From Space to Eye Lens

Monitoring protected sites with Earth Observation: Combining field data with CASI and Sentinel imagery

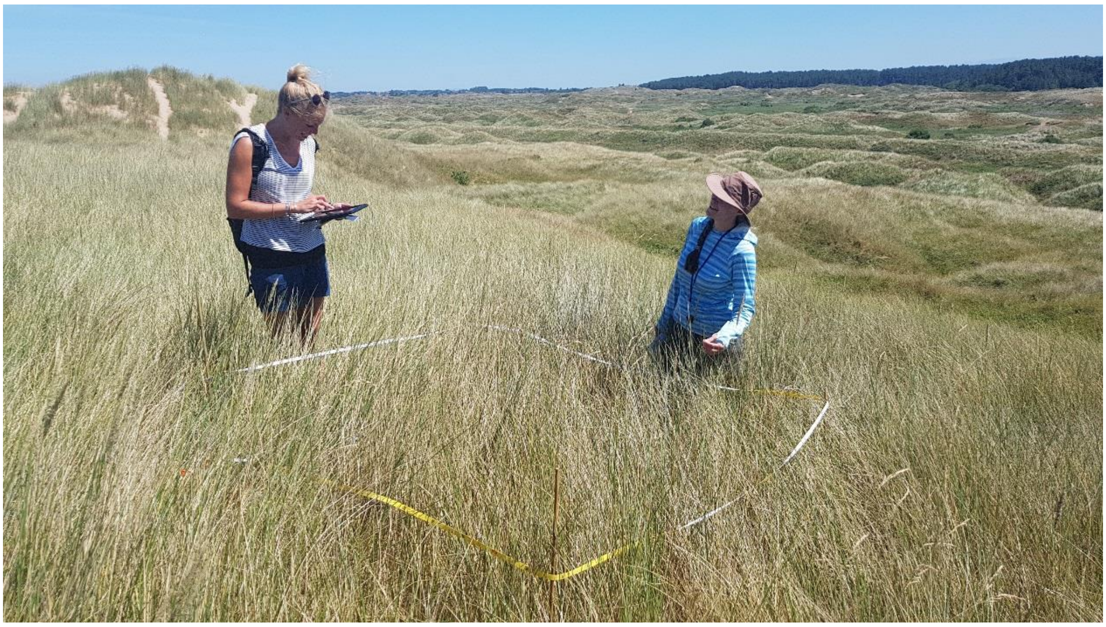

Photo © Rob Keane: Katie Finkill-Coombs and Esther Pawley @ Ainsdale NNR July 2018

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Executive Summary

This report details work undertaken, led by Manchester Metropolitan University in collaboration with Natural England. The aim of this research was to investigate the potential of Earth observation (EO) data to contribute towards the monitoring of protected sites at the landscape scale, to understand resilience, and to map natural capital assets. This was achieved through the integration of field vegetation survey data with Sentinel-2 and CASI imagery to map ecosystem attributes, particularly ecological gradients and species and plant communities. Two contrasting areas in the north-west of England were used as case studies: Ainsdale National Nature Reserve (NNR) sand dunes and the Forest of Bowland blanket bog. Based on the outcomes of this research, a number of recommendations for future study and implementation have been outlined.

The key outcomes of this research are:

- Vegetation data from 331 survey quadrats across both pilot areas were used to train models, based on Sentinel-2 imagery from the European Space Agency's Copernicus programme.
- Compact Airborne Spectrographic Imager (CASI) Hyperspectral and Light Detection and Ranging (LiDAR) data were also available for Ainsdale NNR.
- The models were able to reproduce broad patterns and trends in habitats observed on the ground at both Ainsdale NNR sand dunes and the Forest of Bowland blanket bog with reasonable accuracies for predictive mapping of vegetation communities.
- Ainsdale habitat mapping was 44% accurate at NVC level and 53% accurate at Annex 1 habitat level, based on cross validation. Predictive accuracy was higher in the more stable habitats, such as dune slacks. Predictive accuracy was lower in transition and less spatially common habitats, such as shifting and embryo dunes, the latter due to limited training data.
- Bowland habitat mapping accuracy was higher, achieving 44% based on a seven-habitat classification model, and 70% based on a binary bog-heath classification. Mapping was stronger in areas of good quality bog, whereas degraded bog was more easily associated with heath; some species are common in both habitats.
- Field validation during a ground data collection exercise at Ainsdale suggested slightly lower accuracies of 29% for CASI and 32% for the Sentinel-2 models; quadrats in more difficult classes i.e. H2110 (Embryonic Shifting Dunes) occupy a smaller proportion of the habitat area and the original survey data but were equally present in the validation exercise. Further data was collected during ground data collection in these habitats to be incorporated into Phase 2 to understand if model accuracy can be improved.
- There appears potential to use EO to address some targets used in Favourable Condition Tables (FCT) Assessments: habitat extent, bare ground, vegetation and tree cover should be possible using the current approaches. There is potential for cover of dominant species such as *Calluna vulgaris*, *Sphagnum* spp. or *Salix repens*

to be predicted given improved model training using additional quadrat data from areas dominant in those species.

- Canopy/sward height was not possible to accurately measure in the sand dunes due to the 'soft' nature of the surface, however, where LiDAR data is available, it should be achievable in other habitats.
- EO data also showed some potential to monitor long-term environmental change including wetness and fertility. Ellenberg Indicator Values (EIV) for wetness (F; Ainsdale 47%, Bowland 49%) and light (L; Ainsdale 49%, Bowland 55%) were the most consistently accurate. Ellenberg fertility (N) at Bowland (48% accurate) and pH (R) at Ainsdale (36% accurate) also showed promise, but Ellenberg acidity (R) was poor at Bowland (11% accurate), as was fertility at Ainsdale (14% accurate). However, EIVs from quadrat data may lag behind actual changes in conditions due to the time it takes for a community to respond.
- Vegetation Indices (VIs) such as NDMI (Normalised Difference Moisture Index) and NDWI (Normalised Difference Wetness Index) also offer potential to observe changes in surface wetness, although further work is needed to link changes in species composition and restoration of bare ground with NDMI and NDWI. In general, the relationships between VIs and EIVs was poor and inconsistent, perhaps reflecting the date of image collection and lag in community responses.
- There does appear potential to use both EIVs and NDMI/NDWI types of indicator to understand the impact of landscape and environmental change and site management interventions on condition, especially in conjunction with changes in broad habitat structure and extent. There may also be future potential to combine these indices to develop a stronger Wetness Index and also to link these observations with atmospheric and soil biogeochemical responses from data collected through LTMN monitoring.
- The project demonstrates that data gathered as part of Natural England's Long Term Monitoring Network, National Vegetation Classification (NVC) and protected sites monitoring can be combined, adapted and used to train EO-based models that offer potential to monitor long-term habitat responses to environmental change at the landscape scale. Extra ground data may need to be gathered to improve model accuracy for plant communities not fully represented in the existing surveys used. The models could contribute to the reform of protected sites monitoring and also assist with Natural Capital Asset Mapping particularly through developing a Wetness Index for informing flood risk management soft engineering in the uplands to slow the flow in flash rainfall events.
- Opportunities exist to refine field data collection to be better suited to the modelling process, including: the collection of training data could incorporate polygons of stands of single or dominant species; habitats that are less spatially represented should be included in larger quantities; where possible surveyors should note quadrat NVC/Annex 1 classification.

In terms of recommendations for future research, the following areas would merit more investigation:

- What are the best methods for the pre-processing and handling of Sentinel-2 imagery, and what procedures are necessary?
- How can ecological survey data be processed into categories for classification more effectively and is NVC appropriate for such robust use?
- How do changes in specific species or communities affect vegetation index values given the potential lag of community response to changing condition?

Contents

1 Delivery Outcomes

The overall aim of 'From Space to Eye Lens' is to 'test and develop Earth observation spatial tools for mapping habitat condition and extent at the landscape scale and monitoring environmental change over time across Focus Areas and the Long Term Monitoring Network'.

Specific long-term objectives are:

1. Baseline habitat condition models for monitoring change across coastal dunes of Dee to Ribble Estuary Focus Area.
2. Baseline habitat condition and wetness index models for upland blanket bog restoration across Bowland Focus Area.
    a) Informing Upland Management Long Term Plan options and monitoring success, over time.
    b) Development of a wetness index used to map natural capital assets for targeting re-wetting to improve ability to hold water acting as an ecosystem service.
3. Spatial analytical tools for use by advisers to easily access, use model outputs and enable skilled GIS users to run models.
    a) Non-technical advisers have improved access to spatial evidence for working at the landscape scale.
4. Time-series visualisation tools for mapping spatial habitat change over time to detect signals of change.
5. Analysis of change in spatial extent of habitats and potentially plant communities to improve the ability to detect significant changes across LTMN network and Focus Areas.
6. Ecosystem interactive models for spatial analysis of the drivers of change for informing the resilience of landscapes related to climatic or air quality changes long-term.
    a) Correlative analysis with climate, nitrogen deposition and species dispersal models.
    b) Improve the ability to investigate relationships and identify key drivers of change across differing geographical landscapes and their habitats.
    c) Inform management targeting across Focus Areas to allow species adaptation along predicted environmental changes.

Specifically, this report will focus on the scientific methods underpinning objectives 1, 2, 5, and 6.

Conservation Strategy (C21) and 25 Year Plan

This project has been developed to help inform the government's ambition for England to be a great place to live, with a healthy natural environment on land and at sea that benefits people and the economy.

Conservation Strategy 21: Natural England's conservation strategy for the 21st century [GOV.UK] sets out our thinking on what we need to do differently and how we need to work with others, to better deliver this shared ambition. It should frame everything we do.

It brings together our own and others' experiences of what works and the latest science and evidence, with innovative approaches, new partnerships and different ways of thinking about nature and the benefits it provides.

Three guiding principles:

- creating **resilient landscapes** and **seas**
- putting **people at the heart** of the environment
- growing **natural capital**

It is underpinned by the **outcomes approach** – delivering better long term outcomes for the environment by understanding people's interests and needs, and working towards a shared vision.

Protected Sites Monitoring Reform

This pilot is to also inform the Protected Sites Monitoring Reform Project that is aiming to develop a new monitoring approach for terrestrial and freshwater SSSI sites in Natural England. Three key reasons for reviewing our approach to Protected Sites Monitoring are:

1. We need our Protected Sites Monitoring to provide the evidence needed to deliver the key principles of Natural England's Conservation Strategy (C21), and help us understand our sites in a wider landscape context.
2. We want to build on the **innovative new approaches** that are already being trialled across the organisation, to improve our delivery of environmental outcomes.
3. **New technologies** and greater involvement of our partners and the public provide exciting opportunities to improve the quality and variety of our Protected Sites evidence.

2 Pilot Areas

Two contrasting areas of semi-natural habitat were used for the pilot phase of this study, 1) Sefton Coast SSSI, encompassing Ainsdale SSSI Sand dunes, is a large SSSI extending over 20 km between Liverpool and Southport. It hosts a number of rare habitats including embryonic shifting dunes, mobile dunes, dunes with creeping willow (*Salix arenaria*), humid dune slacks, fixed dunes, dune grasslands and dune heath; 2) Bowland Fells is a large upland SSSI over 15,000 ha in size located in Lancashire, North West England. Bowland is also designated a Special Protection Area (SPA) due to the rare bird communities the site supports (Figure 1). The main habitats at Bowland are blanket bog and moorland both dominated by the shrub heather (*Calluna vulgaris*).

Ainsdale National Nature Reserve (NNR) is part of Natural England's Long Term Monitoring Network (LTMN) consisting of 37 sites across England which is designed to monitor, analyse and predict environmental change in the United Kingdom.

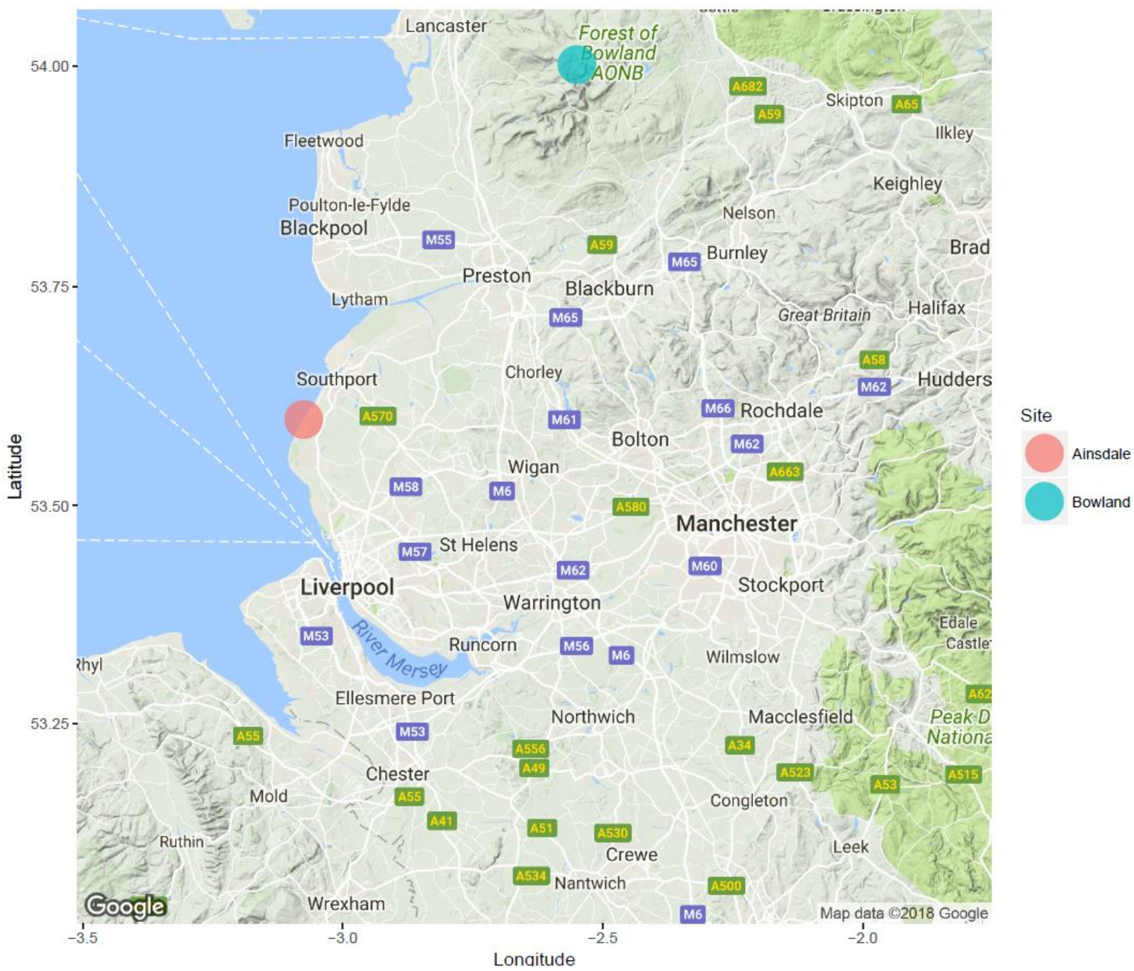


Figure 1: Location of the pilot study sites in North West England

3 General Data and Methods

3.1 Vegetation Training Data Method and Analysis

Ainsdale Pilot

For Ainsdale Sand dunes we used existing survey data from 3 sources: 1) The Long Term Monitoring Network (LTMN). This surveys fifty 2 x 2 m plots stratified to coastal dune and pine forest, divided into 25 cells in which vegetation height, species and bare ground/litter/rock presence are recorded along with percentage cover of each species at plot level. LTMN surveys are repeated every 4 years, for this project we used data from the 2016 survey; 2) The Centre of Ecology and Hydrology (CEH) surveyed 80 2 x 2 m quadrats at various dates up to 2015 with a focus on dune slacks and semi-fixed dunes. Percent cover of every species was recorded as was bare ground/litter; 3) Data from a National Vegetation Classification survey of Ainsdale (NNR) of Unit 17 carried out by Graeme Skelcher in 2015. Vegetation data from 2 x 2 m quadrats located across all habitats was recorded using the DOMIN scale, to enable comparison with other survey data, DOMIN values were converted to percent cover using the mid-point percentage of each scale point. The NNR survey also noted plot NVC according to constancy tables.

Bowland Pilot

For Bowland Upland Blanket Bog, an adapted Common Standards Monitoring Assessment (CSM) approach was used to survey the Focus Area in October 2016 and March 2017 recording all species, rather than just indicators. In this, the cover of every species within one hundred and seven 2 x 2 m quadrats was recorded using the DOMIN scale. The height of *Calluna vulgaris* (i.e. Heather), where present, was measured four times in each quadrat and the mean calculated. A CSM Assessment was also made against several criteria. For analysis, DOMIN values were converted to percent cover using the mid-point percentage of each scale point.

The datasets used and their sources are summarised in Table 1.

Following a species name check for consistency across data, the data were processed in the Modular Analysis of Vegetation Information System software (MAVIS) (CEH, 2009) to derive both cover weighted and mean Ellenberg Indicators Values (EIVs) for moisture, pH, fertility and light. National Vegetation Community (NVC) classifications were also obtained from MAVIS and used for mapping plant communities and habitat extant across the landscape.

Table 1. Vegetation datasets used in this report. See Appendix 1 for explanation of NVC codes.

