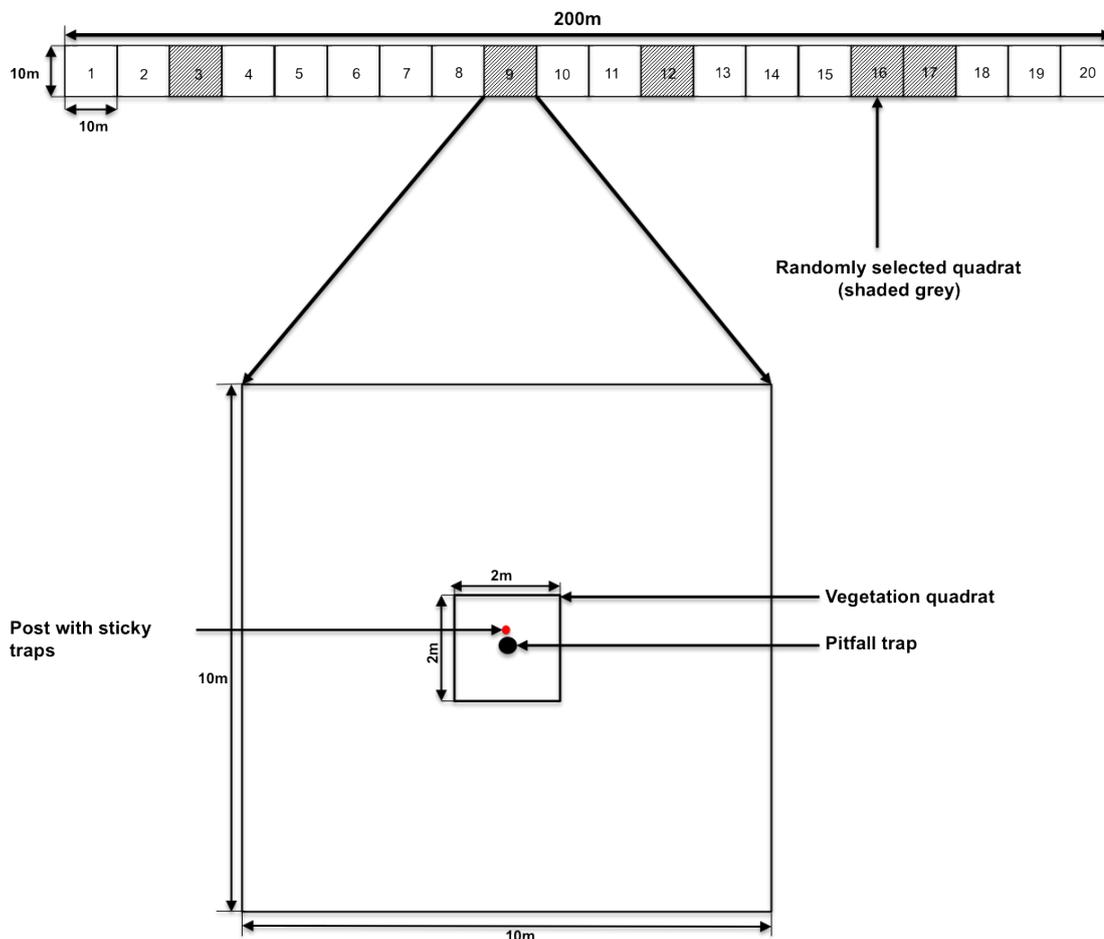
Figure 6.6: Diagram showing method for laying-out 200m transect at Cors Fochno

given towards very wet (pools/hollows) and the slightly drier raised (hummocks) areas of the habitat in this area. The GPS reading was recorded for each sample site and was taken at the centre of each sample quadrat.

Within each selected quadrat a vegetation survey and an insect survey were carried out (Figure 6.6). Plots were numbered 1 to 40 with 1 to 10 being in area A, 11 to 20 in area B, 21 to 30 in area C and 31 to 40 in area D.

For each sampling quadrat the following field data were recorded:

1)vegetation survey - a)composition and b)height

2)invertebrate survey - a)pitfall traps for surface active Araneae and Coleoptera and

b)aerial sticky traps for Diptera (Figures 6.7,6.8)

Figure 6.7: Sticky traps in situ in area A, central dome.

Figure 6.8: Sticky traps in situ in area D, *Molinia* dominated.

6.2.4 Vegetation Survey

For each selected quadrat a photographic record of the 2x2m quadrat area was made monthly to provide a visual record of seasonal changes in cover (Figure 6.17). Species

composition within a 2×2m area within each 10×10m quadrat was recorded in July. An area of 2×2m was selected and not the full 10×10m due to restrictions placed by reserve management to prevent trampling of protected vegetation areas. The height of vegetation was recorded to provide information on vegetation structure. The % cover of dead plant litter was also recorded for correlation with satellite data and providing information that could be valuable to determining invertebrate diversity.

6.2.5 Invertebrates surveys

Data previously recorded from a single year (Figure 6.9) was used to assess best times for sampling invertebrates. Using this information as a guide invertebrate surveys were carried out from the end of March until November within the centre of the same randomly selected quadrats mentioned in the vegetation survey section.
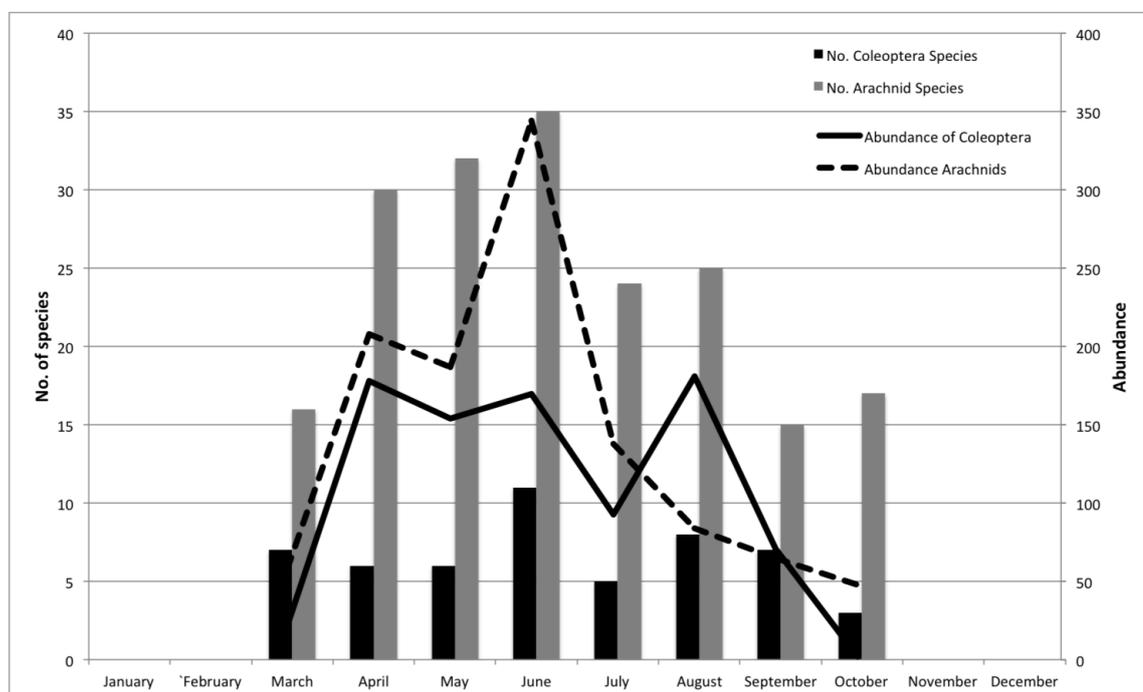
Figure 6.9: Seasonal pitfall data from 2009.(Source:data provided by NRW)

Surface active invertebrates - Pitfall traps

Surface active invertebrates were sampled by placing one pitfall trap (Figure 6.10) in the centre of each selected 10x10m quadrat along each transect giving a total of 10 per sample area (Cole et al., 2005).

Each pitfall trap consisted of a plastic pot (depth 22cm, diameter 8cm) filled to a depth of ca. 5cm with a mixture of 70% ethylene glycol, 30% water and a small drop of detergent to lower viscosity. In order to prevent rain from entering and causing overflowing an upturned pot tray was placed on short canes approximately 10cm above the pitfall trap. The contents of each trap were collected on a monthly basis (Antonovic et al., 2012) from March 2013 until November 2013. The contents were counted and identified to species level for Coleoptera and Araneae.
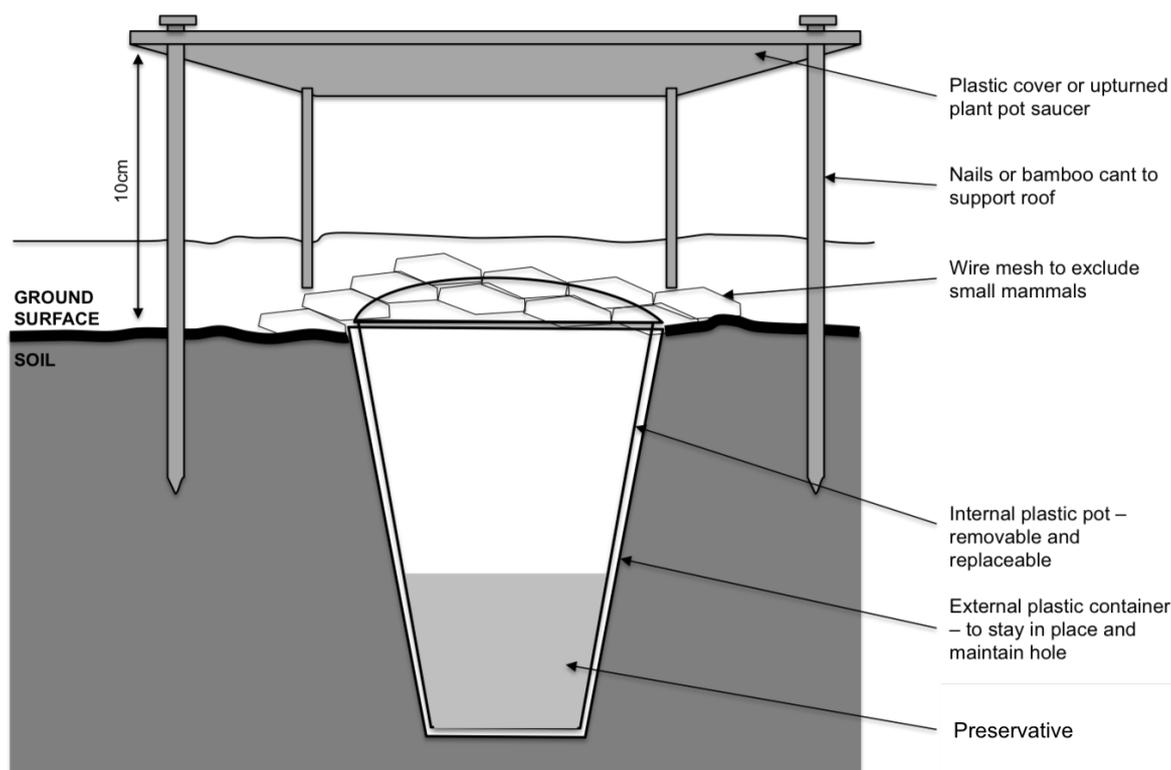
Figure 6.10: Pitfall trap design and set up.

All captured invertebrates were seperated into their respective orders. Coleoptera were preserved in 85% alcohol whilst Araneae were preserved in 70% until identification (Luff and Woiwod, 1995). From each pitfall trap a count of all Araneae and Coleoptera species were recorded over an 8 month period from April to November. There were a total of 320 traps recorded for the whole period across all areas with each divided into Araneae and Coleoptera making a total of 640 identification units.

Aerial invertebrates - sticky traps

Aerial invertebrates were sampled using double sided sticky traps (10cm$\times$25cm) which were secured on bamboo canes (Figure 6.11).
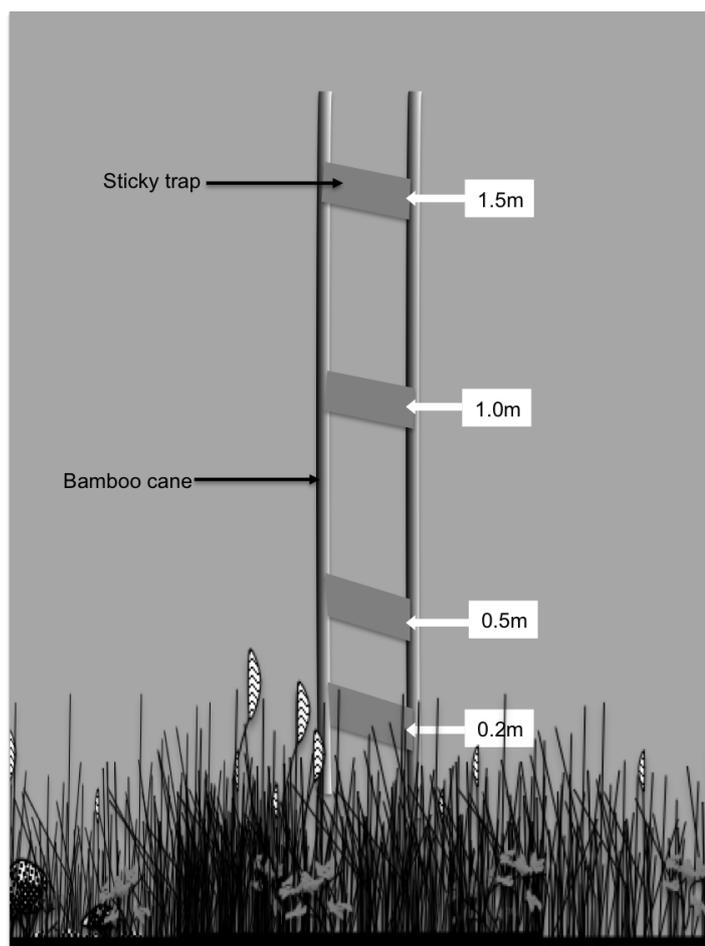
Figure 6.11: Sticky trap method.

The sticky trap canes were placed at the centre of the selected quadrat at the same time as the pitfall traps. Sticky traps were placed on these canes at several fixed heights (0.2m, 0.5m, 1.0m and 1.5m) in order to collect insects that use different zones of vegetation structure (Figure 6.11).The heights that traps were placed correspond with LCCS classification heights. As wind direction is known to influence the effectiveness of traps (i.e. the windward side may not catch any (p.c. Laidlaw)) double-sided traps were used. As some species are less active at certain periods of the year or have life cycles dictated by seasons, these traps were set on 3 equidistant occasions over a year in April, July and October. To ensure they all trapped equally they were all facing in one direction only (south/north). After 48hrs these traps were removed. Once collected the traps were then stored wrapped in cling film in a cool dry place until identification (Eglington et al., 2010)(Figure 6.12). There were a total of 480 collated sticky traps over 3 collection periods and all areas. The number used for recording purposes were reduced to 192 by subsampling.

Figure 6.12: Sample sticky trap with Diptera from Area A.

Identification and recording of invertebrates

All invertebrate recording was carried out specifically for this project with focus on certain orders, Araneae, Coleoptera and Diptera. For Araneae and Coleoptera identification was contracted to qualified experts.

Araneae

These were identified to species level by the reserve manager who is experienced in Araneae identification. Juveniles were not recorded due to the difficulty in accurate identification at this stage in their life cycle. Rarer species (Notably Scarce) were sent to the British Arachnological Society for confirmation of identification and for their records.

Coleoptera

Coleoptera were identified to species level by a specialist entomologist used by Natural Resources Wales. Since identification of larval stages was difficult only data for adult beetles was used to avoid any inaccuracies in identification.

Diptera

Diptera were identified to sub-order level of Brachycera, Cyclorrhapha, Nematocera using Chinery (1997). (Figure 6.13).

Brachycera	Cyclorrhapha	Nematocera
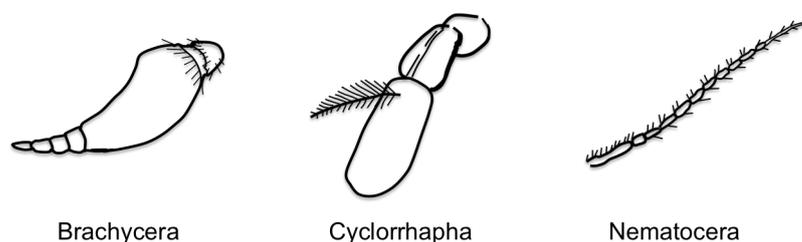
Figure 6.13: Antenna of Diptera used for identification of Diptera sub-orders, a)Brachycera, b)Cyclorrhapha, and c)Nematocera. (adapted from Chinery (1997)).

One species in particular was identified due to it's large numbers associated with area A at a specific trapping period, to help explain possible data skews and association reasons. There were a total of 480 double sided sticky traps collected over the 3 sampling periods. Due to the number of samples to record per trap a subset of samples were selected from this for a detailed sub-order identification. The subset was selected randomly so that 4 out of the 10 plots per area were selected with 2 from each transect. For each subset sample sticky trap a count of Diptera sub-order and Diptera sub-order body length was

recorded for each trapping height (Table 6.2).

Diptera sub-order	Trap height (cm)	Abbreviation
Brachycera	20	Bra20
Brachycera	50	Bra50
Brachycera	100	Bra100
Brachycera	150	Bra150
Cyclorrhapha	20	Cyc20
Cyclorrhapha	50	Cyc50
Cyclorrhapha	100	Cyc100
Cyclorrhapha	150	Cyc150
Nematocera	20	Nem20
Nematocera	50	Nem50
Nematocera	100	Nem100
Nematocera	150	Nem150

Table 6.2: Diptera height categories recorded.

Body lengths were divided into sizes present for each sub-order (Table 6.3).

Diptera sub-order	Size range (mm)	Abbreviation
Brachycera	1 to 2	Bra1.2
Brachycera	3 to 4	Bra3.4
Brachycera	5 to 6	Bra5.6
Cyclorrhapha	2 to 3	Cyc2.3
Cyclorrhapha	5 to 6	Cyc5.6
Cyclorrhapha	7 to 8	Cyc7.8
Cyclorrhapha	8 to 10	Cyc8.10
Cyclorrhapha	11 to 13	Cyc11.13
Cyclorrhapha	15 to 17	Cyc15.17
Nematocera	1 to 2	Nem1.2
Nematocera	3	Nem3
Nematocera	4 to 5	Nem4.5

Table 6.3: Diptera size categories recorded.

6.2.6   Further invertebrate data calculations

From all the invertebrate data the following were calculated:

1) Biomass for Diptera sub-orders

2) Diversity indices for Araneae and Coleoptera species

a) Simpson's index of diversity

b) Shannon-Wiener index

c) Pielou's evenness index

Biomass calculations

Body length records were used to calculate an estimated typical biomass for each Diptera length using the best model developed by Ganihar (1997). He tested 4 models on a variety of terrestrial arthropods and for Diptera he found that a power function model (equ. 6.1) was the best predictor of Diptera biomass.

$$weight = b_0 + (length)^{b_1} \tag{6.1}$$

w

$$(b_0 = e^{(-3.42940.01994)}, b_1 = 2.5943 \pm 0.0334)$$

b_0 and b_1 being parameters of the model.

Diversity indices

Simpson's index of diversity, Shannon-Wiener diversity index and a Pielou's evenness index were calculated for both Araneae and Coleoptera. An indication of the diversity of the areas was useful to provide a comparison of the areas. As Cors Fochno is home to a large number of endemic and rare species, more than one index was used for comparisons. Simpson's index gives more weight to common or dominant species whilst the Shannon-Wiener index is equally sensitive to rare and abundant species (Morris et al., 2014). Pileou's evenness gives a measure of the similarity in species relative abundance in a community (Heip et al., 1998)

Simpson's Index of Diversity (Jost, 2006)

$$D = 1 - (\frac{\sum n(n-1)}{N(N-1)}) \tag{6.2}$$

n = the total number of organisms of a particular species

N = the total number of organisms of all species

This index ranges from 0 to 1 and has been manipulated to give a more logical system of a larger value for greater sampling diversity. In this case, the index represents the probability that two individuals randomly selected from a sample will belong to different species.

Shannon Wiener Diversity Index(H) (Hurlbert, 1971)

This is a diversity index otherwise known as the Shannon-Weaver index and is the measure of species diversity in a given community. It is different from species richness in that unlike richness it also shows community composition and takes into account the relative abundance of species that are present in the community (Hurlbert, 1971).

$$H = -\sum (P_i * lnP_i) \tag{6.3}$$

$i{=}1$

where,

H = the Shannon diversity index

P_i = fraction of the entire population made up of species i (proportion of a species i relative to TOTAL number of species present, not encountered)

S = numbers of species encountered

Pielou's evenness (Pielou, 1975)

Pielou's or Species evenness refers to how close in numbers each species in an environment are. The closer the number gets to 1, the more even the quantities of the different species are,

$$J = H/ln(S) \tag{6.4}$$

H = Shannon Wiener index value, S = species number

6.2.7   Satellite derived data

Satellite data was used to create a spatial data set of suitable biophysical attributes and species data with which to assess associations for invertebrate data collated across the sample areas. Data was then used with these associations to improve spatial coverage of the SSSI.

Creation of raster layers

Raster layers were created using the classification method in Chapter 5. These layers were then used in order to extract values for use as environmental variables within analysis and model creation and prediction.

For each sampling area data was extracted for each 10x10m area from:

1) Species data - WV2 derived classification layers of dominant plant species.

2) Indices data - WV2 derived indices layers created during the EODHaM classifcication process.

Vegetation species data

Species maps and layers were from the analysis undertaken in Chapter 5. Separate raster layers were created for each vegetation species, representing the percentage cover. The % of pixels containing a selected vegetation species was created from a box of 5×5 pixels to denote a 10×10m buffer region around a central pixel which was given this value (Figure 6.14). The 10×10m buffer was selected to equate to the 10×10m quadrat in the transect sample areas.
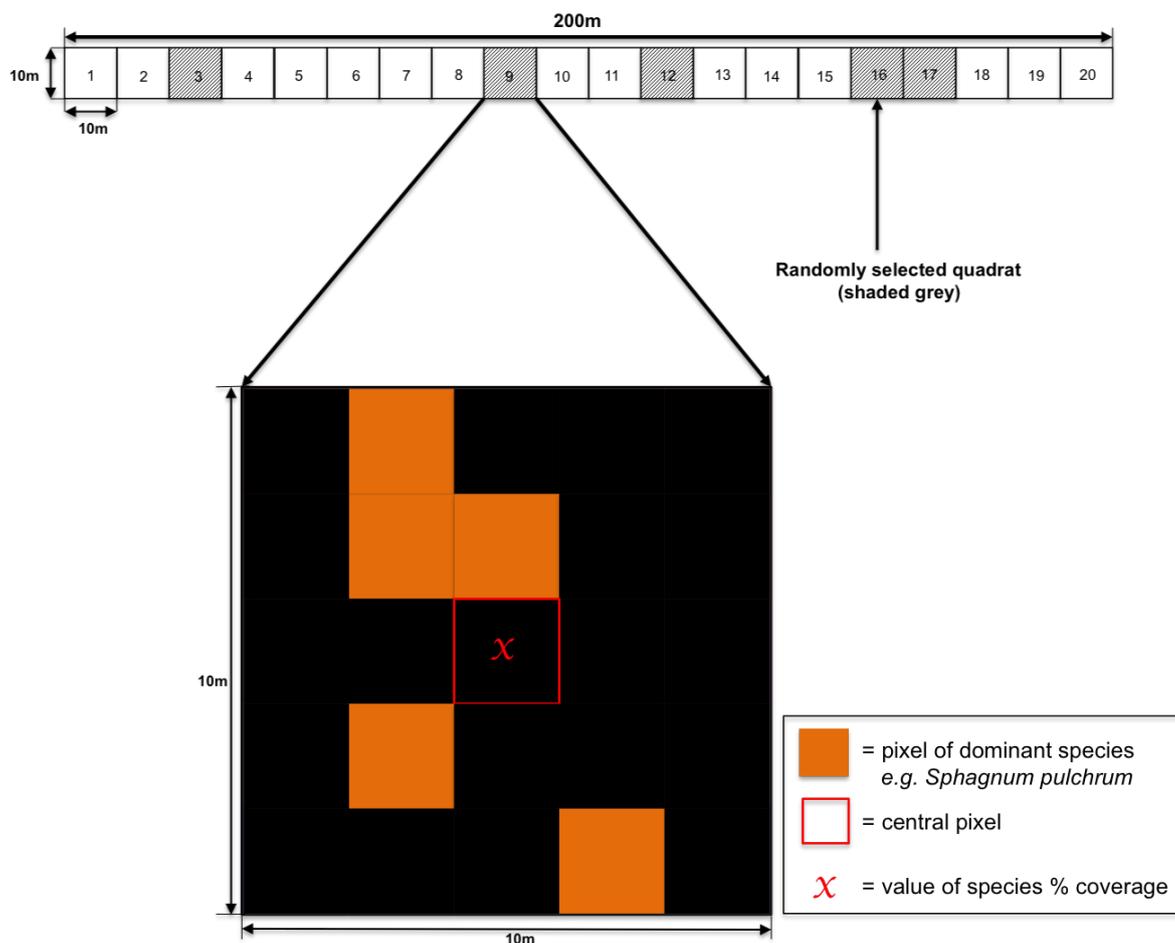
Figure 6.14: Diagram showing method for: 10x10m buffer for extraction of pixel values at Cors Fochno. See equation 6.6 also.

The raster layer for each vegetation species had the same treatment. For each layer each pixel (2×2m) was given a value which was the percentage coverage classed as the dominant vegetation species in a 10×10m region surrounding it. With pixels being 2×2m this was straight forward as a box of 5×5 pixels (10×10m) surrounding the central pixel. A count of the number of pixels that were classified as the vegetation species was then divided by the total number of pixels in the sample area (25 pixels) and multiplied by 100 to get % coverage. This process then changed the categorical vegetation species data into conditional data.

$$x = \left(\frac{P_s}{P_T} \right) \times 100 \tag{6.5}$$

P_s = count of pixels in 10x10m area with dominant species.

P_T = Total number of pixels in 10x10m area.

Satellite indices data

Suitable indices variables were divided into those that represent variables known to influence invertebrate species distributions (Williams et al., 2014; Galle et al., 2011). To cross seasonality and make use of the best choice of indices investigated in previous chapters both Pre and Peak indices were used. Unless there was good reason, the peak indices were selected for all, as Chapter 5 showed this period to give the best performance in terms of separation of vegetations types.

The variables that characterise environmental conditions were chosen to represent ecosystem functioning but are also known to influence invertebrate orders. Moisture is an important factor to consider when investigating invertebrate distributions. Fo mnay orders such as Diptera and Coleoptera vegetation productivity and availability of dead litter can be important habitat factors (Williams et al., 2014; Frouz, 1999). Plant phenology is an important factor in insect lifecycles particularly phytophages (Southwood et al., 2004).For Araneae plant structure and its heterogeneity are important (Robinson, 1981). Araneae are also known to prefer habitats with heterogeneous vegetation (Robinson, 1981) and some also require this variation due to their requirement for different vegetation in different stages of their lifecycle (Sheppard, 2009).

Variables characterising environmental conditions are as follows:

Moisture (vegetative and ground)

During the classification process in Chapter 4 the Water Band Index (WBI) was used to detect water and is also used to detect canopy moisture as was done in Chapter 4 for *Sphagnum* classification. From Pre and Peak WBI the Peak WBI was chosen as the Pre WBI would give results that may be more related to the increase in the layer of dead vegetation in the winter months.

Photosynthesis (productivity and dead litter)

This index is used to indicate photosynthetic vegetation or productivity in vegetation. High NDVI values indicate higher productivity or greenness (Rouse et al., 1973). Low values of NDVI could indicate dead vegetation or dead litter. High values of PSRI are also used to indicate deadlitter (Merzlyak et al., 1999) so Peak PSRI was also selected.

Phenology

For seasonal data, such as to denote evergreen or deciduous or to indicate highly competitive vegetation which is very productive in summer and has complete coverage with dead litter in winter peakpreNDVIDiff was selected to provide this information.

Plant structure (e.g. shrubby etc.)

Pre Woody index was used to determine shrubby branched vegetation (Lucas et al., 2011b). The use of the pre index provides data not confounded by overgrowing vegetation that could mask woody branches.

Heterogeneity

Standard deviation of NDVI has been used previously to indicate vegetation heterogeneity often with respect to areas of vegetation versus dead vegetation or bare ground (ref). Variation (larger standard deviations) in NDVI in the 10×10m areas could indicate different vegetation species present or greater vegetation heterogeneity.

Height

LiDAR data was used to create a Canopy Height Model (CHM) for the classification

process in Chapter 5. However, as the LiDAR gathered by the Geomatics Group of the Environment Agency had been acquired in winter 'leaves off' conditions for flood plain modelling, the short vegetation height over the bog area introduced inaccuracies to the CHM. In the event it was decided not to select this as a variable.

As with the species data for each index layer each pixel (2×2m) was given a value which was the average indicex value for a 10×10m region surrounding it. The heterogeneity layer used the same process but instead of average calculated the standard deviation of the indices. Each index then had its own raster layer created for model and prediction value input. For each raster layer of species and index data the value of the pixel (2×2m) that each GPS point was recorded for was extracted and used in analysis.

Variable name	Description	Representation of variable	Calculation
Response			
Aran	Araneae species	Araneae community data	Mean count over 8 month period (Total count/8)
Cole	Coleoptera species	Coleoptera community data	Mean count over 8 month period (Total count/8)
Dipt	Diptera orders	Diptera community data	Mean count and biomass over 3 trappings (Total/3),
			body size and trapping height data.
Ago.eri	*Agonum ericiceti*, species of Coleoptera	Species endemic to sphagnum bogs	Mean count and presence absence data
Continuous Predictor			
Vegetation Species			
*Cal vul**	*Calluna vulgaris*	Estimation of *Cal vul* present	% pixels (2x2m) classified as *Cal vul* in buffered 10x10m area
*Eri ang**	*Eriophorum angustifolium*	Estimation of *Eri ang* present	% pixels (2x2m) classified as *Eri ang* in buffered 10x10m area
*Mol cae**	*Molinea caerulea*	Estimation of *Mol cae* present	% pixels (2x2m) classified as *Mol cae* in buffered 10x10m area
Phr aus	*Phragmites australis*	Estimation of *Phr aus* present	% pixels (2x2m) classified as *Phr aus* in buffered 10x10m area
*Sph cus**	*Sphagnum cuspidatum*	Estimation of *Sph cus* present	% pixels (2x2m) classified as *Sph cus* in buffered 10x10m area
*Sph pul**	*Sphagnum pulchrum*	Estimation of *Sph pul* present	% pixels (2x2m) classified as *Sph pul* in buffered 10x10m area
Indices			
peakNDVI*	Normalised Difference Vegetation Index - March WV2	Vegetation productivity	Mean NDVI of pixels in a 10x10m area.
peakNDVIStd*	Normalised Difference Vegetation Index - July WV2	Vegetation heterogeneity	Standard deviation of NDVI of pixels in a 10x10m area.
peakpreDiffNDVI*	Normalised Difference Vegetation Index - March and July WV2	Phenology	Mean of (preNDVI-peakNDVI) for pixels in a 10x10m area.
peakPSRI	Normalised Difference Vegetation Index - March WV2	Dead litter	Mean NDVI of pixels in a 10x10m area.
peakWBI	WaterBand Index - July image	Moisture	Mean WBI of pixels in a 10x10m area.
preWoody	Woody - March WV2 image	Structure (woody, branched)	Mean Woody index of pixels in a 10x10m area.
CHM	Canopy Height Model derived from LiDAR (2013? Winter?)	Vegetation height	Mean of DTM - DSM for pixels in a 10x10m area

Table 6.4: List of Variables used in analysis (Note: All predictor variable sources were produced within the EODHaM classification method.* represents final variables selected for analysis

6.2.8   Treatment of data used in analysis

Vegetation species percentage data was standardised using the Arcsine transformation in R. As the indices data were generated from ratios and fractions of spectral band values there was no need to standardise/transform this data. Invertebrate species count data were standardised using log +1 method in R.

6.2.9   Analysis of vegetation data

In order to ascertain if the areas selected were really distinct in terms of vegetation species present, a cluster analysis was performed on the vegetation ground data using the % species compositions recorded in the 2×2m areas.

The EODHaM method of classification was also carried out to try and classify the Annex 1 regions using the same method as that used in chapter 5. The 4 areas selected for sampling were identified as a class: Area A, Area B, Area C and Area D, corresponding with Annex 1 regions (Figure 6.3). Indices and thresholds were selected as in Chapter 5 using sample data extracted from known classes. These two methods were employed to demonstrate that areas were distinct both on the ground and with the use of satellite derived data.