Site	Survey	Number of quadrats	Habitats (NVC)	Date
Ainsdale sand dunes	Long Term Monitoring Network	50 2x2 m	Survey of whole site (SD7,8,10,12,14,15,16 H1, MG6, OV27, W4,10,11,24)	2016
Ainsdale sand dunes	CEH Dunes Survey	80 2x2 m quadrats	Dune slack focus with acid dune grassland and semi-fixed dunes (SD7,8,9,12,14,15,16 OV27, U1)	Various up to 2015
Ainsdale sand dunes	NNR Unit 17 survey by Graeme Skelcher	94 2x2 m quadrats	Survey of whole site (SD6,7,8,10,15,16,17,18 OV27, W10, W23)	2015
Bowland upland heath and blanket bog	SSSI Survey	107 2 x 2 m quadrats (81 bog, 26 heath)	Heath (Dry, Wet), blanket bog (Active and degraded)	2016, 2017

Ainsdale NNR

For Ainsdale, good agreement was observed between these MAVIS NVC classifications and those from Graeme Skelcher (NE) and CEH. A further 10% of all classifications were checked using NVC tables and good general agreement was found. It should be noted that for sand dunes, quadrats could not always be confidently placed in any single NVC and multiple options existed, this reflects the often transient nature of these habitats. In these instances, a field ecologist on the ground would be able to make a more robust decision based on topographical context, whereas a decision based on data alone may not always be accurate. NVC codes were also related to Annex 1 Habitats (see Appendix) and, given their more general nature, these classifications could be treated as more robust.

Mean sand dune Annex 1 EIVs for light, wetness, acidity and fertility are shown in Figure 2, they illustrate the general environmental and ecological conditions of each Annex 1 community. H2110 Embryonic shifting dunes are new communities of pioneer plants characterised by high percentages of bare ground, open and dry habitats with no soil formation and a low fertility score. The moisture and nutrient requirements gradually increase as distance from the shore increases and soil become more established. H2170 Dunes with *Salix repens* and H2190 Humid dune slacks have a notably greater EIV for moisture that the other communities, reflecting their lower topographies relative to the water table. Other EIV values across communities appear to differ little with the possible exception that H2130 Fixed dunes with herbaceous vegetation and woodland communities both appear to have a lower acidity value (lower pH); Fixed dunes often have a greater organic layer and the woodland at Ainsdale is dominated by pine trees which drop litter known for its acidic properties.

The species at Ainsdale that show the greatest changes in percent cover across habitats and the strongest association with specific habitats are often those that are key components of Annex 1 and NVC communities (see explanation of codes in Appendix 1 and Principle Components Analysis (PCA in Appendix 2). Such species include *Salix repens* (H2190), *Calliergon cuspidatum* (H2170 and H2190), *Pseudoscleropdodium purum* and *Hydrocotyle vulgaris* (H2170), *Ammophila arenaria* and *Carex Arenaria* (H2120 Shifting dunes along the shoreline). Bare ground is also strongly associated with heath and H2110 Embryonic dunes. Other species not visible in the PCA but important in the data structure (following cluster analysis, not shown) include *Agrostis stolonifera, Anthoxanthum odoratum, Arrhenatherum elatius, Kindbergia praelonga (Eurhynchium praelongum), Festuca rubra, Holcus lanatus, Hypnum spp., Ononis repens* and *Rubus caesius*.

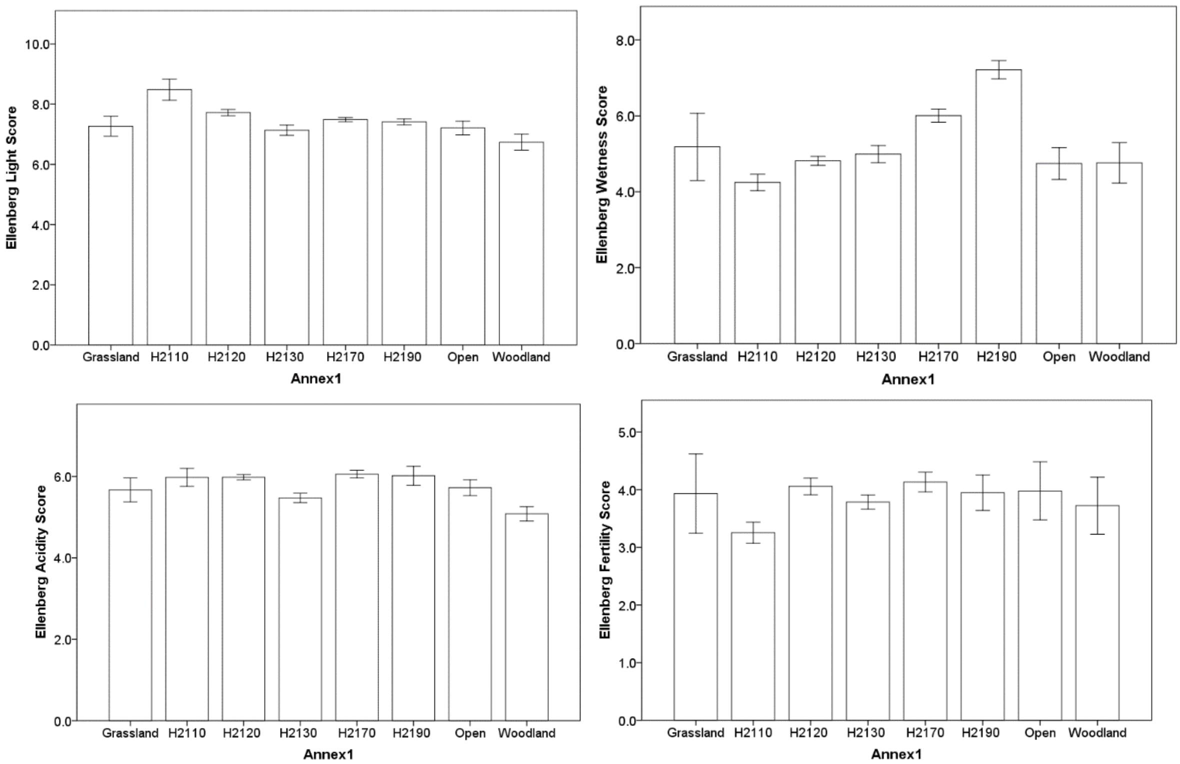


Figure 2: Mean habitat (Annex 1) EIV for light, wetness, acidity and fertility, for Ainsdale dunes

<u>Bowland</u>

Figure 3 illustrates mean habitat EIVs for light, wetness, acidity and fertility for the survey quadrats split by habitat. Subtle differences were observed between bog and heath with marginally greater EIV light and wetness in bogs, demonstrating a higher light requirement and moisture requirement of bog species, lower acidity score for bogs i.e. a lower pH and higher acidity, and a higher fertility score in heaths suggesting the preference of more fertile, slightly less acidic conditions for heath species. However, these differences are marginal and both habitats are relatively acidic and of low nutrient status.

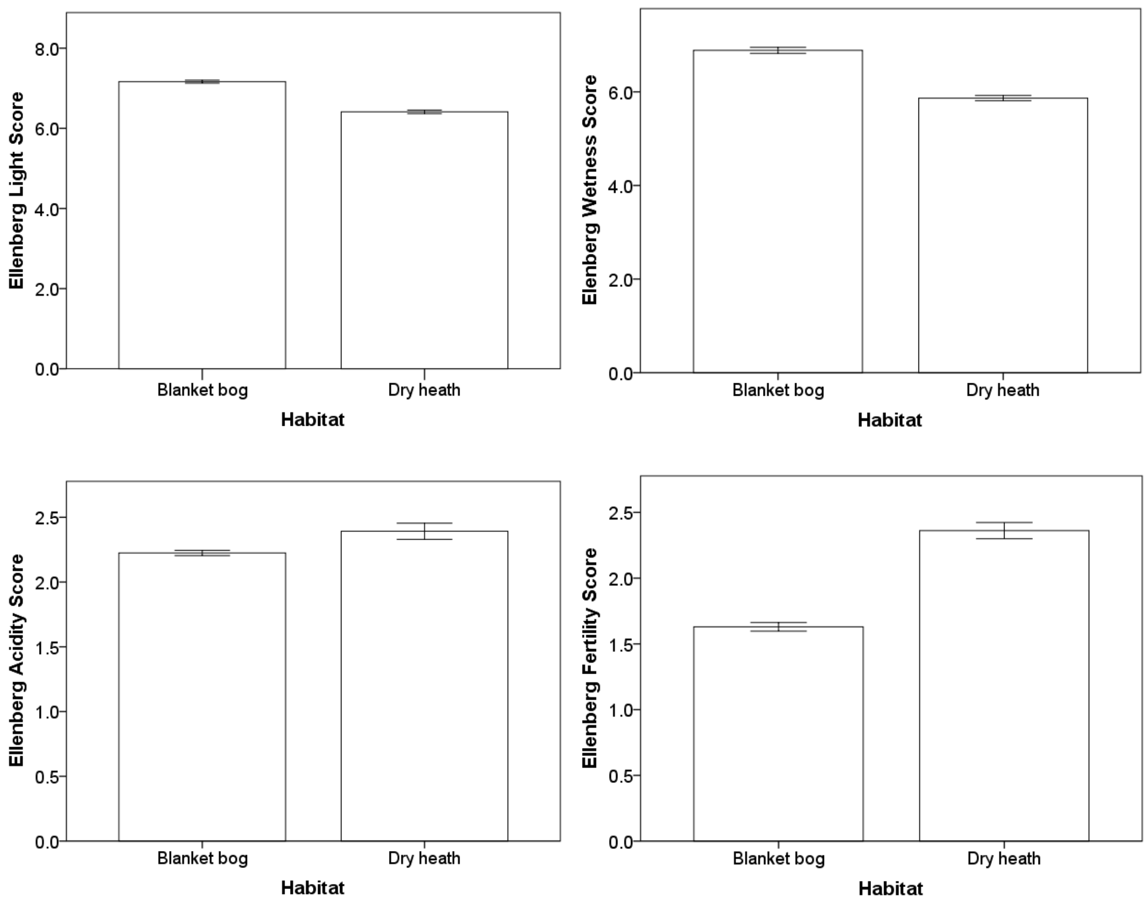


Figure 3: Mean habitat EIV for light, wetness, acidity and fertility, for Bowland blanket bog and dry heath communities

The species that show the greatest changes in percent cover across habitats and the strongest association with specific habitats are often those that are key components of both heath (moorland) and blanket bog communities. *Vaccinium myrtillus, Dechamspia exusosa, Festuca ovina, Juncus squarrosus, Gallium saxatile and Lophocolia bidenta* have strong heathland associations (See Principle Components Analysis in Appendix), whilst *Erioporum vaginatum & E. angustifolium, Polytrichum commune* and *Sphagnum spp*. Are strongly linked with moisture rich bogs. There is a significant overlap between both heath and bog communities at Bowland with many species including *Calluna vulgaris* appearing in both. This reflects the genuine overlap that exists between heath and bog vegetation and also that a degraded blanket bog and dry heath are often different only in name and the greater peat content of the bog. As restoration work continues at Bowland and moisture levels increase, the communities should separate further.

3.2 Sentinel-2 Satellites

Sentinel-2 is the land monitoring component of the European Space Agency's (ESA) Copernicus programme. It carries a Multi Spectral Instrument (MSI) that captures data across 13 spectral bands. Of these bands, four have a 10 m pixel resolution, six a 20 m, with three 60 m bands primarily for atmospheric applications (Figure 4). There are currently two Sentinel-2 satellites in orbit; Sentinel-2A was launched in June 2015 and was joined by Sentinel-2B in March 2017. Each mission has a 10-day repeat overpass, for the majority of the Earth, resulting in a combined revisit rate of five days.

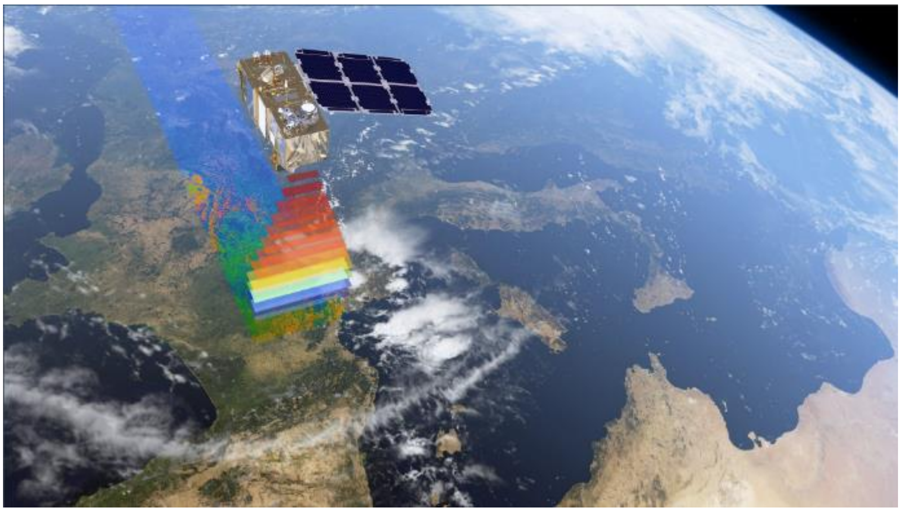


Figure 4a: Sentinel Satellite 2 orbit (ESA medialab)

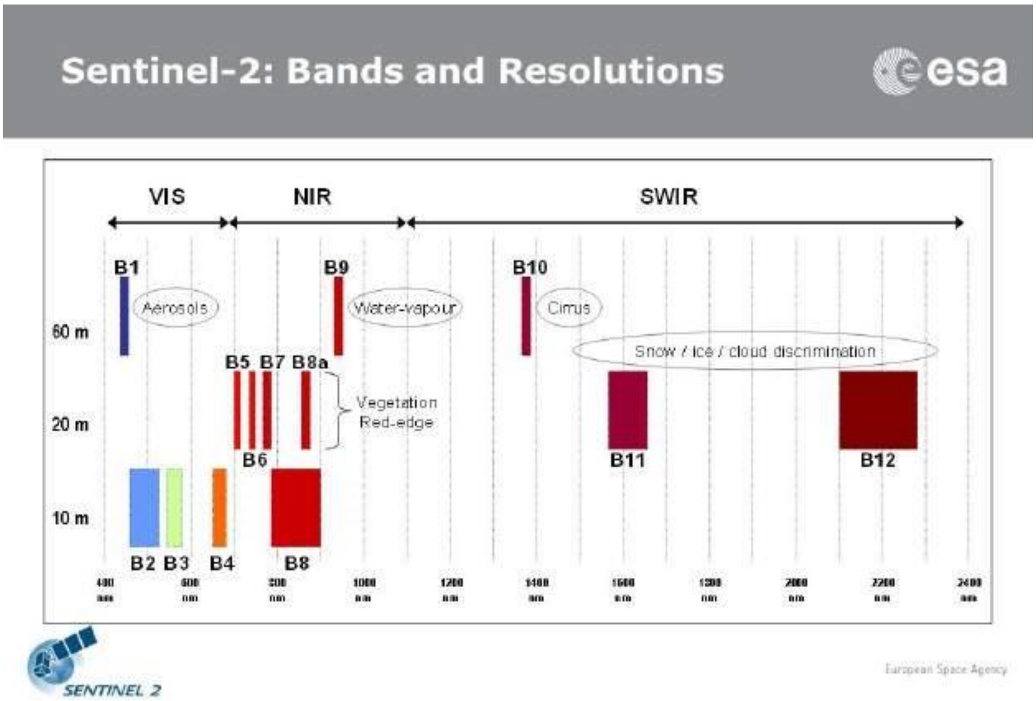


Figure 4b: Sentinel-2 wavebands and resolutions

Geolocation issues

Since launching, it has become apparent that the imagery acquired by Sentinel-2A has a suboptimal geolocation accuracy. Geolocation accuracy refers to the alignment of multi-temporal images. Ideally, this error should be less than the resolution of a single pixel, as this allows multiple images to correctly overlap. Imagery acquired between June 2015 and June 2016 has a miss-registration of 1.6 10 m pixels (0.9 pixels). However, the ESA updated the processing software in June 2016, reducing this error to roughly 0.4 pixels. Data acquired pre June 2016 have not been reprocessed, although this has been scheduled for early 2019. For this reason, only images acquired after July 2016 have been used in this report

3.3 Compact Airborne Spectrographic Imager (CASI)

The Sefton coast was imaged by a Compact Airborne Spectrographic Imager (CASI) in August 2015. This provides a 24- band hyperspectral image at 1 m resolution. Furthermore, the Sefton coast is has also been surveyed by the Environment Agency Light Detection and Ranging (LiDAR). This instrument measures the surface of the Earth using thousands of laser pulses over each metre, allowing highly accurate terrain and canopy models to be generated.

3.4 Statistical Analysis

Regression and classifications

The majority of the analyses in this report are attempting to generate predictions of a candidate variable, based on a machine learning model. These models are either focused on predicting a numeric value (regression) or a categorical factor (classification). In both cases, the underlying rationale is the same. Firstly, known values from field data are compared to co-located predictor values derived from the Earth observation imagery. A machine learning method then attempts to derive a statistical relationship, allowing the known values to be predicted based on the imagery. This model is then used to predict the candidate variable onto the other pixels in the image, resulting in continuous map of predicted values.

When generating predictive models it is important to assess accuracy (i.e. model testing), otherwise the models are of little use. An accuracy assessment is undertaken by comparing the values predicted by a model against known values. It is important that these comparisons be undertaken on data not used in the training process, otherwise the accuracy will be overly optimistic. In situations where the total available data are limited it is not practical to divide the data into training and testing subsets, as there will be too little data to develop models. In this situation, Cross Validation (CV) is an appropriate method for model testing.

Cross Validation is a technique to assess model accuracy in the absence of independent testing data. The data are split into *n* folds, with *n-1* used to train the model and the unused fold reserved for testing. This is repeated until each fold has been used for testing (Figure 5). The final accuracy is calculated based on the average of the testing folds. To maximise the benefit, this procedure can be repeated a number of times, with different combinations of folds.

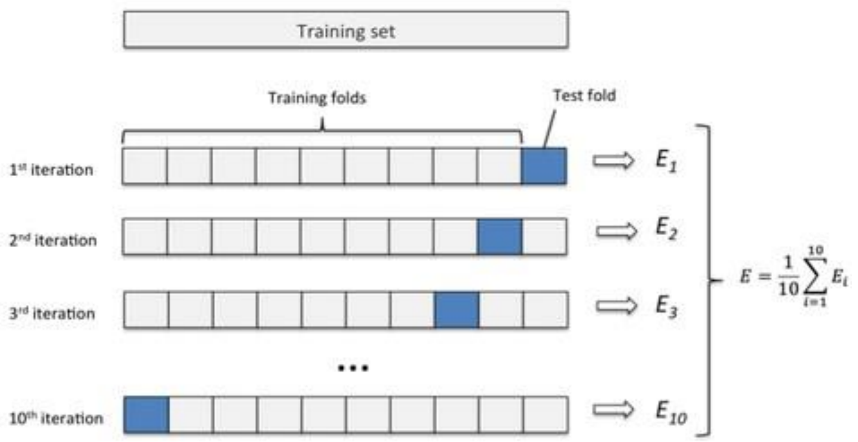


Figure 5: Diagram representation of K-fold cross validation. The final accuracy is derived as an average of each individual accuracy measure.

There are a large number of metrics that can be used for accuracy assessment. In this report, we focus on four commonly used measures:

1. Root Mean Square Error (RMSE) – (regressions)
2. Mean Absolute Error (MAE) – (regressions)
3. R^2 co-efficient of determination – (regressions)
4. Overall Accuracy (AO) – (classifications)

RMSE and MAE are different ways of expressing the average error associated with a prediction; they are expressed in units of the variable being predicted. RMSE is more influence by large errors than MAE, so will be higher with occasional instances of large errors. The R^2 is the proportion of variance in the predicted values explained by the observed values. This is synonyms with a simple linear regression line between the two vectors. Overall accuracy is the percentage of correctly classified values, out of the total.

4 Forest of Bowland

4.1 Data

Two Sentinel-2 images were downloaded, one for summer (17th July 2017) and one from winter (5th January 2017). Both images were atmospherically corrected using Dark Object Subtraction (DOS) in QGIS, and topographically corrected using cosine correction with an STRM elevation model in SagaGIS. Both images were cloud free, so no masking was required.

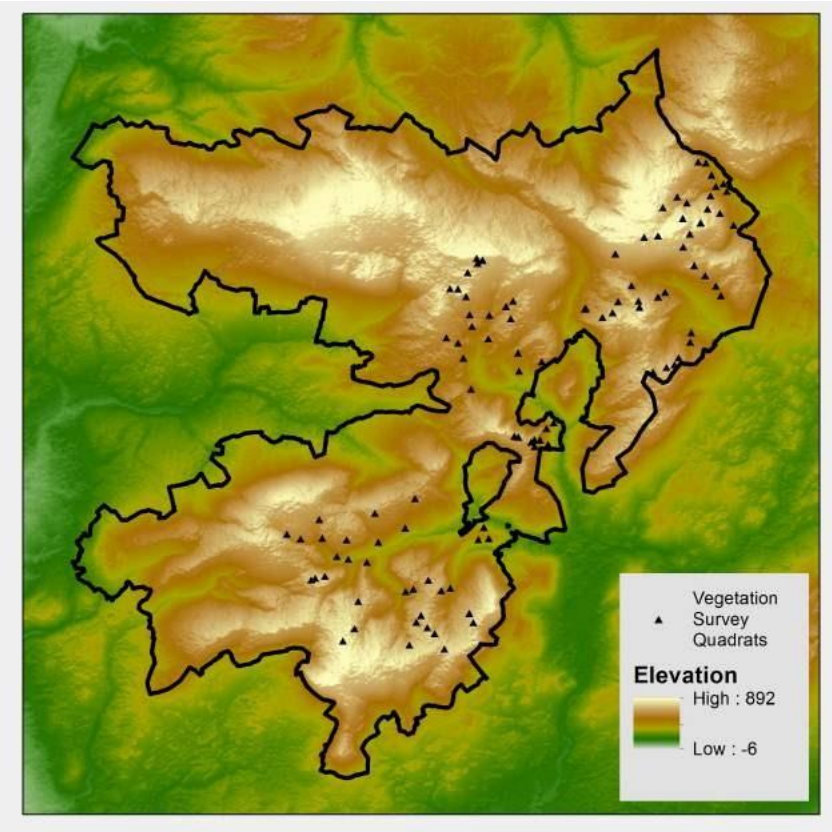


Figure 6: Location of the Forest of Bowland with Area of Outstanding Natural Beauty (AONB) and field sites shown

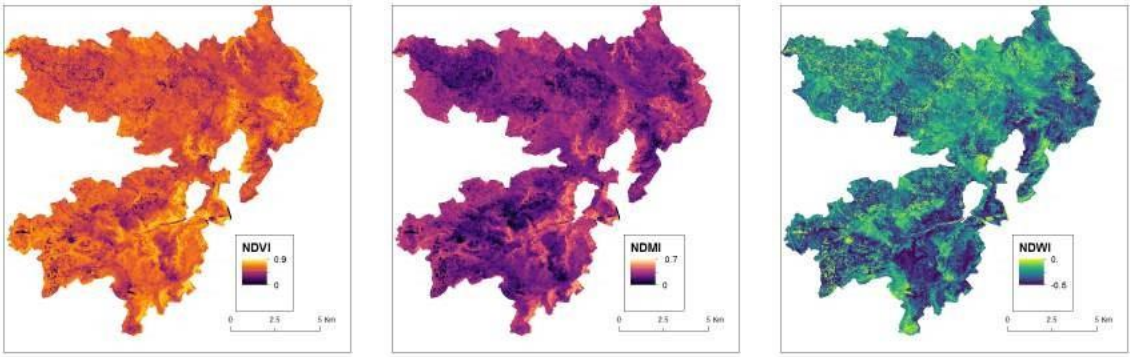
4.2 Vegetation Indices (VIs)

Three vegetation indices were generated from both the summer and winter images:

1. Normalised Difference Vegetation Index (NDVI), a proxy of *greenness* or photosynthetic activity
2. Normalised Difference Moisture Index (NDMI), a proxy for *vegetation* water content or the spongy mesophyll structure within the canopy
3. Normalised Difference Water Index (NDWI), an indicator of *surface* water coverage.

These indices were chosen as they are commonly used, have a long history in the scientific literature, and are relatively simple to explain.

Maps of these indices for summer 2017 are shown in Figure 7. A bivariate choropleth for NDVI and NDMI is shown in Figure 8; this allows an easy comparison of the NDMI and NDVI layers, highlighting areas of agreement and contrast.



(a) NDV I (b) NDMI (c) NDWI

Figure 7: Candidate vegetation indices from summer 2017

Can NDVI be used as an indicator of productivity?

NDVI on its own is not a meaningful ecological indicator. Mathematically, NDVI is the normalised difference between the wavelengths of light that are absorbed for photosynthesis, and those reflected to avoid cellular overheating. This ratio is broadly comparable to the fraction of photosynthetically available radiation (*f* PAR), i.e. the total amount of radiation available for absorption by a plant. However, this is not directly related to the productivity of a plant or community. Gross Primary Production (GPP) is determined by how efficiently photosynthesis converts radiation into biomass, as measured according to Light Use Efficiency (i.e. how efficiently plants convert light to carbohydrates). This conversion is highly variable, *Sphagnum* and other bog plants typically have LUE's much lower than grass species, and LUE will change under climatic and nutrient limitations. Net Primary Production (NPP), is calculated based on accumulated NPP, minus maintenance respiratory losses. In summary, NDVI is suitable, as a *very broad-brush* indicator of vegetation, but obtaining an ecological parameter, such as productivity, requires more complex analysis, e.g. radiative transfer models or field data for empirical modelling.

Can NDMI or NDWI be used as an indicator of wetness?

These indicators are suitable for a basic overview of wetness conditions. However, the relative contributions of bare soil and vegetation to the index value is unspecific. This may make assessing wetness more difficult, particularly on areas with bare peat coverage. Furthermore, the influence of species composition on wetness indicators requires further investigation; for example, a small coverage of very wet plants may have a disproportionate influence. One final consideration is that the role of mosses and under-canopy plants on VI values has not been studied.

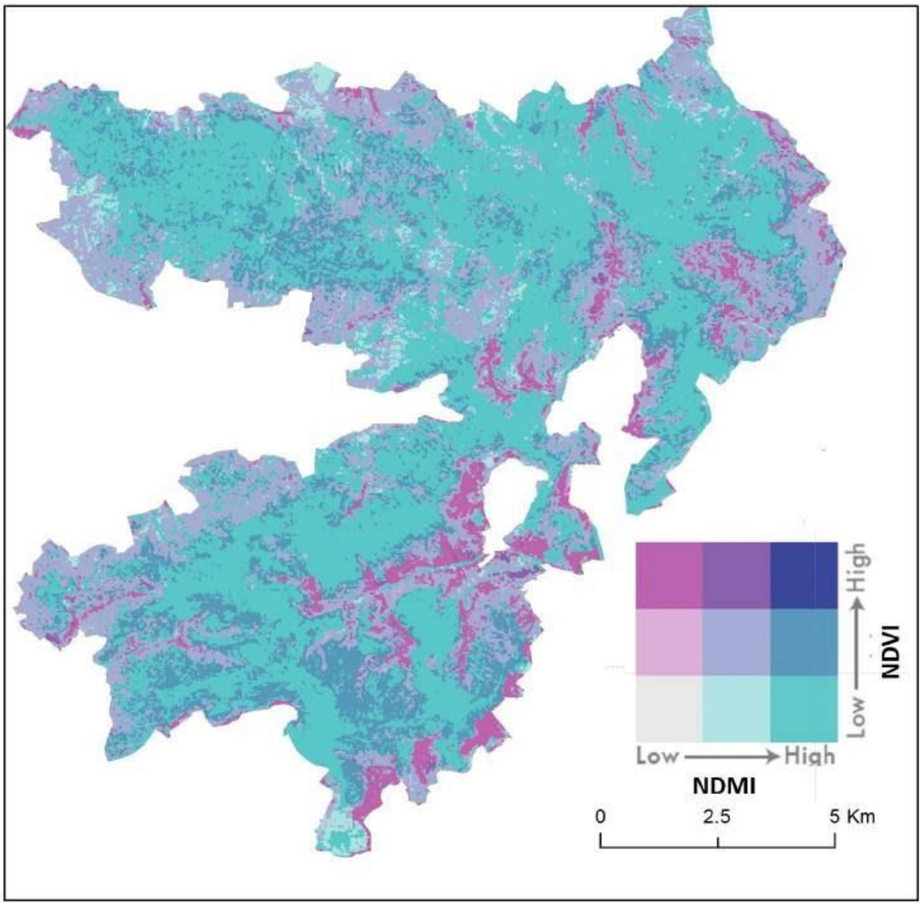


Figure 8: Bivariate choropleth map of NDVI and NDMI

4.3 Ellenberg indicator values (EIV)

Ellenberg indicators values (EIV) were generated from the field data using the Modular analysis of vegetation information system (MAVIS) software from the Centre for Ecology and Hydrology (CEH). Derived indicators included wetness, fertility, pH, and light.

Relationships between Ellenberg indicators values (EIV) and satellite-derived Vegetation Indices (VI)

As the selected VI are considered proxy measurements for moisture and productivity, it is reasonable to hypothesise that they may relate to the associated EIV (NDVI – Ellenberg fertility, NDMI/NDWI – Ellenberg wetness). To test this hypothesis, for each EI linear regression, models were developed against each seasonal VI. The accuracy of these models was assessed using fifteen repeats of 5-fold cross validation

Scatter plots of the VI-EI relationships are shown in Figure 9, with linear regression lines included. These plots and the associated accuracy metrics (Table 2) show that the VI-EI relationships are weak with low R^2 and often contrasting direction of lines of best fit. This may be surprising, given the both metrics purport to imply the same attributes. However, the method by which the values are obtained, and what they measure, partly explains the lack of a strong relationship. EIV are measures of the collective species from a plot and integrate site conditions over the longer-term, independent of the *in situ* conditions at any specific time. Conversely, VI's are a proxy of the condition of the pixel at that precise snap-shot in time, regardless of the species composition. It is therefore possible that a community resulting in a high wetness Ellenberg score will, in a contemporary dry period, have a lower NDMI/NDWI than low wetness species experiencing wet conditions. Furthermore, EIV can often lag behind real on the ground changes and communities take time to respond to a change in conditions. In summary, individual VI are a poor indicator of EI, more complex analysis is required.

Table 2: Accuracy metrics for predicting Ellenberg indicators using only a single Vegetation Index (VI).

Season	VI	Ellenberg	R2	RMSE	Season	VI	Ellenberg	R2	RMSE
Summer	NDMI	pH	0.12	0.23	Winter	NDMI	pH	0.10	0.23
	NDMI	Light	0.12	0.44		NDMI	Light	0.10	0.44
	NDMI	Wetness	0.09	0.67		NDMI	Wetness	0.09	0.67
	NDMI	Fertility	0.12	0.42		NDMI	Fertility	0.11	0.42
Summer	NDVI	pH	0.05	0.23	Winter	NDVI	pH	0.06	0.23
	NDVI	Light	0.14	0.44		NDVI	Light	0.24	0.40
	NDVI	Wetness	0.13	0.66		NDVI	Wetness	0.22	0.61
	NDVI	Fertility	0.11	0.43		NDVI	Fertility	0.24	0.38
Summer	NDWI	pH	0.08	0.24	Winter	NDWI	pH	0.03	0.23
	NDWI	Light	0.07	0.46		NDWI	Light	0.13	0.43
	NDWI	Wetness	0.05	0.68		NDWI	Wetness	0.16	0.63
	NDWI	Fertility	0.07	0.43		NDWI	Fertility	0.12	0.41

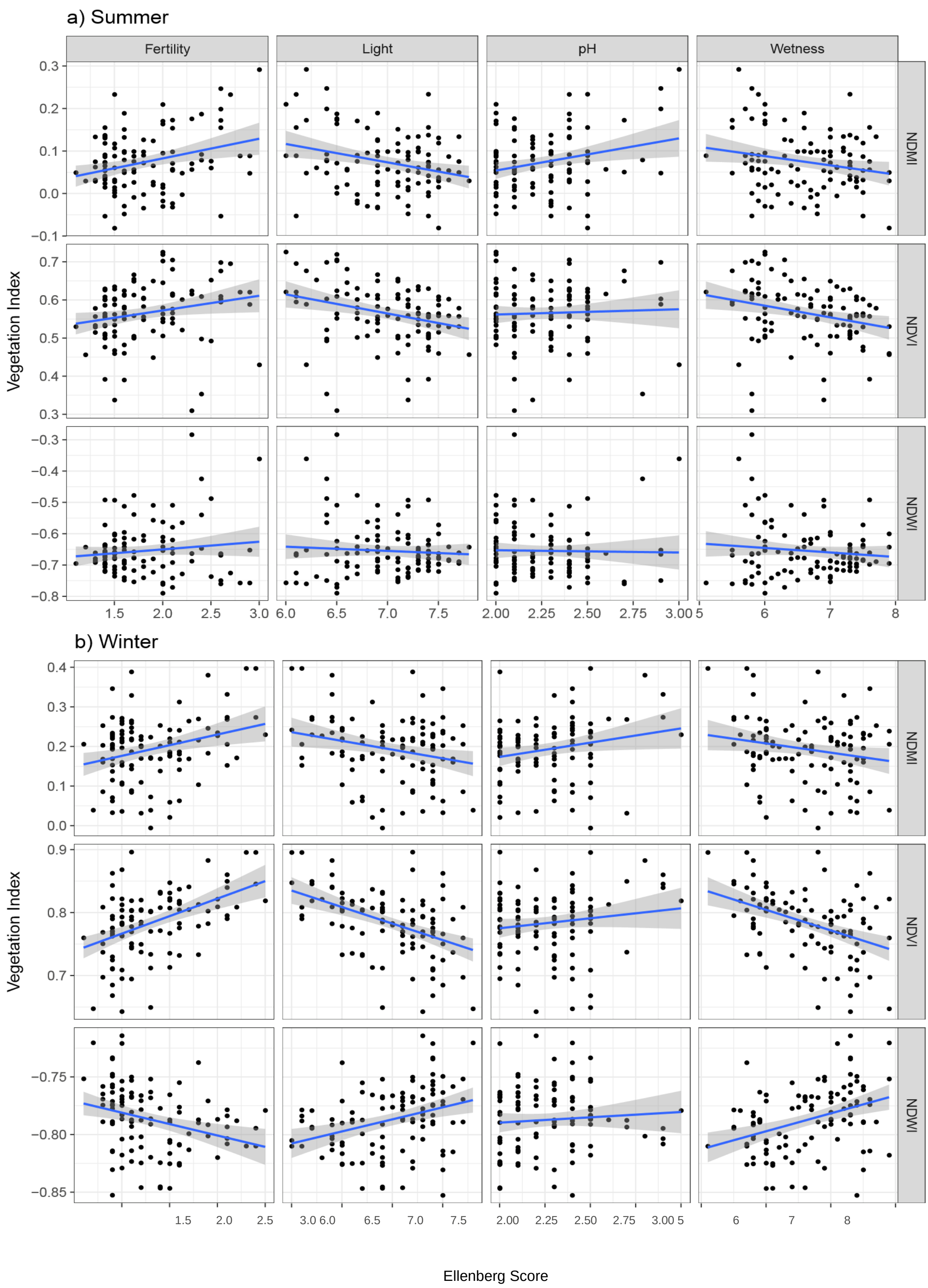


Figure 9: Scatter plots of seasonal vegetation indices against Ellenberg indicators

Using machine learning to model Ellenberg indicators

Given the weak relationship between any individual VI and the EI, a selection of machine learning methods were used to test in the EI could be predicted from all of the Sentinel-2 bands. The models chosen were: cubist, boosted regression trees (GBM), and random forests (RF). Models were assessed using 15 repeats of 5-fold cross validation.