6.2.10   Environmental Variable reduction

A Principal Components Analysis (PCA) was carried out in R on all selected environmental variables to assess their suitability and strength of relationship to areas. The PCA at this point was used specifically to identify patterns in the data and assess the associations of sites and satellite derived variables and not for the usual method of data compression.

All variables were also tested for co-linearity in order to minimise multiple co-linearity using a Pearson's correlation matrix in R. Pearson's correlation coefficient r ranges from -1 to 1. An r value of -1 can indicate a perfect negative linear relationship between variables whereas an r value of 1 indicates a perfect positive linear relationship. An r value of 0 shows no linear relationship. It has been suggested that the threshold of this correlation coefficient at which a predictor variable's co-linearity can cause distortion in models is $r \geq \pm 0.7$ (Dormann et al., 2013). All variables with an r value of $> \pm 0.5$ were selected for rejection but their association with sites and these relationship strengths in the PCA were considered first as although co-linear they may still show important associations in further analysis. Some co-linearity may be due to functional relationships of variables.

6.2.11 Relationships between environmental variables and invertebrate species assemblages, suborder and individual species

A direct gradient analysis of Araneae and Coleoptera assemblage count data with the selected environmental variables (Figure 6.4) was carried out using Canonical Correspondence Analysis (CCA). Both ground data and satellite data were used in the analysis. The ground data analysis was used as an approximate comparison due the unavoidable differences in collation methods. Generalised Linear Modeling (GLM) was used to analyse the Diptera suborders count data. ANOVA was used to show whether differences existed in the Diptera count and Diptera biomass data within each sample area. Bayesian Generalised Linear Modeling (bayesGLM) was used to analyse an individual species. This was done in order to consider differences or similarities between invertebrate assemblage analysis and individual species analysis and to investigate its use in reserve management potential. Both count data and this translated to presence /absence data were

used.

Araneae and Coleoptera species assemblages

A CCA analysis was selected for analysis of invertebrate and environmental variable associations. CCA in R was used in order to investigate community assemblages that are explained by their environment (ter Braak and Verdonschot, 1995). Simulation studies show that CCA is a robust analysis method which is not significantly affected by skew or outliers (Palmer, 1993). The proportion of the total inertia in the species data that is explained by each canonical axis was computed. Eigen values and % variance of species were calculated for each axis and used to indicate the degree of separation of species along this axis and serve as a measure of the importance of the axis (Smilauer and Leps, 2007; ter Braak, 1995)).

Monte Carlo permutation tests were used to calculate the statistical significance of all the axes as a whole and also to test individually the significance of each axis in the analysis. The intraset correlations, otherwise known as the environmental axes weighted correlations, were used to provide information on the correlation between each axis and the environmental variables (ter Braak and Verdonschot, 1995). Species scores were used to interpret a species' relationship to an axis or variable associated with the axis. Dispersion of the values can be used to show how a variable explains species data (ter Braak, 1995) Biplots were produced which gave a visual interpretation of multiple associations by plotting the species and environmental variables.

Diptera suborder

An ANOVA was carried out initially to assess if there were any significant differences between areas of Diptera count and biomass. Once this was assessed a GLM of the suborders was carried out to investigate if these differences were due to significant as-

Figure 6.15: *Agonum ericeti*(6.5-8.5mm).

sociations between suborders and satellite derived data. The Diptera count and Diptera biomass data was of poisson distribution so a GLM poisson regression in R was used. Three GLM models were performed one for each suborder.

Agonum ericeti - single species

The distribution of both the response data (*Agonum ericeti*) and the predictor data (satellite variables) was taken into consideration before analysis of relationships between individual species and satellite derived variables. The relationship with a habitat will be most pronounced for species with a low dispersal ability, i.e. flight-less species. One of these such species present in the trappings and endemic to bog habitat was *Agonum ericeti* (Sushko, 2014). This is a stenotopic carabid species and a specialist of primary peat bog found in Europe (Drees et al., 2007). It does not fly and rarely bridges distances that exceed 200m so is an ideal candidate to use in investigating variable associations. It has seen considerable research investigating the survival of populations in relation to small or fragmented populations (Drees et al., 2007).

Poisson regression models provide a standard framework for the analysis of count data. In practice, however, count data are often overdispersed relative to the Poisson distribution. One frequent manifestation of overdispersion is the incidence of zero counts (Ridout, 1998). Count data, however, can be over-dispersed relative to the Poisson

distribution. One of the main causes being a preponderance of zeros (Ridout, 1998). This is particularly important to acknowledge for an area like Cors Fochno where there are many rare species and species that are endemic to particular habitats/areas. In this case *Agonum ericeti* is endemic to area A in our trapping data. This response data has a large number of zeros and is of Poisson distribution but heavily zero weighted. Not all predictor variables show linear relationships with the response variable so it is therefore better to use a method that will take both of these factors into account. A Poisson GLM is not necessarily suitable due to the preponderance of zeros leading to over-dispersion within the model and zero-weighted regression is less effective with small samples (Ridout, 1998). Issues can also occur where a predictor variable perfectly separates zeroes and ones in response variables. Bayesian GLM (Gelman et al., 2008) is an alternative which helps to default this seperation phenomenon. Problems with co-linearity can also be minimised using Bayesian methods (Dormann et al., 2013).

Four Bayesian generalized linear models were performed and tested (Table 6.5). Three of these used satellite derived data and one model used ground data only to provide comparison for discussion. Model 1 was carried out using a quasipoisson bayesGLM and Models 2 to 4 used binomial bayesGLM models. Model 1 used *Agonum ericeti* count data from pitfall trapping as a response variable. For predictor variables satellite derived vegetation species data and satellite derived indices data were used, as previously with Coleoptera and other previous CCA analysis. Model 2 used *Agonum ericeti* presence/absence data derived from the count data as the response variable and as before both satelite derived species data and satellite derived indices data as predictor variables. Model 3 used *Agonum ericeti* presence absence data as the response variable and satellite derived species data only as predictor variables and model 4 used *Agonum ericeti* presence absence data as a response variable and species recorded ground data as predictor variables. Once models were formed, predictions were mapped using corresponding satellite derived layers. No prior parameters were set and the default values supplied for Poisson (link='logit') and Binomial (link='log') models in R were used.

Model	BayesGLM Model family	*Ago eri* **species data**	Satellite data	Ground data
1	quasipoissson	count	*Cal vul*	-
			Eri ang	-
			Mol cae	-
			Sph cus	-
			Sph pul	-
			peakpreDiffNDVI	-
			peakNDVIStd	-
			peakNDVI	-
2	binomial	presence/absence	*Cal vul*	-
			Eri ang	-
			Mol cae	-
			Sph cus	-
			Sph pul	-
			peakpreDiffNDVI	-
			peakNDVIStd	-
			peakNDVI	-
3	binomial	presence/absence	*Cal vul*	-
			Eri ang	-
			Mol cae	-
			Sph cus	-
			Sph pul	-
4	binomial	presence/absence	-	*Cal vul*
			-	*Eri ang*
			-	*Mol cae*
			-	*Sph cus*
			-	*Sph pul*

Table 6.5: Bayesian Generalized Linear Models (BayesGLM) used to model *Agonum ericeti* (*Ago eri*) species habitat suitability.

The Akaike Information Criterion (AIC) and Leave One Out Cross Validation (LOOCV) methods of model comparison were used to compare the GLM models. The use of AIC is a common method for assessing the quality of models however, this value is not in itself meaningful. However, when used to compare models it provides a method for assessing the quality of the model through comparison of related models (Johnson and Wichern, 2007). The model with the smallest AIC value should be the best. A comparison of AIC

cannot be used for the quasipoisson method as this model method does not provide an AIC value. K-fold cross validation prediction error for generalized linear models can be used as an alternative for testing model efficiency (Davison and Hinkley, 1997). If k-fold is set to the number of cases (rows), then a complete Leave One Out Cross Validation (LOOCV) is done. For this method one case is left out as the testing set and the rest of the data is used as the training set. This process is then repeated so that each response variable case is rotated to become the testing case.

A prediction method in R using the bayesGLM results was used to produce a map of habitat suitability for *Agonum ericeti*. This method used the raster layers (predictor layers) already produced along with the coefficients of the bayes GLM to produce maps of probabilities of *Agonum ericeti* presence.

6.3 Results

6.3.1 Ground vegetation in sample areas

This section describes the vegetation of sampled areas and shows the significance of the selection of the subdivisions used in terms of distinctiveness and conditional gradients.

Both ground based photographic records (digital SLR) and species composition surveys showed selected sampling areas to be distinct (Figure 6.16). Although similar vegetation species may be present in more than one area they have varying compositions (Figure 6.16). Vegetation composition surveys showed certain species to be more dominant in certain areas. This dominance however was not necessarily what stood out in photographic imagery. For example the central bog area has visually distinct areas of orange tinged *Sphagnum pulchrum* (Figures 6.17,6.16).
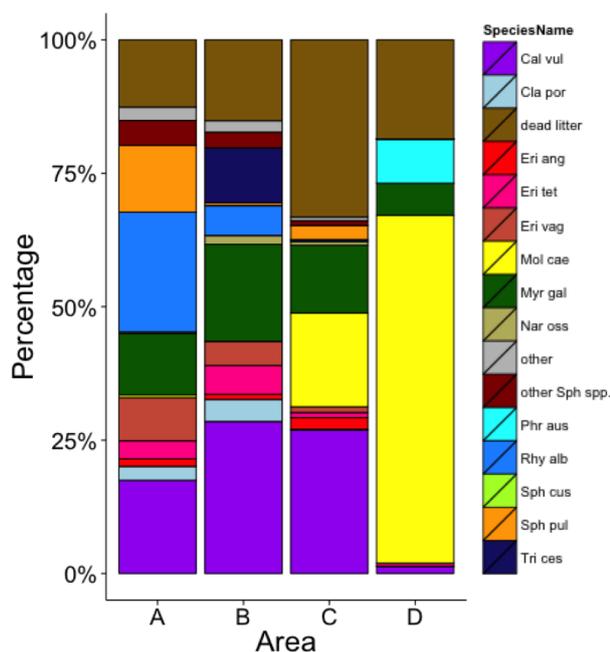
Figure 6.16: Areas selected for invertebrate sampling with typical scenery and vegetation plots found in each area. Each point on the aerial image is an invertebrate sampling point. The graphs show average % of species present recorded from each 2×2m quadrat from each sampling point

The species composition data shows that *Calluna vulgaris* and *Rhyncospora alba* have a greater % coverage (Figure 6.16), however these are very mixed within the sample area so are not easily separated using satellite or photographic imagery. This phenomenon is not so apparent for other areas where the ground survey does correspond with the satellite classification of dominant species. Overall relationships between vegetation dominant in imagery and the previous Chapter 5 classification (Figure 5.23) could be explained by their preferential niches. *Sphagnum* species which require greater soil/peat moisture levels such as *Sphagnum pulchrum* were present in the central dome of the acid bog (Figure 6.21). The edge of the dome which is drier with fewer wet hollows had a greater coverage of *Calluna vulgaris* (Figure 6.21) which has a preference for drier conditions. The degraded bog area D had an almost monoculture of *Molinia caerulea* with some *Phragmites australis* (Figure 6.21), both of which are well known to invade areas of bog degradation.
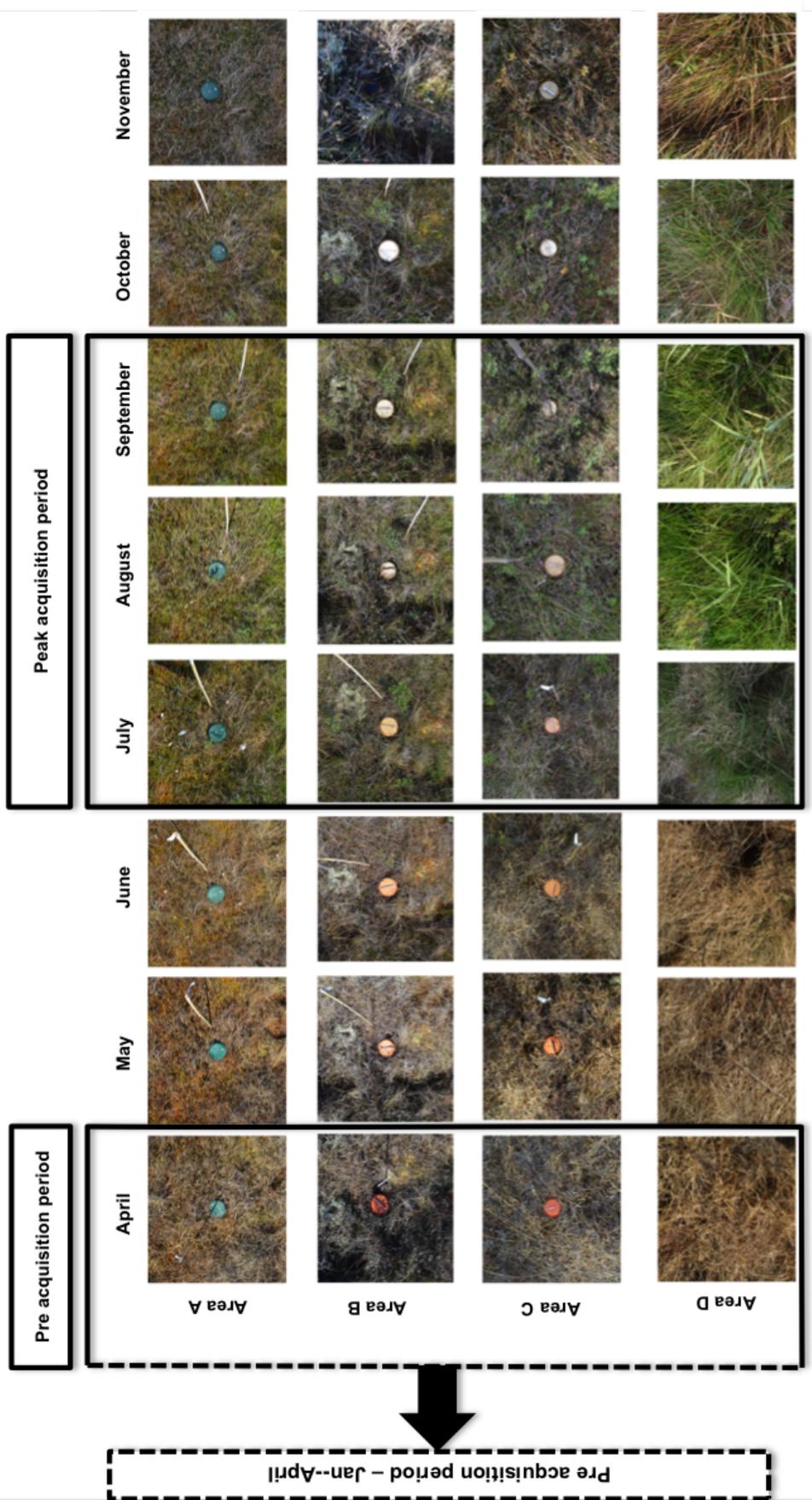
Figure 6.17: Seasonal changes for a sample of quadrats recorded with pitfall traps placed at the centre showing the acquisition periods suitable for the following data analysis. Actual months of acquisitions were March and July.

A cluster analysis of species for each sample quadrat showed distinct groupings of vegetation types into their respective Annex 1 areas (Figure 6.18). The use of the same EODHaM method used in Chapter 5 for separating areas also showed (Figure 6.19) that indices can be used to seperate these distinct Annex 1 areas. Indices used in this classification were NDVI (productivity), PSRI (dead litter) and prepeakDiffNDVI (phenology). Using the methods developed in Chapter 5 these were the best indices selected for distinguishing these areas in a pixel based classification.
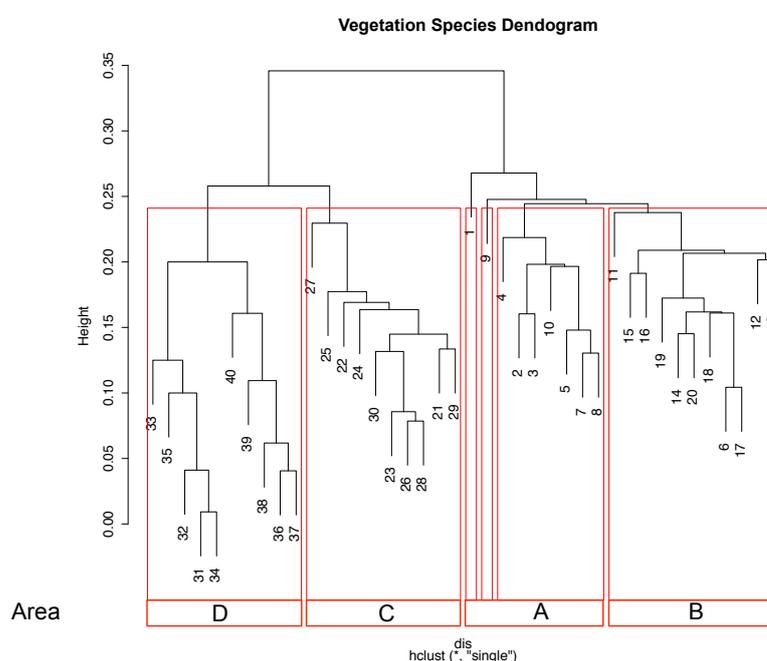
Figure 6.18: Cluster diagram showing Area separation in terms of species composition derived from field data. Numbers correspond with sampled quadrat numbers. (1 to 10 = Area A, 11 to 20 = Area B, 21 to 30 = Area C, 31 to 40 = Area D.)

From these data it could be seen that visible species dominance seemed to be related to degradation and moisture gradients. Photographic records (Figure 6.17) showed agreement with chapter 4 field spectroradiometer results by showing the Peak period of growth to be July to September with a Pre growth period as expected in the winter period. There is also visibly less change in overall greenness/deadlitter in area A and B than in area D (Figure 6.19).
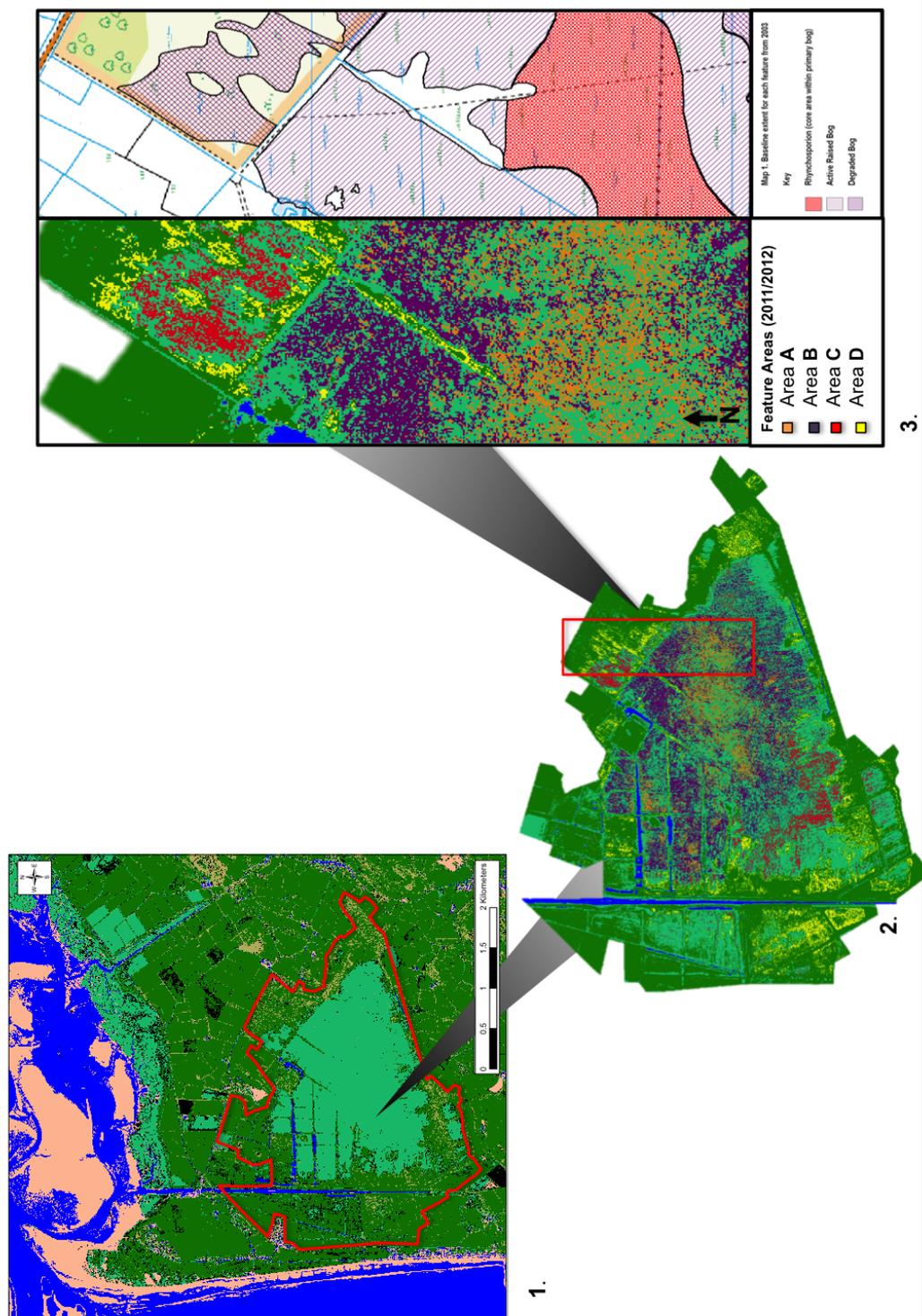
Figure 6.19: Areas A, B, C, and D as classified using the same methods as the species classification within Chapter 5

6.3.2 Raster layers used in analysis

Raster layers for input into the analysis were produced (Figures 6.21 and 6.20).The classification map produced in chapter 5 was by this method changed from categorical data to continuous data which was for each species the percentage of pixels in a 10×10m area that was classified as that dominant species. As indices data is also continuous this allowed the species data and the indices data to be treated the same in analysis.

(a)   (b)

(c)
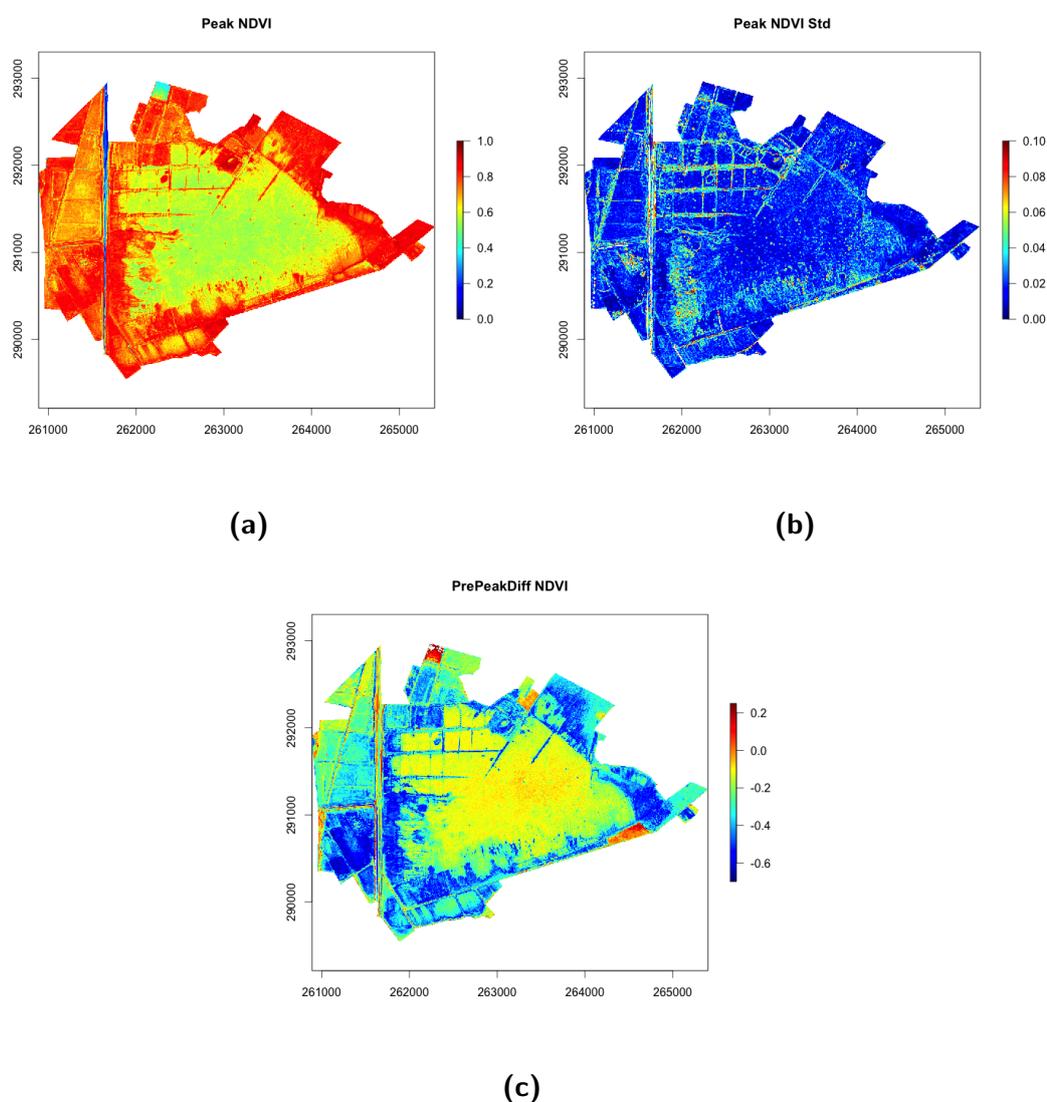
Figure 6.20: Selected Variables - indices layers created as part of the vegetation classification process and a standard deviation created from these for an area 10mx10m.
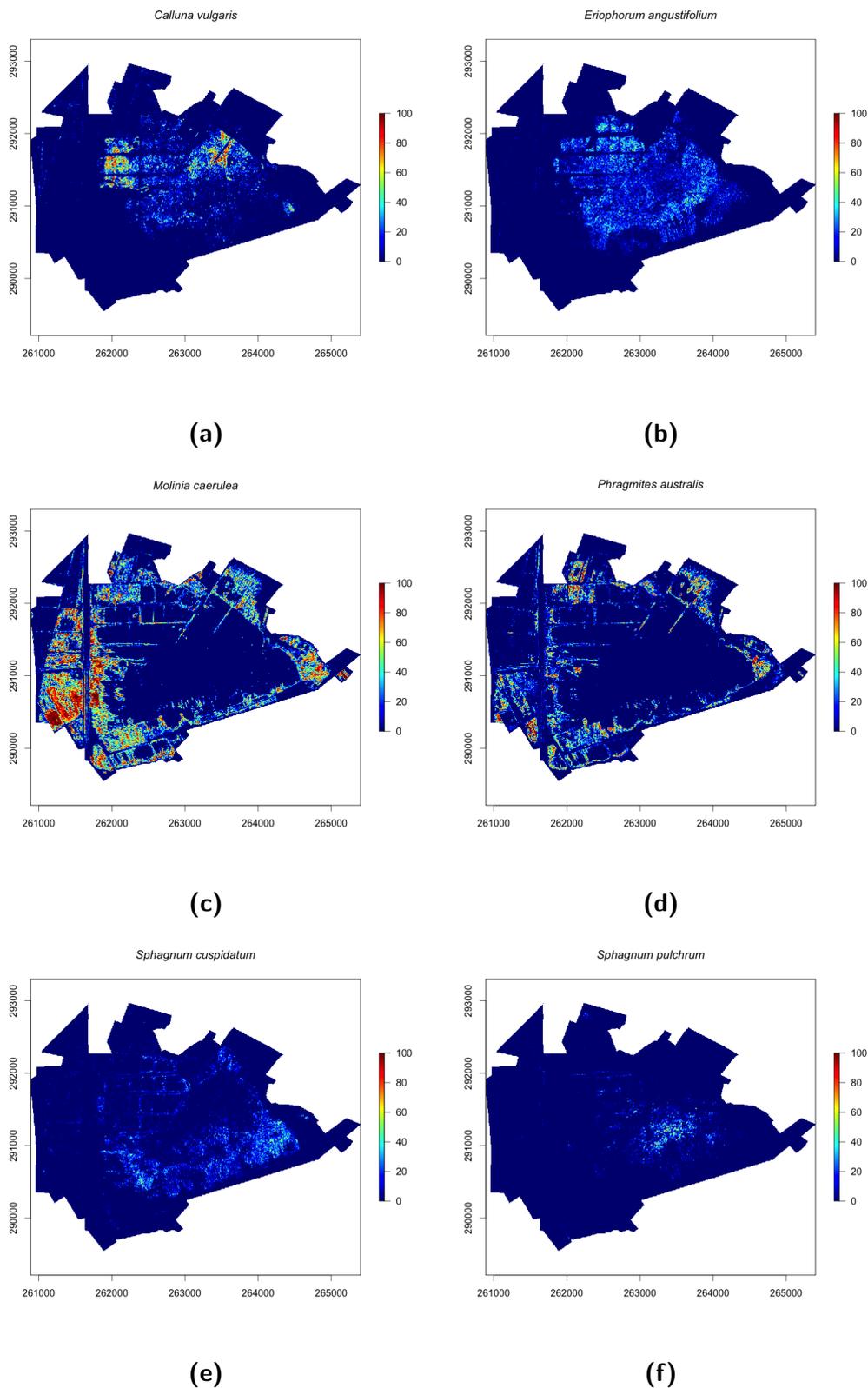
Figure 6.21: From classification - percentage dominant species coverage (percentage of pixels in an area classified as dominant for that species) for 10mx10m area.

6.3.3 Selecting satellite variables for analysis

This section describes the selection process for the use of satellite variables in invertebrate association analysis. As was previously mentioned in Chapter 5, CHM values were not suitable for use as a vegetation height variable in classification. For areas A to C values were mostly 0 which, as can be seen from the ground data, (Figure **??**) are not true. The vegetation in these areas is low and it is known that it is difficult to use LiDAR data for this purpose where vegetation is lower than 1m in height (Zhuang and Mountrakis, 2014). Also the LiDAR data used was 1m resolution flown in winter months when vegetation has died back. For these reasons it was decided not to use the CHM data.

Cumulative % variance of variables in the PCA analysis was 58.6% in the first axis and 86% in the first 3 axes. This demonstrates the variables selected have a strong relationship with the specified areas sampled. To refine variables for analysis in order to avoid co-linearity those variables which displayed co-linearity in a Pearson's correlation matrix were identified (Table 6.7).

	PCA1	PCA2	PCA3
Importance of components Standard deviation	2.652131	1.4074203	1.1664950
Cumulative % variance of variables	0.586150	0.7512193	0.8646119
Cal vul	-0.118	-0.388	**0.588**
Eri ang	-0.201	-0.414	-0.28
Mol cae	**0.351**		
Phr aus	**0.336**		
Sph cus	-0.153	0.143	**-0.637**
Sph pul	-0.162	**0.547**	
peakpreDiffNDVI	**-0.373**		
peakNDVIStd		**-0.506**	-0.382
peakNDVI	**0.372**		
peakPSRI	**-0.334**	0.28	
peakWBI	**-0.367**		
preWoody	**-0.368**	-0.104	

Table 6.6: PCA of variables showing strength of relationship of environmental variables with all areas sampled.
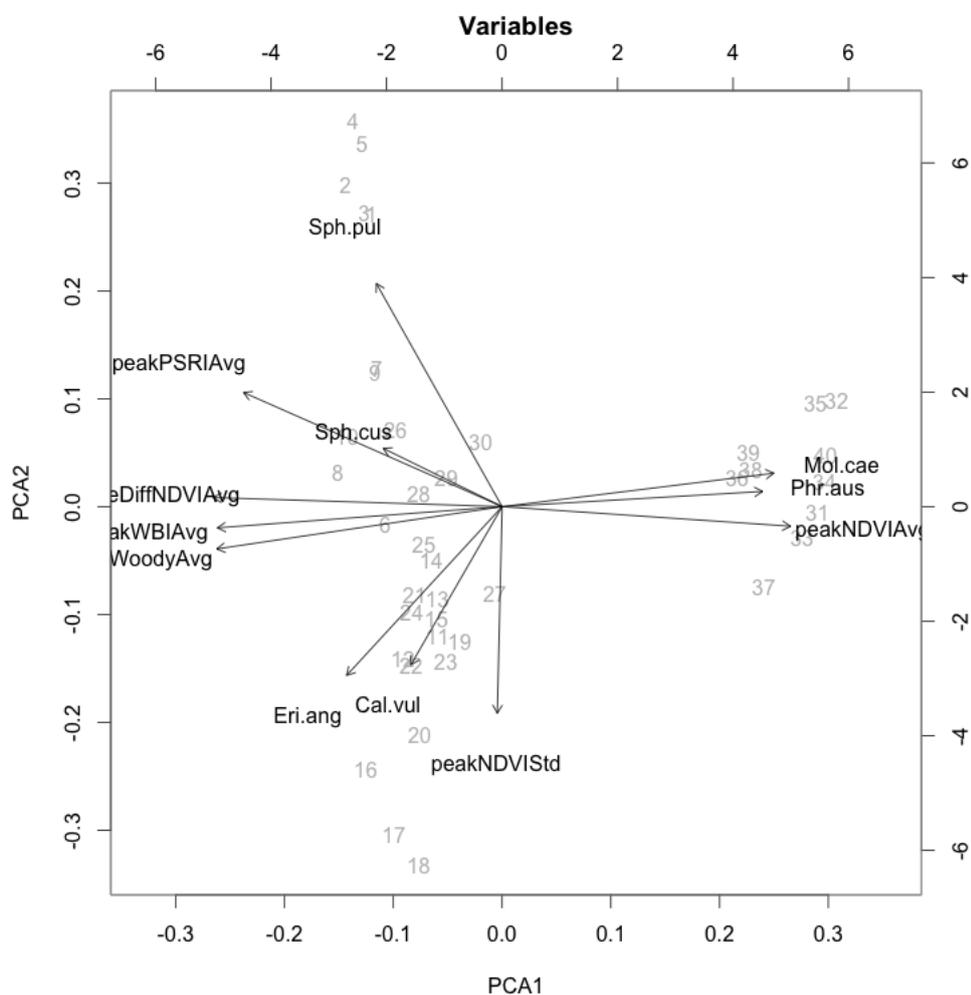
Figure 6.22: PCA of variables to test strength of relationship to sites. (1 to 10 = Area A, 11 to 20 = Area B, 21 to 30 = Area C, 31 to 40 = Area D.)