A comparison of model accuracy from three different machine learning methods is shown in Figure 10. Models were trained using all Sentinel-2 bands and VI from both the summer and winter images. The techniques had similar performance, however, the cubist models showed the best overall accuracy with the lowest error and highest R^2, although there was some variability in success. Cubist models were particularly effective at avoiding the very low values returned by the other methods. The one exception to this was pH, which featured low accuracy from all methods. Accordingly for the next analysis steps, only cubist models were used.

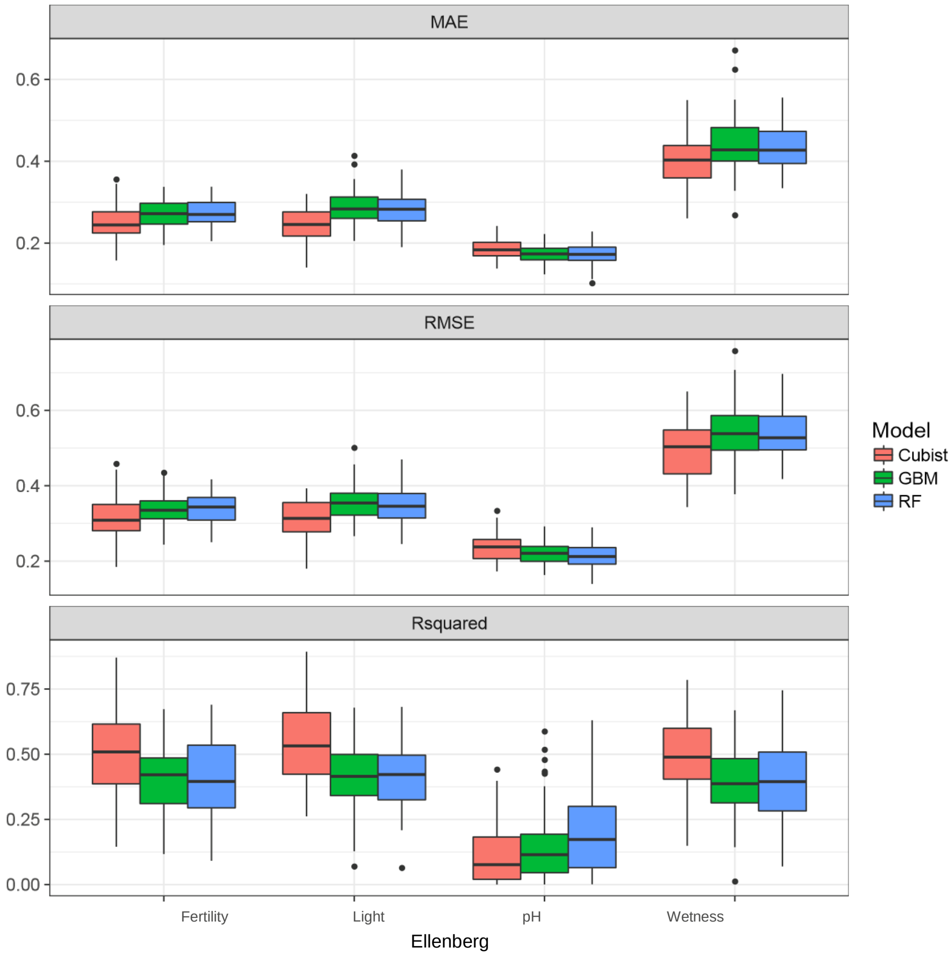


Figure 10: Comparison of three machine learning methods for predicting Ellenberg indicators. Values are from 15 repeats of 5-fold cross validations. RF - Random Forest, GBM - Boosted Regression Tree.

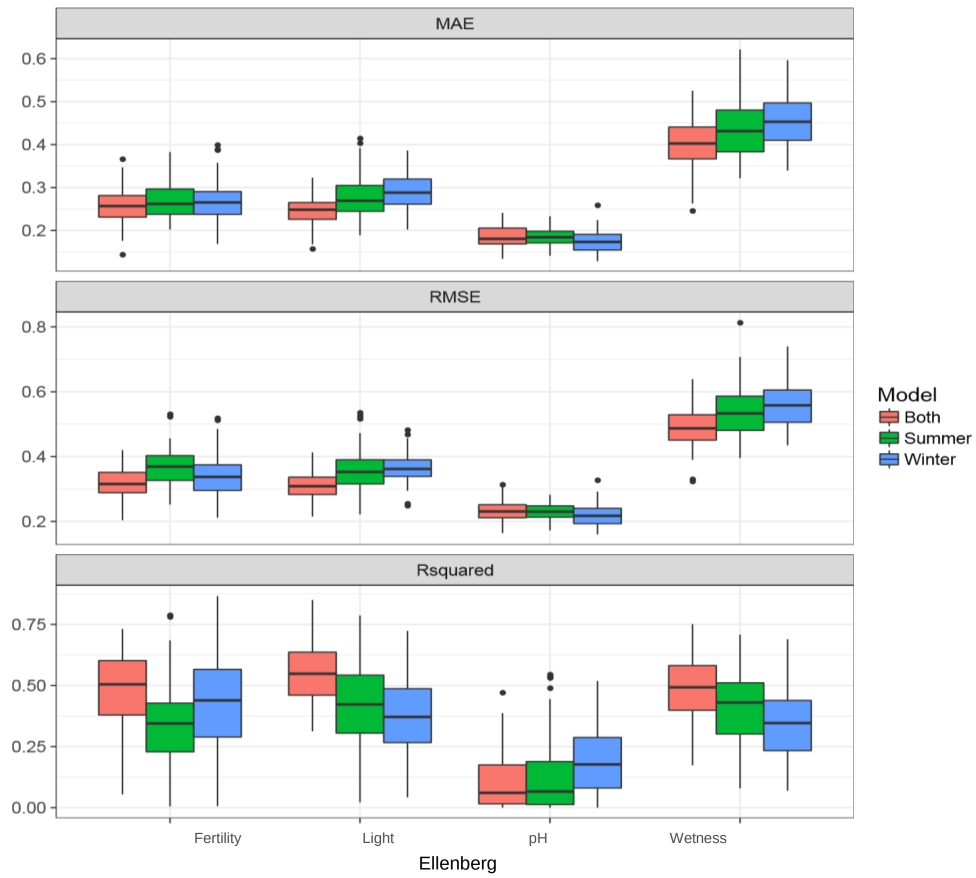


Figure 11: Comparison of using single or multi-seasonal data on Ellenberg prediction accuracies. Values are from 15 repeats of 5-fold cross validations.

To test the influence of season on model accuracy, models were trained using i) winter, ii) summer, and iii) both (bi-seasonal) data. The cross validation accuracies are shown in Figure 11, and overall statistics given in Table 3. In general, the use of multi-seasonal data was most effective, achieving the highest accuracies for three out of four indicators (light, wetness, and fertility). Light was the only variable for which another season, winter, performed better. After multi-seasonal data, summer imagery was 2nd best for light and wetness, with winter being second for fertility.

Heat scatters of predicted and observed EIV, based on the multi-seasonal cubist models, are shown in Figure 12. The most accurately modelled EIV was light, this is not surprising as optical remote sensing is based on light reflectance. The least accurate model was for pH, this is also understandable, as pH is unlikely to result in major spectral variation, in addition to the low range of values present; the habitat is acidic throughout. Whereas the models are moderately accurate, with R^2 of 0.11-0.55, this needs to be considered with the high variation to be expected of ecological data. Factors such as: quadrat placement, surveyor experience, and time of year, are all associated with errors in exceedance of the modelled uncertainty. Furthermore, the Sentinel imagery is also affected by factors such as geolocation errors, atmospheric compositions, and directional artefacts (i.e. bidirectional reflectance distribution functions). It must also be cautioned that the 2 m quadrats may not be representative of the 10-20 m Sentinel resolution. Mapped predictions based on these models are shown in Figure 13.

Table 2: Model accuracy metrics for the EI predictions, using cubist models

Season	**Ellenberg**	**R^2**	**RMSE**	**MAE**
Both seasons	pH	0.11	0.23	0.18
	Light	0.55	0.31	0.24
	Fertility	0.48	0.32	0.26
	Wetness	0.49	0.49	0.40
Winter	pH	0.19	0.22	0.17
	Light	0.38	0.36	0.29
	Fertility	0.43	0.34	0.27
	Wetness	0.35	0.56	0.45
Summer	pH	0.13	0.23	0.18
	Light	0.42	0.36	0.28
	Fertility	0.35	0.37	0.27
	Wetness	0.41	0.54	0.43

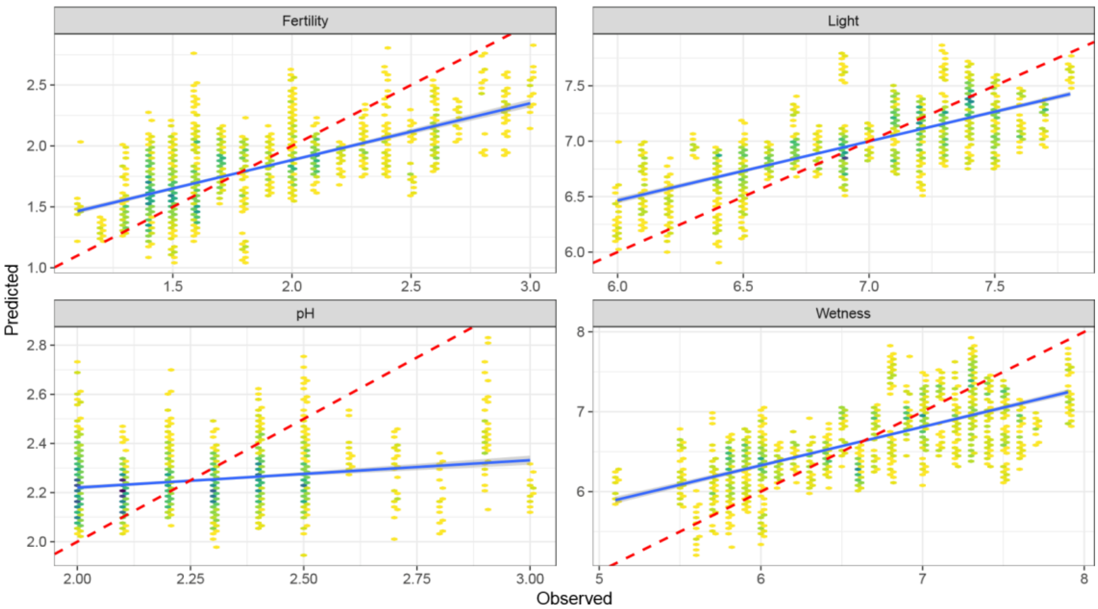
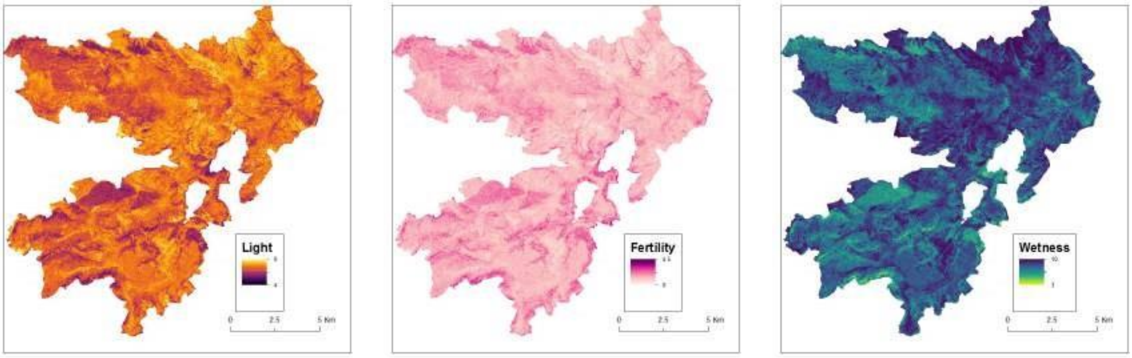


Figure 12: Heat scatter of predicted v observed values



(a) L ight (b) Fertility (c) Wetness

Figure 13: Mapping of modelled Ellenberg values

In summary, machine learning methods have been shown to be moderately effective at predicting some Ellenberg indicators. Cubist models were the preferred modelling technique, and multi-seasonal imagery generally out-performed single season data. Whereas light, wetness, and fertility were reasonably accurately modelled, pH was associated with a high degree of uncertainly potentially due to the low range of values at the site. There appears potential to use EO derived Ellenberg indicators to monitor long-term changes in wetness and bog condition based on vegetation, however, community responses tend to lag behind environmental changes on the ground.

4.4 Habitat and NVC Mapping

The species count quadrats were analysed in the MAVIS software to generate NVC codes. For each plot, MAVIS returns the top 10 matching communities and an accompanying score of percentage agreement. This data is problematic for generating land cover classifications for a number of reasons. Firstly, as shown in Figure 17, the only codes for which there are sufficient values to train a classifier are M19a and H12a, resulting in a binary mire-heath model. Secondly, if all MAVIS NVC codes are considered (Figure 18) the situation is not much improved. Whereas a considerable variety of NVC codes are now represented, M19a and H12a are still by far the most prevalent, similar communities (H12, M19, M19b) are also heavily represented (all in the top 7). Furthermore, these common classes represent a disproportionate number of the top ranked codes.

When classifiers are presented with data dominated by one class or a number of proportionally over represented classes, they tend to perform poorly. This occurs as the classier "feature-space" cannot find a niche for the smaller classes. One potential solution to this can be the use of weights, which assign a greater emphasis to certain data points allowing them to develop an aperture. However, in this situation a weighting variable (derived from the MAVIS score) would simply exaggerate the common classes due to their higher ranking.

Considering these issues, a number of classification schemes were developed to investigate the potential of using MAVIS-NVC data in land cover habitat classification:

1. A binary H12-M19 model
2. A model containing all codes with over 20 occurrences, simplified into seven classes
3. The model used in two modified by additional synthetic samples

To generate the binary classification, all top-ranked (MAVIS plot ranking 1) H12 and M19, and their subclasses, were used (n = 80). These were input into a Gradient Boosted Tree classier, and validated by fifteen repeats of 10-fold CV. Figure 15.a shows the mapped classes, whilst Figure 15.b shows the probability of class occurrence. The overall accuracy of this model was 70%; future ground truthing will test the usefulness of this approach.

Comparing the vegetation indices of the H12 and M19 plots is illustrative of the classification issues. As shown in Figures 14a and b, the M19 class does occupy a clear niche in the data. However, this is contained within the more broad heath category. This makes separating the two classes more challenging than if they were distinct. When additional subclasses are considered, these broad categories are smaller apertures, further hampered by the smaller sample size of rarer classes.

For the seven-class model, all records with an NVC code that occurred over 20 times were selected. This results in the duplications of predictor variables (i.e. the Sentinel2 values), as plots may contribute multiple NVC codes. This duplication will likely result in a low accuracy; however, it is hoped that the models will be able to develop appropriate predictions by reducing the variance. The data were then classified using a Gradient Boosted classification tree, and CV used for accuracy assessment. This produced an overall accuracy of 25%, the results of this classification are shown in Figure 16. As a further step, the data were modified using the Synthetic Minority Over-sampling Technique (SMOTE), this is a method to generate *synthetic* samples of underrepresented classes, by placing additional points along vectors between real points. Using SMOTE altered data increased the model accuracy to 44%. However, the mapped output was identical to the original model.

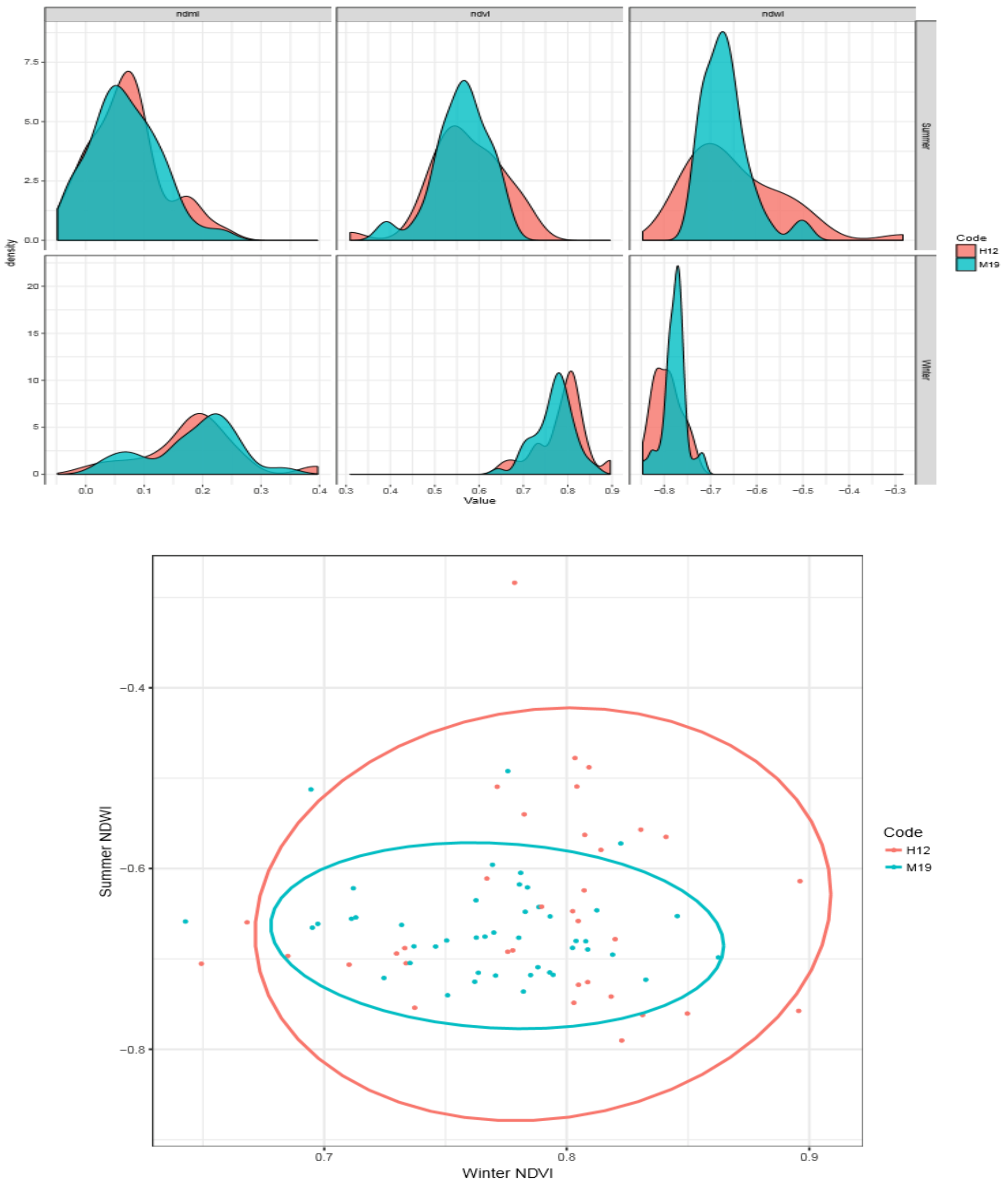
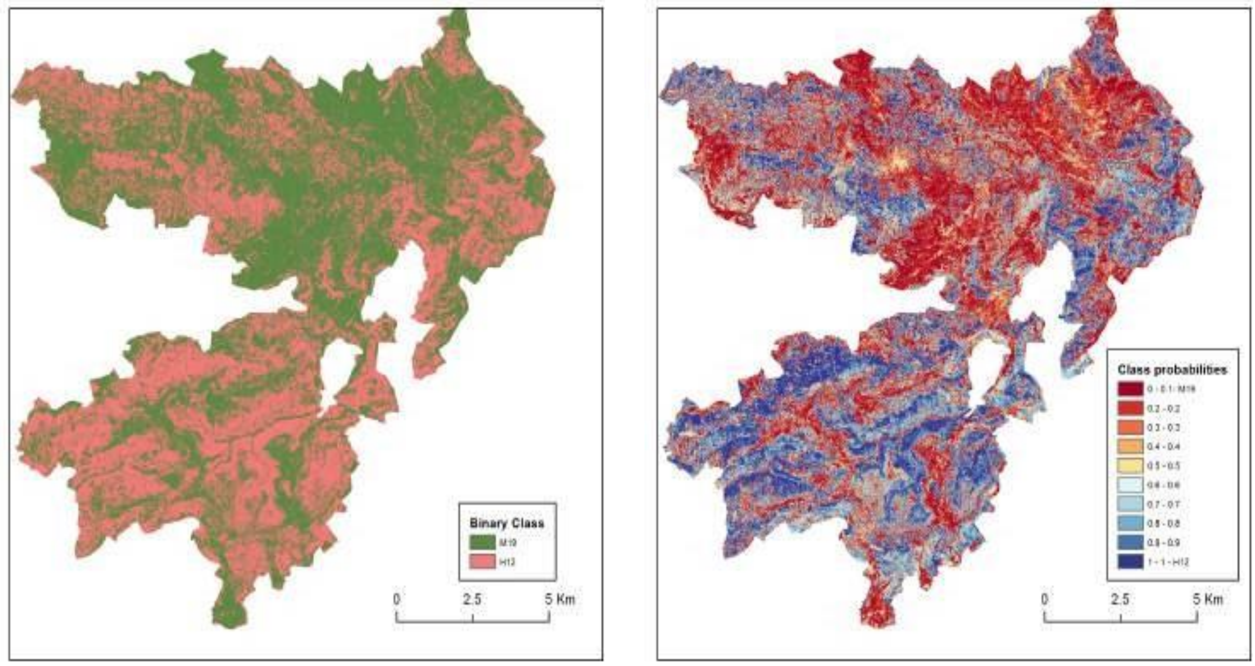


Figure 14: a) Comparison of the frequency distributions of H12 and M19 classes for the vegetation indices, and b) the relative distribution of H12 and M19 for the vegetation indices, with 95% ellipses.

Generating a reliable accuracy score for the mapped predictions is difficult, as except for the binary models there is no "true" value against which to compare. However, the models return generally similar predictions, with disagreements in the more minor classes, indicating good performance. The binary model is effective and archives a good accuracy, this approach is good at highlighting transitional areas mapped by the class probabilities. Further work on manipulating the class probabilities into proportional cover estimates may be possible. The effect of using the SMOTE is interesting, as the accuracy increases but predictions remained constant. This indicates the model is performing adequately, as additional points are well classified by the existing definitions.



(a) Classification (b) Class probabilities

Figure 15: Binary model outputs and probability scores for a heathland-mire classification

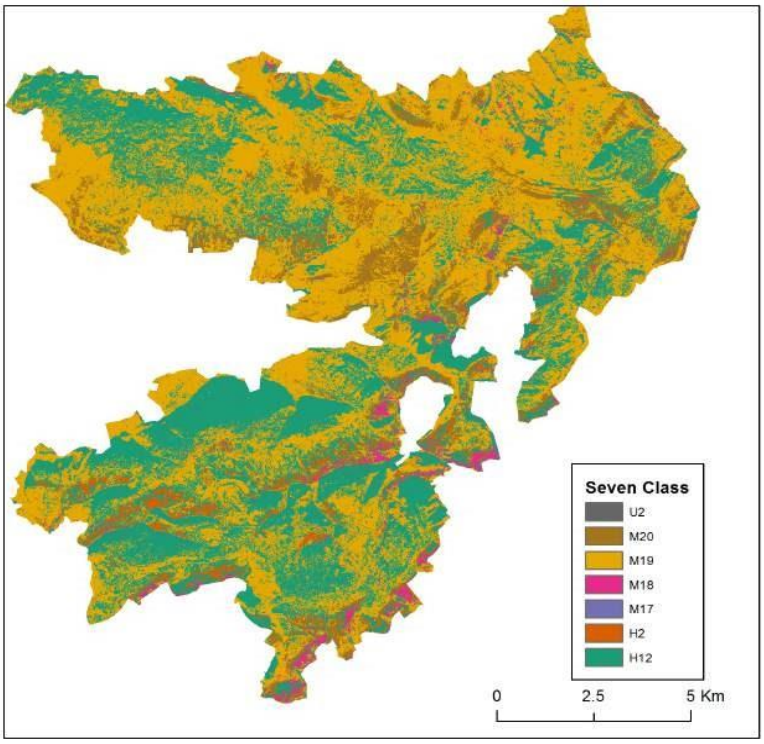


Figure 16: Classification of seven NVC codes

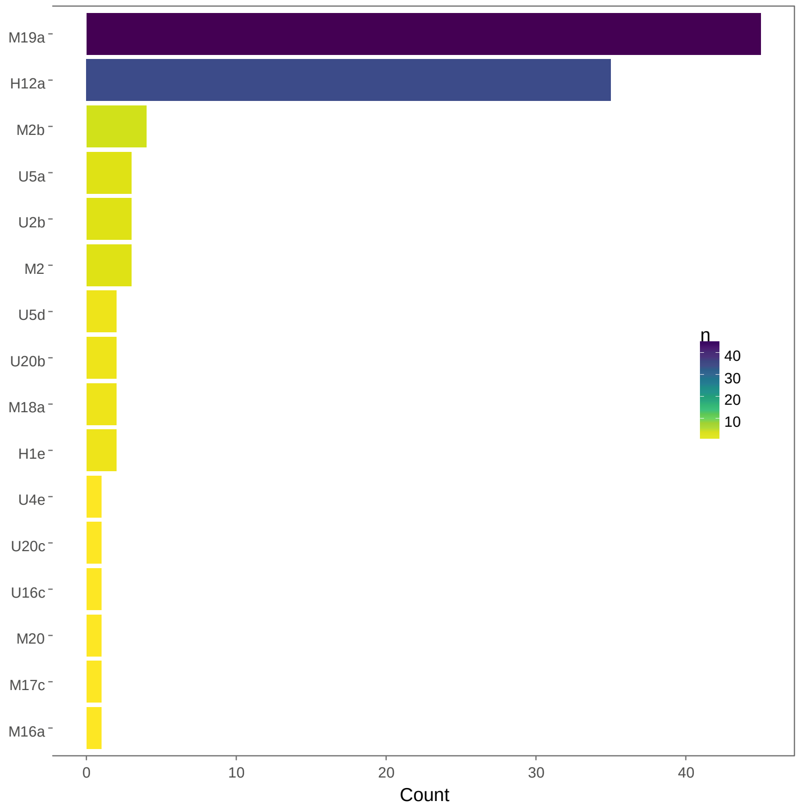


Figure 17: Histogram of the top MAVIS NVC code

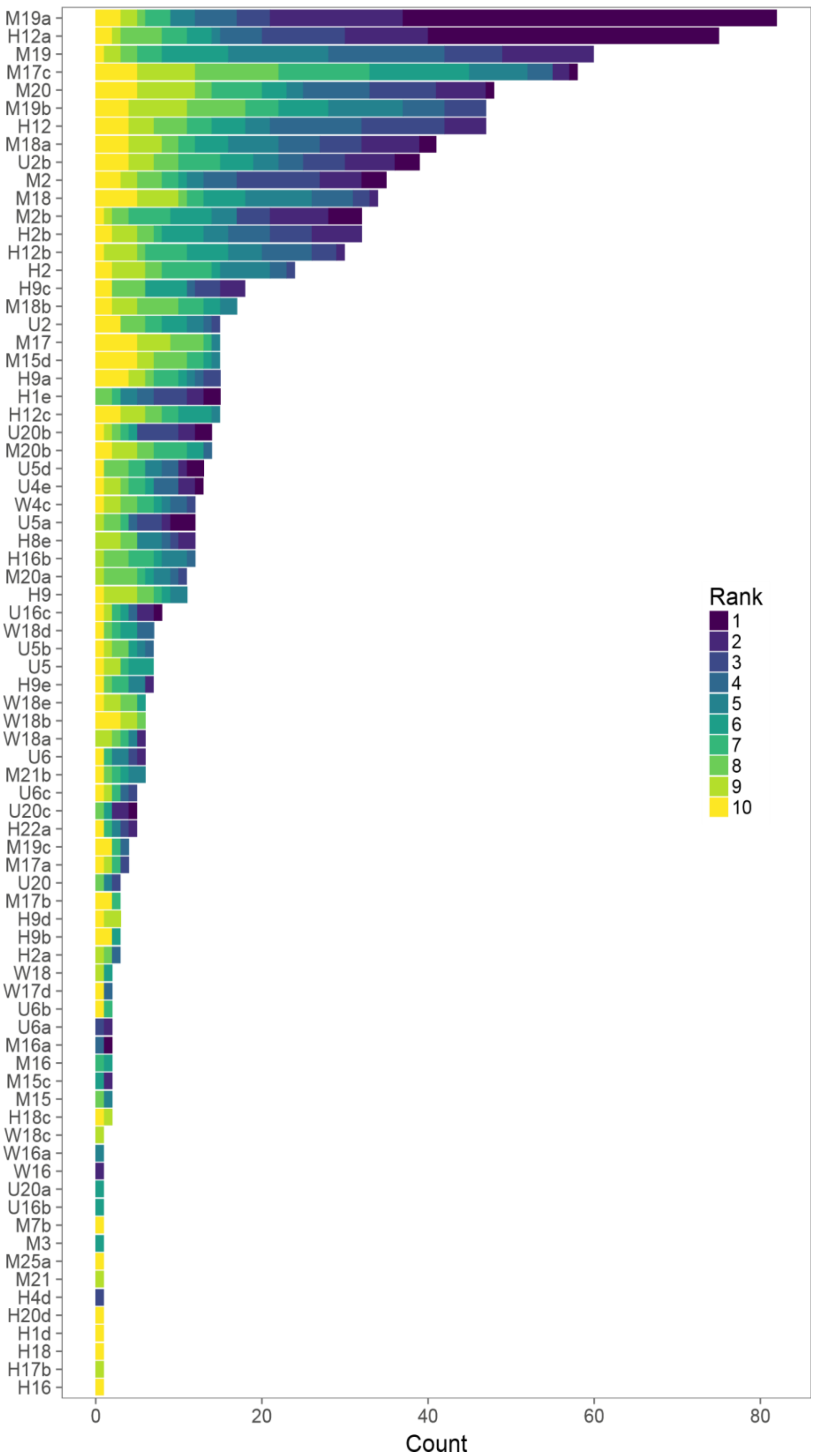
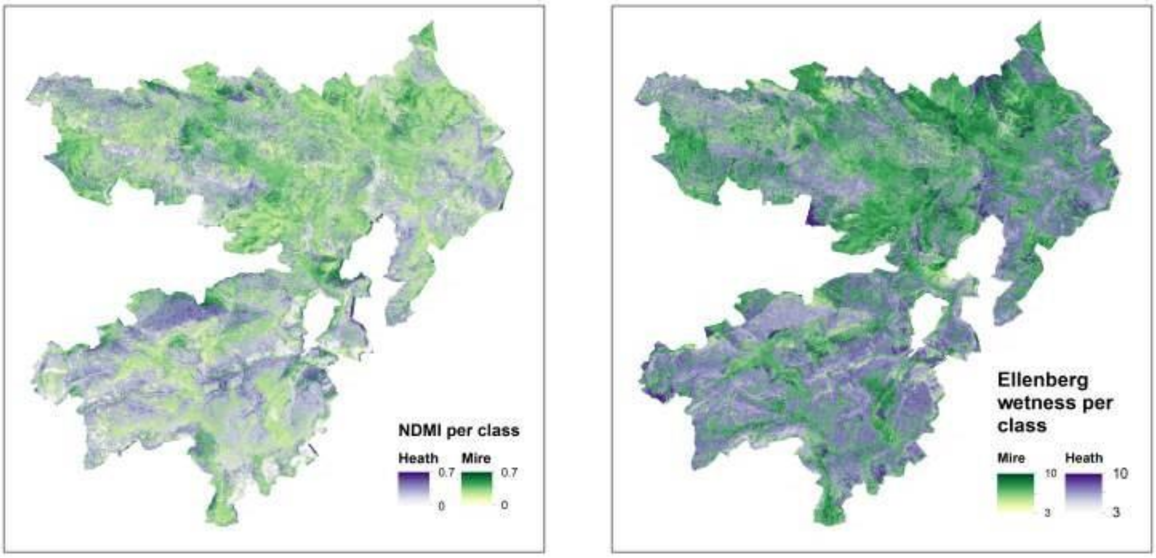


Figure 18: Histogram of MAVIS NVC codes using all MAVIS outputs – a 'Fingerprint' of the frequency of different NVC classes obtained from MAVIS from site data.

4.5 Combining NVC maps with wetness indicators for habitat assessment

Having generated maps of the vegetation communities and a number of wetness variables, it is now possible to combine these layers into a wetness index. The aims of this index is to highlight areas of habitats that can be inferred as being in good condition, or where intervention measures may be beneficial. As the study area can be broadly divided into heath and mire categories, the binary habitat map was selected. For each of the classes in this layer the NDMI and wetness Ellenberg indicator maps were segmented and the value mapped to independent colours (Figure 19).



(a) NDMI (b) Ellenberg wetness

Figure 19: Combined wetness index using a) the NDMI, and b) the modelled Ellenberg wetness layer

5 Ainsdale Sand Dunes

1. Two Sentinel-2 images were downloaded, one for summer (17th July 2017) and one from winter (1st December 2017). Both images were atmospherically corrected using Dark Object Subtraction (DOS) in QGIS, no topographic correction was applied. Both images were cloud free for the study area so no masking was required. Vegetation indices

As with the Forest of Bowland, three vegetation indices were generated from both the summer and winter images (Figure 20):

2. Normalised Difference Vegetation Index (NDVI), a proxy of *greenness* or photosynthetic activity
3. Normalised Difference Moisture Index (NDMI), a proxy for *vegetation* water content or the spongy mesophyll structure within the canopy
4. Normalised Difference Water Index (NDWI), an indicator of *surface* water coverage

These indices were chosen as they are commonly used, have a long history in the scientific literature, and are relatively simple to explain.