Pearson's correlation analyses of the predictor variables showed many correlations although mainly between the indices used. From these co-linear variables only one predictor each was used in the same analysis.

	Cal vul	Eri ang	Mol cae	Phr aus	Sph cus	Sph pul	peakpreDiffNDVI	peakNDVIStd	peakNDVI	peakPSRI	peakWBI	preWoody
Cal vul	1	0.22	-0.33	-0.31	-0.35	-0.23	0.37	0.08	-0.26	0.02	0.35	0.45
Eri ang	0.22	1	-0.51	-0.48	0.25	-0.16	0.47	0.46	-0.46	0.27	**0.52**	**0.54**
Mol.cae	-0.33	-0.51	1	**0.75**	-0.4	-0.29	**-0.91**	-0.11	**0.91**	-0.76	**-0.92**	**-0.94**
Phr aus	-0.31	-0.48	**0.75**	1	-0.38	-0.27	**-0.87**	0.03	**0.86**	-0.73	**-0.86**	**-0.89**
Sph cus	-0.35	0.25	-0.4	-0.38	1	0.19	0.3	0.07	-0.38	0.39	0.34	0.3
Sph pul	-0.23	-0.16	-0.29	-0.27	0.19	1	0.48	-0.39	-0.46	**0.73**	0.32	0.29
peakpreDiffNDVI	0.37	0.47	**-0.91**	**-0.87**	0.3	0.48	1	-0.03	**-0.98**	**0.9**	**0.96**	**0.97**
peakNDVIStd	0.08	0.46	-0.11	0.03	0.07	-0.39	-0.03	1	0.03	-0.18	0.03	0.08
peakNDVI	-0.26	-0.46	**0.91**	**0.86**	-0.38	-0.46	**-0.98**	0.03	1	**-0.91**	**-0.98**	**-0.95**
peakPSRI	0.02	0.27	-0.76	-0.73	0.39	**0.73**	**0.9**	-0.18	**-0.91**	1	0.82	0.79
peakWBI	0.35	**0.52**	**-0.92**	**-0.86**	0.34	0.32	**0.96**	0.03	**-0.98**	0.82	1	**0.97**
preWoody	0.45	**0.54**	**-0.94**	**-0.89**	0.3	0.29	**0.97**	0.08	**-0.95**	0.79	**0.97**	1

Table 6.7: Pearson's correlation matrix of variables to highlight colinearity.

Two of the species *Molinia caerulea* and *Phragmites australis* showed high co-linearity with each other with a Pearson's correlation r of 0.75. The *Molinia caerulea* coefficient value within the PCA, as demonstrated by the length of the arrow in the PCA axes diagram (Figure 6.22), showed a slightly stronger relationship with selected sites with a coefficient loading of 0.351 (Table 6.6). *Molinia caerulea* is the most dominant species around the drier degraded verges of the bog, so this combined with the coefficient loading ensured its selection over *Phragmites australis*.

For the index variables peakNDVIStd is the only one which does not show co-linearity. In the PCA, NDVI has the strongest relationship with site with a coefficient score of 0.372 whilst peakpreDiffNDVI gave an almost 100% negative correlation of -0.98. Using the negatively correlated peakpreDiffNDVI within a canonical correspondence analysis could however provide useful information so this variable was kept in any further analysis of relationships with invertebrates.

Every one of the indices selected correlated with *Molinia caerulea* and *Phragmites australis* however the peakNDVI and peakpreDiffNDVI indices were still used due to them giving information on important areas that did not contain *Molinia caerulea* or *Phragmites australis* but may have had dead litter present or vegetation identifiable as evergreen or non senescent (e.g. *Calluna vulgaris* or *Sphagnum* spp.).

All other indices correlated and were therefore discarded in any further analysis. Variables selected following the co-linearity test and PCA were *Calluna vulgaris*, *Eriophorum angustifolium*, *Molinia caerulea*, *Sphagnum cuspidatum*, *Sphagnum pulchrum*, peakNDVI, peakNDVIStd, and peakpreDiffNDVI. NDVI has been used as an indicator of faunal species distributions in a number of studies as indicators of their distributions (Pettorelli et al., 2011). Although most invertebrate studies focus mainly on it's use to provide information on pest species and provide information on areas of foliage stripping or likely areas of pestilence.

6.3.4   Invertebrate associations

This section discusses the distributions of the invertebrate assemblage and the results from the analysis of their relationships/associations with satellite derived environment variables and habitat subdivisions.

Araneae species assemblage associations

In total there were 64 Araneae species collected in pitfall traps across all areas sampled. Of the 4 areas sampled area B, the drier edge of the central primary bog area had the largest number of individuals caught (Table 6.8) as well as the largest number of species. This is an area with high percentage coverage of *Calluna vulgaris* and more shrubby structure which would be more suitable to certain web constructions. A small number of individuals and species were found in the mostly homogeneous area D with a low Shannon-Weaver and Simpson's diversity index score.

Values for Pielou's evenness for each area are all $\geq$0.95 and show that there are very similar numbers of the same species found within each sample area (Table 6.8).

Rare species or low numbers (e.g.less than 5) of a particular species are often left out of analysis investigating environment-species relationships so as not to skew results.

However, in this case there are only 24 species that account for those where there are 5 or more recorded species for the whole recording period. This meant that if following the procedure of removal of rare (infrequent) species, 40 species would be thrown out of the analysis. Cors Fochno is a unique habitat which has many endemic and rare species. As the Araneae community of species is made up of a majority of rarer or less frequent species all 64 species of Araneae (Table 6.8) were included in analysis. There are a also a number of aerial disperser species of Araneae such as *Dicymbium nigrum* and *Pardosa pillata* which may confound the results so this too must be accounted for. Care needs to be taken with these.

A Monte Carlo permutation test of the overall CCA results gave a significance of P < 0.001 (Table 6.9) indicating that the observed relationship between satellite derived environmental variables and ecological distance is not due to chance. For the 'environmental variables' CCA of the Araneae species assemblage, a Monte Carlo permutation test of the relationships found that the first four CCA axes (P<0.001) were highly significant (Table 6.9), indicating that the axes of CCA significantly explain Araneae species assemblages. The total variation in the Araneae species assemblages (total inertia) is 3.435 (Table 6.9). The first four CCA axes accounted respectively for a total of 30.1% of the extracted variance in the species-environment relationship.

6. Evaluation of remotely sensed attributes of habitat as indicators of invertebrate biodiversity.

Scientific name	Family	Code	Total N	Area A	Area B	Area C	Area D
Agraecina striata	Liocranidae	*Agr str*	81	9.9	**70.4**	19.8	0
Agroeca proxima	Liocranidae	*Agr pro*	45	11.1	**75.6**	13.3	0
Agyneta ramosa	Linyphiidae	*Agy ram*	2	0	0	**100**	0
Agyneta subtilis	Linyphiidae	*Agy sub*	2	0	**100**	0	0
Antistea elegans	Hahniidae	*Ant ele*	2	0	50	0	50
Centromerus arcanus	Linyphiidae	*Cen arc*	94	26.6	**44.7**	28.7	0
Ceratinella brevis	Linyphiidae	*Cer bre*	7	0	**57.1**	42.9	0
Clubiona trivialis	Clubionidae	*Clu tri*	3	**66.7**	0	33.3	0
Dicymbium nigrum	Linyphiidae	*Dic nig*	1	0	**100**	0	0
Dipoena prona*	Theridiidae	*Dip pro*	1	0	**100**	0	0
Drassodes cupreus	Gnaphosidae	*Dra cup*	12	50	50	0	0
Drassyllus lutetiana	Gnaphosidae	*Dra lut*	4	**50**	25	25	0
Episinus angulatus	Theridiidae	*Epi ang*	1	0	**100**	0	0
Erigone atra	Linyphiidae	*Eri atr*	1	**100**	0	0	0
Euophrys frontalis	Salticidae	*Euo fron*	8	**87.5**	0	12.5	0
Euryopus flavomaculatus	Theridiidae	*Eur fla*	32	**93.8**	6.2	0	0
Gongylidiellum vivum	Linyphiidae	*Gon viv*	4	50	50	0	0
Hahnia helveola	Hahniidae	*Hah hel*	1	0	**100**	0	0
Hahnia montana	Hahniidae	*Hah mon*	1	0	**100**	0	0
Hyposinga albovittata	Araneidae	*Hyp alb*	2	50	50	0	0
Jacksonella falconeri*	Linyphiidae	*Jac fal*	2	0	50	50	0
Lepthyphantes ericaeus	Linyphiidae	*Lep eri*	4	0	0	**75**	25
Lepthyphantes mengei	Linyphiidae	*Lep men*	2	0	0	**100**	0
Lepthyphantes pallidus	Linyphiidae	*Lep pal*	3	0	0	0	**100**
Lepthyphantes tenuis	Linyphiidae	*Lep ten*	18	0	27.8	38.9	33.3
Lepthyphantes zimmermanni	Linyphiidae	*Lep zim*	5	0	0	40	**60**
Linyphia triangularis	Linyphiidae	*Lin tri*	6	16.7	**50**	33.3	0
Lophomma punctatum	Linyphiidae	*Lop pun*	9	0	0	22.2	**77.8**
Marpissa nivoyi	Salticidae	*Mar niv*	1	0	0	**100**	0
Maso gallicus	Linyphiidae	*Mas gal*	1	**100**	0	0	0
Maso sundevalli	Linyphiidae	*Mas sun*	2	0	**100**	0	0
Metellina segmentata	Tetragnathidae	*Met seg*	1	0	0	**100**	0
Metopobactrus prominulus	Linyphiidae	*Met pro*	1	**100**	0	0	0
Micrargus herbigradus	Linyphiidae	*Mic her*	2	0	50	50	0
Neon reticulatus	Salticidae	*Neo ret*	21	**76.2**	23.8	0	0
Neottiura bimaculata	Theridiidae	*Neo bim*	2	0	**100**	0	0
Oedothorax gibbosus	Linyphiidae	*Oed gib*	28	0	7.1	**67.9**	25
Ozyptila trux 1 amb	Thomisidae	*Ozy tru*	37	24.3	**73**	2.7	0
Pachygnatha clercki	Tetragnathidae	*Pac cle*	15	0	0	6.7	**93.3**
Pachygnatha degeeri	Tetragnathidae	*Pac deg*	2	50	0	0	50
Pardosa nigriceps	Lycosidae	*Par nig*	19	0	**89.5**	10.5	0
Pardosa pullata	Lycosidae	*Par pul*	148	36.4	**62.2**	1.4	0
Pirata hygrophilus	Lycosidae	*Pir hyg*	426	29.8	36.4	33.1	0.7
Pirata latitans	Lycosidae	*Pir lat*	1	0	0	**100**	0
Pirata piraticus	Lycosidae	*Pir pir*	4	**50**	25	25	0
Pirata piscatorius	Lycosidae	*Pir pis*	16	0	0	**100**	0
Pirata uliginosus	Lycosidae	*Pir ulg*	140	17.1	**73.9**	9	0
Pocadicnemis pumilla	Linyphiidae	*Poc pum*	172	20.9	**61.6**	16.9	0.6
Robertus arundineti	Theridiidae	*Rob aru*	4	**100**	0	0	0
Robertus lividus	Theridiidae	*Rob liv*	7	14.2	42.9	42.9	0
Saaristoa abnormis	Linyphiidae	*Saa abn*	2	0	0	0	**100**
Scotina gracilipes	Liocranidae	*Sco gra*	1	**100**	0	0	0
Taranucnus setosus	Linyphiidae	*Tar set*	6	16.7	0	16.7	**66.6**
Theonoe minutissima	Theridiidae	*The min*	5	0	0	**100**	0
Trichopterna thorelli	Linyphiidae	*Tri tho*	8	**100**	0	0	0
Trochosa terricola	Lycosidae	*Tro ter*	199	36.1	**54.3**	9.6	0
Walckenaeria acuminata	Linyphiidae	*Wal acu*	3	0	33.3	0	**66.7**
Walckenaeria alticeps	Linyphiidae	*Wal alt*	72	29.2	41.6	29.2	0
Walckenaeria atrotibialis	Linyphiidae	*Wal atr*	35	11.4	**62.9**	25.7	0
Walckenaeria nudipalpis	Linyphiidae	*Wal nud*	12	33.3	**50**	16.7	0
Walckenaeria unicornis	Linyphiidae	*Wal uni*	1	0	0	**100**	0
Walckenaeria vigilax	Linyphiidae	*Wal vig*	2	50	0	50	0
Zelotes latreillei	Gnaphosidae	*Zel lat*	36	30.6	36.1	33.3	0
Zora spinimana	Zoridae	*Zor spi*	4	25	**75**	0	0
Mean N				49	86.7	37.9	5.5
Mean S				14.6	16.7	12.4	3.9
Simpson diversity				0.91	0.92	0.89	0.67
Shannon-Weaver				2.55	2.66	2.35	1.23
Pielou's evenness				0.96	0.95	0.95	0.99

Table 6.8: Numbers of Araneae individuals (N) and their distribution by percentage across the 4 habitat areas. Mean number of individuals (Mean N) and species (Mean S) per pitfall trap, respectively, and Simpson diversity for each habitat zone are additionally included at the bottom.

Canonical Correspondance Analysis - Araneae count data				
Model				
cca(formula = Araneae $\sim Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul +$ peakpreDiffNDVIAvg + peakNDVIStd + peakNDVIAvg, data =AranVariables)				

Mean squared contingency coefficient		**Inertia**		**Proportion**
	Total	3.435		1.000
	Constrained	1		0.349
	Unconstrained	2.236		0.6507

Significance of all canonical axis				
	F-ratio		2.080	
	P value		0.001	

		Axis 1	**Axis 2**	**Axis 3**	**Axis 4**
Significance of each canonical axis					
	F-ratio	8.4408	2.4921	1.8359	1.5719
	P value	0.001	0.001	0.001	0.001
Eigenvalues		0.609	0.180	0.132	0.113
Cumulative % variance of species		17.7	22.9	26.8	30.1
Speciesenvironmental correlations		0.959	0.911	0.865	0.864

Environmental axes weighted correlations				
Cal vul	0.237	0.014	**0.843**	0.243
Eri ang	0.241	-0.255	0.205	0.321
Mol cae	**-0.947**	0.270	0.084	0.143
Sph cus	0.047	-0.334	-0.767	-0.062
Sph pul	0.198	**0.600**	-0.405	**-0.627**
peakpreDiffNDVIAvg	**0.927**	0.360	-0.055	-0.090
peakNDVIStd	-0.007	-0.288	0.101	0.220
peakNDVIAvg	**-0.873**	-0.276	0.294	0.080

Species scores (Codes & Area (≥50% occurance))		**Axis 1**	**Axis 2**	**Axis 3**	**Axis 4**
Eri atr	A	0.700	1.014	-0.787	1.560
Sco gra	A	0.700	1.014	-0.787	-0.291
Tri tho	A	0.441	0.932	-0.703	-0.170
Mas gal	A	0.433	1.547	-0.800	-0.454
Rob aru	A	0.429	1.170	-0.668	0.958
Eur fla	A	0.403	1.007	-0.522	0.027
Clu tri	A	0.385	0.422	-0.839	0.241
Neo ret	A	0.384	0.817	-0.403	-0.761
Par pul	B	0.318	0.343	0.208	1.267
Ozy tru	B	0.295	0.197	0.389	-3.054
Epi ang	B	0.294	-0.050	0.922	-1.309
Hah hel	B	0.294	-0.050	0.922	-0.504
Lin tri	B	0.274	-0.174	-0.315	-0.434
Pir ulg	B	0.267	-0.002	0.384	-0.210
Dic nig	B	0.265	0.202	0.261	0.854
Tro ter	B	0.264	0.253	-0.003	-0.438
Wal nun	B	0.245	0.066	0.277	-0.668
Dip pro	B	0.217	-0.324	0.903	2.115
Agy sub	B	0.215	-0.239	1.018	2.115
Hah mon	B	0.213	-0.153	1.133	0.172
Mas sun	B	0.213	-0.153	1.133	-0.090
Par nig	B	0.206	-0.263	0.765	-0.022
Agr pro	B	0.200	-0.198	0.520	0.195
Agr str	B	0.187	-0.233	0.283	0.113
Poc pum	B	0.166	-0.030	0.126	0.048
Neo bim	B	0.145	-0.491	0.902	0.211
Pir lat	C	-0.056	-1.183	-1.037	-0.591
The min	C	-0.087	-1.276	-1.186	0.238
Lep men	C	-0.098	-1.282	-1.098	0.313
Pir pis	C	-0.185	-1.408	-1.064	-0.442
Agy ram	C	-0.252	-1.472	-1.096	-0.039
Mar niv	C	-0.261	-1.624	-0.768	0.094
Wal uni	C	-0.448	-1.761	-1.154	0.289
Lep zim	D	-2.802	-0.036	-0.198	-2.340
Wal acu	D	-2.968	-0.405	1.037	-0.057
Tar set	D	-3.347	1.758	-0.585	-0.992
Lop pun	D	-3.657	-0.491	0.380	1.629
Pac cle	D	-4.312	0.577	0.346	-1.082
Saa abn	D	-4.570	-1.158	1.342	0.228
Lep pal	D	-4.677	2.162	-0.182	-0.180

Table 6.9: CCA table of results for Aranaea

The first axis (CCA1) accounting for 17.7% (eigenvalue = 0.609) of Araneae variation of species assemblages was positively correlated with peakpreDiffNDVI and negatively correlated with *Molinia caerulea*. This negative and positive correlation combination is not surprising as *Molinia caerulea*, although very green and lush with very high NDVI figures in summer, will have complete coverage of dead litter when it dies back in winter thereby giving a very significant peakpreDiffNDVI reading for dead litter. The correlations are synonymous with the low individual numbers caught (mean=5.5, (Table 6.8)) and low numbers of species caught (mean=3.9, (Table 6.8)) in *Molinia caerulea* in comparison to the other 3 areas. The species scores show very low negative values for axis 1 for species which have been recorded within the *Molinia* dominated areas (area D). Species with high scores where there is a correlation with peakpreDiffNDVI were *Scotina gracilipes, Maso gallicus* and *Europys flavomaculata* which are associated with raised bog, mosses and low vegetation (Harvey et al., 2002).

Also the species with the highest species scores (Table 6.9) and therefore the least correlation with the *Molinia* area are those species which are found only in the central dome area that does not contain any *Molinia*. The second axis explains 5.2% (eigenvalue = 0.180) of Araneae variation of species assemblages. This axes was positively correlated with *Sphagnum pulchrum* which is mostly found in the central dome area, area A. Species scores are high for species (e.g. *Scotina gracilipes*) found in area A which are more commonly associated with bog habitats, low vegetation and mosses (Harvey et al., 2002). The third axis (eigenvalue =0.132) accounts for 3.9% of variation in species assemblages of Araneae. *Erigone atra* has a very high species scores that correlates with the variables associated with area A. This axes shows a positive correlation with *Calluna vulgaris*. Species such as *Pardosa nigriceps* and *Agroeca proxima* were amongst the highest positive species scores in this axes. These species are common on wet heathland and moorland (areas where *Calluna* commonly grows) with preference for drier low vegetation. These species were, as the analysis indicates found, mostly in area B which is an area with the highest percentage of *Calluna vulgaris* coverage (Figure 6.23).

Calluna tends to grow in drier areas either on raised hummocks in the central dome of the acid bog or towards the edge of the dome where the surface is drier. This is also the area with the highest mean individuals number (Mean N = 86.7) and mean species diversity (Shannon-Weaver diversity=2.66) (Table 6.8).

The fourth axis (eigenvalue = 0.113) only explains about 3.3% of the Aranea species composition and is less significant although this shows an inverse correlation with *Sphagnum pulchrum*.

The species scores show the direction of higher abundance of a particular species. Segregation/sorting of species scores from high to low scores in the first axes has produced a grouping of species into their respective suitable habitat areas (Table 6.9) showing that these species are mainly specific to certain areas and relationships with vegetation and biophysical parameters in the form of indices are present, with the exception of a few species found in equal numbers throughout more than one area.
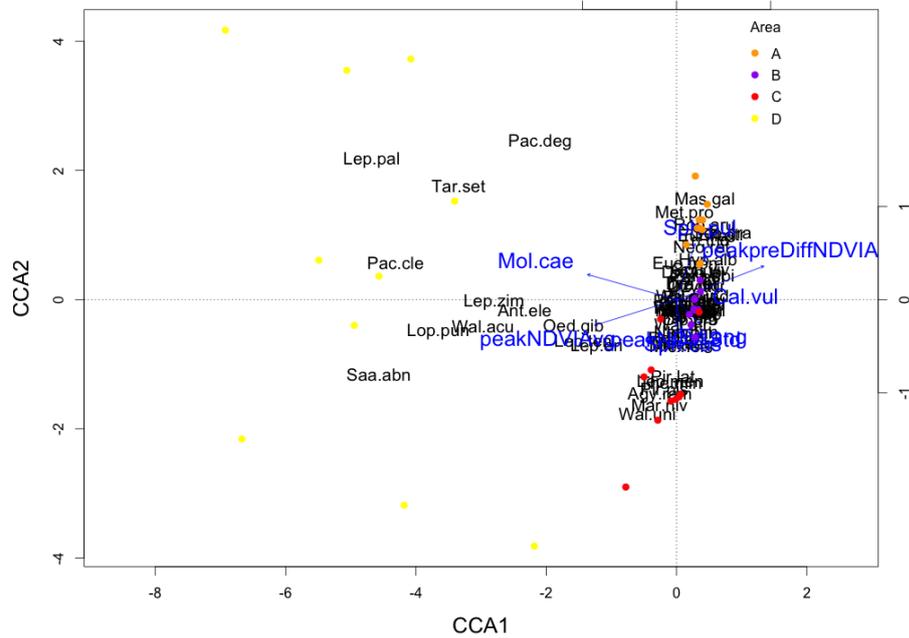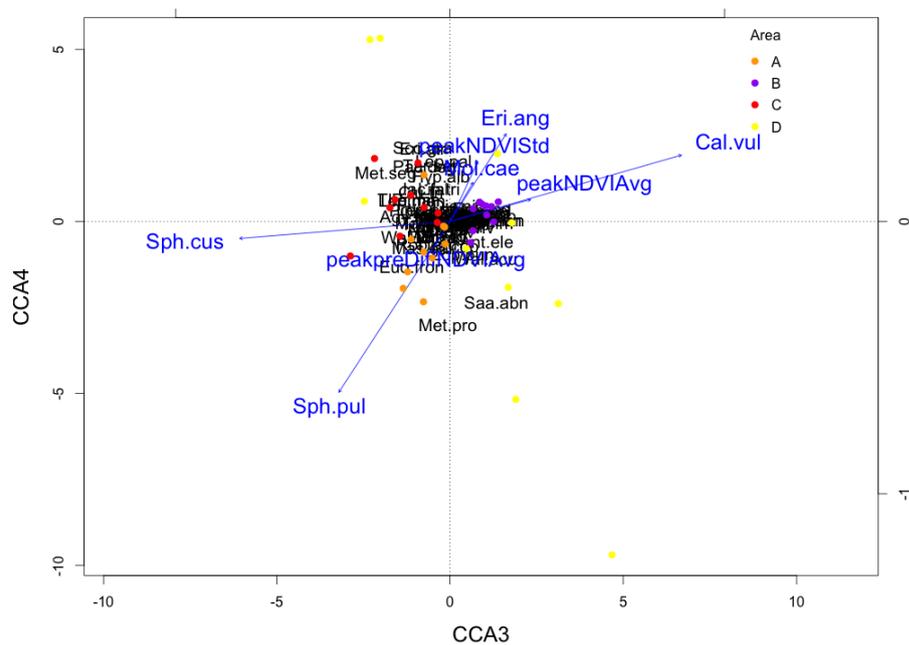
Figure 6.23: Araneae CCA plot 1 and 2. Ordination biplots depicting a) the first two axes of the environmental Canonical Correspondence Analysis of the species assemblages and b) the third and fourth axes. Environmental variables are represented by lines and their acronyms, and species locations by their code, as indicated in Table 6.8.

The species environment biplots illustrate some distinct differences in the distribution of species (Figure 6.23). *Taranucnus setosus* typically associated with lowland bogs and known to exploit areas with *Phragmites australis* and *Lepthyphantes pallidus* which is common to grassland and known to frequent litter were found mainly in area D (an area where Molinia and Phragmites dominate). The direction of ordination arrows and their repective length indicate that variables Mol.cae (*Molinia caerulea*) and peakNDVI (high summer productivity) are closely correlated with these particular species. The species found mostly within the sphagnum central dome area (e.g. *Maso gallicus* (Nationally scarce) and *Robertus arundinetti*) are as indicated within the ordination strongly associated with variables of *Sphagnum pulchrum* (Figure 6.23).

Variable	F	Pr(>F)	
Cal vul	1.526	0.001	***
Eri ang	0.793	0.076	.
Mol cae	4.231	0.001	***
Sph cus	0.739	0.141	
Sph pul	1.521	0.002	**
peakpreDiffNDVIAvg	2.065	0.001	***
peakNDVIStd	0.629	0.421	
peakNDVIAvg	0.394	0.978	

Table 6.10: Monte Carlo permutation test of variables in the Araneae CCA analyis. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (1000 permutations).

The Monte Carlo test of significance confirmed that there were significant associations between the environmental variables *Calluna vulgaris*, *Eriophorum angustifolium*, *Molinia caerulea*, *Sphagnum pulchrum* and peakpreDiffNDVI and the response variables (Araneae species) (Table 6.10).

Coleoptera species assemblage associations

In total there were 49 Coleoptera species collected in pitfall traps across all areas sampled. Of the 4 areas sampled area A, the central primary bog area, had the largest number of

individuals caught (Table 6.11). Area A and area B had the greatest number of species (mean = 5.5) with the same average number of species present (Table 6.11). Area C had the lowest number of species possibly because of the lack of suitable pupation and larvae conditions (very dry ridges with water filled ditches at the side).

Pielou's evenness index values for *Coleoptera* in areas A and D were ≤ 0.71 indicating that there were some dissimilarities in species numbers and types, however, Pielou's values for areas B and C show that traps sampled in each area had very similar numbers of the same species (Table 6.11).

As with the *Araneae*, rare species or low numbers (e.g.less than = 5) of a particular species were used within the analysis. There are only 13 species that account for those where there are 5 or more recorded for the whole recording period. This leaves 36 species that would be thrown out of the analysis if this procedure was used therefore this was not practical. The *Coleoptera* community captured on Cors Fochno for this period consisted mostly of species that were rarer or less frequent species.

A Monte Carlo permutation test of the overall CCA results gave a significance of $P<0.001$ (Table 6.12) indicating that for *Coleoptera* data the observed relationship between satellite derived environmental variables and ecological distance is not due to chance. For the 'environmental variables' CCA of the Coleoptera species assemblage, a Monte Carlo permutation test of the relationships found that the first three CCA axes ($P<0.001$) were highly significant (Table 6.12), indicating that the axes of CCA significantly explain Coleoptera species assemblages. The total variation in the Coleoptera species assemblages (total inertia) is 6.680 (Table 6.12). The first three CCA axes accounted collectively for a total of 21.1% of the extracted variance in the species-environment relationship.

Scientific name	Family	Code	Total N	Area A	Area B	Area C	Area D
Agathidium atrum	Leiodidae	*Aga atr*	5	40	40	20	0
Agabus bipustulatus	Dytiscidae	*Aga bip*	2	0	50	50	0
Agonum ericeti	Carabidae	*Ago eri*	54	100	0	0	0
Agonum fuliginosum	Carabidae	*Ago ful*	10	0	0	0	100
Agonum thoreyi	Carabidae	*Ago tho*	1	0	0	0	100
Anacaena globulus	Hydrophilidae	*Ana glo*	2	0	0	0	100
Anotylus rugosus	Staphylinidae	*Ano rug*	1	0	0	0	100
Atheta hypnorum	Staphylinidae	*Ath hyp*	1	0	0	0	100
Bolitobius castaneus	Staphylinidae	*Bol cas*	2	0	100	0	0
Bolitobius cingulatus	Staphylinidae	*Bol cin*	5	0	60	40	0
Brachygluta fossulata	Staphylinidae	*Bra fos*	1	0	0	100	0
Bradycellus ruficollis	Carabidae	*Bra ruf*	1	0	0	0	100
Carabus granulatus	Carabidae	*Car gra*	53	81.1	15	1.9	1.9
Carabus violaceus	Carabidae	*Car vio*	2	50	50	0	0
Catops morio	Leiodidae	*Cat mor*	3	0	33.3	33.3	33.3
Choleva lederiana	Leiodidae	*Cho led*	2	0	0	0	100
Cychrus caraboides	Carabidae	*Cyc car*	2	0	100	0	0
Cyphon hilaris	Scirtidae	*Cyp hil*	4	25	25	50	0
Cyphon kongsbergensis	Scirtidae	*Cyp kon*	226	99.1	0.9	0	0
Erichsonius cinerascens	Staphylinidae	*Eri cin*	1	0	100	0	0
Euconnus hirticollis	Scydmaenidae	*Euc hir*	1	100	0	0	0
Hydroporus melanarius	Dytiscidae	*Hyd mel*	3	0	33.3	33.3	33.3
Ischnosoma splendidum	Staphylinidae	*Isc spl*	3	33.3	66.7	0	0
Lesteva sicula	Staphylinidae	*Les sic*	14	0	0	0	100
Lochmaea suturalis	Chrysomelidae	*Loc sut*	5	0	40	60	0
Megasternum concinnum	Hydrophilidae	*Meg con*	1	100	0	0	0
Nicrophorus vespilloides	Silphidae	*Nic ves*	6	16.7	33.3	50	0
Ocypus brunnipes	Staphylinidae	*Ocy bru*	1	0	0	100	0
Olophrum fuscum	Staphylinidae	*Olo fus*	2	0	0	100	0
Olophrum piceum	Staphylinidae	*Olo pic*	153	2	20.3	9.2	68.6
Othius punctulatus	Staphylinidae	*Oth pun*	1	0	0	0	100
Othius subuliformis	Staphylinidae	*Oth sub*	2	0	0	50	50
Oxypoda procerula	Staphylinidae	*Oxy pro*	1	0	100	0	0
Philonthus laminatus	Staphylinidae	*Phi lam*	1	0	0	0	100
Platydracus stercorarius	Staphylinidae	*Pla ste*	15	0	100	0	0
Pselaphus heisei	Staphylinidae	*Pse hei*	1	0	0	100	0
Pterostichus diligens	Carabidae	*Pte dil*	20	85	0	15	0
Pterostichus rhaeticus	Carabidae	*Pte rha*	84	98.8	1.2	0	0
Quedius fuliginosus	Staphylinidae	*Que ful*	2	0	0	0	100
Quedius fumatus	Staphylinidae	*Que fum*	1	0	100	0	0
Quedius maurorufus	Staphylinidae	*Que mau*	10	0	0	0	100
Quedius molochinus	Staphylinidae	*Que mol*	1	0	0	0	100
Silpha atrata	Silphidae	*Sil atr*	15	0	26.7	53.3	20
Stenus geniculatus	Staphylinidae	*Ste gen*	2	0	100	0	0
Stenus impressus	Staphylinidae	*Ste imp*	2	0	0	0	100
Stenus lustrator	Staphylinidae	*Ste lus*	6	16.7	33.3	33.3	16.7
Stenus providus	Staphylinidae	*Ste pro*	1	0	0	0	100
Tachyporus dispar	Staphylinidae	*Tac dis*	2	0	50	50	0
Tachinus signatus	Staphylinidae	*Tac sig*	1	0	0	0	100
Mean N of individuals				43.3	8.9	4.9	16.4
Mean number of species				5.5	5.5	3.5	4.6
Simpson diversity				0.59	0.72	0.53	0.44
Shannon-Weaver				1.22	1.51	1.0	0.89
Pielou's evenness				0.71	0.90	0.94	0.69

Table 6.11: Numbers of *Coleoptera* individuals (N) and their distribution by percentage across the 4 habitat areas. Mean number of individuals (Mean N) and species (Mean S) per pitfall trap, respectively, and Simpson diversity for each habitat zone are additionally included at the bottom.