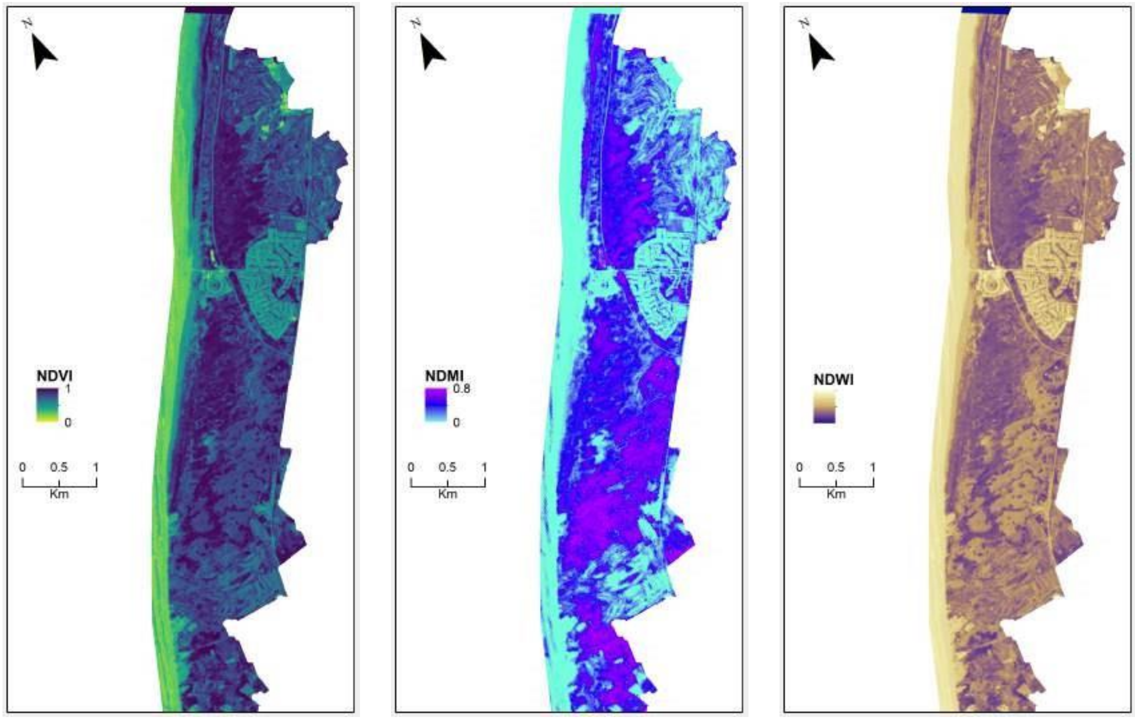
5.1 Ellenberg Indicators

Relationship between Ellenberg indicators and vegetation indices

Linear regression models between the EI and VI are shown in Figure 21 and Table 4. The relationships show generally good directions with clear trends visible for a number of features. However, there is a large scatter for all models, and the associated uncertainty is high. Of the candidate indicators light and wetness were modelled with a reasonable degree of accuracy by the VI, with errors below 1 and the R^2 being around 0.28-0.31. However, the spread of prediction makes using this relationship for mapping predicted values imprudent.

Using machine learning to model Ellenberg indicators

A series of machine learning models were used to test the ability of Sentinel-2 imagery to model the Ellenberg indicators. A comparison of three common techniques, using both images is shown in Figure 22.



(a) NDV I (b) NDMI (c) NDWI

Figure 20: Candidate vegetation indices from summer 2017 at Ainsdale

These models all returned similar accuracies, based on cross validation, with only minor differences between them. Overall, the Random Forest was least accurate for three indicators (wetness, pH, fertility). Between the boosted regression and Cubist models, there was negligible differences; therefore, for further analysis we opted to use the Cubist approach as this was comparable for the Forest of Bowland.

A comparison of the seasonal models showed minor differences (Table 5 and Figure 23). The overall distribution of errors was similar between the different seasonal combinations, with a difference in RMSE of 0.05. However, based on the final R^2, multi-seasonal imagery preformed best for light, fertility and wetness (Table 5). The pH indicator was best predicted by the winter image; however, this was still a very low accuracy relative to the other indicators. The accuracies obtained by light, fertility and wetness are reasonable, with errors less than 0.5 scores. This accuracy is within the range of other error sources (surveyor experience, time of year etc.) when surveying is done manually. Maps of these indicators are shown in Figure 25.

Sand dunes are a highly heterogeneous environment. It is therefore reasonable to assume that the use of 20 m imagery may compromise the models. To test this, we compared models using only the 10 m Sentinel-2 bands (red, green, blue, near-infrared) against models using all bands. There were only minor differences between the model accuracies (Figure 24). However, the 10 m only models did show less variability relative to the all bands. This can be seen in the outlier points in the RMSE scores, which have a greater range in all bands than the 10 m.

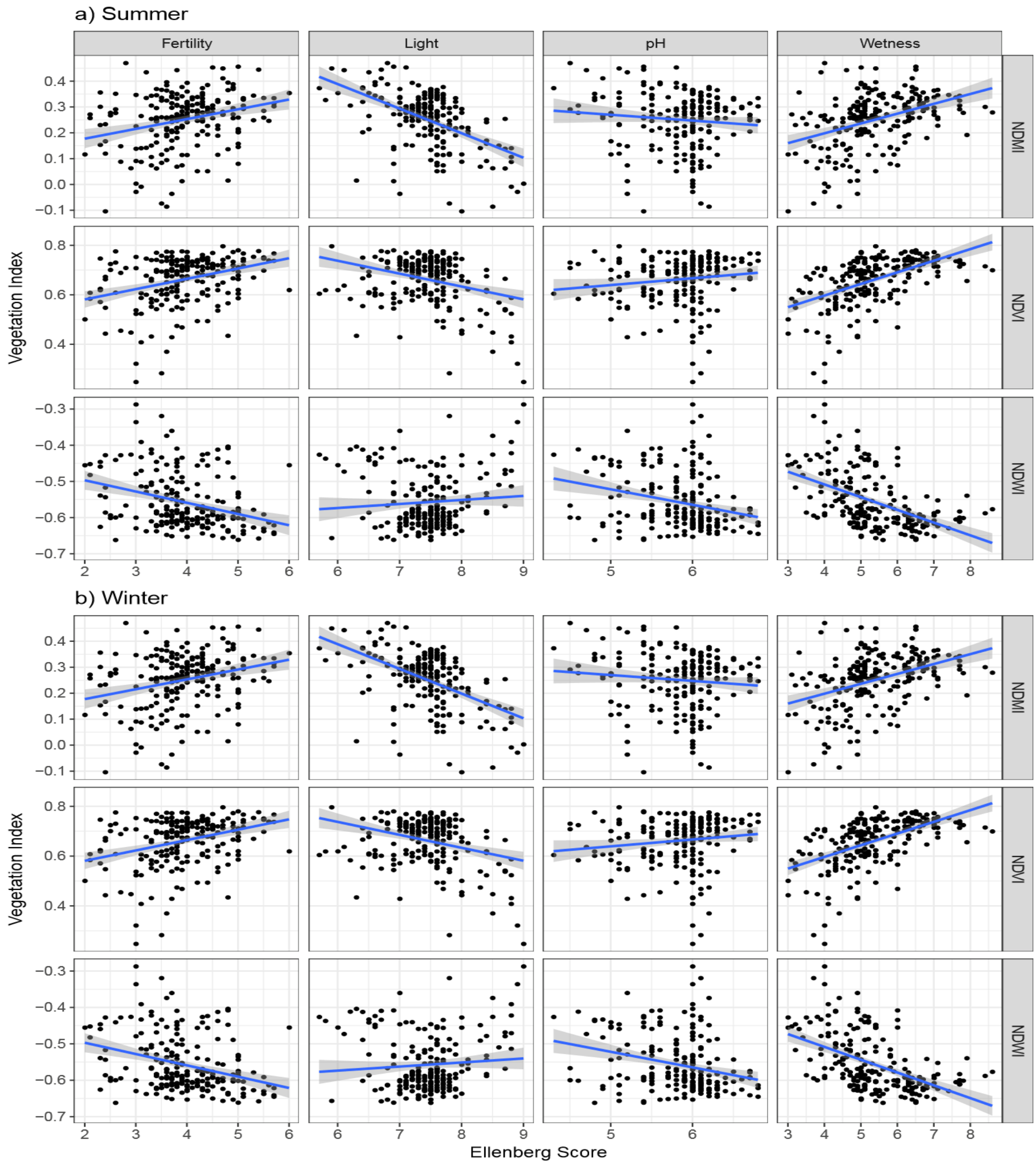


Figure 21: Linear relationships between Ellenberg indicators and vegetation indices at Ainsdale

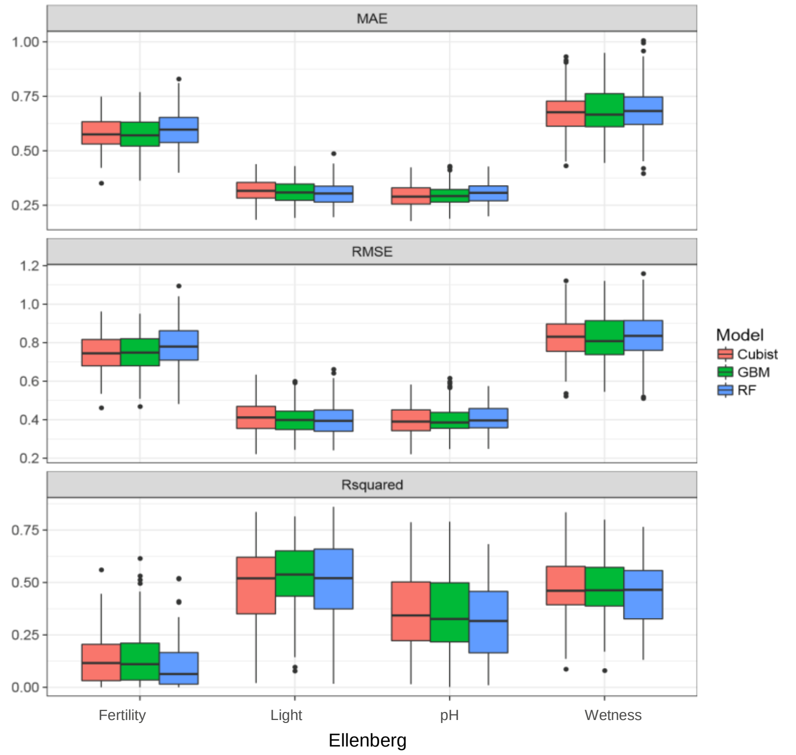


Figure 22: Comparison of Machine learning models for predicting Ellenberg indicators at Ainsdale

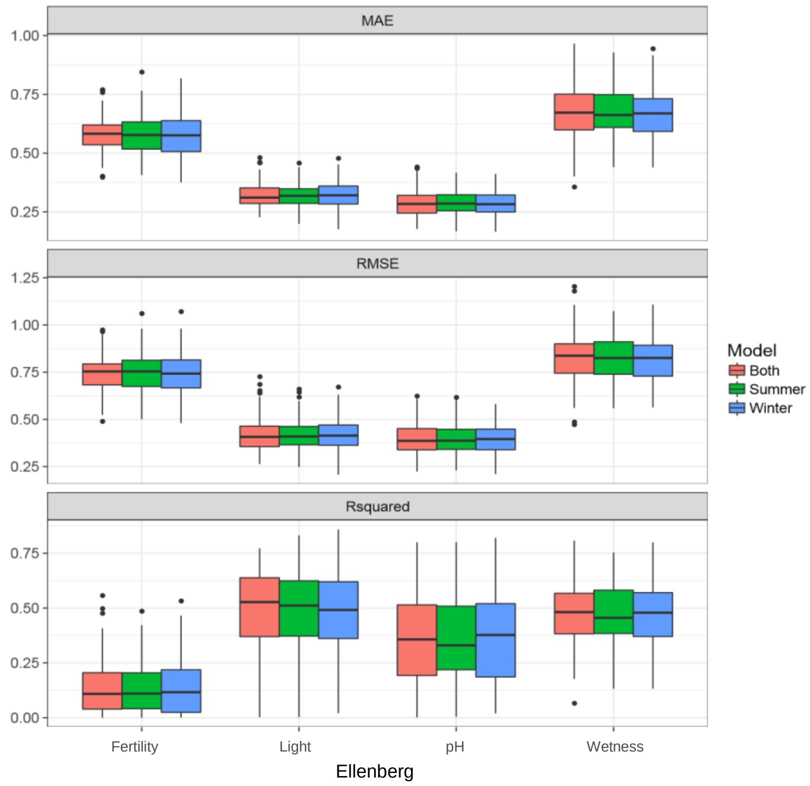


Figure 23: Comparison of seasonal models for predicting Ellenberg indicators at Ainsdale

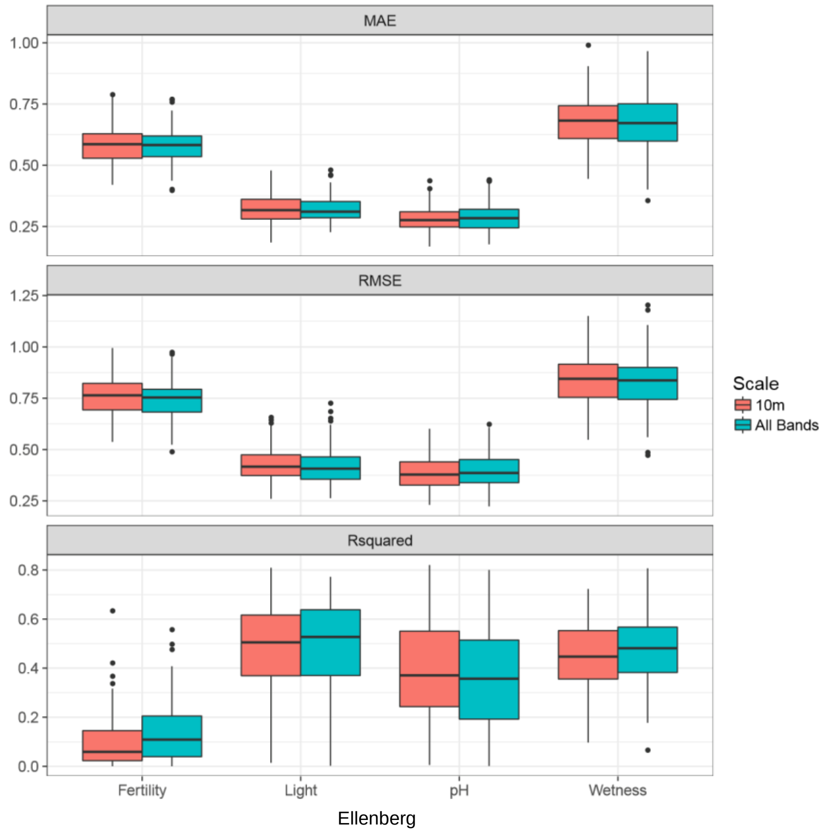
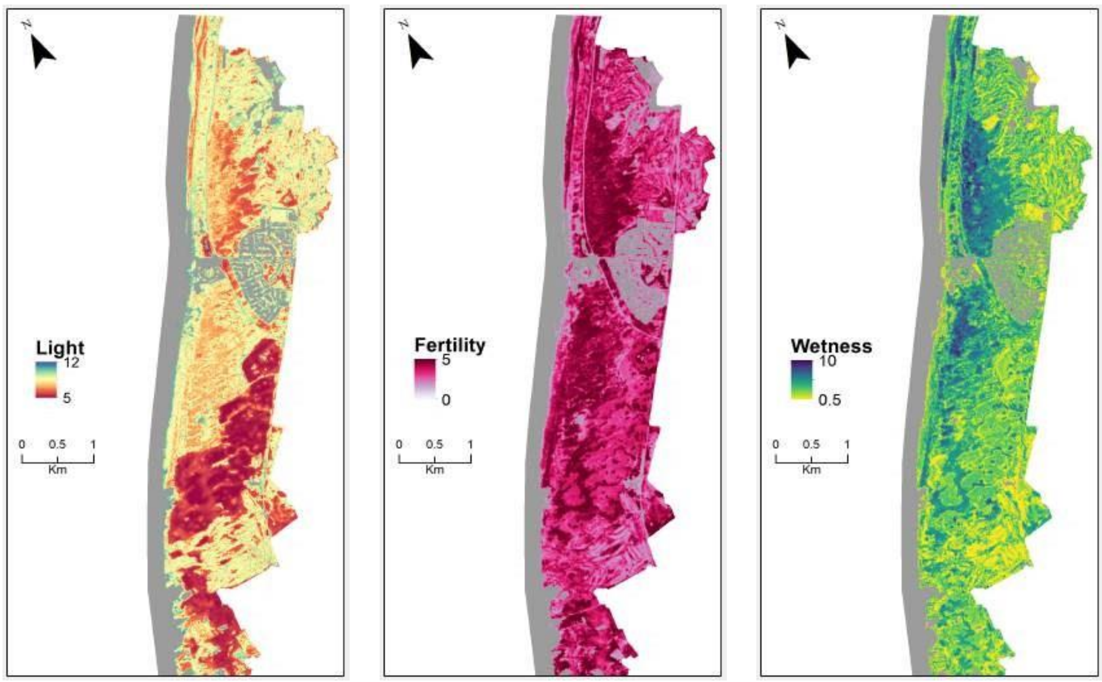


Figure 24: Comparison of models trained with 10 m and all Sentinel-2 bands



(a) Light (b) Fertility (c) Wetness

Figure 25: Mapping of modelled Ellenberg values for Ainsdale dunes. Areas with an NDVI less than 0.35 are masked to remove bare sand and impervious surfaces.

Table 4: Accuracy metrics for predicting Ellenberg indicators using only a single vegetation index.