6. Evaluation of remotely sensed attributes of habitat as indicators of invertebrate biodiversity.

Canonical Correspondance Analysis - Coleoptera count data			
Model			
cca(formula = Coleoptera $\sim Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul +$ peakpreDiffNDVIAvg + peakNDVIStd + peakNDVIAvg, data =ColeVariables)			
Mean squared contingency coefficient		**Inertia**	**Proportion**
Total		6.680	1.000
Constrained		1.951	0.292
Unconstrained		4.729	0.708
Significance of all canonical axis			
F-ratio		1.599	
P value		0.001	
	Axis 1	**Axis 2**	**Axis 3**
Significance of each canonical axis			
F-ratio	5.198	2.444	1.602
P value	0.001	0.001	0.006
Eigenvalues	0.793	0.373	0.244
Cumulative % variance of species	11.9	17.5	21.1
Speciesenvironmental correlations	0.959	0.911	0.865
Environmental axes weighted correlations			
Cal vul	0.007	-0.565	**0.676**
Eri ang	-0.268	**-0.639**	-0.190
Mol cae	**0.775**	**0.574**	-0.012
Sph cus	-0.459	-0.092	-0.406
Sph pul	**-0.889**	0.409	-0.078
peakpreDiffNDVIAvg	**-0.912**	-0.403	0.115
peakNDVIStd	0.262	-0.384	0.104
peakNDVIAvg	**0.918**	0.388	-0.036
Species scores (Codes & Area ($\geq$50% occurance))	**Axis 1**	**Axis 2**	**Axis 3**
Bra.ruf D	1.665	0.960	-1.077
Cho.led D	1.616	0.957	-0.703
Ago.tho D	1.566	0.954	-0.329
Tac.sig D	1.566	0.954	-0.329
Ath.hyp D	1.556	1.053	-0.255
Phi.lam D	1.545	0.698	-0.353
Ste.pro D	1.545	0.698	-0.353
Ago.ful D	1.538	0.920	-0.638
Ana.glo D	1.499	0.761	-0.232
Que.mau D	1.463	0.820	-0.206
Ano.rug D	1.452	0.823	-0.112
Que.ful D	1.452	0.823	-0.112
Que.mol D	1.452	0.823	-0.112
Les.sic D	1.304	0.925	0.168
Oth.pun D	1.082	0.883	0.098
Olo.pic D	0.938	0.111	0.158
Sil.atr C	0.556	-1.044	-0.435
Que.fum B	0.431	-1.097	3.161
Bra.fos C	0.392	-1.599	-2.323
Olo.fus C	0.392	-1.599	-2.323
Pse.hei C	0.392	-1.599	-2.323
Oxy.pro B	0.373	-0.960	2.634
Ocy.bru C	0.369	-1.559	-1.820
Cyc.car B	0.365	-1.095	1.694
Eri.cin B	0.358	-1.718	-1.968
Ste.imp D	0.320	-0.818	-0.321
Pla.ste B	0.312	-1.343	0.967
Bol.cing B	0.308	-1.347	-0.099
Bol.cas B	0.279	-1.159	2.022
Ste.gen B	0.274	-1.334	1.045
Loc.sut C	0.234	-1.550	-1.004
Nic.ves C	0.111	-0.947	-0.136
Euc.hir A	-0.079	-1.555	0.305
Isc.spl B	-0.118	-0.591	1.280
Cyp.hil C	-0.149	-0.890	-0.967
Car.gra A	-0.642	0.024	0.143
Cyp.kon A	-0.786	-0.042	-0.100
Pte.dil A	-0.816	0.281	-0.136
Ago.eri A	-0.989	0.389	-0.056
Pte.rha A	-1.008	0.461	0.026
Meg.con A	-1.334	1.009	-0.269

Table 6.12: *Coleoptera* CCA Results

The first axis (CCA1) accounting for 11.9% (eigenvalue $= 0.793$)(Table 6.12) of Coleoptera variation of species assemblages was positively correlated with peakNDVI and *Molinia caerulea* and negatively correlated with peakpreDiffNDVI and *Sphagnum pulchrum*. As with the Araneae distributions there is again separation of species into areas by sorting species scores in the first axis from high to low scores (Table 6.12). This indicates that many of the species in table 6.11 are more specific to certain areas. Species scores for species such as *Agonum ericeti* in the first axis shows an association with *Sphagnum pulchrum*. Species such as *Lesteva sicicula* known to frequent damp areas in reeds were associated with Area D only and had high positive species scores in this axes.

The second axis explains 5.6% (eigenvalue $= 0.373$)(Table 6.12) of Coleoptera variation of species assemblages. This axes was also positively correlated with *Molinia caerulea* but negatively correlated with *Eriophorum angustifolium*. Those species collected from area D also showed the larger positive species scores in this axis and had a propensity to be associated with drier conditions (*Bradycellus rificollis*), or wet soil in dense vegetation (*Agonum thereyi*), or deep litter (*Lesteva sicula*). Those with the smallest values (negative scores) were therefore correlating positively with the presence of *Eriophorum angustifolium*. These species are mainly from areas B and C where *Eriophorum angustifolium* is found in abundance in areas B and C with less in area A and none present in area D.

The third axis (eigenvalue $=0.244$) accounts for 3.6% of variation in species assemblages of Coleoptera (Table 6.12). This axis shows a positive correlation with *Calluna vulgaris*. The highest percentage coverage of *Calluna vulgaris* is found in area B (Table 6.12) which is the drier edge of the central dome. The species with the higher species scores in the third axis such as *Cychrus caraboides* and *Bolitobius castaneus* are found within area B which has the largest concentration of *Calluna vulgaris* both preferring drier more heath like conditions (Harvey et al., 2002).
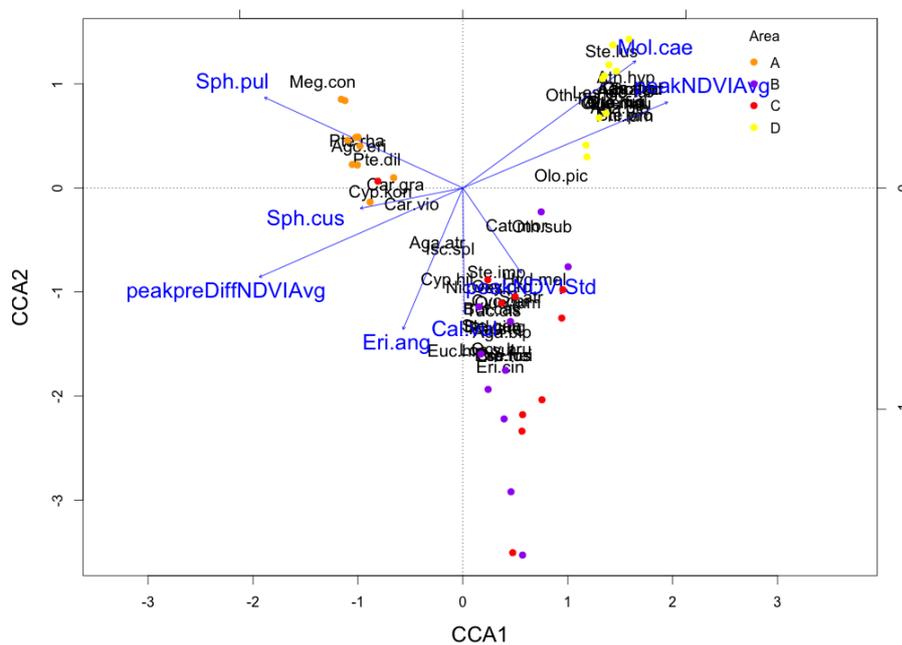
(a)
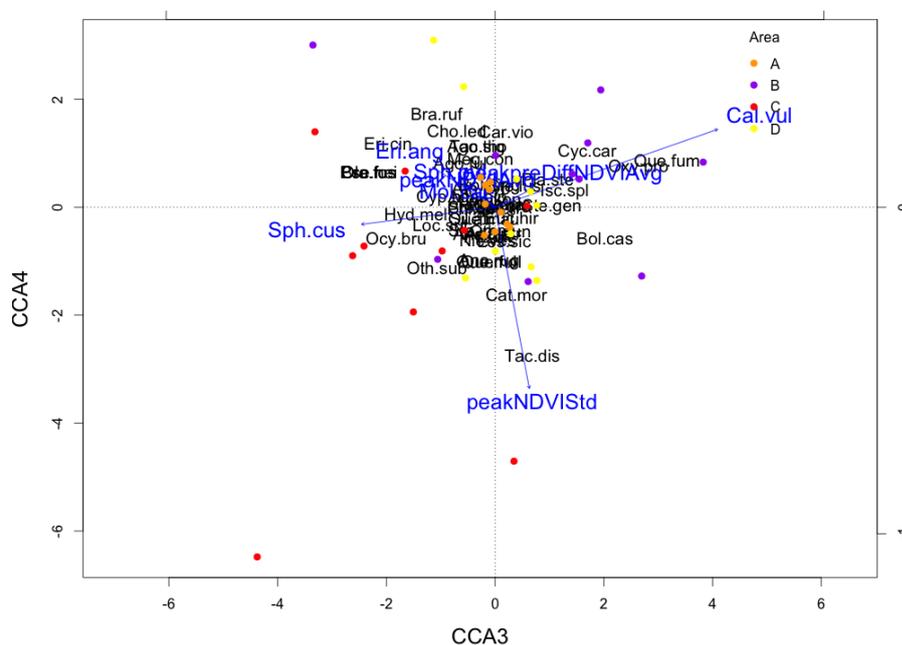
(b)

Figure 6.24: Coleoptera CCA plot 1 and 2. Ordination biplots depicting a) the first two axes of the 'environmental' Canonical Correspondence Analysis of the species assemblages and b) the third and fourth axes. Environmental variables are represented by lines and their acronyms, and species locations by their code, as indicated in Table 6.11

The species-environment biplots (Figure 6.24) show distributions of species and environmental variables, indicating continuous changes in and along ecological gradients. These plots illustrated distinct differences in the distribution of species. Strong associations can be seen with *Lesteva sicula* and *Agonum fuliginosum* (Figure 6.24) being found mainly in areas of *Molinia* for which the direction of ordination arrows, and their respective length, indicate variables Mol.cae (*Molinia caerulea*) and peakNDVI (high summer productivity) are closely correlated with those species. Other visible strong associations can be seen with species such as *Agonum ericeti* (a species of primary bog and particular to areas of *Sphagnum*) and the *Sphagnum pulchrum* (Figure 6.24).

Interestingly *Sphagnum cuspidatum* and prepeakDiffNDVI are pointing in the same direction. This is to be expected as the prepeakDfffNDVI is indicating little change in vegetation productivity or greenness between winter and summer. This can be seen with the seasonal growth patterns of *Sphagnum cuspidatum* which shows very little difference in greenness between summer and winter periods (Figure 4.2)

Variable	F	Pr(>F)
Cal vul	1.617	0.033 *
Eri ang	1.757	0.029 *
Mol cae	3.547	0.001 ***
Sph cus	0.479	0.977
Sph pul	2.648	0.002 **
peakpreDiffNDVIAvg	0.926	0.501
peakNDVIStd	1.127	0.281
peakNDVIAvg	0.686	0.890

Table 6.13: Monte Carlo permutation test of variables in the Coleoptera CCA analyis. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (1000 permutations).

Monte Carlo test of significance confirmed that there were significant associations between the environmental variables *Calluna vulgaris*, *Molinia caerulea*, *Sphagnum pulchrum* and peakpreDiffNDVI and Coleoptera communities as the response variable (Table 6.13).

Comparison of satellite and ground data for Araneae and Coleoptera data.

Canonical Correspondance Analysis - Count data				
Model cca(formula = CountData $\sim Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul+$ peakpreDiffNDVIAvg + peakNDVIStd + peakNDVIAvg, data =CountVariables)				
Araneae	**Satellite derived data**		**Ground data**	
Mean squared contingency coefficient	**Inertia**	**Proportion**	**Inertia**	**Proportion**
Total	3.435	1.000	3.435	1.000
Constrained	1.086	0.316	0.994	0.289
Unconstrained	2.349	0.684	2.441	0.711
Significance of all canonical axis				
F-ratio	3.145		2.769	
P value	0.001		0.001	
	Axis 1	**Axis 2**	**Axis 1**	**Axis 2**
Significance of each canonical axis				
F-ratio	8.974	2.357	8.015	2.424
P value	0.001	0.001	0.001	0.001
Eigenvalues	0.620	0.163	0.576	0.174
Cumulative % variance of species	18.1	22.8	16.8	21.8
Speciesenvironmental correlations	0.965	0.833	0.932	0.866
Environmental axes weighted correlations				
Cal vul	0.223	**-0.385**	-0.515	0.183
Eri ang	0.239	-0.123	-0.430	0.474
Mol cae	**-0.937**	0.219	**0.818**	**0.538**
Phr aus	**-0.950**	-0.323	**0.893**	-0.390
Sph pul	0.1840	0.109	-0.188	-0.063
Coleoptera	**Satellite derived data**		**Ground data**	
Mean squared contingency coefficient	**Inertia**	**Proportion**	**Inertia**	**Proportion**
Total	6.680	1.000	6.680	1.000
Constrained	1.603	0.240	1.393	0.209
Unconstrained	5.077	0.769	5.287	0.791
Significance of all canonical axis				
F-ratio	2.147		1.792	
P value	0.001		0.001	
	Axis 1	**Axis 2**	**Axis 1**	**Axis 2**
Significance of each canonical axis				
F-ratio	5.177	2.651	4.75	1.913
P value	0.001	0.001	0.001	0.001
Eigenvalues	0.773	0.396	0.739	0.297
Cumulative % variance of species	11.6	17.5	11.1	15.5
Speciesenvironmental correlations	0.956	0.880	0.942	0.804
Environmental axes weighted correlations				
Cal vul	0.003	**-0.554**	-0.470	**-0.822**
Eri ang	-0.280	**-0.592**	-0.756	-0.321
Mol cae	**0.795**	**0.530**	**0.918**	0.358
Phr aus	**0.794**	**0.538**	**0.808**	**0.491**
Sph pul	**-0.896**	0.4211	**-0.789**	**0.491**

Table 6.14: Satellite Ground comparisons CCA Results using only main dominant species within area sampled. (Note: Satellite sampling covers a 10x10m area and the ground data is only 2×2m which will account for some differences).

6.3.5 Comparion of analysis with satellite data and analysis with ground data

(a)

(b)
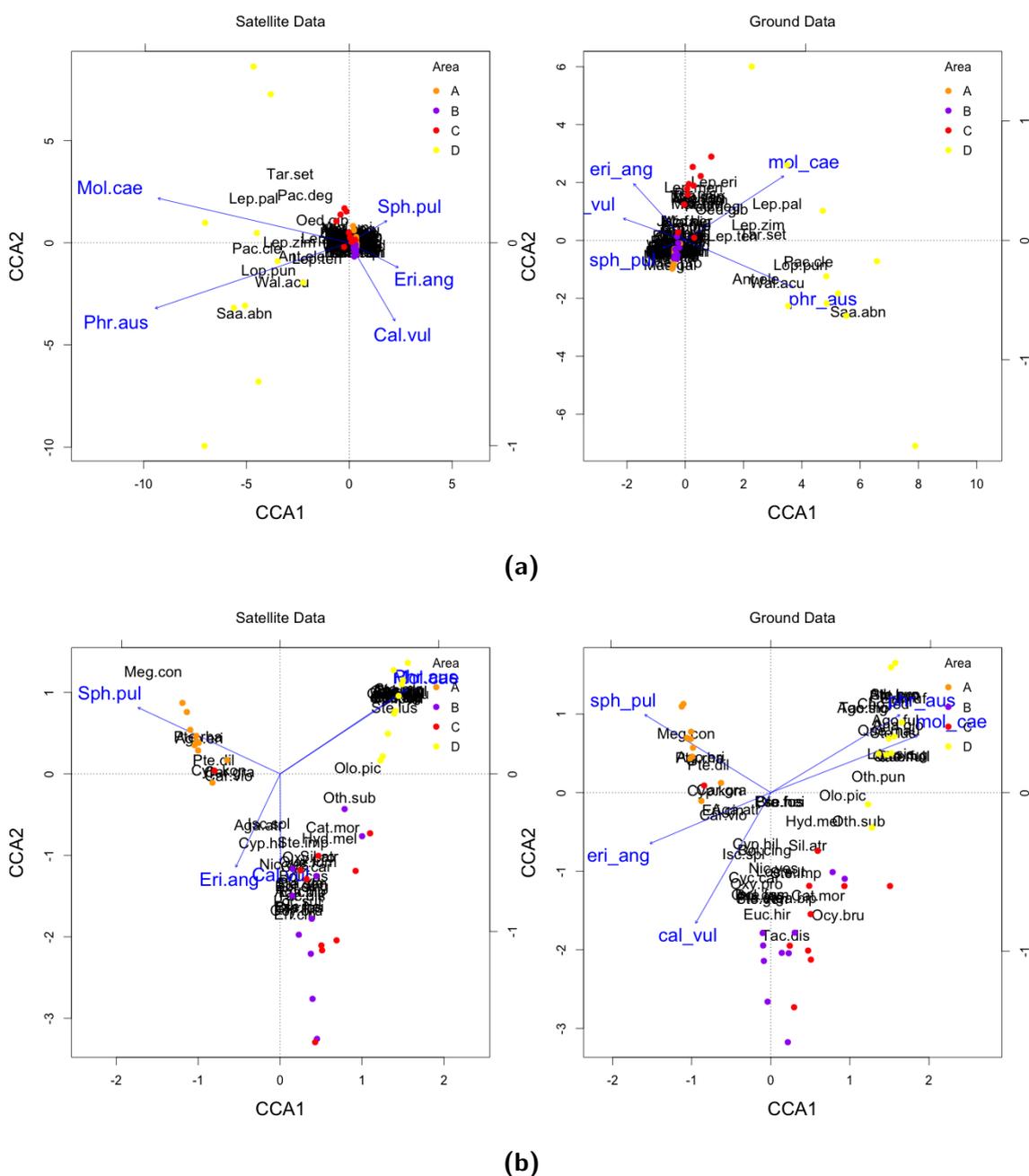
Figure 6.25: Comparison of CCA of using just dominant species used as variables and the CCA of species recorded from ground data. a) Aranae, b) Coleoptera (Note some differences may be due to area recorded- Sat covers a 10×10m and the ground data is 2×2m). *note there is also more separation of species in satellite data CCA

	Satellite data		Ground data	
Araneae				
Variable	F	Pr(>F)	F	Pr(>F)
Cal vul	2.2122	0.001 ***	3.3126	0.001 ***
Eri ang	1.2962	0.008 **	2.1510	0.003 **
Mol cae	7.2814	0.001 ***	4.8612	0.001 ***
Phr aus	2.8822	0.001 ***	2.4522	0.002 **
Sph pul	2.0512	0.002 **	1.0666	0.063 .
Coleoptera				
Variable	F	Pr(>F)	F	Pr(>F)
Cal vul	1.6525	0.045 *	2.3707	0.007 **
Eri ang	1.7947	0.028 *	2.2103	0.009 **
Mol cae	3.6240	0.001 ***	2.4681	0.004 **
Phr aus	1.1209	0.338	0.6515	0.865
Sph pul	2.5447	0.002 **	1.2590	0.137

Table 6.15: Monte Carlo permutation test of variables in the Satellite and Ground data CCA comparison analyses. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (1000 permutations).

For each order both the satellite and ground data show very similar results in the first axis (Figure 6.25). Comparisons of the Monte Carlo permutation tests (Table 6.15) show that ground and satellite variables produce slightly different results, with certain species being more significant in one method than the other. Some of this variation may possibly be due to the fact that this is a comparison of 2×2m ground sampling area with 10×10m satellite derived data sampling area. This can therefore only be used as a rough indication of similarity. Ground sampling larger areas that are the same coverage as the 10×10m areas sampled from satellite data would be ideal but initial testing with quadrats of this size threw up two issues;

1) Trampling sensitive vegetation areas was forbidden on the central dome areas by the Reserve Manager

2) When an individual records a percentage cover of vegetation for a larger area it is more difficult to be accurate with % coverage estimates. Had the same size quadrats been sampled on the ground as those used to produce the satellite species data (i.e. both 10×10m) then the Monte Carlo permutation test could have been used to signify an over or under representation of a species in satellite classification data. For example these results (Table 6.15) could suggest an over estimation of *Sphagnum pulchrum*.

6. Evaluation of remotely sensed attributes of habitat as indicators of invertebrate biodiversity.

Diptera sub-order associations

Three Diptera suborders were recorded from the four areas, Brachycera, Cyclorrhapha and Nematocera. Of the four areas, area D had the largest number and biomass of diptera species (Table 6.16). The average trap catch for area D was nearly twice the biomass of area A (Table 6.16). This was demonstrated to be of significance (P=0.0349). The larger numbers and biomass being in the orders Cyclorrhapha and Nematocera whilst Area A contains the largest number and biomass of Brachycera (Table 6.16). Both biomass and numbers of sub-orders gave similar percentage distribution information across the 4 habitat areas (Table 6.16).

Order	Trap height (cm)	Code	Total N	Total Biomass (mg)	Area A	Area B	Area C	Area D
Nematocera	20	Nem 20	1274	7620.96	32.4 (36.6)	35.5 (31.0)	29.0 (26.6)	3.1 (5.8)
	50	Nem 50	1087	8164.92	22.2 (22.5)	21.6 (21.7)	23.7 (23.6)	32.59 (32.1)
	100	Nem 100	963	7651.72	13.5 (16.1)	16.6 (19.5)	16.9 (20.8)	53.0 (43.5)
	150	Nem 150	723	5697.43	14.7 (18.1)	14.5 (16.4)	23.0 (27.7)	47.7 (37.8)
Total Nematocera	Total	Nem Total	4047	29135.03	22.0 (23.7)	23.5 (22.5)	23.6 (24.5)	30.8 (29.3)
Cyclorrhapha	20	Cyc 20	135	27996.95	20.5 (22.8)	35.3 (32.9)	30.6 (42.0)	13.6 (2.3)
	50	Cyc 50	158	28457.06	13.9 (15.7)	24.5 (22.6)	33.3 (34.5)	28.3 (27.3)
	100	Cyc 100	144	27443.04	7.9 (9.4)	10.9 (12.9)	22.6 (19.0)	58.7 (58.7)
	150	Cyc 150	131	19104.63	7.1 (3.8)	8.4 (5.7)	21.1 (24.0)	63.4 (66.5)
Total Cyclorrhapha	Total	Cyc Total	568	103001.68	12.4 (13.8)	19.9 (19.7)	27.2 (30.5)	40.6 (36.1)
Brachycera	20	Bra 20	72	4932.97	96.3 (96.7)	3.2 (3.2)	0.5 (0.0)	0.0 (0.0)
	50	Bra 50	4	195.46	61.5 (93.4)	0.0 (0.0)	0.0 (0.0)	38.5 (6.6)
	100	Bra 100	4	55.73	0.0 (0.0)	0.0 (0.0)	25.0 (37.2)	75.0 (62.8)
	150	Bra 150	2	26.63	0.0 (0.0)	0.0 (0.0)	14.3 (25.9)	85.7 (74.1)
Total Brachycera	Total	Bra Total	83	5210.78	87.1 (95.1)	2.8 (3.1)	2.0 (0.6)	8.0 (1.3)
Diptera	20	Dipt 20	1481	40551	34 (34.4)	33.9 (28.9)	28 (34.0)	3.9 (2.7)
	50	Dipt 50	1249	36817	21 (17.6)	21.9 (22.3)	25 (31.9)	32.0 (28.2)
	100	Dipt 100	1111	35150	13 (10.9)	15.8 (14.3)	18 (19.4)	53.9 (55.4)
	150	Dipt 150	857	24829	14 (7.1)	13.5 (8.2)	23 (24.9)	50.2 (59.9)
Total Diptera	Total	Dipt Total	4698	137347.50	22.0 (18.9)	22.7 (19.6)	23.7 (28.0)	31.6 (33.4)
Mean N of individuals					258	267	278	371
Mean Biomass (mg)					6489.67	6730.03	9614.32	11468.52

Table 6.16: Total number of Diptera individuals (N) and their distribution by percentage across the 4 habitat areas averaged from 3 sampling periods. Figures in brackets() are biomass distribution by percentage. Mean number of individuals (Mean N) and biomass (Mean Biomass) are per complete aerial trap, respectively.

Percentage distribution varied according to trap height and showed that most diptera were trapped at the height that the vegetation was as opposed to being trapped at a height above the vegetation (Table 6.16). It could be assumed they were using the area immediate to the surface of the vegetation to fly in. This is useful in interpreting the data as this could indicate that everything found at the height of the vegetation in the lower vegetation areas such as the central dome was more or less endemic to that area and not an individual that may have blown across the habitats from elsewhere.

An ANOVA of overall Diptera count (Table 6.17) showed that there were significant differences between areas and Figure 6.26 showed the main difference to be larger numbers of Diptera being trapped in area D. Graphs (Figure 6.26) also showed suborders Cyclorrhapha and Brachycera to have the largest variation between areas.
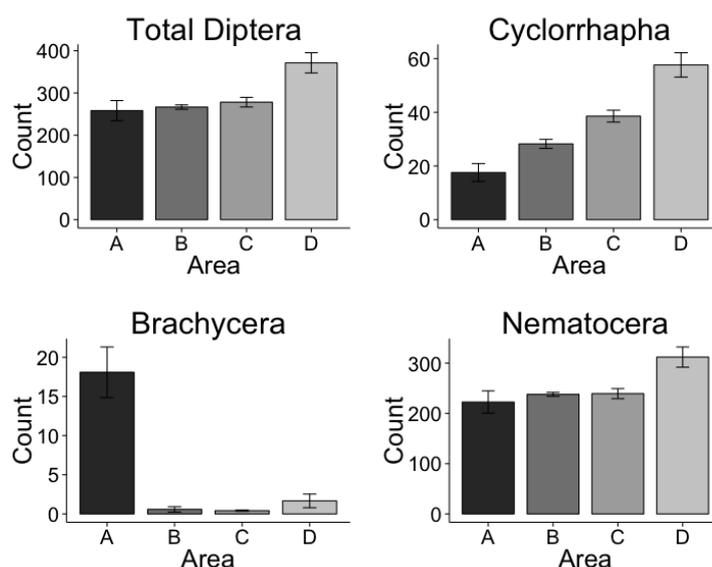
Figure 6.26: Mean Diptera count and Diptera sub-order count

A Generalised Linear Model (GLM) of each suborder showed only the Brachycera suborder to have any significant correlations with satellite derived data. A glm showed a significant positive correlation with *Molinia caerulea* (P=0.000491) and a significant very high inverse correlation with the peakpreNDVI indices (P=0.000213). The other suborders Cyclorrhapha and Nematocera did not show any significant correlations with

the derived satellite data.

Measure	df	SS	MS	F	p
Count	3	33012	11004	8.51	0.00267 **
Biomass	3	68116204	22705401	3.987	0.0349 *

Table 6.17: An ANOVA of Diptera count and Diptera biomass of each trap for Areas A, B, C and D. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (1000 permutations).

6.3.6 Single species Agonum ericeti association

This section investigates the relationships between *Agonum ericeti* and the satellite derived variables. This species has known associations in ecological literature. This information is therefore useful along with the ground data model produced in this chapter as confirmation of the satellite derived variable associations.

All 4 models showed a positive correlation with *Sphagnum pulchrum* and gave the most significant result with Model 3 (P=0.0002) using only satellite derived species coverage. Model 4 used only species ground data and showed a significant positive correlation to *Sphagnum pulchrum* (P=0.0056) and a negative correlation with *Molinia caerulea* (P=0.0431). In concurrence with these results, Drees et al. (2007) studied the relationship of the abundance of this species on peat bogs in north-west Germany in order to investigate the relationship of *Agonum ericeti* abundance with habitat quality. Their analysis revealed that the cover of sphagnum species was positively related to trapping numbers of *Agonum ericeti*, whilst an increasing cover of grass led to a decrease in their numbers. As mentioned previously comparisons of ground data models should be regarded with care due to different size sampling areas.

a) **Brachycera count data + satellite data**				
Model 1				
glm(formula = Brachycera count $\sim$ Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul + peakpreDiffNDVI + peakNDVIStd + peakNDVI, family = **poisson**, data = Diptera)				
Variable	**Estimate**	**Std. Error**	**t value**	**Pr(> |z|)**
(Intercept)	-25.3556	12.3135	-2.059	0.039478 *
Cal vul	-5.0534	1.8126	-2.788	0.005304 **
Eri ang	-0.4594	1.8507	-0.248	0.803972
Mol cae	9.1664	2.6296	3.486	0.000491 ***
Sph cus	1.9039	1.5250	1.249	0.211845
Sph pul	1.6611	1.5066	1.102	0.270250
peakNDVI	58.5138	24.0346	2.435	0.014910 *
peakNDVIStd	-49.9219	81.1665	-0.615	0.538518
peakpreDiffNDVI	-55.2348	14.9172	-3.703	0.000213 ***
b) **Cyclorrhapha count data + satellite data**				
Model 2				
glm(formula = Cyclorrhapha count $\sim$ Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul + peakpreDiffNDVI + peakNDVIStd + peakNDVI, family = **poisson**, data = Diptera)				
Variable	**Estimate**	**Std. Error**	**z value**	**Pr(> |z|)**
(Intercept)	3.55608	2.65804	1.338	0.1809
Cal vul	0.08783	0.57863	0.152	0.8793
Eri ang	-0.39604	0.40731	-0.972	0.3309
Mol cae	0.40043	0.47739	0.839	0.4016
Sph cus	0.60752	0.39999	1.519	0.1288
Sph pul	-0.79123	0.42502	-1.862	0.0627 .
peakNDVI	-0.87394	5.32553	-0.164	0.8696
peakNDVIStd	11.24729	9.50126	1.184	0.2365
peakpreDiffNDVI	1.32294	3.53151	0.375	0.7080
c) **Nematocera sub-order count data + satellite data**				
Model 3 - reduced				
glm(formula = Nematocera count $\sim$ Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul + peakpreDiffNDVI + peakNDVIStd + peakNDVI, family = **poisson**, data = Diptera)				
Variable	**Estimate**	**Std. Error**	**z value**	**Pr(> |z|)**
(Intercept)	5.900261	1.007668	5.855	4.76e-09 ***
Cal vul	-0.008409	0.188762	-0.045	0.9645
Eri ang	-0.143472	0.146018	-0.983	0.3258
Mol cae	-0.213489	0.194426	-1.098	0.2722
Sph cus	-0.260489	0.142866	-1.823	0.0683 .
Sph pul	0.082954	0.146258	0.567	0.5706
peakNDVI	-1.205461	1.975814	-0.610	0.5418
peakNDVIStd	3.902202	3.425632	1.139	0.2547
peakpreDiffNDVI	1.815639	1.254949	1.447	0.1480

Table 6.18: Generalized Linear Model results for Diptera suborders a) Brachycera, b) Cyclorrhapha, c) Nematocera. (Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)

a) **Species count data + satellite data**				
Model 1				
bayesglm(formula = Ago.eriCount ~ *Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul +* peakpreDiffNDVI + peakNDVIStd + peakNDVI, family = **quasipoisson**, data = GLM)				
Variable	**Estimate**	**Std. Error**	**t value**	**Pr(> |t|)**
(Intercept)	-0.88435	1.33335	-0.663	0.51207
Cal vul	-0.18131	0.77924	-0.233	0.81754
Eri ang	-0.01495	0.73392	-0.020	0.98388
Mol cae	-0.17008	0.42325	-0.402	0.69057
Sph cus	0.84115	0.82916	1.014	0.31821
Sph pul	1.97091	0.56145	3.510	0.00139 **
peakpreDiffNDVI	-1.32029	1.12182	-1.177	0.24819
peakNDVIStd	-3.66140	25.73079	-0.142	0.88777
peakNDVI	-2.33994	2.05798	-1.137	0.26425
b) **Species presence/absence data + satellite data**				
Model 2				
bayesglm(formula = Ago.eriPA ~ *Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul+* peakpreDiffNDVI + peakNDVIStd + peakNDVI, family = **binomial**, data = GLM)				
Variable	**Estimate**	**Std. Error**	**z value**	**Pr(> |z|)**
(Intercept)	3.33261	7.78998	0.428	0.669
Cal vul	-1.59338	3.67786	-0.433	0.665
Eri ang	-0.34138	3.87276	-0.088	0.930
Mol cae	-0.23475	2.58434	-0.091	0.928
Sph cus	0.06657	4.04160	0.016	0.987
Sph pul	8.87986	3.16364	2.807	0.005 **
peakpreDiffNDVI	-4.37454	6.84547	-0.639	0.523
peakNDVIStd	-54.43953	139.60775	-0.390	0.697
peakNDVI	-7.20489	12.49943	-0.576	0.564
c) **Species presence/absence data + satellite data**				
Model 3 - reduced				
bayesglm(formula = Ago.eriPA ~ *Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul+* , family = **binomial**, data = GLM)				
Variable	**Estimate**	**Std. Error**	**z value**	**Pr(> |z|)**
(Intercept)	-2.93556	1.58946	-1.847	0.064763 .
Cal vul	-1.11311	3.57261	-0.312	0.755369
Eri ang	-0.18674	3.39696	-0.055	0.956161
Mol cae	-1.19836	2.12329	-0.564	0.572489
Sph cus	0.09431	3.87557	0.024	0.980585
Sph pul	10.42923	2.85756	3.650	0.000263 ***
d) **Species presence/absence data + ground data**				
Model 4				
bayesglm(formula = Ago.eriPA ~ *Cal.vul + Eri.ang + Mol.cae + Sph.cus + Sph.pul+* , family = **binomial**, data = GLM)				
Variable	**Estimate**	**Std. Error**	**z value**	**Pr(> |z|)**
(Intercept)	-0.6744	2.2642	-0.298	0.7658
Cal vul	-2.3696	3.7341	-0.635	0.5257
Eri ang	-4.6057	12.0743	-0.381	0.7029
Mol cae	-4.0992	2.0268	-2.023	0.0431 *
Sph cus	-7.1258	19.7879	-0.360	0.7188
Sph pul	11.2425	4.0581	2.770	0.0056 **

Table 6.19: Bayesian Generalized Linear Model results for *Agonum ericeti* using a) species count as the response variable and satellites derived data which includes species and indices data, b) species presence/absence data as the response variable and satellites derived data which includes species and indices data, c) species presence/absence data as the response variable and satellites derived data which contains species data only, d) species presence/absence data as the response variable and ground data which contains species data only. (Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)

Evaluation of models

Model type	Response variable type	df	AIC	Fischer score	Dispersion	Residual deviance	Raw cv estimate	Adjusted cv estimate	cv estimate difference
Satellite data with indices									
(1) bayesglm (Quasipoisson)	Count	31	NA	28	0.2434	7.8889	0.0645	0.0641	0.0004
(2) bayesglm (Binomial)	Presence Absence	31	21.607	8	1	3.607	0.0000	0.0000	0.0000
Satellite data without indices									
(3) bayesglm (Binomial)	Presence Absence	34	16.261	7	1	4.261	0.0250	0.0125	0.0125
Ground data									
(4) bayesglm (Binomial)	Presence Absence	34	23.171	7	1	11.171	0.1000	0.0938	0.0063

Table 6.20: Evaluation of all models showing AIC and K-fold cross validation values.

The results of the cross validation estimates for this method show slightly different results in terms of model efficiency (Table 6.20). However, if one cannot compare AIC values for all models, then it may be best to use these. Cross-validation was carried out with a 'leave one out cross validation'(LO) method. The best outcome here was Model 2 which gave delta values of 0.00 for the raw cross-validation estimate of prediction error and 0.00 for the adjusted cross-validation estimate (Table 6.20).

These results show the best model to be Model 2. This model is that which includes not only the satellite derived species variables, but also the indices relating to the vegetation productivity, seasonality and heterogeneity. However, the indices in this model do not show any significant correlations with the distribution of *Agonum ericeti* (Table 6.19). In Model 2 vegetation species and peakNDVIStd (surrogate for species diversity) influence *Agonum ericitum* positively, while peak NDVI and prepeakDiffNDVI have a negative effect. The coefficient of *Sphagnum pulchrum* is highly significant ($p<0.001$), while the coefficients of the other variables are not significant ($p>0.05$) (Table 6.19)

Habitat Suitability Maps were produced for each of the 3 binomial models produced (Figure 6.27). These illustrate the differences in models produced using satellite data for the original bayesGLM analysis or ground data for the original analysis.

a)

b)

c)
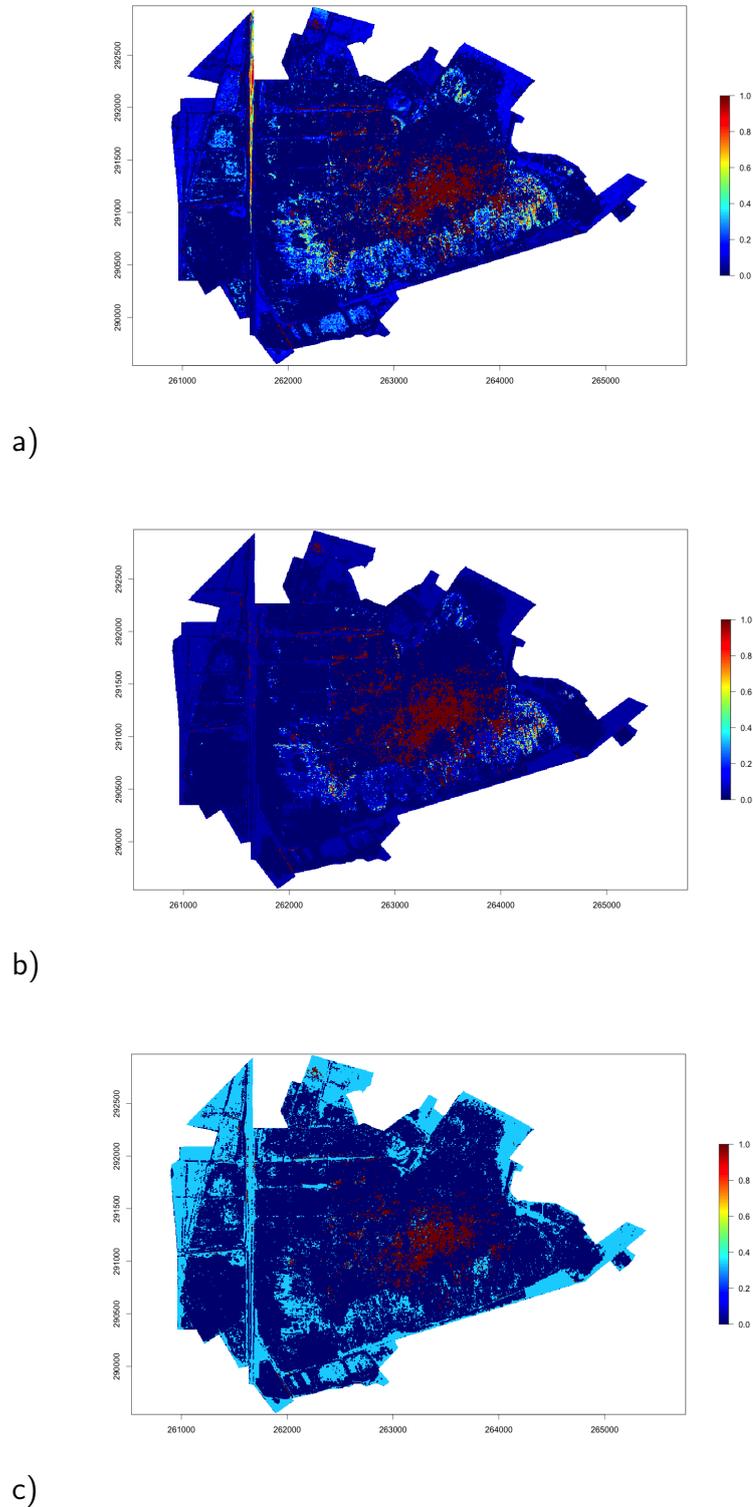
Figure 6.27: Habitat Suitability Model for *Agonum ericeti* using bayesglm binomial model with presence absence data. (Probability 0 to 1) a) using satellite data with indices, b) using satellite data without indices, c) using ground data.

All models show similar results with the highest probabilities being were *Sphagnum pulchrum* is mapped. The main difference between the species only satellite HSM (Figure 6.27) and the species only ground data HSM (Figure 6.27) is the scale of the probability. The HSM using the indices as well as derived species satellite data, however, shows areas with a greater probability of occurance than with the other models. Areas highlighted with a greater probability of occurance in this model (Figure 6.27) are also areas with higher moisture levels. It is entirely possible that soil moisture is really what is preferred habitat for this species, especially for pupation (Drees et al., 2007; De Vries and Den Boer, 1990). *Sphagnum* may merely be an indicator of those conditions.

6.4   Discussion

This study has used both the satellite classification of the relevant dominant plant species that demonstrate ecological gradients and satellite derived indices to attain variables that can be used as indicators of some invertebrate distributions. Results for Araneae and Coleoptera showed associations that correlate well with their ecological knowledge. The results show that the derived satellite data has the required level of detail that could prove useful as a tool to assess changes that demonstrate losses or gains in certain invertebrate species distributions.

Associations were made between invertebrate species and dominant plant species as well as the satellite derived indices that reflected the habitat and ecological gradients present. Dominant species and the selection of indices proved suitable for reflecting the gradients that define invertebrate associations either by the plants present or the environmental factors/conditions that may effect invertebrate distributions.

6.4.1   Representation of ecological gradients

Environmental factors influence the flora and fauna of a habitat. The relationship between plant species distribution and environmental factors has been studied by many (Pellerin et al., 2009; Kleinebecker et al., 2007). Furthermore these very same environmental factors can influence invertebrate distributions by affecting aspects such as egg hatching, larval activity, pupation and food availability (Davies, 1988). Typical raised bog habitats can be divided into areas that are descriptive of their environmental gradients (Wheeler and Proctor, 2000). This study has shown that satellite data can be used to help determine these gradients and suitable species and biophysical properties derived from the satellite data can be used to define them. The wettest regions form a system of hummocks and hollows with *Sphagnum pulchrum* and *Sphagnum cuspidatum* found in the floating or hollow areas (Figures 6.19 & 5.23, Area A). The hummock areas are the drier patches within this wet area created by the the process of growth of *Calluna*, and tussock forming plants such as *Eriophorum*. Where the water levels have sunk and the bog is drier these small patches become a more continuous carpet of these hummock communities (Figures 6.19 & 5.23, Area B) (Masing, 2013). As a result of damage from peat cuttings, these peat layers can dry out and the wet peatland becomes almost completely dominated by *Molinia* (Figures 6.19 & 5.23, Area D) (JNCC, 2011). Ground data in this project shows that vegetation height changes from area A to area D, with taller vegetation found in the drier or more degraded areas. The height and size of vegetation present depends on its specific relationship with both water and nutrient supply (Bragazza et al., 2005). Increases in heights of the same species may be explained by an increase in nutrient availability (Bragazza et al., 2005). Areas/subdivisions selected in this chapter can therefore be recognised as gradients of moisture, gradients of degradation and eutrophic gradients from oligotrophic to mesotrophic conditions. Results from mapping of dominant species and indices confirmed these ecological subdivisions previously recognised on Cors Fochno (Figure 6.3) as Annex1 areas. These plant species and

subdivisions in this case show some associations with particular invertebrate distribution and abundance.

Photographic records were useful to show seasonal differences in vegetation in subdivision (Figure 6.17). A cluster analysis of ground data showed that these species, or increases in the dominance of these species, were particular to the selected subdivisions. A subdivision classification using indices also demonstrated that it was possible to segregate the subdivisions by using indices, such as NDVI. The classification map of Annex 1 areas (Areas A to D) shows that some of the indices that were useful in creating the classification were found to be useful as environmental variables (e.g. peakNDVI (productivity) and PrePeakDiffNDVI (phenology)) in the invertebrate analysis. Indices best for use in associations with invertebrate analysis may be the same as those used to the discriminate plant species or habitat areas that the invertebrate species is associated with.

It was important to use the PCA in selection of variables. Using a PCA to show relationships of variables and sample sites helped in the removal of many highly correlated variables, and gave information that was useful in assuring that a reasonable balance of variables showed associations with each subdivision/area. It also showed that the indices were able to add a few extra indicator dimensions. Futher advantages of using indices are that more subtle differences in the vegetation characteristics can be analysed; these are useful in producing more accurate predictive maps with better spatial and temporal capacity (Sillero et al., 2012; Lucas et al., 2012a; Turner et al., 2003c; Kerr and Ostrovsky, 2003a). However, due to their high co-linearity a large number of the indices were discarded.

6.4.2 Invertebrate species associations with satellite derived variables

The selection of suitable plant species for use as input as environmental variables in analysis was effective. Results demonstrated that Araneae and Coleoptera assemblages showed distribution subdivisions that mirrored the environmental subdivisions. These appeared to be influenced by their environmental gradients.

Most invertebrate species with high species scores and showing positive associations with *Sphagnum pulchrum* were known to be commonly associated with bog habitats for both Coleoptera and Araneae. Araneae and Coleoptera species that are typical of active primary bog and have previously been noted as ecological indicators of the health of active bogs (Koivula, 2011; Rainio and Niemela, 2003; Allred, 1975). In the analysis of associations these were shown to be associated with *Sphagnum pulchrum* the plant indicator species for the central dome area A.

Aranea species associations

Araneae distribution depends on biotic and abiotic environmental factors reflected by habitat type (Haase and Balkenhol, 2014). The Araneae results show that there are at least four main dominant factors (peakpreDiffNDVI, *Molinia caerulea*, *Sphagnum pulchrum* and *Calluna vulgaris*) which show relationships or influence on Araneae species distributions. They also show that there is potential for their use in extrapolating Araneae communities and diversity to the full extent of habitat present within a protected site (Table 6.10).

Araneae species distributions appeared to show some distinct groupings on Cors Fochno. Species that prefer low vegetation were predominantly associated with the more central areas A and B, and the litter frequenting species were shown to be associated with area

D. These are similar to results obtained by Haase and Balkenhol (2014) who investigated Araneae distributions on peat bog areas using ground data.

Interestingly many of those species (*Pirata latitans, Pirata piscatoria*) showing larger distributions within area C (Figure 6.23) are often found in wetlands, bogs, fens and alongside the edges of open water. Area C is an area of peat cuttings with sphagnum covered open ditches.

Species such as *Pardosa nigriceps* and *Agroeca proxima* which showed a positive correlation with *Calluna vulgaris* are common on wet heathland and moorland (areas where *Calluna* commonly grows) with preference for drier low vegetation (Harvey et al., 2002). These species were, as the analysis indicates found, mostly in area B which is an area with the highest percentage of *Calluna vulgaris* coverage (Figure 6.23). *Calluna* tends to grow in drier areas either on raised hummocks in the central dome of the acid bog or towards the edge of the dome where the surface is drier

Although radiation and water balance are often named in the literature as some of the most important environmental factors for spiders (Entling et al., 2007; Ehmann, 1994), so too is vegetation structure (Dennis et al., 2015; Robinson, 1981). This structural information could have been sourced from a better LiDAR data souce and could have been used to provide more accurate CHM data. Vierling et al. (2011) used LiDAR variables such as the penetration rate and laser echo which gave a metric reflecting microclimate conditions. This was found to have significant associations with spider species occurrence. Although not sufficiently researched this could be a useful parameter for determining other orders such as Coleoptera distribution.

The NDVI index and associated index (peakpreNDVIdiff) were the most useful indices with a strong association with the Aranea and Coleoptera species assemblages. Lassau et al. (2005) investigated the use of multispectral data and found there to be strong associations of ant species assemblages with NDVI. This was however, in areas of forest habitats. The NDVI in Lassau's research was positively correlated to habitat complexity

whereas on Cors Fochno high NDVI (Peak times) indicated areas of *Molinia caerulea* which were very homogeneous and with less habitat complexity present than the other regions of the bog.

Coleoptera species associations

Results for Coleoptera did not show associations with variables to be as strong as that for Araneae. Some of this may be explained by Coleoptera movement and the movement of flying Coleoptera in and out of trapping areas. There were two main significant factors, *Sphagnum pulchrum*, and *Molinia caerulea* (Table 6.13). These variables showed significant separation of typical species found in bog and those that prefer drier conditions or deep litter.

Species such as *Lephyphantes pallidus* and *Saarista abnormis* which were recorded in Area D are species that are often found in wetland habitats amongst dead litter (Harvey et al., 2002) which *Molinia* produces in large quantities. Many of the species showing higher association with area D are species that frequent leaf litter (*Saarista abnormis* and *Lepthyphantes pallidus*), inhabit grass clumps (*Lepthyphantes zimmermani*) or are known to exploit reed beds (*Taranucnus setosus*) as shown in axis 1 (Table 6.12) by their very low negative species scores, associated with Molinia.

Variables such as *Calluna vulgaris* which grows more profusely in drier areas proved to be a useful indicator of drier heath type areas. Coleoptera species *Cychrus caraboides* and *Bolitobius castaneus* prefer drier more heath like conditions (Harvey et al., 2002) and these were associated with *Calluna vulgaris* in the analysis.

In the case of species such as *Agonum ericeti* and *Pterostichus rhaeticus*, which are endemic to Area A (Table 6.11) in the sampling, these separations are very distinct. Notably these two species are used in conservation as indicators of peatlands (Brigic et al., 2014; Drees et al., 2007). *Agonum ericeti* (Figure 6.15), a species which is scarce

in Britain, is known to only be found on oligotrophic mires with active *Sphagnum growth* (Fowles, 1997). Using the bayesGLM analysis on the satellite variables, it could be seen that the one main variable showing a significant association with *Agonum ericeti* was *Sphagnum pulchrum* (Table 6.19). This relationship has been shown in previous studies (Drees et al., 2007; De Vries and Den Boer, 1990) and it has been found that an increasing amount of grass in peat bogs is seen to be linked with a deterioration and reduction of suitable habitat for this species (Drees et al., 2007).

6.4.3   Diptera suborder associations

The Diptera results showed differences in areas but few significant correlations with the satellite derived data. This may have been due to using less refined (e.g. no species) data as well as less sample quadrats due to sub-sampling. There was little difference in results with the use of count or biomass. Results were only significant for Brachycera due to the preponderance of the numbers of a single species present in traps in area A.

It is entirely possible that aside from other variables, wind speeds could be a variable affecting the distribution of Diptera orders (Batista-da Silva, 2014). It was noted that there was a significantly greater number of Brachycera in Area A (Table 6.26). Brachycera species are known to be swifter and strong fliers whereas Nematocera and Cyclorrhapha are slow fliers. The stronger swifter flier (Brachycera) would be better adapted for the less sheltered central areas of bog.

These results show that although area D is degraded bog, it is not providing a valuable habitat for many of the species endemic to primary active bog. However area D does have a larger number of Diptera according to the trapping results. The reasons for this may be as discussed before, due to areas of *Molinia caerulea* being surrounded by trees and shrubs (species that grow and develop in regions that are damaged, draining

and drying out - all part of the process of encroachment). These provide shelter and therefore provide a more suitable habitat for some of these flying invertebrates. This means that this outer verge area (area D) of the bog is actually a valuable part of the protected site in that it provides a valuable food source for other species further up the food chain, e.g. birds and bats. When considering the food chain and processes such as food availability it is also surprising that there are not more Araneae individuals present in area D; here their supply of Diptera food would be more plentiful than Area B, where Aranea were more prevalent. Smaller numbers of individuals, though not necessarily smaller numbers of species of Araneae recorded within area D are most likely due to the method of trapping. Many species found in this area D may be found higher in the canopy and do not venture into the dead litter section partly due to their food being present higher up (as indicated by the trapping of diptera); the deadlitter section below the lush growth is also quite impenetrable. For future studies it may be better to employ an alternative method for Araneae trapping, for example a vacuum sampling or sweep nets (Spafford and Lortie, 2013; Buffington and Redak, 1998).

6.4.4   Methodology issues

It is recognised that the 2x2m pixels of the WV2 data would not have lined up exactly with the ground 2x2m plots. Comparing both 2x2m plots on the ground with 2x2m satellite data could be partly responsible for any differences in associations when comparing the ground data and satellite data analysis (Table 6.25 & 6.15). The subsequent comparison of 10x10m satellite data with the 2x2m ground data would also provide inaccurate comparisons. Ideally a ground survey of a 10x10m area would have been better as a comparison as it would have given a clearer idea of vegetation coverage for an area that invertebrates (Coleoptera and Arachnidae) move about in, however, this was not possible due to the nature of the site and consequential trampling and damage of protected species.

Care should be taken in the interpretation of all trapping data. Temperature differences can play a part in annual turnover and species dominance (Saska et al., 2013). The effect of temperature on pitfall catches is important when interpreting the results. High variation in species composition and abundance can occur in peat bogs from year to year (Fowles, 1997). Changes in yearly temperatures may explain differences in annual turnover and any dominance-changes in invertebrate species. This should be a consideration when considering models, their apparent associations and when using habitat suitability models.

There are also issues regarding the varying effectiveness of trap colour and height positions within vegetation (Rodriguez-Saona et al., 2012). Using the same methods within each area should ensure a comparison is valid but it should not be assumed. Any overall influence must be taken into account when considering community distributions. Other issues to account for in trap colour included a request from reserve managers that they needed to be as discrete as possible. The blue sticky traps were the best option in this scenario so these were used instead of the more standard bright yellow (better trapping efficiency). Sticky trap data for Diptera also demonstrates that trapping methods could be altered to provide an easier, and less time consuming, method of sampling. Traps placed just at the height of the tallest vegetation present may be more efficient and be sufficient to provide a comprehensive data set. An important factor for providing information for food chains and also worth noting when formulating management plans.

Sampling from the same locations over time can also cause a decrease in species numbers for each subsequent trapping (Ausden and Drake, 2006), however, the effect of this should be lessened by averaging the seasonal catch. Issues can also arise from the trapping of species that may not usually be found in areas. Many beetles have the ability to fly and may have come into a region they do not usually frequent and have ended up being trapped. Some Araneae species are aerial disperser species and may have

been blown into the site, explaining their unexpected appearance within certain areas. All these factors need to be considered when drawing conclusions from the analysis.

6.4.5 Further interpretation from species associations

Associations of variables that represent dominant species and ecological gradients with some invertebrate species can be used to produce habitat suitability models. The way in which the species are trapped or indeed their habits that effect their trapping can influence these models so care needs to be taken. It was important therefore to focus on a species whose habits were unlikely to effect the trapping data and the best trapping method was employed for this species.

Agonum ericeti is a flightless species bound to the bog and so has no external influences to the count data (e.g visitors, blown off course etc.). This species is also designated as 'Nationally Scarce' which means this species only occurs in 16-100 hectads (10×10km) in Great Britain. Cors Fochno is one of only five sites in Great Britain where it is found.

The single species bayesGLM model providing the most significant result was using satellite variables with no index variables included (Table 6.19). However, according to K-fold cross validation methods the model using satellite derived species and index variables was marginally better (Table 6.20), possibly an anomaly of the cross validation method or a difference due to the more continuous spatial data supplied by the indices data.

Ground data models were not wholly satisfactory in this case as the grain size of the vegetation data was too small at 2×2m. This was not large enough to encompass the area traversed daily by this species, and did not illustrate the full extent of the vegetation area that it may use. It is important to consider too that models which quantify habitat quality, and do not identify habitat and non-habitat, provide better data for linking

population viability to environmental conditions (Larson et al., 2004).

The relationship between stenotopic species such as *Agonum ericeti* and their habitats combined with the spatial data provided by satellite derived models can be used to assess extinction rates and prediction possibilities and from this the survival time of small isolated populations may be more accurately calculated to assess their viability dependant upon management actions. Habitat suitability maps could be combined with density data and a relationship between the two investigated (Torres et al., 2012). These both have broad implications for conservation management (VanDerWal et al., 2009).

6.4.6   Nationally Scarce species rediscovered

Two species of Araneae, *Dipoena prona* and *Jacksonella falconeri*, discovered during the monitoring process had not been recorded on site or indeed anywhere in Britain, in recent years. These species were sent off to have their identification authenticated and reported on the British Arachnological Society records. Both were found in Area B and have a preference for drier heathland areas. Both had high species scores in the CCA analysis which were positively correlated with axis 3, highly correlated with *Calluna vulgaris* (Table 6.9). Again care needs to be taken of these results as the high score is due to only one individual of each being found for the whole survey. Species such as *Jacksonella falconeri* are small and may be missed easily in trapping. Although the reason for the lack of species in the past years could be partly due to a decrease in trapping effort, it may also be possible that species samples are going unmissed in trapping samples due to is size. A habitat suitability map produced with similar methods as were employed for the Coleoptera species *Agonum ericeti*, could provide a more focused area of sampling, something that would be possible for monitoring many rarer or illusive species.

6.4.7   Potential for further work

1) Habitat suitability models need validating with further field data.

2) Methods can be applied to historic remote sensing data to assess change and its impacts on Araneae and Coleoptera diversity.

3) Diptera species need identifying to species level for further analysis.

4) Investigate more indices - to find more indices that provide further biophysical properties yet are not collinear with one another. Using alternative methods such as a stepwise linear regression with a larger number of indices may provide valuable information regarding associations despite the possible high collinearity of indices (Thenkabail et al., 2011)

5) Investigate more classification methods - maybe not threshold based.

6) Use plant species Shannons diversity index as as heterogeneity measure?

7) Investigate possibilities of using the HSM in estimating the population viabilty for *Agonum ericeti* potential for SDMs and HSMs - layered community layers and single species maps.

8) LiDAR data is required that can provide more data as demonstrated by Lassau et al. (2005). Leaf on and leaf off would be useful too.

9) Need to assess other possible heterogeneity variables (e.g LiDAR data), other index measures or classification data.

6.5   Summary conclusions

1. Ecological subdivisions of a raised bog system that signify environmental gradients can be identified by the coverage of dominant species that are particular to those conditions.

2. The dominant vegetation species that were selected to represent their respective sub-divisions gave the best results for all analyses when assessing species/environment relationships.

3. Satellite derived indices (continuous data) were more useful when assessing associations of communities/assemblages than with an individual species (although this may be dependant upon the individual species used).

4. The use of larger categories such as Diptera sub-orders did provide some useful information but it is evident that identification to species level is necessary to provide any accurate information. Sub-order data is not nearly sufficient but did provide valuable information on which area provided the largest number and biomass.

5. Extra care needs to be taken when assessing or choosing models to analyse associations when in a habitat that contains a large proportion of rare or endemic species.

Chapter 7

Discussion and Conclusions

This concluding discussion focuses on the aspects of the research which have contributed to an improvement of existing monitoring systems and the implications and recommendations these results carry. This discussion also outlines how these techniques can be applied to other sites at specific geographical locations as well as their application to climate and anthropogenic change and predictions. A final section on how these results and their further application can feed into national and international policy, and enable Wales to meet the European Biodiversity strategy 2020, is included.

7.1   Main outcomes

Monitoring protected sites has usually revolved around the collation of field data and remote sensing data for this purpose has been under utilized (Nagendra et al., 2013). This research has utilised remote sensing data and field data developing a synergy of the two to create a method for a baseline for use in monitoring. The method was developed with a view to using this to identify change and trends in the condition of habitats and provides information on the state of biodiversity. The methods have the potential to produce predictions on the consequences of anthropogenic or climate change scenarios.

This research has established the use of remote sensing data for retrieving key biophysical properties of vegetation and with methods which allow for further investigation of these. Many previous studies have used satellite derived biophysical properties to map flora

(Lucas et al., 2011a; Xie et al., 2008) with less for mapping fauna distributions (Vierling et al., 2011; Lafage et al., 2013). However, few have investigated exactly how these properties change through the year and whether the biophysical attributes, plant species and their seasonality can be exploited and used to improve invertebrate associations models.

This research has shown that there are useful relationships that can be derived from satellite data (i.e. the biophysical properties, classifications) that relates to invertebrate diversity. The associations found were used to develop and validate spatial models that predict distribution of species and communities.

Others have found ground derived vegetation types and biophysical properties of vegetation to be effective in species distribution modelling (Davies and Melbourne, 1999) and species associations (Drees et al., 2007). However, these models rarely use satellite or other remote sensing data for this purpose. Remote sensing data in invertebrate distribution modelling has more often been used for monitoring distributions of pest species (Robinson et al., 1997; Dale et al., 1998; Wang et al., 2010b) usually of an individual species and not of species assemblages. Developing habitat suitability models for invertebrates from these associations with satellite derived data is of major importance to biodiversity assessment and can be recognised as a proxy for species occurrence and richness (Kuenzera et al., 2014).

The amalgamation of methods demonstrated with chapters 4, 5 and 6 contribute to the development of an observation/monitoring system within Wales with recommended methods and routes. The main outcomes were split into flora and fauna associations and distributions. For flora the appropriateness of seasonal acquisition and indices was assessed using field spectrometer data and WV2 data. Results showed a Pre (winter), Peak (summer) and Post (autumn) period to be most effective. This period for acquisition may vary for different sensors. More recently Feret et al. (2015) used field spectroradiometer to assess best periods for seasonal acquisitions in terms of using it to identify

habitats. They found that Sentinal 2 gave the best performance during spring and beginning of summer (from April to July), while WorldView 2 performed better during winter, end of summer, and autumn reflecting similar periods to this research.

The layers of biophysical properties created using indices using the EODHaM system were successfully used in classifications and as input into HSMs. Vegetation and dominant species maps were generated to cover the whole site and surrounding landscape. Methods of zooming in or multilevel masking used in this hierarchical mapping system helped to improve threshold extraction and accuracy. Others have used methods of multi-level classification systems for mapping tree species and demonstrated this to increase accuracy (Townsend and Walsh, 2001; Xiao et al., 2004). Pu and Landry (2012) used indices in a similar way to create three masking levels which included a vegetated, non-vegetated level at the beginning. Their study confirmed the effectiveness of this approach.

This system allows for the input of any spatial data (thematic or satellite etc.) and through the running of the system produces all the components such as biophysical properties of vegetation in the form of indices layers and vegetation classifications (Lucas et al., 2015) for input into further invertebrate association modelling. This ensures a continuous flow from input of data to the output of the required variables for fauna association analysis.

For fauna relationships between the remote sensing derived data (biophysical properties, dominant species classified) and invertebrate communities and individuals were made. Few studies have looked at invertebrate species assemblages until recently (Vierling et al., 2011; Lafage et al., 2013) and some have found plant species or NDVI to be effective at discerning associations (Lassau et al., 2005). Due to the invertebrate orders chosen in this study and their use as ecological indicators there should indeed be associations with the plant species or biophysical properties present. Using suitable suites that indicate ecological gradients and combining these with biophysical attributes such as NDVI

have proved to be successful in showing expected associations. This meant that suitable variables derived from satellite data could be used to provide spatial coverage previously unattainable without remote sensing data. Assessments of the most suitable layers for input into HSMs were made with the most effective in this case being dominant plant species. Many studies have used remote sensing derived variables such as these (vegetation classification or vegetation indices) to predict a spatial distribution of mammals or birds (Pettorelli et al., 2011; Cherlet, 2011; Swatantran et al., 2012; Coops and Catling, 2002). However, very few have done so for invertebrate species and least of all invertebrate species assemblages (Lassau et al., 2005; Lassau and Hochuli, 2007b). The HSMs for the individual species *Agonum ericeti* created will require further validation by reserve managers in order to validate them as SDMs. The same methods can be used to create further species habitat suitability models and these can be combined to create species assemblages maps (Guisan and Rahbek, 2011).

The aims of this research have been met and a monitoring strategy recommended and demonstrated. Links were made between ground based surveys and remote sensing data that contribute towards the formation of a remote sensing monitoring system. Some of the methods formed from biophysical variables, remote sensing data and vegetation indices etc. can be used to advise on the impacts of past, present and proposed management. This study leads to a better understanding of the dynamics of Cors Fochno ecosystem and the application of these methods to other sites is now possible, with further use, to show implications of natural, anthropogenic and climate change upon them. Franklin (2008b) states that a comprehensive framework for the effective use of remote sensing data in biodiversity mapping - one that matches the spatial, spectral and temporal characteristics of the sensor to specific biodiversity mapping goals is still lacking. This research has made a strong contribution to improving this situation.

7.2 The importance of field data, vegetation ecology, phenology and data fusion for successful classification

Having a good knowledge of the site to be classified is of major importance. The process of carrying out this classification has shown how important it is to have ground data (Leyequien et al., 2007a). Very few classifications can be successfully completed without visiting a site and collating data on the vegetation. It is imperative that the individual creating a classification has a good grasp of the main species and conditions present, for a successful classification. The ground data (vegetation composition, photography and field spectroradiometer data) provided further information on the ecology of the site, ecological gradients present and seasonal aspects of the vegetation. All these aspects of the classification process have helped to contribute to the selection of a suite of species to classify, an assessment of their discrimination, selection of timings of image acquisitions, and the input of the ecological knowledge into the adjusted EODHaM system developed in this research.