Season	VI	Ellenberg	R2	RMSE	Season	VI	Ellenberg	R2	RMSE
Summer	NDMI	pH	0.03	0.48	Winter	NDMI	pH	0.03	0.48
	NDMI	Light	0.28	0.49		NDMI	Light	0.28	0.49
	NDMI	Wetness	0.18	1.02		NDMI	Wetness	0.18	1.02
	NDMI	Fertility	0.09	0.75		NDMI	Fertility	0.09	0.75
	NDVI	pH	0.04	0.48		NDVI	pH	0.04	0.48
	NDVI	Light	0.11	0.54		NDVI	Light	0.12	0.55
	NDVI	Wetness	0.30	0.94		NDVI	Wetness	0.31	0.94
	NDVI	Fertility	0.13	0.74		NDVI	Fertility	0.13	0.74
	NDWI	pH	0.10	0.47		NDWI	pH	0.09	0.47
	NDWI	Light	0.04	0.57		NDWI	Light	0.04	0.57
	NDWI	Wetness	0.28	0.96		NDWI	Wetness	0.27	0.95
	NDWI	Fertility	0.12	0.74		NDWI	Fertility	0.12	0.74

Table 5: Model accuracy metrics for the EI predictions, using cubist models.

Season	Ellenberg	R^2	RMSE	MAE
Both	pH	0.36	0.40	0.29
	Light	0.49	0.42	0.32
	Fertility	0.14	0.75	0.58
	Wetness	0.47	0.83	0.68
Winter	pH	0.37	0.40	0.29
	Light	0.48	0.42	0.32
	Fertility	0.14	0.74	0.58
	Wetness	0.47	0.82	0.67
Summer	pH	0.36	0.40	0.29
	Light	0.48	0.42	0.32
	Fertility	0.13	0.74	0.58
	Wetness	0.47	0.83	0.67

5.2 NVC mapping

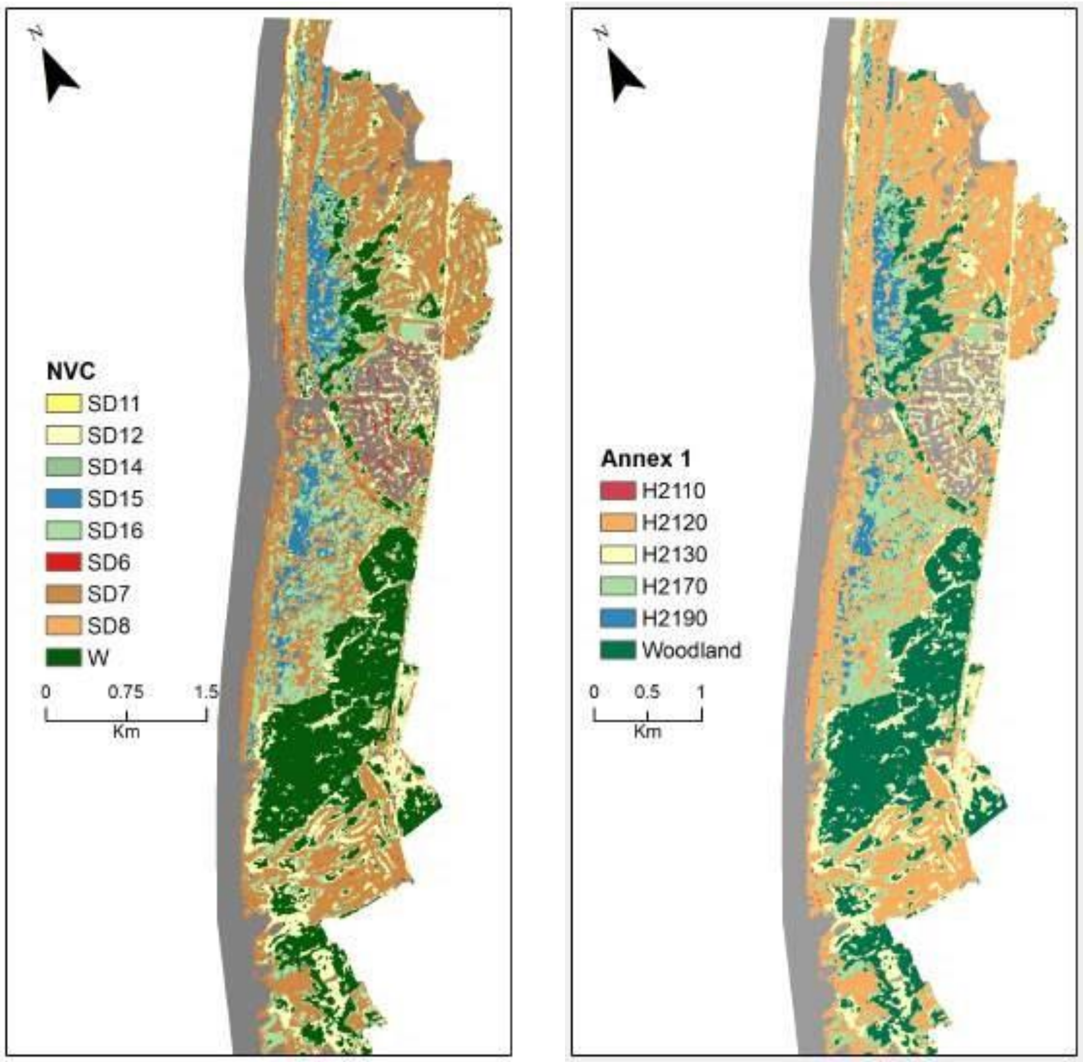
The survey datasets were classified into NVC codes using the MAVIS software. The outputs codes were simplified into the base classes (e.g. SD12a to SD12) and classes known not to be present (e.g. heath) were removed. As a further step, the NVC codes were aggregated into Annex 1 classes. Predictive Gradient Boosted classification models were developed and validated using 10 repeats of 10-fold cross validation.

Maps of the resulting classifications are shown in Figure 26. For the NVC model, the accuracy was 44%. This accuracy then increases to 53% after aggregation to Annex 1 level. In both classifications the accuracies were closely related to sample size (Table 6), with rarer classes being poorly predicted - if not missed completely. This highlights a key issue with the use of random quadrat sampling to generate classification models. If sufficient samples are not obtained from habitats of less spatial area, they are unlikely to be reliably mapped. A comparison with maps produced from an ecological survey (Appendix 4) revealed a good broad agreement in habitat mapping. The areas of humid dune slacks were well defined as were dunes with *Salix repens*, however, fixed dunes were often classified as shifting dunes along the shoreline and embryonic shifting dunes were over predicted. Further data collection in under-represented habitats should improve the model further.

Given the small sample size relative to the number of classes (n = 195, p = 10/6) and the highly heterogeneous nature of sand dunes, accuracy in the 40-50% range should be considered realistic. A stratified sampling strategy would likely increase the performance of the smaller classes. However, the high heterogeneity of sand dunes may make non-categorical models a plausible option.

Table 6: Accuracy of Sentinel-2 classifications for Annex 1 and NVC Habitat classifications. H2110: Embryonic shifting dunes; H2120: Shifting dunes along the shoreline; H2130: Fixed dunes with herbaceous vegetation; H2170: Dunes with Salix repens; H2190: Humid dune Slacks. See Appendix 1 for further explanation of Annex 1 and NVC codes.

	Producer's	**User's**
H2110	0.00	0.00
H2120	0.55	0.48
H2130	0.30	0.49
H2170	0.60	0.51
H2190	0.56	0.66
Woodland	0.74	0.64
Overall Accuracy (Annex 1)	0.53	
SD10	0.00	0.00
SD11	0.00	0.00
SD12	0.31	0.42
SD14	0.12	0.17
SD15	0.63	0.57
SD16	0.42	0.35
SD6	0.00	0.00
SD7	0.59	0.45
SD8	0.02	0.14
Woodland	0.77	0.67
Overall Accuracy (NVC)	0.44	



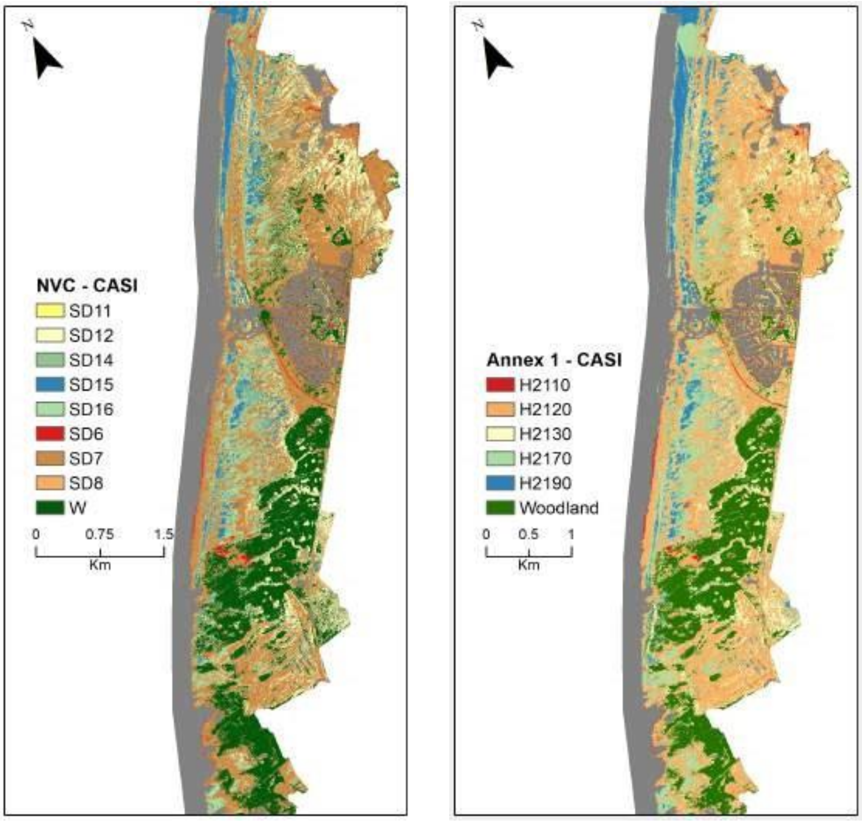
(a) NVC (b) Annex 1

Figure 26: Mapping of the modelled classes for Ainsdale dunes, a) NVC classes, b) Annex 1 classes. H2110: Embryonic shifting dunes; H2120: Shifting dunes along the shoreline; H2130: Fixed dunes with herbaceous vegetation; H2170: Dunes with Salix repens; H2190: Humid dune Slacks. Areas with an NDVI less than 0.35 are masked to remove bare sand and impervious surfaces. Only sand dune habitats have been mapped, so areas beyond the dune system should be discounted. See Appendix 1 for further explanation of Annex 1 and NVC codes and Appendix 4 for comparison with maps from ecological survey.

5.3 CASI and LiDAR Fusion

The Sefton Coast was imaged by a CASI hyperspectral scanner in August 2015. This instrument collects 1 m resolution imagery across 24 spectral channels. Furthermore, Environment Agency LiDAR data is available, this was processed to generate a Canopy Height Model (CHM) and Digital Surface Model (DSM). These data were then combined with the CASI image and used as predictors of the NVC/Annex 1 data and Ellenberg indicators

The accuracies of the high-resolution models are comparable to those using the Sentinel data. Similarly, classes with a low sample size were poorly classified. The Sentinel-2 and CASI classifications show similar overall patters. The key difference is in areas to the north, where the Sentinel-2 models predict more woodland. This area is dominated with low shrubs and trees and is therefore closer to woodland than dune system. The better performance of Sentinel data in this area is probably due to the multi-seasonal data allowing easier discrimination of the woodland, which may be subtle in the summer months.



(a) NVC (b) Annex 1

Figure 27: Mapping of the modelled classes for Ainsdale dunes, a) NVC classes, b) Annex 1 classes using CASI hyper-spectral and LiDAR. Areas with an NDVI less than 0.35 are masked to remove bare sand and impervious surfaces. Only sand dune habitats have been mapped, so areas beyond the dune system should be discounted. H2110: Embryonic shifting dunes; H2120: Shifting dunes along the shoreline; H2130: Fixed dunes with herbaceous vegetation; H2170: Dunes with Salix repens; H2190: Humid dune Slacks. See Appendix 1 for further explanation of Annex 1 and NVC codes.

5.4 Field Validation

Independent field data collection was undertaken in June and July 2018 at Ainsdale Sand dunes. Validation quadrats were randomly chosen across the survey area with further quadrats located in habitat classes that were under-represented in the initial survey data and more difficult to model. These further quadrats are to be used in Phase 2 of the Project for further model development to improve accuracy, however, they were also incorporated into this validation exercise, therefore, the independent accuracy measures are likely to be somewhat punitive.

The overall accuracies based on the independent validation were 29% for CASI and 32% for the Sentinel-2 models, these scores are roughly 20% lower than the cross-validated scores but this is to be expected due to incorporation of quadrats in more difficult classes i.e. classes such as H2110 (Embryonic Shifting Dunes) occupy a small proportion of the habitat area and the original survey data.

For the Sentinel-2 predictions, there was a high degree of confusion between H2110 and H2120 (embryo dunes and shifting dunes along the shoreline, see Confusion Matrix in Table 7). This is understandable as the species composition of the classes is similar, with the main differentiation being the bare ground coverage, therefore the spectral signatures of the vegetation will be similar; embryo dunes were poorly presented in the training data. In general, shifting dunes were over predicted at the expense of other classes, as this class had the most training data (histogram in appendix) an over representation is somewhat expected. Dunes with *Salix Repens* (H2170) were well mapped, with a moderate degree of confusion with humid dune slacks (H2190), again these communities have a common, dominant species, in the form of *Salix repens*.

For the CASI predictions, dunes with *Salix Repens* (H2170) were over predicted at the expense of other communities (see Confusion Matrix in Table 8). There was also confusion between H2130 and H2120 (Shifting dunes and Fixed Dunes). Again, this issue is most likely due to similar species composition, with the differences between communities being determined by coverage and structure.

Sentinel-2 generally performed better than the CASI imagery in overall accuracy, with the exception of H2190 – humid dune slacks where CASI performed best.

Further data collection from these 'difficult' classes took pace during the validation exercise and can be incorporated into future iterations of the model to strengthen accuracy.

Table 7: Confusion matrix of field data (columns) compared to the Sentinel-2 Annex 1 predictions (rows)

		Reference				
		H2110	H2120	H2130	H2170	H2190
Prediction	H2110	0	0	0	0	0
	H2120	15	14	23	3	1
	H2130	0	0	3	0	0
	H2170	0	0	4	6	6
	H2190	0	0	0	1	1

Table 8: Confusion matrix of field data (columns) compared to the CASI Annex 1 predictions (rows)

		Reference				
		H2110	H2120	H2130	H2170	H2190
Prediction	H2110	0	7	0	0	0
	H2120	0	7	20	3	1
	H2130	0	0	6	1	0
	H2170	15	0	4	6	4
	H2190	0	0	0	0	3

Table 9: Balanced accuracy of Annex 1 classes for the two models based on independent field validation data

	H2110	H2120	H2130	H2170	H2190
Sentinel-2	0.50	0.67	0.56	0.72	0.55
CASI	0.44	0.56	0.59	0.63	0.69

6 Ecological and Environmental Summary

The overarching aim to this work was to assess the potential for Earth-observation to monitor the habitats and conditions of protected sites at the landscape scale. This could inform the protected sites monitoring reform project and how resilient landscapes are able to keep meeting the needs of people and nature in a changing world.

More specifically to:

1. Assess Earth-observation and Remote Sensing capability for accurately mapping habitat and potentially plant community condition and monitor change at the landscape scale.
2. Detect significant change in habitat & plant community spatial extent and their productivity over the long term across LTMN sites
3. Baseline habitat and plant community maps at the landscape scale used for modelling ecological connectivity and ecosystem functionality
4. Informing better understanding of the resilience of landscapes for species to adapt to Climate Change and identify the Natural Capital assets they provide, working towards the Conservation Strategy (C21).

To investigate this, a number of modelling scenarios were developed focussing on the prediction and mapping of Ellenberg indicator values and NVC/Annex 1 habitats. From the generated models, we draw a number of observations concerning their successes, weaknesses, limitations, and potential.

6.1 Habitat Mapping and Condition Assessment: Informing Protected Sites Monitoring Reform

The majority of models resulted in variable accuracies for all ecological criteria, using Sentinel-2 or CASI hyperspectral imagery, varying across habitat type. For habitat mapping, at Bowland a binary classification between the dominant habitats of heath and bog achieved a high accuracy of 70%, with a seven-class habitat model reducing this to 44%; at Ainsdale, NVC's achieved 44% accuracy, with aggregating to Annex 1 classes increasing this to 53%.

The accuracy of the models generated show potential- in some cases - for broad-scale assessment of habitat and condition. However, further model development is needed to more confidently assess change over time. Change monitoring over time would benefit from two developments. Firstly, for NVC mapping, overall accuracies of 70% should be achieved; which would allow a bi-temporal change accuracy of 50% (two maps at 70% results in a change map with accuracy of $0.7 * 0.7 = 0.49$). Secondly, for Ellenberg mapping, the consistency of models across different time periods should be analysed to test the potential robustness of mapped trends.