A number of classifications (Hill et al., 2010; Lucas et al., 2007, 2010) have used methods which employ phenological data to improve species discrimination although these have tended to be mostly for woodland/forest species. This seasonal approach however, has not been pursued for peatlands where plant species of degraded and intact bog have seasonally distinct characteristics (apart from BIOSOS). For example invasive monoculture species are likely to occupy degraded areas of bog (e.g. *Molinia caerulea*); for Cors Fochno this method appears to be extremely effective at picking out the degraded vegetation areas (Figure 7.1).
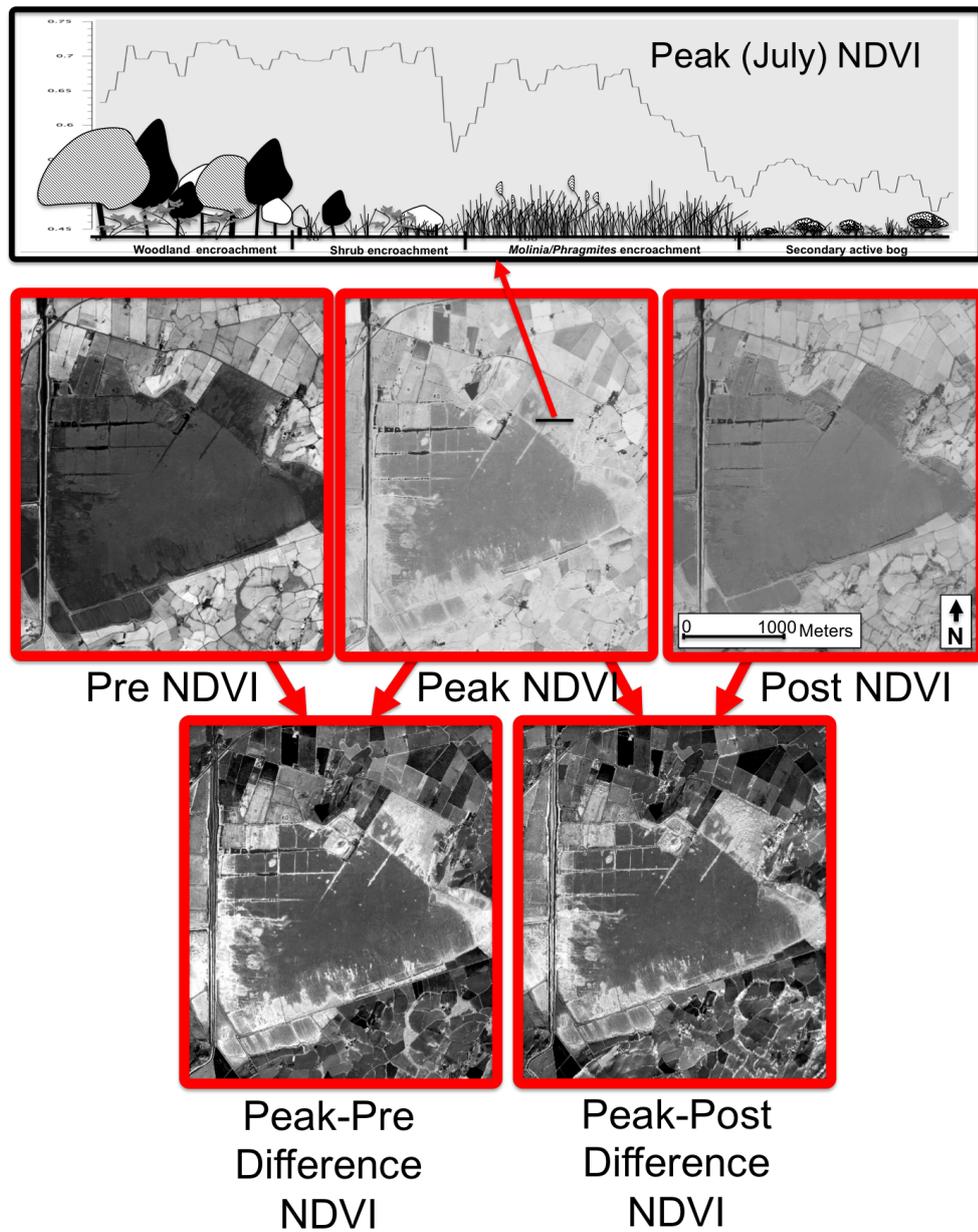
Figure 7.1: Images of seasonal NDVI showing differences between peak (optimum growing season) and pre or post (little or no growth) images. Very light areas in the difference NDVI images correlate with areas of *Molinia caerulea* and *Phragmites australis*, areas of high seasonal productivity/growth.

The vegetation in degraded areas is very lush with substantial green growth in the summer, in winter masses of dead litter smothers anything else that tries to grow. In contrast areas of intact primary bog which contain species typical to healthy raised bog

do not show such dramatic differences. These areas are fairly mixed in terms of species, but include species such as *Sphagnum pulchrum* - an indicator of healthy bog which changes very little throughout the season (Figure 4.15). It is also noticeable that the healthy central bog area does not have the lush growth of the outer degraded bog due to the species there and the environmental conditions (lack of nitrogen, acidity etc.). The use of two seasonal images provided data to make use of these facts and significantly improved species discrimination.

In order to improve discrimination further, fusions of data were very effective. Combining LiDAR in this case helped with some discrimination. However, had summer flown Li-DAR with a better resolution been available, discrimination may have been even better. Classification of some BIOSOS sites also had thematic layers added to the classification system that added to a better discrimination and classification of categories. This could be added to this classification to improve road and urban area classification.

The flexibility of the EODHaM system to data fusion is further improved by a 'zooming in process' (Figure 7.2). This zooming in process involved clipping the SSSI area (effectively masking all surrounding landscape) and focusing on only classifying the SSSI area to species level. Further masking of areas by classifying those species which were ecologically distinctive (i.e. not found in wet areas), helped to narrow down the final area classified. The use of the LCCS system helped in particular by allowing focus on aquatic vegetated areas such that dominant species within this area could be classified.
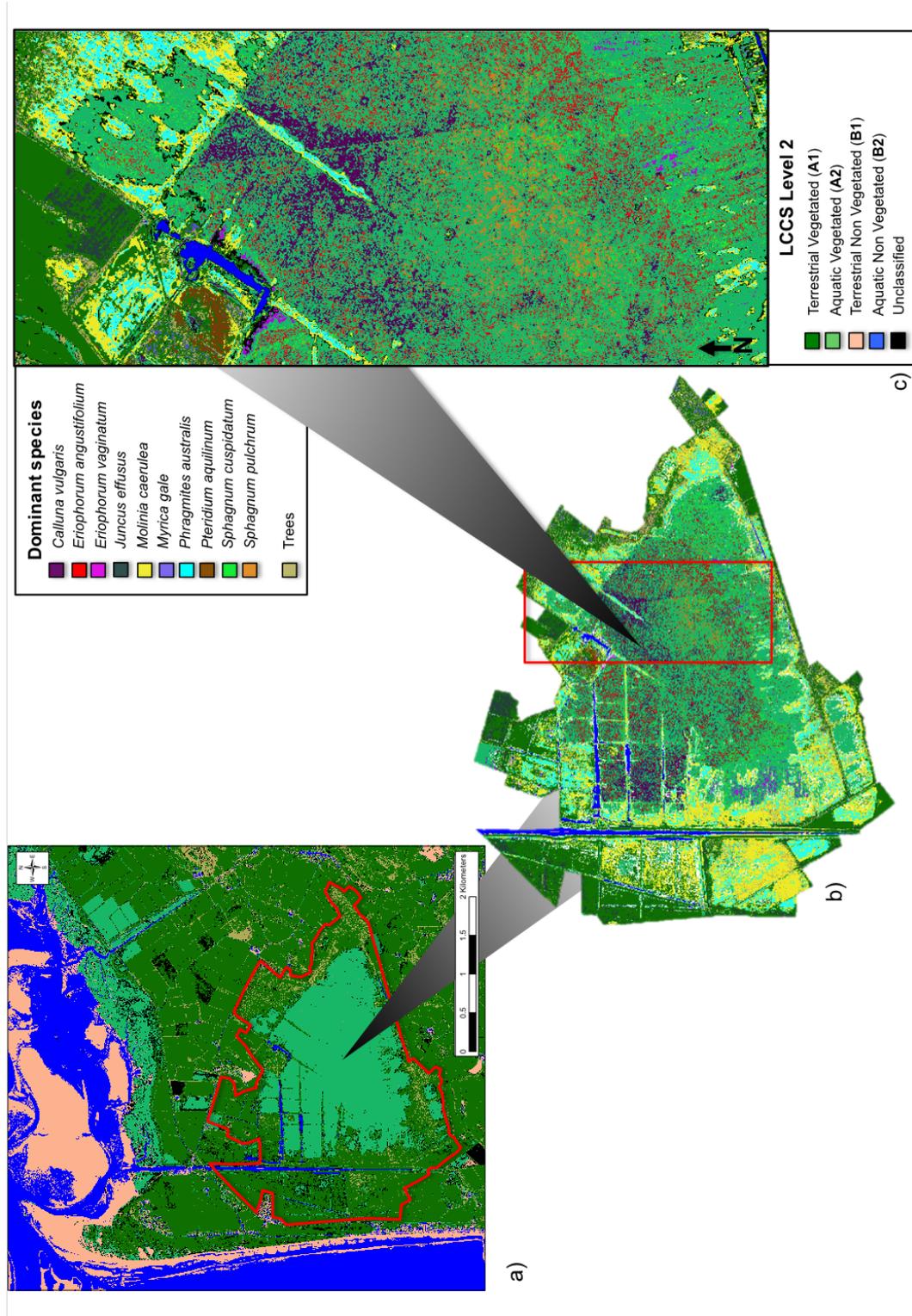
Figure 7.2: Processs of zooming in. Classification map of dominant species - using adjusted thresholds

7.3   Vegetation mapping of Cors Fochno

Current assessments of protected sites such as Cors Fochno and other protected habitats in Wales are carried out using field-derived quadrat data and mapping based on GIS and aerial photography. However, Cors Fochno in particular, is difficult to traverse and hence detailed mapping has not been undertaken. These methods have provided maps and detailed ground data, however there remained an area of the central primary bog with limited mapping detail and most of the detailed quadrat results which inform on the type of species present are mostly along the board-walk area. These quadrat positions are mapped but no classification is developed from them. There is also no detailed mapping of the water-bodies and ditching present. The same is the case for fauna data as shown in chapter 3 (Figure 3.8) with little data recorded or mapped in central areas. All detailed data is recorded around the readily accessible bog peripheries and along the board-walk.

The methods used in this project have improved both the spatial coverage and the detail of mapping using the classification method developed here. Figure 7.3 shows the central areas of Cors Fochno SSSI to have little mapped detail (Figure 7.3a, b and c) using the traditional GIS method. However, the classification developed in this research (Figure 7.3d) shows a far more detailed map of dominant species within the central areas in particular. All water bodies and ditching are mapped and the detailed quadrat data is present for both methods of map making.

All mapping of Cors Fochno Phase 1 and NVC (Figure 7.3a, b, c) does not include any detailed information on the central areas of the bog. The classification produced using the WV2 imagery on the other hand provides detailed species data for the whole of the active bog area (Figure 7.3d) including more detail in the more degraded areas (Figure 7.4). Additional to this, a landscape map of the surrounding landscape which is provided further classification with a little more work on anthropogenic practices agri-

culture, forestry, etc. Changes in this surrounding area, may have an effect on habitats or species, whether transient or endemic for the Cors Fochno SSSI.
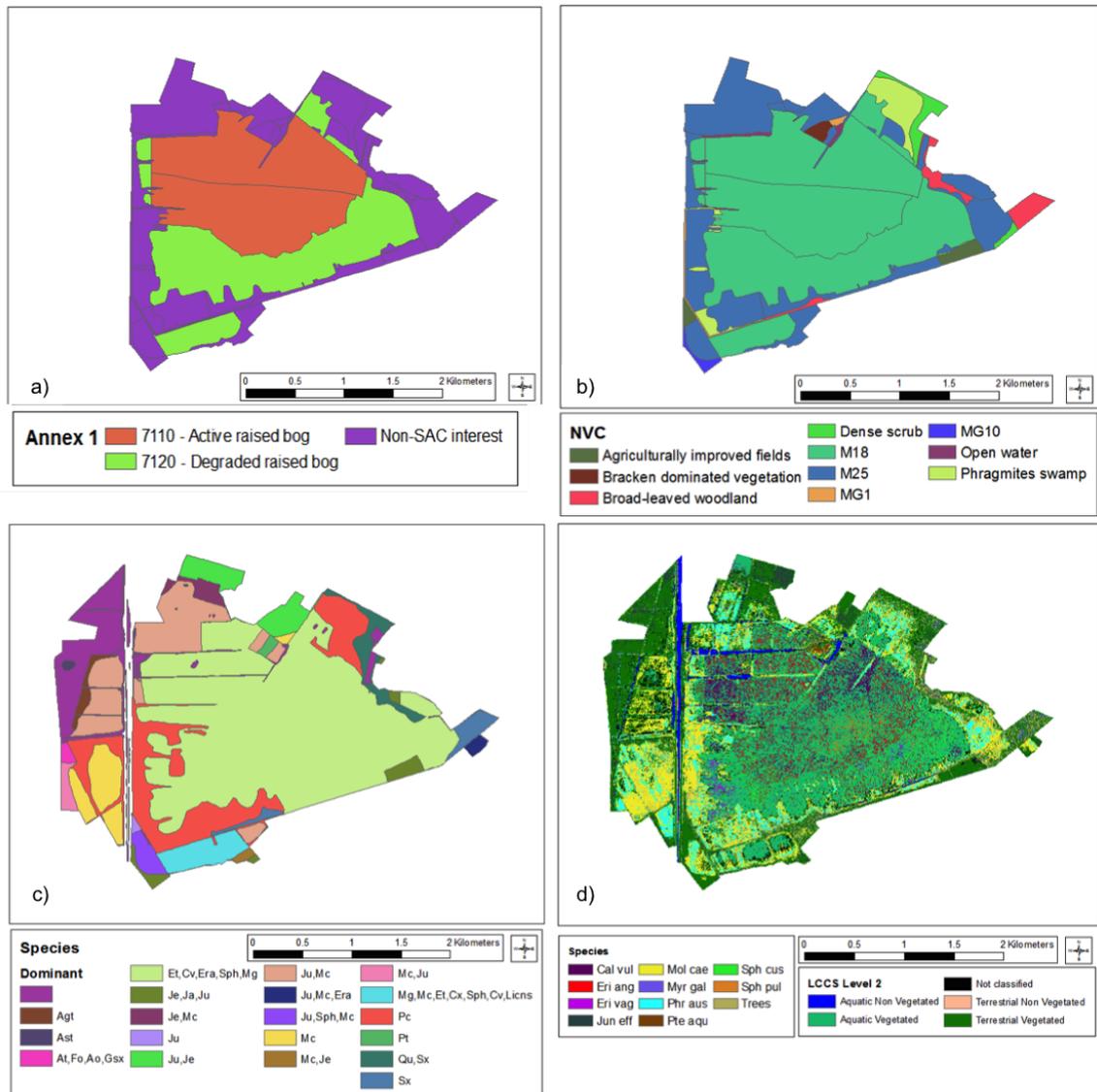
Figure 7.3: Comparison of traditional GIS methods with the EODHaM system adaptation classification. a) Annex 1 Cors Fochno 2008, b) NVC Cors Fochno 2008, c) Phase 1 Cors Fochno 2008, d) WV2 created Cors Fochno 2012/13.

Dominant species such as *Molinia caerulea* play a large role in ecological function and the very existence of some ecosystems depends on these species to create or be modified to a significant level. When looking at change and the reasons for, it is important

to acknowledge that dominant species have a large significant impact on ecosystem function (Chapin et al., 2002) and are important in determining resistance to invasion and degradation (Smith and Knapp, 2003; Smith et al., 2004). These species are known as an engineer of that system (Clive G. Jones, 1994). Equally, organisms with small individual impacts can also have huge ecological effects (Clive G. Jones, 1994). Bog-forming *Sphagnum* mosses are good examples of this (Tansey, 1965). Recording these major engineers is of as much importance as recording overall diversity and heterogeneity.
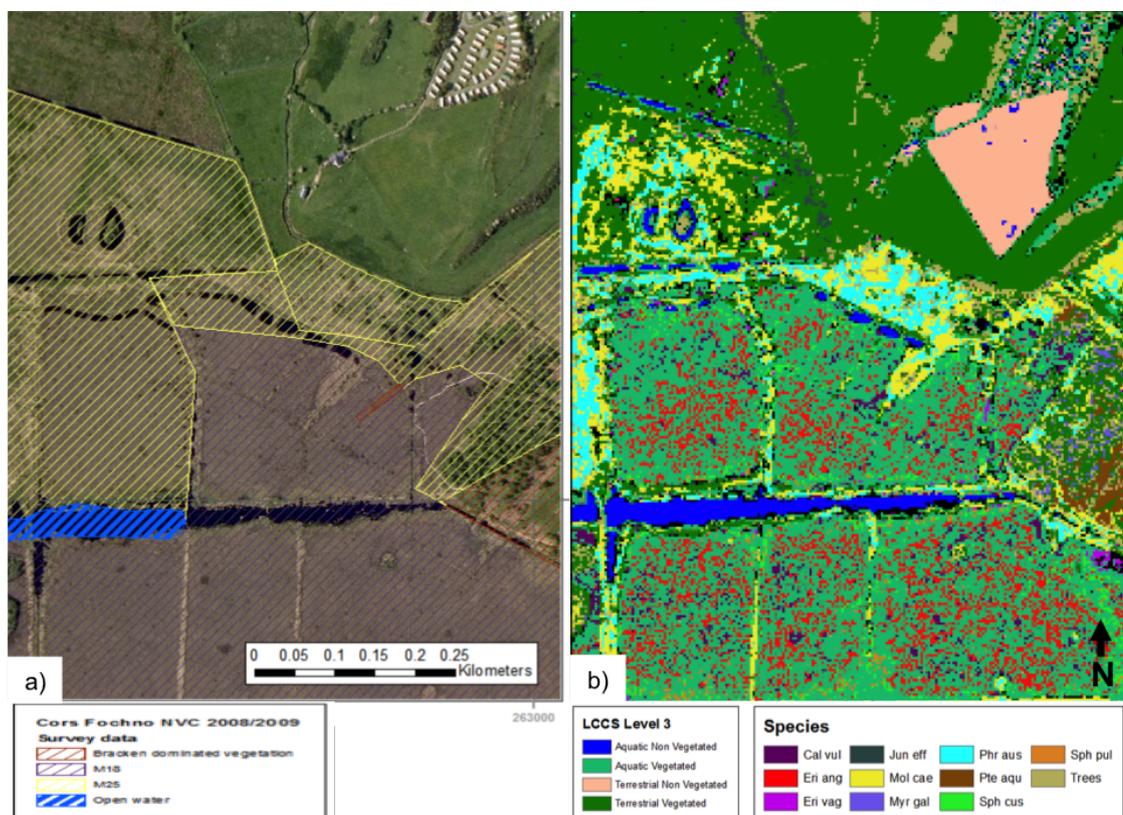
Figure 7.4: Improvements in mapped detail and resolution a)NVC mapped vegetation 2008/2009. (Source:data provided by NRW) and b)WV2 species classification completed for this PhD 2011/2012 (note large newly ploughed field recorded as bare ground).

Having a more detailed dominant species map and data set for the whole of Cors Fochno helps to show ecological gradients present providing a more cohesive data set for further monitoring. Other research (Smith and Knapp, 2003) suggested that dominant species

can strongly influence diversity. Observations in the differences in their abundance can provide information on the variation in community attributes and ecosystem processes in space and time. These theories were observed and used in chapter 6 when investigating invertebrate relationships with the dominant species present as well as other biophysical attributes.

7.4 Beyond a classification.

It is important to recognise the many other uses that a remote sensing classification could provide. It can be used to provide much more than just a map of the vegetation position and extent. For example the central dome was mapped with a DTM for the first time, and combining this with the classification of *Sphagnum* coverage the condition of the SSSI could be assessed. This has not been done for raised bogs before, and provided a solid reproducible method of keeping a check on the hydrological condition of the bog. Any significant changes in this would most likely be due to drying out or conversely improvement in prevention of drainage. This method therefore provides an effective way to assess these indicators of raised bog condition.

More recently acquired WV2 or even historical WV2 data could be used in the same way with these methods. Past and more recent mapping in particular of areas of *Molinia caerulea* could be compared against the baseline produced in Chapter 5 to assess any advancement in the encroaching *Molinia caerulea* species into the outer central bog areas. In addition to this a measure of *Sphagnum* within the central dome (as produced in chapter 5) could also be made for comparison. This could provide information on any changes in condition of the hydrology of the bog. A decrease in Sphagnum species in the central dome area would indicate a drying out of the bog. A factor of major importance to the management of the protection or restoration of the bog.

Also of great importance is the use of remote sensing in the further assessment of fauna

present. This work has shown that the classification can be used to give a habitat suitability model (HSM) for selected species, in this case those endemic to the raised bog (e.g. *Agonum ericeti*). Further work using the HSM produced could provide valuable species viability information (Chauvenet et al., 2012) and thereby provide evidence of the urgency of habitat restoration or improvement. This could inform on how to channel funds to the most necessary protected sites. It is important to consider too that the use of the term 'habitat suitability model' rather than 'species distribution model' needs to be used to reduce confusion over the validity of these models (Bradley et al., 2012).

A substantial survey of invertebrates was previously carried out on Cors Fochno as part of the 'Welsh peatland invertebrate survey'. This was carried out for a 3 year period from 1986-1989 (Figure 7.5a). Surveys were also carried out from 2009 to 2011. However, these surveys traversed the central dome area where the main sample areas were primary bog and did not include areas that were more degenerated with mono-cultures such as the *Molinia* areas. There was therefore no information with which to infer any losses and gains of assemblages and species if trends indicated increases or even decreases in the area of degenerated bog and *Molinia* encroachment. Nor did it give a comparison to provide evidence to show the importance of the primary and secondary bog over this. This data could however be used as a tool to show whether data collated within the similar area was unnoticeably different or to illustrate that there may be natural fluctuations within populations that are not necessarily a result of habitat conditions changing. In this study research sampling was carried out across ecological gradients (Figure 7.5b) to provide information that can be used to assess and predict losses and gains to the invertebrate assemblage of the SSSI site. It was also important to sample across the ecological gradients in order to obtain enough information/data that could be used to compile a HSM (Figure 7.5b) to assess any fauna species and fauna assemblage associations with flora species and satellite derived indices/biophysical variables.
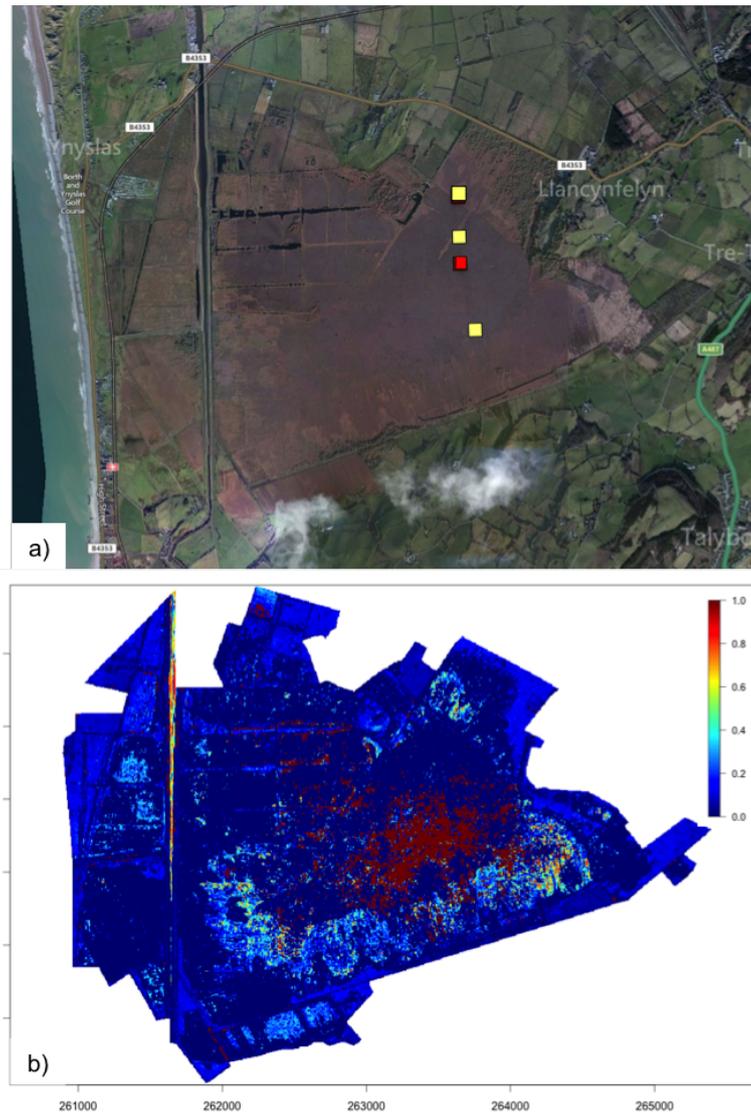
Figure 7.5: Comparison of previous invertebrate survey a) Welsh Peatland Invertebrate Survey 1986-1989, ■ = *Agonum ericeti* presence, ■ = *Agonum ericeti* absence (Source: NBN Gateway data (WPIS)) and the current research invertebrate survey results b) using the methods to provide spatial data in a habitat suitability model showing the probability of the presence of *Agonum ericeti*.

The research finding presented here also show the importance of these ecological gradients to the overall gamma diversity of species present. Without the heterogeneous nature of the combination of several habitats within the site, including the degraded areas, the overall diversity of species present at the site would be less (Souza et al.,

2015). There are also protected species (e.g. adders) that inhabit the *Molinia* areas. Degraded areas are therefore also of equal importance as the central raised bog areas for preservation and conservation in the future. The largest biomass of flying invertebrates was collated from the *Molinia* area showing this to be a valuable area for food supply for birds, bats and any other insectivores. This does not however, mean that further encroachment of the raised bog is necessarily acceptable as this would cause great stress on populations endemic to this region. It means that one should acknowledge the worth of the degraded areas when applying management to this habitat with due cognisance paid to the value of degraded and raised bog areas.

The prevention of the destruction and degradation of peatland or bog should be of paramount importance to humans. Its destruction and degradation can lead to it changing from a valuable carbon sink to a carbon source (Lenart, 2010). Aside from possible anthropogenic effects that may have caused this, of equal importance, are effects or predictions of climate change scenarios. The methods developed here can easily be used to look at change over time and can also be adapted to create prediction models. Climate warming has been shown to promote vascular plant growth in peatlands, especially ericaceous shrubs (Bragazza et al., 2013). Classifying species such as *Sphagnum* spp. and *Calluna* on a temporal basis could provide evidence of these processes. Field spectroradiometer and photo records could be useful in tracking any seasonal shifts that may occur either due to yearly differences in climate or indeed due to climate change. Any seasonal shifts or species changes could have large effects on invertebrate distribution and diversity and consequently complete ecosystem food chains. Regular monitoring using the methods developed of landscapes, vegetation, habitats, and species both fauna and flora on a 5 to 10 year basis could provide valuable information on effects of anthropogenic and climate change within and surrounding sites. The methods employed in this research have shown to support multi-temporal data. Using corresponding seasonal imagery from different years would provide information on any changes that may have occurred over that time period for both habitats and species.

This work moves beyond the use of species richness as an indicator of biodiversity. It includes other levels of analysis such as communities, populations (e.g. HSM - *Agonum ericeti*) and landscapes (e.g. LCCS landscape classification). Management of sites rarely looks at species communities and their mapping. Monitoring of protected sites rarely includes landscape mapping (Souza et al., 2015). However, recent reviews have suggested when monitoring sites there is a need to accommodate landscape effects into the analysis (Curran et al., 2011; Koellner and Geyer, 2013).

7.5 General applicability of the methods

Many widespread and abundant species associated with peatlands are very similar to that of the Cors Fochno site and these same species could be classified for other sites in Wales. Such species would give an indication of plant species associated with ecological gradients present (Grime, 1998). Combining this with a fusion of other data (e.g. vegetation heights, slope and elevation) and thematic information could prove to be a powerful tool to assess floral and faunal biodiversity. Many of these habitats have similar issues such as encroachment of *Molinia caerulea* and many other species such as *Calluna vulgaris*, and Eriophorums being present on blanket bogs and other raised bogs. Areas of peat habitats are now of great significance where trends in the uplands have led to a failure to achieve early BAP and government biodiversity targets. There is a need to develop large-scale initiatives to target particular areas for appropriate conservation management, to restore upland woodland and scrub and the natural altitudinal succession of vegetation, extend priority habitats and restore degraded stands (Blackstock et al., 2012).

For other sites a set of plant species associated with relevant ecological gradients could be compiled that can be identified from satellite imagery using the same process. Grazed versus ungrazed areas would also be highlighted and it is also possible to focus on a man-

agement practise rather than a dominant species. For example, farming practises and crops grown in fields could be classified using the same system (Lucas et al., 2015). Habitats could be distinguishable although it may be found that some very heterogeneous habitats or those that are very similar in species composition but named differently may be difficult to classify. For each of these classifications and biophysical parameters derived from this, associations with fauna and flora species could be assessed and habitat suitability or species distribution models made for assemblages or individual species (Guisan and Rahbek, 2011).

Recent research has developed methods for compiling layered species distribution models (Guisan and Rahbek, 2011) to provide information on community interactions important to ecosystem functioning (Kirwan et al., 2009). This research was produced with the aim that a multi-layered species distribution (Figure 7.6) could be compiled using the associations found in the analysis. While significant progress towards this goal has been made, more research needs be done with other sites both similar and very different to test this process.
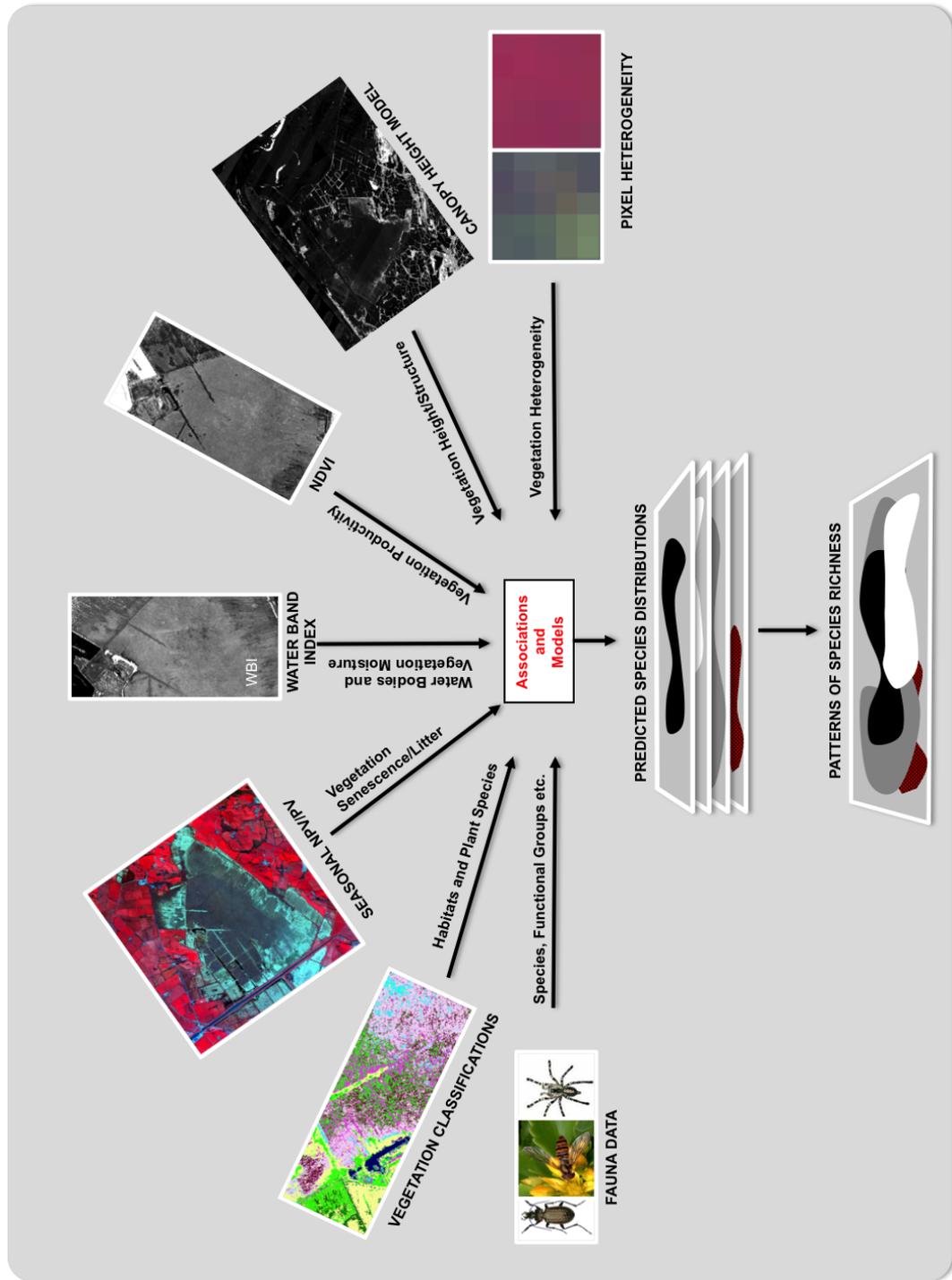
Figure 7.6: SDM overview.

7.6 Application to policy: Welsh, European and International

The EU signed up to a set of new global biodiversity targets under the auspices of the UN Convention on Biological Diversity (CBD), at its meeting in October 2010. Parties to the CBD are required to develop or update national biodiversity strategies/action plans with a view to implementing CBD commitments.

Cors Fochno SSSI is also a Natura 2000 site. Natura 2000 is the centrepiece of EU nature & biodiversity policy and was established under the 1992 Habitats Directive. European and Welsh strategy plans have targeted measures that need to be met to ensure the survival of many species and habitats that are already under threat. Natura 2000 aims to assure the long-term survival of Europe's most vulnerable species and habitats.

A 2010 EU biodiversity document produced information about the current status of biodiversity in the EU and Wales (Brown, 2010). However, a lack of a clear baseline against which to measure progress was a key shortcoming of the EU biodiversity strategy 2010 reports (Brown, 2010). In Wales this baseline information produced valuable scientific data on the status of biodiversity. However it was noted that the conservation status of 18% of habitats and 31% of species are still unknown in Europe (European European (2011). Habitats and species in Wales have been assessed ready for the 2010 EU biodiversity baseline and it was found that 60% of Welsh habitats were in unfavourable condition and only 25% in a favourable condition (Figure 7.5a). This negative outlook is similar for priority Welsh BAP habitats with more than 50% declining and a significant number with no clear trend (Figure 7.5c). This therefore represents a situation where those habitats that are recovering or indeed declining need baseline information to track possible improvements or further decline where to occur between 2010 and 2020. Those that are unfavourable, stable or show no clear trend will require monitoring to ensure

management practices are helping to improve the habitat. With limited resources it is imperative to know these efforts are not wasted and if present management regimes are adequate, or whether a change is required. For species in Wales, 45% are in a favourable state and 54% unfavourable. For priority species 34% are stable or increasing 16% declining, 5% lost and insufficient information for 35% (Figure 7.7d) (Brown, 2010).
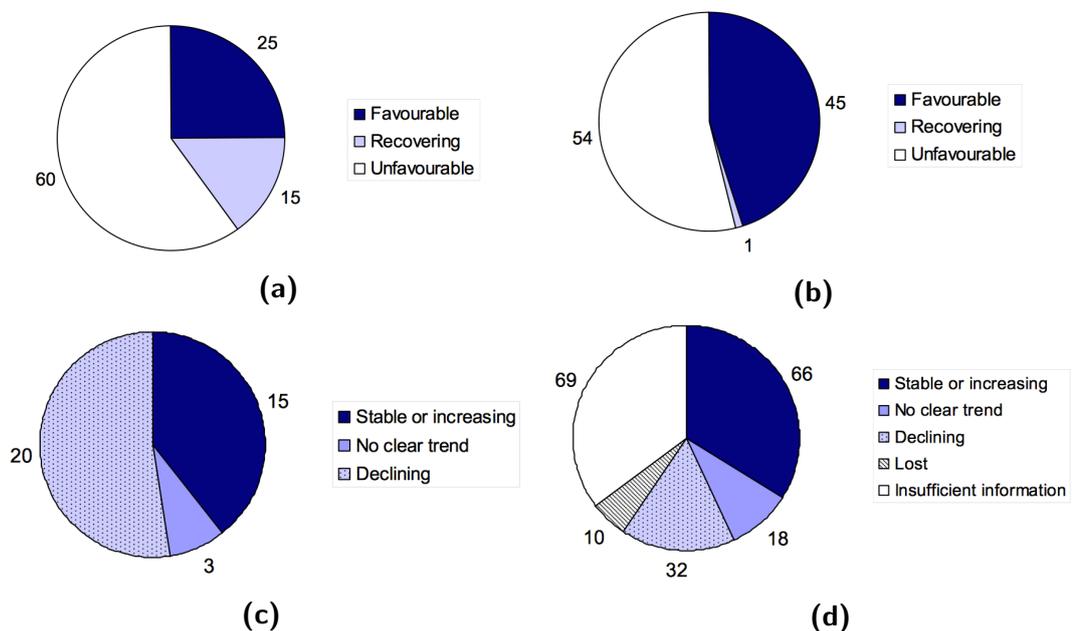
Figure 7.7: a)Percentage of habitats in favourable, recovering or unfavourable condition in Wales, 2000 to 2008, b)Percentage of species in favourable, recovering or unfavourable condition in Wales, 2000 to 2008, c) Wales trend for priority BAP habitats, using 2008 reporting trend estimates, d)Wales trend for priority BAP species, using 2008 reporting trend estimates. (Brown, 2010).

In light of these figures, it is of great importance that evidence is acquired to fulfil the EU biodiversity strategy targets for 2020. For this, a species' known habitats, habitat suitability (often unknown existence in these) and their current, past and predicted distributions need to be mapped and modelled. These methods are important for use to find and ensure protection of suitable habitats. The Lawton et al. (2010) report produced for Department for Environment, Food and Rural Affairs in 2010 suggests

that ecological networks are of vital importance to ensure connectivity and support sustainable populations. These methods could be employed for mapping habitats suitable for vulnerable species that require protection.

Habitat condition - current, past and predicted - could use this method to help produce models and associations which provide evidence of trends of species and habitats. This research could fulfil most of the CBD requirements and could be exercised with additional expert help from wardens and those with knowledge of the habitats and species.

To gather this evidence and improve the statistics recorded, the EU biodiversity strategy has set out targets that follow the international CBD Aichi targets. Welsh Government is responsible for the delivery of the CBD and EU targets in Wales but it has also set its own targets relating to biodiversity at a national level (Brown, 2010). Wales aims to improve the integration of habitat and species-based work using an integrated ecosystem approach (Brown, 2010). This project contributes towards the Welsh biodiversity plans, EU biodiversity strategy 2020 targets as well as the global CBD Aichi Biodiversity Targets and provides a system and methods towards achieving these targets.

In Wales methods are required to help provide spatial and temporal information on species and habitats so that data can be provided on positive outcomes for the Welsh Biodiversity strategy (JNCC, 2012c). Outcomes 19 and 20 (Brown, 2010) can be met by evidence that this research can provide. As an example of its use in the Welsh biodiversity strategy, and very topical (however, not noted as priority species), are pollinator distribution data. It must be noted that there is a current Wales action plan for pollinators. Pollinators are however, not represented by just bees. It is apparent that not only bees and butterflies are valuable as pollinators, but flies too, and recent research has now found that on farmland flies made up 67% of the total abundance of pollinators with 84% of pollen carried by non-hover flies (Orford et al., 2014). Research in this thesis demonstrates the importance of protected sites for providing suitable habitats and connectivity to provide an abundance of *Diptera* species/ potential pollinators. It also demonstrates methods

that could also be employed in areas outside of protected areas, including road verges and farmland, and methods (employed in this research) for assessing connectivity and relationships between habitats tested. Using these methods the frequency/population of pollinators could provide information to drive policy.

The CBD has a number of Aichi Biodiversity Targets that this research could help to provide information/evidence for. CBD Target 1 requires knowledge in the trends of extent, condition and vulnerability of ecosystems, biomes and habitats (Leadley et al., 2014). Mapping species that indicate ecological gradients can provide information on the condition and vulnerability of a habitat or ecosystem (Grime et al., 2007). This method also provides data on species distribution and abundance for both flora and fauna. As with the invertebrate associations methods, other more scarce or smaller patches of flora species can be associated with the more dominant patches or indices which are indicative of the ecological gradients (Beck et al., 2008); e.g. *Sphagnum pulchrum* being present can show that an area is more likely to have species such as *Drosera* present. All that is required is a habitat suitability map which can be assessed with some further field work to give an accuracy estimate. Compiling a habitat suitability model would cut down on a significant workload for assessing this.

These methods also fulfil CBD target 2 by providing a method to assess trends in abundance, distribution and also using the habitat suitability modelling can provide information on viability or extinction risk for a species. External pressures can be monitored by using the landscape classification method demonstrated here to record and assess any external pressures that agriculture and forestry may incur. Although in this research this method is providing a baseline, it could be used with temporal data to reflect changes/trends in habitat condition (Lucas et al., 2015).

7.7 Summary with recommendations of suitable variables to measure biodiversity

A recent publication from GEOBON members concerned at the lack of agreement on biodiversity variables to monitor biodiversity using satellites, proposed a set of variables for monitoring progress towards the CBD Aichi Biodiversity targets (Skidmore et al., 2015). These include continuous and biophysical variables, and threshold-based measures such as those employed in this research. Of the ten variables suggested by the 'intergovernmental GEO', all could be monitored using this process with eight of the proposed variables employed within this research. These are highlighted in bold in the following text.

A baseline map of **species populations** were created for the dominant flora species and selected invertebrate species. Associations were made with species assemblages and the ecological gradients, flora species and biophysical parameters derived from satellite data. These associations could be developed further into layered habitat suitability maps useful for assessing community interaction, an important part of **ecosystem function** (Guisan et al. (2013), Schimming et al. (2010). Classification maps and habitat suitability, as well as associations recognised provided information on the invertebrate species occurrence. Further work looking at other fauna and invertebrate associations would provide evidence of which species are more likely to show associations with biodiversity variables. Invertebrate surveys ideally should be undertaken for more than one year in order to avoid associations that may be reflecting other unidentified variables (e.g freak weather event or an unusual weather year) (Drake et al., 2007). To improve the system and assess the methods, an accuracy assessment of the habitat suitability model presented needs to be carried out. This can then be approved as the 'species probability distribution' if accuracy is found to be good.

Indices such as NDVI were used with seasonal imagery to provide information on **species traits** (e.g. large expanses of dead vegetation in winter and very lush green vegetation in the summer may indicate competitive/monoculture species). This helped to classify some species and associations that indicated *Araneae, Coleoptera* and *Diptera* species diversity and assemblages. **Ecosystem structure** comprises the components that make up an ecosystem (Schimming et al., 2010). **Habitat and species distributions**, the floral and faunal **heterogeneity** of a habitat, **land cover**, habitat, vegetation species and **vegetation height** were calculated for the SSSI site and surrounding landscape. Unfortunately vegetation height was not very accurate showing that better LiDAR coverage was required. Heterogeneity of the vegetation was indicated by the standard deviation of the NDVI in a buffered zone. On a small scale, this was difficult and would have been easier with definite habitat classifications. More work needs to be done to investigate heterogeneity measures.

As part of **ecosystem function**, vegetation phenology and primary productivity were used. **Vegetation phenology** helped to provide useful information also for timing of satellite acquisition. Spatial and temporal variation in **primary productivity** (NDVI) helped to define the ecological gradients present and assisted in defining flora species and fauna associations. Of all the satellite derived indices used, the NDVI and seasonal NDVI difference provided the best overall biophysical variables for association with distribution. It may be useful to find and develop better heterogeneity measures using LiDAR (Mucher et al., 2010) and multi-spectral texture measures (St-Louis et al., 2014), and to investigate other indices specific to the satellite used.

It has been recognised that strong evidence is required for possible climate change impacts (Brown et al., 2012). Any changes in the distributions, phenology data, community compositions and habitat condition (ecological gradients) that were compiled in this research are all of great importance to providing evidence of and information to help manage the effects of climate change (Pearce-Higgins et al., 2015). The research has

been compiled here into a process that can be adapted for monitoring sites. It can be applied to any site and at all scales that span from individual species to landscapes surrounding the site (Figure 7.8). Surrounding landscape maps are also important to show connectivity so that a complete assessment of a species vulnerability can be assessed (Lawton et al., 2010). This process applied to habitats, sites and surrounding landscapes will help to provide a way to satisfy CBD, EU Biodiversity strategy and Welsh Biodiversity strategy targets.
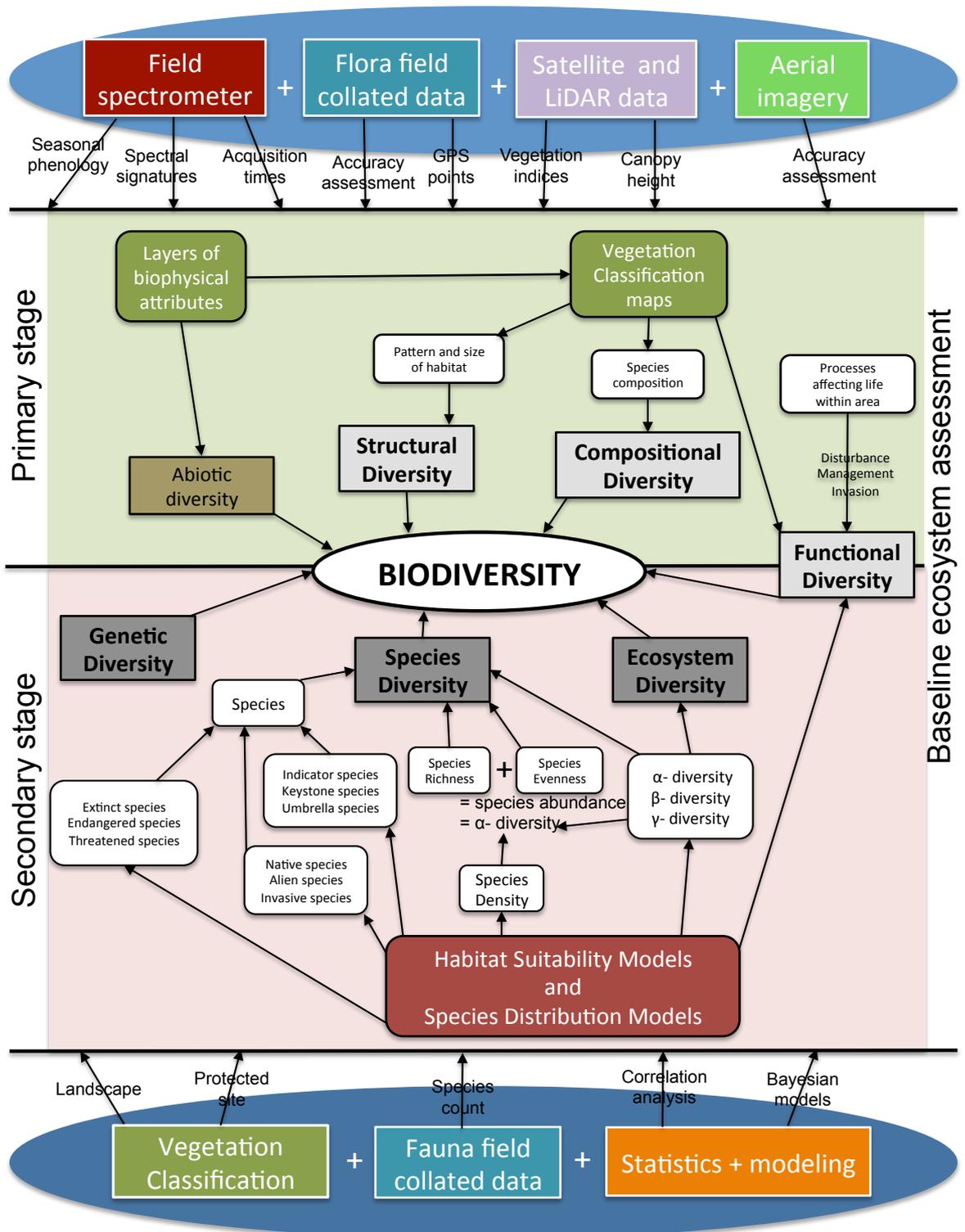
Figure 7.8: Flow chart of monitoring process.

7.8   Recommendations for monitoring Welsh habitats.

On the basis of this project the following are recommended for assessing and monitoring protected sites in Wales:

Acquisition of data

1. Acquisition of higher resolution airborne leaves-on LiDAR to both assist with geometric correction and provide valuable vegetation height data.

2. Multi-temporal acquisitions to capture the seasonal variation (in relation to phenology). Pre (Jan-March) and Peak (June-Sept) times preferable.

3. Ensure acquisition is at a spatial resolution that is appropriate to the size of targets.

4. Ensure robust atmospheric correction of data.

5. Ensure accurate geometric correction.

6. Monthly collection of ground reflectance spectra from specific targets (also bright, dark and intermediate for atmospheric correction improvements) to assess vegetation for seasonal attributes. (Can also be used in possible climatic studies).

7. Collection of sufficient ground data with GPS points from the centre of suitably large areas of dominant species , surface materials or any other to use for satellite data extraction. High quality in-situ and timely ground data is required or the quality of the RS products may be severely limited (Gillespie et al., 2008; Xie et al., 2008).

8. Inclusion of UAV data at very high resolution to allow interpretation of multi-spectral images and validation of output products.

Process

1. Extract all suitable data, biophysical attributes, vegetation heights, and heterogeneity measures for analysis using a suitable percentage of the pre-recorded ground points.

2. Assess other methods of index selection.

3. Assess other indices specific to a satellite for their suitability with certain species and habitats.

4. Develop better heterogeneity measures, possibly using LiDAR or multi-spectral texture analysis.

5. Develop further script for simple classification running which will extract data from given GPS points, create the statistical analysis and provide the threshold data all in one contained system.

Long-term monitoring

1. Repeat process every 5 years at least to assess any changes etc. ground field spec and photography to record seasonal differences and match with climate.

2. Apply methods to other sites to test method:

Recent research assessing bird species in England at risk as a result of climate change have suggested that nearly all species associated with upland heath and blanket bog are at high risk due to climate change (Pearce-Higgins et al., 2015). As Wales contains a high percentage of the UK's upland heath and blanket bog, with 80,000 ha of upland heath in Wales and 70,000 ha of upland bog it is of major importance to monitor these areas as much as is possible. These areas have a very similar suite of species present as in the Cors Fochno SSSI site and for this reason would recommend that these methods could be applied to these first. There are however, a number of additional considerations when producing classifications and species associations. Unlike Cors Fochno the terrain is not flat and its slope differences could influence some of the work. Also present in these regions are areas that are grazed and areas that are not, so adding to the confusion. Despite the flexibility of this system, care does need to be taken and good knowledge of that habitat/s is required before embarking on the process.

7.9   Conclusions

1. Investigation of the **phenology** of vegetation spectral data has enabled the accurate selection of the timing of satellite imagery acquisitions of seasonal imagery. This work shows that for each species between species and within species variation can effect the time that is best for species discrimination. In the case of raised bog vegetation this provided valuable information for best times to discriminate a group of dominant species with the ability to select best periods for individual species discrimination.

2. The multivariate analysis method of selection (**F-ratio**) can be successfully applied to WV2 data and provides useful information on the best indices and images (where multi images are used) to use for input into an adjusted Earth Observation Data Habitat Mapping system (EODHaM) in particular for classification of dominant species relating to ecological gradients of a protected lowland-raised bog. It was shown that the correspondance between the field spectro-radiometer and satellite data was not sufficient to use the field spectroradiometer data for index selection and so the selection process (F-ratio) was used on the satellite data for classification purposes.

3. The **EODHaM system** is a flexible system which provides a suitable frame on which to develop scripts (relating to classification rules) and classification subjects that are applicable to a conservation question or a site. Data fusion (multi dates) which is easily carried out within this system has helped to contribute to the improved discrimination and classification of species.

4. This study establishes that **Land Cover Classification System (LCCS)** categories can be mapped to level 2 using WorldView 2, with discrimination achieved using relationships with biophysical attributes extrapolated from indices based on spectral bands and seasonal imagery. The spectral indices, which relate primarily to plant productivity, the amount of dead/senescent material and moisture content and structural information. The LCCS provides a map of the broad vegetation types occurring together with

information on their biophysical characteristics (e.g., moisture, productivity etc.) which can be combined easily with dominant plant species maps to provide a single map of varying classification scales.

5. It was shown that **associations can be made between invertebrate data and the satellite derived data** (dominant plant species showing ecological gradients and indices indicating biophysical attributes). The classification maps along with other relevant extracted information regarding the biophysical properties, vegetation condition, structure and heterogeneity were used effectively as important ecological input into invertebrate species distribution models.

6. This work demonstrates that spectral indices and derived dominant plant species classifications can be used as **biodiversity indicators** of the composition, structure and functional diversity of the protected site. The study has established that VHR datasets, and particularly if optical and UAV data are combined, can be used as a basis for establishing baselines of habitat extent, state and condition from which biodiversity distributions can be broadly inferred. Such baselines can support monitoring of habitats and associated flora and fauna species using data acquired in subsequent years.

7. The overall aim to use **VHR optical imagery (in this case WV2 data) parameters as indicators of condition for flora and invertebrates** present on lowland raised bog was achieved with further implications of use for creating baseline distributions of other fauna types.

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Appendix A

Chapter 4

A.1 SAM results

A.1.1 Between species

April	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.000	0.277	0.633	0.000	0.600	0.000	0.000	0.000	0.000
eri ang	0.000	**1.000**	0.646	0.112	0.495	0.000	0.840	0.716	0.000	0.000
eri vag	0.277	0.646	**1.000**	0.378	0.198	0.259	0.567	0.450	0.000	0.000
jun eff	0.633	0.112	0.378	**1.000**	0.000	0.548	0.000	0.022	0.000	0.000
mol cae	0.000	0.495	0.198	0.000	**1.000**	0.000	0.613	0.445	0.000	0.000
myr gal	0.600	0.000	0.259	0.548	0.000	**1.000**	0.000	0.000	0.000	0.000
phr aus	0.000	0.840	0.567	0.000	0.613	0.000	**1.000**	0.660	0.000	0.000
pte aqu	0.000	0.716	0.450	0.022	0.445	0.000	0.660	**1.000**	0.000	0.000
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.194
sph pul	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.194	**1.000**

Table A.1: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in April. These calculations were made from reflectance values that were recorded between wavelengths 300 and 2500 nanometers at 1 nanaometer intervals.

May	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.143	0.242	0.641	0.000	0.558	0.074	0.000	0.000	0.000
eri ang	0.143	**1.000**	0.869	0.308	0.480	0.057	0.872	0.570	0.000	0.000
eri vag	0.242	0.869	**1.000**	0.384	0.383	0.156	0.796	0.506	0.000	0.000
jun eff	0.641	0.308	0.384	**1.000**	0.000	0.350	0.242	0.208	0.000	0.000
mol cae	0.000	0.480	0.383	0.000	**1.000**	0.000	0.559	0.452	0.000	0.000
myr gal	0.558	0.057	0.156	0.350	0.000	**1.000**	0.000	0.000	0.072	0.000
phr aus	0.074	0.872	0.796	0.242	0.559	0.000	**1.000**	0.602	0.000	0.000
pte aqu	0.000	0.570	0.506	0.208	0.452	0.000	0.602	**1.000**	0.000	0.000
sph cus	0.000	0.000	0.000	0.000	0.000	0.072	0.000	0.000	**1.000**	0.177
sph pul	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.177	**1.000**

June	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.486	0.664	0.508	0.172	0.459	0.454	0.251	0.000	0.000
eri ang	0.486	**1.000**	0.669	0.113	0.653	0.070	0.099	0.614	0.000	0.000
eri vag	0.664	0.669	**1.000**	0.374	0.403	0.359	0.400	0.338	0.000	0.000
jun eff	0.508	0.113	0.374	**1.000**	0.000	0.739	0.713	0.000	0.000	0.000
mol cae	0.172	0.653	0.403	0.000	**1.000**	0.000	0.000	0.526	0.000	0.000
myr gal	0.459	0.070	0.359	0.739	0.000	**1.000**	0.872	0.000	0.000	0.000
phr aus	0.454	0.099	0.400	0.713	0.000	0.872	**1.000**	0.000	0.000	0.000
pte aqu	0.251	0.614	0.338	0.000	0.526	0.000	0.000	**1.000**	0.000	0.000
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.126
sph pul	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.126	**1.000**

July	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.551	0.640	0.860	0.799	0.054	0.548	0.240	0.000	0.000
eri ang	0.551	**1.000**	0.862	0.000	0.597	0.000	0.164	0.000	0.000	0.000
eri vag	0.640	0.862	**1.000**	0.000	0.686	0.000	0.252	0.000	0.000	0.000
jun eff	0.860	0.000	0.000	**1.000**	0.023	0.689	0.474	0.586	0.000	0.063
mol cae	0.799	0.597	0.686	0.023	**1.000**	0.000	0.508	0.186	0.000	0.000
myr gal	0.054	0.000	0.000	0.689	0.000	**1.000**	0.477	0.769	0.000	0.122
phr aus	0.548	0.164	0.252	0.474	0.508	0.477	**1.000**	0.649	0.000	0.000
pte aqu	0.240	0.000	0.000	0.586	0.186	0.769	0.649	**1.000**	0.000	0.000
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.005
sph pul	0.000	0.000	0.000	0.063	0.000	0.122	0.000	0.000	0.005	**1.000**

Table A.2: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in May, June and July. These calculations were made from reflectance values that were recorded between wavelengths 300 and 2500 nanometers at 1 nanaometer intervals.

August	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.497	0.727	0.691	0.709	0.316	0.686	0.111	0.000	0.000
eri ang	0.497	**1.000**	0.658	0.393	0.317	0.000	0.266	0.000	0.000	0.000
eri vag	0.727	0.658	**1.000**	0.541	0.540	0.124	0.504	0.000	0.000	0.000
jun eff	0.691	0.393	0.541	**1.000**	0.603	0.319	0.656	0.091	0.000	0.007
mol cae	0.709	0.317	0.540	0.603	**1.000**	0.508	0.806	0.298	0.000	0.036
myr gal	0.316	0.000	0.124	0.319	0.508	**1.000**	0.562	0.691	0.000	0.361
phr aus	0.686	0.266	0.504	0.656	0.806	0.562	**1.000**	0.330	0.000	0.109
pte aqu	0.111	0.000	0.000	0.091	0.298	0.691	0.330	**1.000**	0.000	0.494
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.163
sph pul	0.000	0.000	0.000	0.007	0.036	0.361	0.109	0.494	0.163	**1.000**

September	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.736	0.757	0.390	0.672	0.109	0.395	0.000	0.000	0.000
eri ang	0.736	**1.000**	0.821	0.582	0.567	0.000	0.259	0.000	0.000	0.000
eri vag	0.757	0.821	**1.000**	0.503	0.601	0.000	0.255	0.000	0.000	0.000
jun eff	0.390	0.582	0.503	**1.000**	0.189	0.000	0.000	0.000	0.000	0.000
mol cae	0.672	0.567	0.601	0.189	**1.000**	0.323	0.586	0.000	0.000	0.000
myr gal	0.109	0.000	0.000	0.000	0.323	**1.000**	0.618	0.567	0.000	0.386
phr aus	0.395	0.259	0.255	0.000	0.586	0.618	**1.000**	0.221	0.000	0.168
pte aqu	0.000	0.000	0.000	0.000	0.000	0.567	0.221	**1.000**	0.241	0.544
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.241	**1.000**	0.307
sph pul	0.000	0.000	0.000	0.000	0.000	0.386	0.168	0.544	0.307	**1.000**

October	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.568	0.703	0.359	0.778	0.248	0.712	0.169	0.000	0.147
eri ang	0.568	**1.000**	0.505	0.736	0.636	0.000	0.404	0.000	0.000	0.000
eri vag	0.703	0.505	**1.000**	0.279	0.652	0.294	0.640	0.240	0.000	0.234
jun eff	0.359	0.736	0.279	**1.000**	0.402	0.000	0.179	0.000	0.000	0.000
mol cae	0.778	0.636	0.652	0.402	**1.000**	0.188	0.729	0.115	0.000	0.056
myr gal	0.248	0.000	0.294	0.000	0.188	**1.000**	0.409	0.860	0.000	0.420
phr aus	0.712	0.404	0.640	0.179	0.729	0.409	**1.000**	0.325	0.000	0.192
pte aqu	0.169	0.000	0.240	0.000	0.115	0.860	0.325	**1.000**	0.000	0.492
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000
sph pul	0.147	0.000	0.234	0.000	0.056	0.420	0.192	0.492	0.000	**1.000**

Table A.3: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in August, September and October. These calculations were made from reflectance values that were recorded between wavelengths 300 and 2500 nanometers at 1 nanaometer intervals.

November	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.414	0.673	0.571	0.474	0.270	0.249	0.000	0.000	0.000
eri ang	0.414	**1.000**	0.279	0.726	0.711	0.000	0.757	0.461	0.000	0.000
eri vag	0.673	0.279	**1.000**	0.492	0.420	0.378	0.143	0.000	0.000	0.000
jun eff	0.571	0.726	0.492	**1.000**	0.751	0.000	0.615	0.251	0.000	0.000
mol cae	0.474	0.711	0.420	0.751	**1.000**	0.000	0.586	0.312	0.000	0.000
myr gal	0.270	0.000	0.378	0.000	0.000	**1.000**	0.000	0.000	0.000	0.057
phr aus	0.249	0.757	0.143	0.615	0.586	0.000	**1.000**	0.537	0.000	0.000
pte aqu	0.000	0.461	0.000	0.251	0.312	0.000	0.537	**1.000**	0.000	0.000
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000
sph pul	0.000	0.000	0.000	0.000	0.000	0.057	0.000	0.000	0.000	**1.000**

Table A.4: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in November. These calculations were made from reflectance values that were recorded between wavelengths 300 and 2500 nanometers at 1 nanaometer intervals.

300-1000nm section of Spectrum -spectral analysis

April	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.177	0.199	0.641	0.000	0.519	0.000	0.205	0.170	0.575
eri ang	0.177	**1.000**	0.919	0.317	0.425	0.492	0.719	0.726	0.000	0.393
eri vag	0.199	0.919	**1.000**	0.320	0.434	0.516	0.734	0.680	0.003	0.409
jun eff	0.641	0.317	0.320	**1.000**	0.000	0.494	0.061	0.432	0.000	0.575
mol cae	0.000	0.425	0.434	0.000	**1.000**	0.020	0.688	0.212	0.000	0.000
myr gal	0.519	0.492	0.516	0.494	0.020	**1.000**	0.310	0.437	0.174	0.607
phr aus	0.000	0.719	0.734	0.061	0.688	0.310	**1.000**	0.493	0.000	0.173
pte aqu	0.205	0.726	0.680	0.432	0.212	0.437	0.493	**1.000**	0.000	0.355
sph cus	0.170	0.000	0.003	0.000	0.000	0.174	0.000	0.000	**1.000**	0.283
sph pul	0.575	0.393	0.409	0.575	0.000	0.607	0.173	0.355	0.283	**1.000**

May	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.101	0.158	0.536	0.000	0.613	0.000	0.192	0.256	0.439
eri ang	0.101	**1.000**	0.917	0.252	0.450	0.425	0.815	0.641	0.201	0.253
eri vag	0.158	0.917	**1.000**	0.311	0.396	0.473	0.778	0.677	0.214	0.278
jun eff	0.536	0.252	0.311	**1.000**	0.000	0.521	0.109	0.492	0.032	0.278
mol cae	0.000	0.450	0.396	0.000	**1.000**	0.000	0.587	0.173	0.000	0.000
myr gal	0.613	0.425	0.473	0.521	0.000	**1.000**	0.287	0.428	0.434	0.610
phr aus	0.000	0.815	0.778	0.109	0.587	0.287	**1.000**	0.513	0.134	0.134
pte aqu	0.192	0.641	0.677	0.492	0.173	0.428	0.513	**1.000**	0.008	0.167
sph cus	0.256	0.201	0.214	0.032	0.000	0.434	0.134	0.008	**1.000**	0.670
sph pul	0.439	0.253	0.278	0.278	0.000	0.610	0.134	0.167	0.670	**1.000**

June	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.405	0.418	0.736	0.000	0.892	0.744	0.280	0.086	0.452
eri ang	0.405	**1.000**	0.904	0.396	0.492	0.428	0.521	0.696	0.000	0.394
eri vag	0.418	0.904	**1.000**	0.388	0.519	0.450	0.556	0.618	0.000	0.433
jun eff	0.736	0.396	0.388	**1.000**	0.000	0.729	0.691	0.340	0.000	0.355
mol cae	0.000	0.492	0.519	0.000	**1.000**	0.000	0.118	0.332	0.000	0.125
myr gal	0.892	0.428	0.450	0.729	0.000	**1.000**	0.812	0.273	0.165	0.539
phr aus	0.744	0.521	0.556	0.691	0.118	0.812	**1.000**	0.343	0.150	0.544
pte aqu	0.280	0.696	0.618	0.340	0.332	0.273	0.343	**1.000**	0.000	0.145
sph cus	0.086	0.000	0.000	0.000	0.000	0.165	0.150	0.000	**1.000**	0.438
sph pul	0.452	0.394	0.433	0.355	0.125	0.539	0.544	0.145	0.438	**1.000**

Table A.5: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in April, May and June. These calculations were made from reflectance values that were recorded between wavelengths 300 and 1000 nanometers at 1 nanaometer intervals.

July	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.628	0.656	0.503	0.765	0.576	0.721	0.659	0.306	0.537
eri ang	0.628	**1.000**	0.858	0.341	0.582	0.307	0.510	0.350	0.105	0.477
eri vag	0.656	0.858	**1.000**	0.309	0.597	0.323	0.529	0.390	0.193	0.507
jun eff	0.503	0.341	0.309	**1.000**	0.660	0.736	0.694	0.607	0.089	0.310
mol cae	0.765	0.582	0.597	0.660	**1.000**	0.710	0.901	0.723	0.247	0.457
myr gal	0.576	0.307	0.323	0.736	0.710	**1.000**	0.768	0.833	0.267	0.353
phr aus	0.721	0.510	0.529	0.694	0.901	0.768	**1.000**	0.776	0.268	0.444
pte aqu	0.659	0.350	0.390	0.607	0.723	0.833	0.776	**1.000**	0.378	0.420
sph cus	0.306	0.105	0.193	0.089	0.247	0.267	0.268	0.378	**1.000**	0.506
sph pul	0.537	0.477	0.507	0.310	0.457	0.353	0.444	0.420	0.506	**1.000**

Aug	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.776	0.735	0.678	0.645	0.568	0.706	0.518	0.228	0.648
eri ang	0.776	**1.000**	0.762	0.785	0.516	0.423	0.621	0.351	0.101	0.581
eri vag	0.735	0.762	**1.000**	0.589	0.447	0.366	0.534	0.335	0.241	0.594
jun eff	0.678	0.785	0.589	**1.000**	0.570	0.485	0.651	0.361	0.000	0.516
mol cae	0.645	0.516	0.447	0.570	**1.000**	0.853	0.789	0.722	0.095	0.453
myr gal	0.568	0.423	0.366	0.485	0.853	**1.000**	0.735	0.833	0.123	0.424
phr aus	0.706	0.621	0.534	0.651	0.789	0.735	**1.000**	0.647	0.108	0.500
pte aqu	0.518	0.351	0.335	0.361	0.722	0.833	0.647	**1.000**	0.240	0.439
sph cus	0.228	0.101	0.241	0.000	0.095	0.123	0.108	0.240	**1.000**	0.425
sph pul	0.648	0.581	0.594	0.516	0.453	0.424	0.500	0.439	0.425	**1.000**

September	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.734	0.777	0.617	0.587	0.421	0.490	0.301	0.329	0.611
eri ang	0.734	**1.000**	0.748	0.830	0.596	42.000	0.622	0.308	0.186	0.603
eri vag	0.777	0.748	**1.000**	0.669	0.568	0.385	0.474	0.266	0.315	0.580
jun eff	0.617	0.830	0.669	**1.000**	0.479	0.303	0.528	0.207	0.064	0.510
mol cae	0.587	0.596	0.568	0.479	**1.000**	0.786	0.745	0.657	0.358	0.612
myr gal	0.421	0.420	0.385	0.303	0.786	**1.000**	0.681	0.836	0.348	0.510
phr aus	0.490	0.622	0.474	0.528	0.745	0.681	**1.000**	0.593	0.178	0.553
pte aqu	0.301	0.308	0.266	0.207	0.657	0.836	0.593	**1.000**	0.314	0.458
sph cus	0.329	0.186	0.315	0.064	0.358	0.348	0.178	0.314	**1.000**	0.460
sph pul	0.611	0.603	0.580	0.510	0.612	0.510	0.553	0.458	0.460	**1.000**

Table A.6: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in July, August and September. These calculations were made from reflectance values that were recorded between wavelengths 300 and 1000 nanometers at 1 nanaometer intervals.

October	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.788	0.759	0.607	0.736	0.627	0.658	0.637	0.152	0.646
eri ang	0.788	**1.000**	0.717	0.792	0.712	0.513	0.679	0.527	0.000	0.636
eri vag	0.759	0.717	**1.000**	0.641	0.578	0.493	0.538	0.512	0.201	0.643
jun eff	0.607	0.792	0.641	**1.000**	0.529	0.338	0.527	0.352	0.000	0.563
mol cae	0.736	0.712	0.578	0.529	**1.000**	0.729	0.830	0.742	0.030	0.517
myr gal	0.627	0.513	0.493	0.338	0.729	**1.000**	0.694	0.944	0.175	0.451
phr aus	0.658	0.679	0.538	0.527	0.830	0.694	**1.000**	0.697	0.000	0.463
pte aqu	0.637	0.527	0.512	0.352	0.742	0.944	0.697	**1.000**	0.192	0.476
sph cus	0.152	0.000	0.201	0.000	0.030	0.175	0.000	0.192	**1.000**	0.220
sph pul	0.646	0.636	0.643	0.563	0.517	0.451	0.463	0.476	0.220	**1.000**

November	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.593	0.663	0.568	0.365	0.711	0.504	0.213	0.000	0.448
eri ang	0.593	**1.000**	0.628	0.735	0.581	0.527	0.737	0.506	0.000	0.396
eri vag	0.663	0.628	**1.000**	0.782	0.635	0.501	0.660	0.312	0.000	0.565
jun eff	0.568	0.735	0.782	**1.000**	0.709	0.477	0.822	0.486	0.000	0.433
mol cae	0.365	0.581	0.635	0.709	**1.000**	0.222	0.679	0.489	0.000	0.399
myr gal	0.711	0.527	0.501	0.477	0.222	**1.000**	0.419	0.142	0.000	0.329
phr aus	0.504	0.737	0.660	0.822	0.679	0.419	**1.000**	0.614	0.000	0.323
pte aqu	0.213	0.506	0.312	0.486	0.489	0.142	0.614	**1.000**	0.000	0.008
sph cus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.092
sph pul	0.448	0.396	0.565	0.433	0.399	0.329	0.323	0.008	0.092	**1.000**

Table A.7: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in October and November. These calculations were made from reflectance values that were recorded between wavelengths 300 and 1000 nanometers at 1 nanaometer intervals.

Conversion of field spec to WV2 - spectral analysis

April	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.000	0.000	0.004	0.000	0.47	0.000	0.8	0.674	0.633
eri ang	0.000	**1.000**	0.92	0.151	0.347	0.43	0.672	0.767	0.106	0.322
eri vag	0.000	0.92	**1.000**	0.149	0.352	0.46	0.688	0.73	0.139	0.326
jun eff	0.004	0.151	0.149	**1.000**	0.000	0.473	0.000	0.314	0.163	0.674
mol cae	0.000	0.347	0.352	0.000	**1.000**	0.000	0.66	0.155	0.000	0.000
myr gal	0.47	0.43	0.46	0.473	0.000	**1.000**	0.174	0.471	0.405	0.65
phr aus	0	0.672	0.688	0	0.66	0.174	**1.000**	0.473	0.000	0.022
pte aqu	0.8	0.767	0.73	0.314	0.155	0.471	0.473	**1.000**	0.054	0.412
sph cus	0.674	0.106	0.139	0.163	0.000	0.405	0	0.054	**1.000**	0.441
sph pul	0.633	0.322	0.326	0.674	0.000	0.65	0.022	0.412	0.441	**1.000**

May	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.000	0.031	0.481	0.000	0.659	0.000	0.108	0.502	0.694
eri ang	0.000	**1.000**	0.938	0.112	0.363	0.279	0.787	0.683	0.256	0.212
eri vag	0.031	0.938	**1.000**	0.164	0.308	0.332	0.748	0.713	0.305	0.267
jun eff	0.481	0.112	0.164	**1.000**	0.000	0.498	0.000	0.369	0.231	0.497
mol cae	0.000	0.363	0.308	0.000	**1.000**	0.000	0.536	0.095	0.000	0.000
myr gal	0.659	0.279	0.332	0.498	0.000	**1.000**	0.105	0.375	0.666	0.849
phr aus	0.000	0.787	0.748	0.000	0.536	0.105	**1.000**	0.502	0.137	0.047
pte aqu	0.108	0.683	0.713	0.369	0.095	0.375	0.502	**1.000**	0.226	0.301
sph cus	0.502	0.256	0.305	0.231	0.000	0.666	0.137	0.226	**1.000**	0.694
sph pul	0.694	0.212	0.267	0.497	0.000	0.849	0.047	0.301	0.694	**1.000**

June	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.258	0.266	0.656	0.000	0.913	0.686	0.175	0.419	0.598
eri ang	0.258	**1.000**	0.927	0.237	0.422	0.297	0.460	0.758	0.064	0.484
eri vag	0.266	0.927	**1.000**	0.228	0.439	0.307	0.473	0.707	0.101	0.499
jun eff	0.656	0.237	0.228	**1.000**	0.000	0.687	0.691	0.231	0.157	0.435
mol cae	0.000	0.422	0.439	0.000	**1.000**	0.000	0.000	0.343	0.000	0.000
myr gal	0.913	0.297	0.307	0.687	0.000	**1.000**	0.751	0.207	0.440	0.644
phr aus	0.686	0.460	0.473	0.691	0.000	0.751	**1.000**	0.387	0.321	0.637
pte aqu	0.175	0.758	0.707	0.231	0.343	0.207	0.387	**1.000**	0.000	0.307
sph cus	0.419	0.064	0.101	0.157	0.000	0.440	0.321	0.000	**1.000**	0.528
sph pul	0.598	0.484	0.499	0.435	0.000	0.644	0.637	0.307	0.528	**1.000**

Table A.8: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in April, May and June. These calculations were made from reflectance values that were recorded for mean bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

July	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.554	0.548	0.215	0.616	0.441	0.569	0.659	0.666	0.733
eri ang	0.554	**1.000**	0.838	0.118	0.540	0.225	0.451	0.326	0.372	0.710
eri vag	0.548	0.838	**1.000**	0.025	0.485	0.168	0.407	0.313	0.445	0.653
jun eff	0.215	0.118	0.025	**1.000**	0.514	0.693	0.556	0.416	0.020	0.225
mol cae	0.616	0.540	0.485	0.514	**1.000**	0.670	0.895	0.673	0.420	0.610
myr gal	0.441	0.225	0.168	0.693	0.670	**1.000**	0.728	0.703	0.286	0.371
phr aus	0.569	0.451	0.407	0.556	0.895	0.728	**1.000**	0.706	0.393	0.528
pte aqu	0.659	0.326	0.313	0.416	0.673	0.703	0.706	**1.000**	0.553	0.500
sph cus	0.666	0.372	0.445	0.020	0.420	0.286	0.393	0.553	**1.000**	0.533
sph pul	0.733	0.710	0.653	0.225	0.610	0.371	0.528	0.500	0.533	**1.000**

August	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.760	0.670	0.652	0.547	0.452	0.613	0.478	0.504	0.850
eri ang	0.760	**1.000**	0.746	0.753	0.434	0.336	0.548	0.334	0.378	0.772
eri vag	0.670	0.746	**1.000**	0.528	0.277	0.178	0.384	0.202	0.536	0.720
jun eff	0.652	0.753	0.528	**1.000**	0.574	0.478	0.690	0.441	0.201	0.639
mol cae	0.547	0.434	0.277	0.574	**1.000**	0.886	0.835	0.846	0.179	0.487
myr gal	0.452	0.336	0.178	0.478	0.886	**1.000**	0.746	0.894	0.112	0.395
phr aus	0.613	0.548	0.384	0.690	0.835	0.746	**1.000**	0.718	0.211	0.549
pte aqu	0.478	0.334	0.202	0.441	0.846	0.894	0.718	**1.000**	0.185	0.419
sph cus	0.504	0.378	0.536	0.201	0.179	0.112	0.211	0.185	**1.000**	0.541
sph pul	0.850	0.772	0.720	0.639	0.487	0.395	0.549	0.419	0.541	**1.000**

September	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.735	0.741	0.610	0.495	0.287	0.345	0.129	0.506	0.657
eri ang	0.735	**1.000**	0.738	0.835	0.583	0.384	0.512	0.246	0.408	0.736
eri vag	0.741	0.738	**1.000**	0.668	0.455	0.234	0.312	0.082	0.511	0.618
jun eff	0.610	0.835	0.668	**1.000**	0.454	0.274	0.433	0.156	0.275	0.614
mol cae	0.495	0.583	0.455	0.454	**1.000**	0.767	0.742	0.603	0.520	0.756
myr gal	0.287	0.384	0.234	0.274	0.767	**1.000**	0.765	0.828	0.351	0.546
phr aus	0.345	0.512	0.312	0.433	0.742	0.765	**1.000**	0.688	0.268	0.589
pte aqu	0.129	0.246	0.082	0.156	0.603	0.828	0.688	**1.000**	0.199	0.400
sph cus	0.506	0.408	0.511	0.275	0.520	0.351	0.268	0.199	**1.000**	0.562
sph pul	0.657	0.736	0.618	0.614	0.756	0.546	0.589	0.400	0.562	**1.000**

Table A.9: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in July, August and September. These calculations were made from reflectance values that were recorded for mean bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

October	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.789	0.699	0.546	0.658	0.575	0.563	0.596	0.416	0.810
eri ang	0.789	**1.000**	0.700	0.735	0.660	0.531	0.617	0.553	0.261	0.845
eri vag	0.699	0.700	**1.000**	0.626	0.454	0.367	0.400	0.397	0.467	0.761
jun eff	0.546	0.735	0.626	**1.000**	0.431	0.304	0.431	0.324	0.109	0.687
mol cae	0.658	0.660	0.454	0.431	**1.000**	0.818	0.847	0.847	0.203	0.582
myr gal	0.575	0.531	0.367	0.304	0.818	**1.000**	0.775	0.948	0.211	0.475
phr aus	0.563	0.617	0.400	0.431	0.847	0.775	**1.000**	0.785	0.104	0.508
pte aqu	0.596	0.553	0.397	0.324	0.847	0.948	0.785	**1.000**	0.236	0.498
sph cus	0.416	0.261	0.467	0.109	0.203	0.211	0.104	0.236	**1.000**	0.360
sph pul	0.810	0.845	0.761	0.687	0.582	0.475	0.508	0.498	0.360	**1.000**

November	cal vul	eri ang	eri vag	jun eff	mol cae	myr gal	phr aus	pte aqu	sph cus	sph pul
cal vul	**1.000**	0.568	0.573	0.440	0.239	0.656	0.447	0.214	0.187	0.587
eri ang	0.568	**1.000**	0.609	0.710	0.483	0.503	0.705	0.580	0.000	0.52
eri vag	0.573	0.609	**1.000**	0.744	0.612	0.375	0.723	0.422	0.204	0.767
jun eff	0.440	0.710	0.744	**1.000**	0.680	0.350	0.917	0.638	0.000	0.56
mol cae	0.239	0.483	0.612	0.680	**1.000**	0.063	0.663	0.569	0.000	0.514
myr gal	0.656	0.503	0.375	0.350	0.063	**1.000**	0.349	0.155	0.000	0.321
phr aus	0.447	0.705	0.723	0.917	0.663	0.349	**1.000**	0.674	0.000	0.532
pte aqu	0.214	0.580	0.422	0.638	0.569	0.155	0.674	**1.000**	0.000	0.272
sph cus	0.187	0.000	0.204	0.000	0.000	0.000	0.000	0.000	**1.000**	0.331
sph pul	0.587	0.52	0.767	0.56	0.514	0.321	0.532	0.272	0.331	**1.000**

Table A.10: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in October and November. These calculations were made from reflectance values that were recorded for mean bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

A.1.2 Within species

April	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.984	0.97	0.966	0.943	0.991	0.843	0.975	0.981	0.98	0.997
2	0.981	0.957	0.955	0.926	0.992	0.872	0.974	0.992	0.98	0.987
3	0.965	0.907	0.946	0.948	0.985	0.907	0.979	0.98	0.982	0.978
4	0.966	0.947	0.938	0.862	0.979	0.761	0.979	0.988	0.95	0.963
5	0.962	0.951	0.947	0.939	0.976	0.762	0.959	0.977	0.941	0.973
6	0.96	0.948	0.941	0.872	0.972	0.797	0.946	0.976	0.964	0.97
7	0.935	0.951	0.937	0.845	0.987	0.763	0.949	0.985	0.954	0.972
8	0.933	0.948	0.919	0.884	0.974	0.72	0.908	0.915	0.94	0.968
9	0.955	0.933	0.949	0.81	0.978	0.757	0.918	0.984	0.935	0.953
10	0.955	0.926	0.934	0.827	0.978	0.679	0.878	0.965	0.914	0.972
11	0.952	0.937	0.919	0.908	0.974	0.679	0.868	0.973	0.92	0.969
12	0.924	0.927	0.927	0.806	0.97	0.721	0.913	0.976	0.92	0.947
13	0.932	0.948	0.878	0.807	0.971	0.721	0.913	0.972	0.959	0.951
14	0.952	0.934	0.873	0.798	0.966	0.723	0.862	0.96	0.912	0.928
15	0.931	0.896	0.871	0.671	0.97	0.712	0.893	0.939	0.884	0.948
16	0.843	0.882	0.874	0.696	0.974	0.732	0.858	0.911	0.897	0.947
17	0.852	0.882	0.874	0.603	0.972	0.556	0.858	0.903	0.889	0.952
18	0.89	0.882	0.831	0.497	0.953	0.762	0.721	0.95	0.87	0.949
19	0.837	0.912	0.827	0.414	0.946	0.797	0.848	0.911	0.841	0.946
20	0.801	0.896	0.814	0.865	0.946	0.763	0.771	0.966	0.935	0.917

Table A.11: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in April measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

May	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.993	0.944	0.961	0.93	0.992	0.981	0.992	0.978	0.991	0.991
2	0.99	0.986	0.967	0.94	0.999	0.969	0.989	0.99	0.988	0.972
3	0.983	0.977	0.967	0.949	0.991	0.958	0.991	0.985	0.998	0.973
4	0.977	0.961	0.967	0.915	0.9987	0.961	0.99	0.988	0.979	0.987
5	0.973	0.967	0.962	0.951	0.983	0.945	0.991	0.988	0.961	0.974
6	0.964	0.98	0.944	0.928	0.986	0.951	0.978	0.968	0.934	0.976
7	0.951	0.963	0.953	0.914	0.979	0.922	0.974	0.974	0.93	0.971
8	0.959	0.943	0.953	0.926	0.978	0.924	0.967	0.964	0.962	0.964
9	0.964	0.949	0.949	0.895	0.977	0.919	0.963	0.955	0.944	0.947
10	0.954	0.934	0.97	0.859	0.977	0.902	0.961	0.978	0.908	0.958
11	0.959	0.967	0.929	0.903	0.978	0.918	0.961	0.962	0.909	0.965
12	0.953	0.977	0.935	0.9	0.967	0.858	0.965	0.948	0.894	0.944
13	0.953	0.959	0.937	0.856	0.976	0.845	0.942	0.976	0.918	0.934
14	0.937	0.94	0.94	0.843	0.961	0.854	0.937	0.97	0.866	0.93
15	0.948	0.921	0.928	0.833	0.954	0.916	0.939	0.977	0.92	0.932
16	0.932	0.925	0.929	0.773	0.955	0.859	0.95	0.946	0.889	0.917
17	0.929	0.939	0.934	0.667	0.956	0.819	0.922	0.972	0.85	0.918
18	0.939	0.935	0.937	0.723	0.952	0.857	0.892	0.95	0.835	0.939
19	0.934	0.915	0.942	0.699	0.959	0.87	0.878	0.929	0.825	0.905
20	0.926	0.883	0.943	0.648	0.944	0.87	0.856	0.93	0.846	0.88

Table A.12: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in May measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

June	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.994	0.996	0.977	0.995	0.994	0.989	0.97	0.993	0.996	0.987
2	0.979	0.995	0.987	0.992	0.981	0.984	0.966	0.994	0.994	0.99
3	0.98	0.977	0.98	0.992	0.977	0.988	0.952	0.987	0.986	0.986
4	0.877	0.997	0.974	0.979	0.928	0.878	0.943	0.99	0.982	0.991
5	0.97	0.965	0.977	0.974	0.968	0.99	0.903	0.979	0.991	0.977
6	0.965	0.993	0.976	0.958	0.914	0.919	0.915	0.985	0.978	0.99
7	0.966	0.989	0.965	0.977	0.914	0.988	0.917	0.985	0.972	0.974
8	0.964	0.993	0.981	0.986	0.909	0.975	0.929	0.982	0.979	0.981
9	0.959	0.991	0.963	0.972	0.97	0.978	0.935	0.989	0.987	0.965
10	0.963	0.944	0.978	0.978	0.962	0.973	0.941	0.986	0.976	0.958
11	0.961	0.988	0.976	0.948	0.946	0.967	0.941	0.983	0.987	0.956
12	0.951	0.99	0.96	0.951	0.927	0.957	0.878	0.981	0.976	0.954
13	0.862	0.94	0.956	0.928	0.906	0.968	0.933	0.984	0.983	0.953
14	0.947	0.99	0.949	0.929	0.916	0.95	0.929	0.984	0.975	0.951
15	0.944	0.988	0.953	0.956	0.885	0.962	0.915	0.976	0.976	0.972
16	0.928	0.988	0.947	0.916	0.905	0.949	0.878	0.987	0.965	0.965
17	0.915	0.985	0.939	0.85	0.887	0.936	0.852	0.968	0.969	0.957
18	0.918	0.965	0.916	0.841	0.894	0.94	0.875	0.979	0.978	0.947
19	0.916	0.948	0.937	0.988	0.868	0.94	0.928	0.976	0.946	0.946
20	0.918	0.982	0.885	0.965	0.994	0.934	0.864	0.969	0.949	0.939

Table A.13: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in June measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

July	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.966	0.97	0.954	0.919	0.95	0.924	0.927	0.916	0.843	0.836
2	0.957	0.987	0.957	0.915	0.944	0.923	0.924	0.922	0.841	0.827
3	0.94	0.974	0.951	0.927	0.941	0.914	0.93	0.924	0.839	0.809
4	0.931	0.976	0.951	0.916	0.94	0.932	0.927	0.909	0.861	0.81
5	0.947	0.972	0.949	0.912	0.941	0.909	0.925	0.919	0.846	0.805
6	0.947	0.957	0.923	0.91	0.935	0.903	0.91	0.918	0.839	0.824
7	0.927	0.92	0.928	0.91	0.932	0.934	0.911	0.916	0.836	0.847
8	0.948	0.967	0.931	0.909	0.944	0.928	0.908	0.915	0.844	0.787
9	0.924	0.968	0.932	0.906	0.926	0.928	0.916	0.924	0.844	0.843
10	0.934	0.964	0.91	0.906	0.909	0.898	0.907	0.911	0.84	0.832
11	0.93	0.964	0.901	0.898	0.915	0.926	0.935	0.92	0.842	0.855
12	0.943	0.967	0.924	0.891	0.903	0.893	0.933	0.904	0.842	0.824
13	0.938	0.964	0.904	0.881	0.902	0.926	0.899	0.911	0.841	0.866
14	0.927	0.966	0.887	0.859	0.885	0.917	0.908	0.917	0.84	0.829
15	0.937	0.962	0.872	0.853	0.887	0.916	0.921	0.914	0.844	0.859
16	0.932	0.918	0.864	0.829	0.858	0.92	0.905	0.912	0.851	0.817
17	0.922	0.932	0.86	0.915	0.854	0.911	0.91	0.903	0.859	0.827
18	0.9	0.978	0.906	0.921	0.832	0.917	0.898	0.897	0.864	0.797
19	0.877	0.972	0.888	0.916	0.928	0.906	0.891	0.883	0.839	0.798
20	0.934	0.975	0.837	0.91	0.925	0.884	0.935	0.883	0.846	0.798

Table A.14: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in July measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

August	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.992	0.975	0.989	0.976	0.992	0.991	0.993	0.992	0.994	0.991
2	0.99	0.975	0.998	0.95	0.989	0.982	0.989	0.99	0.995	0.983
3	0.99	0.97	0.988	0.954	0.99	0.969	0.98	0.992	0.991	0.985
4	0.988	0.97	0.994	0.94	0.994	0.967	0.983	0.991	0.99	0.968
5	0.991	0.974	0.986	0.912	0.986	0.968	0.972	0.985	0.983	0.97
6	0.99	0.946	0.978	0.91	0.991	0.96	0.975	0.99	0.991	0.967
7	0.986	0.949	0.873	0.96	0.985	0.973	0.971	0.987	0.991	0.974
8	0.992	0.948	0.975	0.905	0.986	0.973	0.966	0.983	0.984	0.972
9	0.989	0.928	0.979	0.901	0.983	0.964	0.958	0.987	0.99	0.981
10	0.985	0.921	0.975	0.918	0.989	0.951	0.957	0.978	0.983	0.977
11	0.99	0.906	0.961	0.916	0.99	0.953	0.959	0.979	0.982	0.967
12	0.989	0.912	0.958	0.91	0.982	0.965	0.948	0.976	0.983	0.967
13	0.982	0.92	0.948	0.907	0.979	0.945	0.938	0.981	0.979	0.969
14	0.983	0.905	0.956	0.907	0.983	0.933	0.936	0.975	0.974	0.973
15	0.981	0.928	0.96	0.927	0.982	0.926	0.934	0.98	0.975	0.96
16	0.977	0.901	0.938	0.919	0.98	0.915	0.932	0.974	0.975	0.969
17	0.98	0.903	0.939	0.909	0.985	0.923	0.93	0.97	0.978	0.972
18	0.975	0.905	0.935	0.923	0.981	0.902	0.91	0.973	0.976	0.975
19	0.964	0.909	0.923	0.901	0.986	0.893	0.913	0.962	0.971	0.957
20	0.97	0.899	0.855	0.881	0.982	0.935	0.853	0.967	0.968	0.969

Table A.15: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in August measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

September	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.997	0.997	0.997	0.995	0.995	0.992	0.969	0.993	0.994	0.992
2	0.993	0.992	0.997	0.992	0.988	0.985	0.975	0.993	0.995	0.991
3	0.992	0.992	0.996	0.991	0.985	0.983	0.966	0.979	0.989	0.992
4	0.99	0.993	0.995	0.992	0.983	0.974	0.96	0.978	0.988	0.984
5	0.989	0.989	0.994	0.99	0.986	0.97	0.96	0.971	0.985	0.985
6	0.993	0.989	0.996	0.988	0.982	0.965	0.967	0.971	0.982	0.979
7	0.992	0.995	0.993	0.984	0.985	0.964	0.956	0.968	0.978	0.978
8	0.988	0.987	0.944	0.987	0.983	0.966	0.955	0.969	0.98	0.974
9	0.988	0.992	0.993	0.78	0.983	0.964	0.953	0.966	0.974	0.963
10	0.992	0.991	0.992	0.976	0.987	0.967	0.961	0.964	0.972	0.961
11	0.988	0.988	0.992	0.984	0.978	0.96	0.943	0.963	0.968	0.958
12	0.988	0.99	0.995	0.985	0.983	0.961	0.936	0.962	0.967	0.958
13	0.992	0.989	0.993	0.979	0.978	0.96	0.947	0.961	0.968	0.957
14	0.986	0.988	0.992	0.981	0.981	0.958	0.933	0.963	0.964	0.955
15	0.983	0.985	0.993	0.882	0.976	0.958	0.941	0.961	0.963	0.953
16	0.984	0.985	0.989	0.894	0.976	0.96	0.951	0.961	0.961	0.954
17	0.988	0.983	0.992	0.976	0.975	0.956	0.949	0.96	0.954	0.957
18	0.993	0.977	0.983	0.901	0.973	0.948	0.935	0.958	0.959	0.951
19	0.984	0.979	0.982	0.973	0.974	0.946	0.937	0.955	0.959	0.953
20	0.99	0.974	0.983	0.963	0.956	0.926	0.909	0.939	0.951	0.938

Table A.16: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in September measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

October	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.992	0.991	0.989	0.963	0.998	0.992	0.985	0.981	0.999	0.998
2	0.992	0.974	0.989	0.58	0.995	0.979	0.987	0.984	0.998	0.994
3	0.992	0.97	0.988	0.943	0.995	0.974	0.98	0.98	0.995	0.993
4	0.979	0.969	0.99	0.931	0.993	0.981	0.98	0.969	0.991	0.992
5	0.977	0.97	0.991	0.916	0.99	0.973	0.982	0.97	0.991	0.992
6	0.984	0.977	0.99	0.904	0.99	0.972	0.979	0.976	0.99	0.993
7	0.983	0.965	0.9989	0.9	0.985	0.971	0.982	0.972	0.993	0.993
8	0.973	0.969	0.988	0.9	0.992	0.97	0.981	0.969	0.991	0.997
9	0.976	0.971	0.986	0.899	0.987	0.97	0.972	0.965	0.993	0.994
10	0.977	0.974	0.99	0.896	0.986	0.968	0.965	0.973	0.991	0.994
11	0.964	0.971	0.988	0.87	0.984	0.966	0.975	0.972	0.992	0.99
12	0.98	0.972	0.987	0.894	0.977	0.966	0.97	0.965	0.991	0.988
13	0.972	0.973	0.986	0.876	0.979	0.965	0.97	0.961	0.989	0.985
14	0.97	0.968	0.985	0.864	0.972	0.961	0.946	0.961	0.986	0.992
15	0.972	0.961	0.981	0.866	0.978	0.963	0.955	0.953	0.987	0.994
16	0.97	0.965	0.987	0.877	0.973	0.959	0.939	0.96	0.983	0.989
17	0.967	0.97	0.984	0.877	0.973	0.956	0.943	0.908	0.989	0.981
18	0.968	0.962	0.98	0.877	0.973	0.959	0.94	0.942	0.987	0.986
19	0.965	0.955	0.983	0.855	0.958	0.958	0.925	0.95	0.984	0.979
20	0.959	0.951	0.981	0.931	0.968	0.955	0.932	0.962	0.98	0.983

Table A.17: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in October measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).

November	Cal vul	Eri ang	Eri vag	Jun eff	Mol cae	Myr gal	Phr aus	Pte aqu	Sph cus	Sph pul
Mean	1	1	1	1	1	1	1	1	1	1
1	0.994	0.944	0.996	0.994	0.994	0.981	0.83	0.997	0.993	0.997
2	0.995	0.99	0.995	0.993	0.987	0.985	0.91	0.992	0.987	0.99
3	0.982	0.991	0.997	0.989	0.994	0.976	0.842	0.995	0.99	0.994
4	0.979	0.992	0.996	0.984	0.989	0.98	0.909	0.988	0.991	0.996
5	0.991	0.981	0.997	0.979	0.992	0.978	0.849	0.987	0.989	0.99
6	0.989	0.984	0.996	0.981	0.994	0.975	0.864	0.991	0.986	0.99
7	0.991	0.981	0.994	0.98	0.994	0.979	0.89	0.985	0.985	0.989
8	0.992	0.991	0.994	0.978	0.99	0.977	0.831	0.988	0.983	0.992
9	0.989	0.992	0.996	0.974	0.986	0.975	0.945	0.984	0.983	0.992
10	0.988	0.989	0.994	0.975	0.985	0.979	0.949	0.977	0.979	0.992
11	0.985	0.982	0.993	0.975	0.991	0.972	0.936	0.973	0.99	0.991
12	0.988	0.989	0.991	0.971	0.987	0.969	0.939	0.981	0.985	0.992
13	0.982	0.99	0.99	0.974	0.981	0.972	0.876	0.972	0.988	0.989
14	0.986	0.99	0.995	0.974	0.992	0.973	0.922	0.96	0.979	0.99
15	0.989	0.981	0.995	0.962	0.981	0.972	0.924	0.939	0.975	0.989
16	0.987	0.976	0.992	0.957	0.978	0.963	0.868	0.911	0.97	0.984
17	0.984	0.98	0.984	0.955	0.976	0.968	0.83	0.886	0.957	0.984
18	0.99	0.971	0.993	0.955	0.981	0.956	0.842	0.861	0.958	0.991
19	0.979	0.965	0.991	0.951	0.973	0.971	0.909	0.834	0.952	0.985
20	0.984	0.967	0.983	0.997	0.961	0.969	0.849	0.966	0.946	0.989

Table A.18: Spectral angle mapping scores for spectral angles set at 0.25 from field spectrometer reflectance data recorded in November measuring spectral difference of mean species data compared with the sample of 20 records of the same species. These calculations were made from reflectance values that were recorded for the bandwidths recorded by the WV2 sensor (**8 WV2 bands** = 429, 480, 548, 608, 659, 723, 825, 915 nanometers).