Table 9. Summary of application testing of remote sensing on example FCT Attributes

Attribute	Measure/ Site-specific targets	Comment
Habitat extent	Estimated extent (ha) e.g. No net loss of extent,	Possible with accuracy of underlying model. Could be studied at site, annex 1 or NVC level. **Ainsdale** (based on cross-validation) Annex 1 Habitat mapping 53% Accuracy NVC Mapping 44% Accuracy **Bowland** (based on cross-validation) Binary heath/bog model 70% accuracy Seven habitat classification 44% accuracy
Bare ground/litter	Record the cover of bare ground in period May-October using aerial photographs and structured walk (or transects). Sources and dates of new maps/surveys/photographs e.g. Bare ground or sand present, but no more than 10% total area.	Possible with accuracy of underlying model, see above.
Vegetation structure: sward height	Record sward height in period mid-May to late-July during structured walk (or transects) e.g. 30-70% of sward to comprise species-rich short turf, 2-10 cm tall.	Soft surface of sand dunes limited accuracy. Possible in heaths/bogs and other habitats if suitable LiDAR data available.
Vegetation structure: flowering/fruiting	Record a visual assessment of cover with modified DAFOR scale using structured walk e.g. Flowering and fruiting of dune grassland to at least frequent level.	Not tested. If suitable training data covering species in flower were available alongside timely imagery then this could be tested.
Vegetation: Functional Groups	Incl. forb/grass ratio but also bryophytes/shrub/sedge.	Limited accuracy as too much within group variation. Testing at Ainsdale produced the following accuracies, RMSE (Root Mean Square Error): Forbs (R^2=0.18, RMSE=19.5%) Graminoid (R^2=0.1, RMSE=25%)
Vegetation: typical species	Record the frequency of typical indicator species (below) in period May- July with modified DAFOR scale using structured walk (or transects).	The underlying data does not currently allow modelling of individual species but where they are dominant at a canopy level (e.g. *Salix repens*, *Calluna vulgaris*) then further training data (e.g. polygons of single species stands) could make this possible. Testing at Ainsdale on two key species produced the following accuracies: *Salix repens* (R^2=0.18, RMSE=21.5%) *Carex arenaria* (R^2=0.02, RMSE=13.8%)
Vegetation composition: negative indicator species	Record the frequency of negative indicator species in period May- October. % cover measured is cover of the entire feature e.g. the cover of negative indicator species no more than 5%.	
Vegetation: forb/grass ratio	The sward should contain >30% cover of forbs and <70% cover of grasses.	
Vegetation composition: cover of Salix repens	Cover of *Salix repens* not more than 33% across 90% of slacks.	
Vegetation composition: scrub/trees	% cover measured is cover of the entire feature e.g. Scrub/trees no more than occasional, or less than 5% cover over the whole SSSI	Tree cover can be measured, scrub layer not tested but assumed not possible.
Other negative indicators	Record visual assessment during site visit e.g. Tree invasion from adjacent plantations absent or rare	Tree invasion should be possible.

There appears to be potential to use EO to address some targets used in Favourable Condition Tables (FCT) Assessments (Table 9) and contribute to the reform of protected sites monitoring: habitat extent, bare ground, vegetation and tree cover should be possible using the current approaches. Prediction of cover of dominant species such as *Calluna vulgaris*, *Sphagnum* spp. or *Salix repens* is likely to be possible with improved model training if additional quadrat data were available covering areas dominant in those species. Canopy/sward height was not possible to accurately measure in the sand dunes due to the 'soft' nature of the surface, however, where LiDAR data is available, it should be achievable in other habitats.

The two case studies present contrasting issues for NVC mapping. At Bowland, there is a dominance of two broad-scale habitats, H12 and M19, which makes the mapping of rarer sub-communities difficult, as these classes cannot develop a feature-space niche. Conversely, at Ainsdale, a large number of habitats occur, resulting in small and often diverse training samples. This is unavoidable here due to the type of training data used. If this were not the case, it is likely that a sampling strategy stratified for the desired communities would improve results as would collection of data covering dominant species.

The use of MAVIS-generated NVC codes alone is not an ideal source of training data for predictive models. Expert surveyors are able to make informed judgements about habitat classification using the context (e.g. nearby species, topographic setting) of a plot, and further insight can be gained by identifying the presence of invasive or atypical species that are not relevant for the classifications at a location. This issue is typified by the presence of Open habitats at Ainsdale. Further inspection noted that these areas were likely miss-classified due to the presence of Rosebay willow herb, leading MAVIS to default towards Open habitat instead of the underlying sand dune community. It is therefore recommended that future surveys note the likely NVC when surveying and this be compared to MAVIS generated codes from the data.

6.2 Monitoring Environmental Change

A key focus of the Long Term Monitoring Network is to understand broad ecosystem responses to environmental change, such as air pollution and climate change, and at a site level, it is also important to monitor the site condition and the success on management intervention on condition, for example, rewetting of a bog.

For the Ellenberg indicator values, models resulted in R^2s of between 0.11 and 0.55, the lower scores occurred for EIVs which showed a more limited range such as pH (EIV R) at Bowland and fertility (EIV N) at Ainsdale. Whereas each site had different successes for different indicators, there were some commonalities. As highlighted, results were poor when there was a low range of values present, conversely, accuracies were improved in cases where there is an ecological explanation for variation in the index; for both sites, light (EIV L) was accurately mapped which is indicative of community light demand being connected to surface reflectance. Similarly, both sites had reasonable accuracies for wetness (EIV F), this is explained by the design of the shortwave infrared bands on Sentinel-2 which are spectrally configured for moisture content quantification.

Air Quality

Responses in Ellenberg fertility or N (for Nutrients) have been linked to nitrogen deposition in gradient survey work, and as such, it is important to understand if a site shows increases in fertility over time. These changes in fertility across habitats at the landscape scale could be studied alongside nitrogen deposition gridded model data to understand the extent to which air quality may be impacting habitat condition.

Wetness Index

Similarly, Ellenberg moisture or F could be used to understand community responses to a change in site management, for example restoration of *Sphagnum* mosses and gully blocking. NDMI (Normalised Difference Moisture Index) and NDWI (Normalised Difference Wetness Index) also offer potential to observe changes in surface wetness, for example gully blocking, although further work is needed to link changes in species composition and restoration of bare ground with NDMI and NDWI. Surface wetness in bogs is a key indicator of habitat condition and carbon (C) storage (a wet bog is a better C store than a drained bog) and could also be used to help with understanding flood risk.

Developing a Wetness Index by combining NDMI, NDWI and EIV Wetness together to get a stronger wetness index could reduce time lag issues and link species composition to NDMI and NDWI to inform bog condition and targeting of agri-environment schemes in the development of Upland Management Long-term Plans, across England. This approach could be useful in understanding community responses to climate change.

Natural Capital Asset Mapping

The development of a Wetness Index for incorporating into protected sites condition monitoring also offers the potential to assist with Natural Capital Asset Mapping for informing flood risk management schemes. Spatially accurately wetness mapping could help target management using agri-environment scheme options to re-wet and restore blanket bogs, improving condition and potentially the ability to hold more water. This could slow the flow in high rainfall, flash flooding events and inform Upland Long-term Management Plans. Combined with Environment Agency (EA) river catchment fluvial modelling there could be potential to inform softer rural flooding engineering solutions.

Therefore, there does appear potential to use both types of indicator to understand landscape and environmental change and condition, especially in conjunction with changes in broad habitat structure and extent and the potential to assist with Natural Capital Asset Mapping. There may also be future potential to link these observations with on-the-ground biogeochemical soil responses from data collected through LTMN monitoring.

7 Summary and Recommendations for future work

The modelling in this report has demonstrated the potential for EO data to monitor both habitat and environmental change. There is opportunity for additional ground truthing and data collection to improve the models further to achieve usable accuracies; at Bowland, a bi-habitat classification into bog and heath showed real promise with a cross-validated accuracy of 70%. How survey data can most appropriately be used as classification inputs requires more research. It is important to balance pre-processing data cleaning, such as identifying atypical habitats, with best practise model building ethics; such as not intentionally removing complex and difficult to classify data to obtain higher accuracy. A series of rules for each site, based on local ecological knowledge, would be beneficial to allow unbiased pre-processing of input data.

In the coming years, the utility of Sentinel-2 imagery is likely to increase. At the time of this analysis, the Sentinel-2 archive was somewhat limited, due to cloud cover and operation time. With the successful launch of Sentinel-2B the number of available images is dramatically increased. Furthermore, the quality of data will improve as pre-processing routines develop. Improvements in geolocation accuracy have already been achieved; and developments in atmospheric correction, especially at high-resolution, are ongoing. It will therefore be possible to use a greater number of images or phonological metrics, which may improve accuracy. These approaches have proved highly beneficial in mapping subtle land covers in a range of environments and would merit investigation.

Based on the research detailed in this report, we propose that the following areas may merit some further investigations, if the use of Earth observation/Sentinel-2 data is to be optimised.

If the use of satellite-based vegetation indices (VI) to infer condition (e.g. wetness or productivity) is desirable, the following questions would merit further study:

1. How does species composition affect VI values, and at what scale should ground data collection or quadrat data be collected to accurately train models for VI values?
2. How sensitive are VI trends to "on-the-ground" changes in conditions such as post flood or following gully blocking? Related to this, do VI indices represent physical changes in the vegetation (e.g. amount of water held in mosses), or do they better reflect changes in species composition as a result of environmental differences?
3. Can combining NDMI, NDWI and EIV Wetness Indices together provide a stronger Wetness Index?
4. Are VI-condition assessments consistent between sites?
5. How do VI’s such as NDVI respond over time to changes in habitat and environmental conditions?

If land cover maps of the NVC classes are desirable, the following topics may be worthy of investigation:

1. Can model accuracy be improved after ground truthing data targeted to habitats with less confidence relating to sample size is incorporated into the models?
2. What is the best way to generate class labels from quadrat data?
3. How should dense temporal image collections be processed?
4. Do classifications or end-member approaches perform better?
5. Can vegetation class probabilities be used to estimate habitat cover?

Finally, the following issues regarding image processing would be of generic benefit to uptake of Sentinel-2 imagery, some of these may be addressed by European or UK Space Agency projects.

1. How should topographic correction be applied in the absence of a comparable resolution DEM?
2. Is bi-directional correction necessary on a UK scale?
3. Do bi-directional artefacts incur a bias between Sentinel-2a and 2b?
4. Can Sentinel-2 be reliably downscaled? potentially using Environment Agency LIDAR data
5. What is the geolocation accuracy of Sentinel-2 in the UK?

8 Acknowledgements

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Appendix 1 – Sand dunes Annex 1 and NVC Habitat Names and key vegetation groups

Annex 1 Habitat	NVC code & community/sub-community name
Grassland	MG5 Cynosurus cristatus-Centaurea nigra grassland
	MG5a Cynosurus cristatus-Centaurea nigra grassland, Lathyrus pratensis sub-community
	MG5b Cynosurus cristatus-Centaurea nigra grassland, Galium verum sub-community
	MG5c Cynosurus cristatus-Centaurea nigra grassland, Danthonia decumbens sub-community
	MG6 Lolium perenne-Cynosurus cristatus grassland
	MG6a Lolium perenne-Cynosurus cristatus grassland, typical sub-community
	MG6b Lolium perenne-Cynosurus cristatus grassland, Anthoxanthum odoratum sub-community
	MG6c Lolium perenne-Cynosurus cristatus grassland, Trisetum flavescens sub-community
H2110	SD4 Elymus farctus ssp. boreali-atlanticus foredune community
Embryonic shifting dunes	SD6 Ammophila arenaria mobile dune community
	SD6a Ammophila arenaria mobile dune community, Elymus farctus sub-community
	SD6b Ammophila arenaria mobile dune community, Elymus farctus-Leymus arenarius sub-community
	SD6c Ammophila arenaria mobile dune community, Leymus arenarius sub-community
	SD6d Ammophila arenaria mobile dune community, Ammophila arenaria sub-community
	SD6e Ammophila arenaria mobile dune community, Festuca rubra sub-community
	SD6f Ammophila arenaria mobile dune community, Poa pratensis sub-community
	SD6g Ammophila arenaria mobile dune community, Carex arenaria sub-community
H2120	SD5 Leymus arenarius mobile dune community
Shifting dunes along the shoreline	SD5a Leymus arenarius mobile dune community, species-poor sub-community
	SD5b Leymus arenarius mobile dune community, Elymus farctus sub-community
	SD5c Leymus arenarius mobile dune community, Festuca rubra sub-community
	SD7 Ammophila arenaria-Festuca rubra semi-fixed dune community
	SD7a Ammophila arenaria-Festuca rubra semi-fixed dune community, typical sub-community
	SD7b Ammophila arenaria-Festuca rubra semi-fixed dune community, Hypnum cupressiforme sub-community
	SD7c Ammophila arenaria-Festuca rubra semi-fixed dune community, Ononis repens sub-community
	SD7d Ammophila arenaria-Festuca rubra semi-fixed dune community, Elymus pycnanthus sub-community
	SD8 Festuca rubra-Galium verum fixed dune grassland
	SD8a Festuca rubra-Galium verum fixed dune grassland, typical sub-community
	SD8b Festuca rubra-Galium verum fixed dune grassland, Luzula campestris sub-community
	SD8c Festuca rubra-Galium verum fixed dune grassland, Tortula ruralis ssp. ruraliformis sub-community
	SD8d Festuca rubra-Galium verum fixed dune grassland, Bellis perennis-Ranunculus acris sub-community
	SD8e Festuca rubra-Galium verum fixed dune grassland, Prunella vulgaris sub-community
	SD9 Ammophila arenaria-Arrhenatherum elatius dune grassland
	SD9a Ammophila arenaria-Arrhenatherum elatius dune grassland, typical sub-community
	SD9b Ammophila arenaria-Arrhenatherum elatius dune grassland, Geranium sanguineum sub-community
H2130	SD11 Carex arenaria-Cornicularia aculeata dune community
Fixed dunes with herbacious vegetation	SD11a Carex arenaria-Cornicularia aculeata dune community, Ammophila arenaria sub-community
	SD11b Carex arenaria-Cornicularia aculeata dune community, Festuca ovina sub-community
	SD12 Carex arenaria-Festuca ovina-Agrostis capillaris dune grassland
	SD12a Carex arenaria-Festuca ovina-Agrostis capillaris dune grassland, Anthoxanthum odoratum sub-community
	SD12b Carex arenaria-Festuca ovina-Agrostis capillaris dune grassland, Holcus lanatus sub-community
	SD13 Sagina nodosa-Bryum pseudotriquetrum dune-slack community
	SD13a Sagina nodosa-Bryum pseudotriquetrum dune-slack community, Poa annua-Moerckia hibernica sub-community
	SD13b Sagina nodosa-Bryum pseudotriquetrum dune-slack community, Holcus lanatus-Festuca rubra sub-community
	SD19 Phleum arenarium-Arenaria serpyllifolia dune annual community
H2170	SD14 Salix repens-Campylium stellatum dune-slack community
Dunes with Salix repens (Slacks)	SD14a Salix repens-Campylium stellatum dune-slack community, Carex serotina-Drepanocladus sendtneri sub-community
	SD14b Salix repens-Campylium stellatum dune-slack community, Rubus caesius-Galium palustre sub-community
	SD14c Salix repens-Campylium stellatum dune-slack community, Bryum pseudotriquetrum-Aneura pinguis sub-community
	SD14d Salix repens-Campylium stellatum dune-slack community, Festuca rubra sub-community
	SD16 Salix repens-Holcus lanatus dune-slack community
	SD16a Salix repens-Holcus lanatus dune-slack community, Ononis repens sub-community
	SD16b Salix repens-Holcus lanatus dune-slack community, Rubus caesius sub-community
	SD16c Salix repens-Holcus lanatus dune-slack community, Prunella vulgaris-Equisetum variegatum sub-community
	SD16d Salix repens-Holcus lanatus dune-slack community, Agrostis stolonifera sub-community
	SD17 Potentilla anserina-Carex nigra dune-slack community
	SD17a Potentilla anserina-Carex nigra dune-slack community, Festuca rubra-Ranunculus repens sub-community
	SD17b Potentilla anserina-Carex nigra dune-slack community, Carex flacca sub-community
	SD17c Potentilla anserina-Carex nigra dune-slack community, Caltha palustris sub-community
	SD17d Potentilla anserina-Carex nigra dune-slack community, Hydrocotyle vulgaris-Ranunculus flammula sub-community
	SD18 Hippophae rhamnoides dune scrub
	SD18a Hippophae rhamnoides dune scrub, Festuca rubra sub-community
	SD18b Hippophae rhamnoides dune scrub, Urtica dioica-Arrhenatherum elatius sub-community
H2190	SD15 Salix repens-Calliergon cuspidatum dune-slack community
Humid dune slacks	SD15a Salix repens-Calliergon cuspidatum dune-slack community, Carex nigra sub-community
	SD15b Salix repens-Calliergon cuspidatum dune-slack community, Equisetum variegatum sub-community
	SD15c Salix repens-Calliergon cuspidatum dune-slack community, Carex flacca-Pulicaria dysenterica sub-community
	SD15d Salix repens-Calliergon cuspidatum dune-slack community, Holcus lanatus-Angelica sylvestris sub-community
Heath	H1 Calluna vulgaris-Festuca ovina heath
	H11 Calluna vulgaris-Carex arenaria heath
	H11a Calluna vulgaris-Carex arenaria heath, Erica cinerea sub-community
	H11b Calluna vulgaris-Carex arenaria heath, Empetrum nigrum ssp. nigrum sub-community
	H11c Calluna vulgaris-Carex arenaria heath, species-poor sub-community
Open	OV27 Epilobium angustifolium community
	OV27a Epilobium angustifolium community, Holcus lanatus-Festuca ovina sub-community
	OV27b Epilobium angustifolium community, Urtica dioica-Cirsium arvense sub-community
	OV27c Epilobium angustifolium community, Rubus fruticosus agg.-Dryopteris dilatata sub-community
	OV27d Epilobium angustifolium community, Acer pseudoplatanus-Sambucus nigra sub-community
	OV27e Epilobium angustifolium community, Ammophila arenaria sub-community
	SD10 Carex arenaria dune community
	SD10a Carex arenaria dune community, Festuca rubra sub-community
	SD10b Carex arenaria dune community, Festuca ovina sub-community

Appendix 2 – Principle Components Analysis of vegetation communities

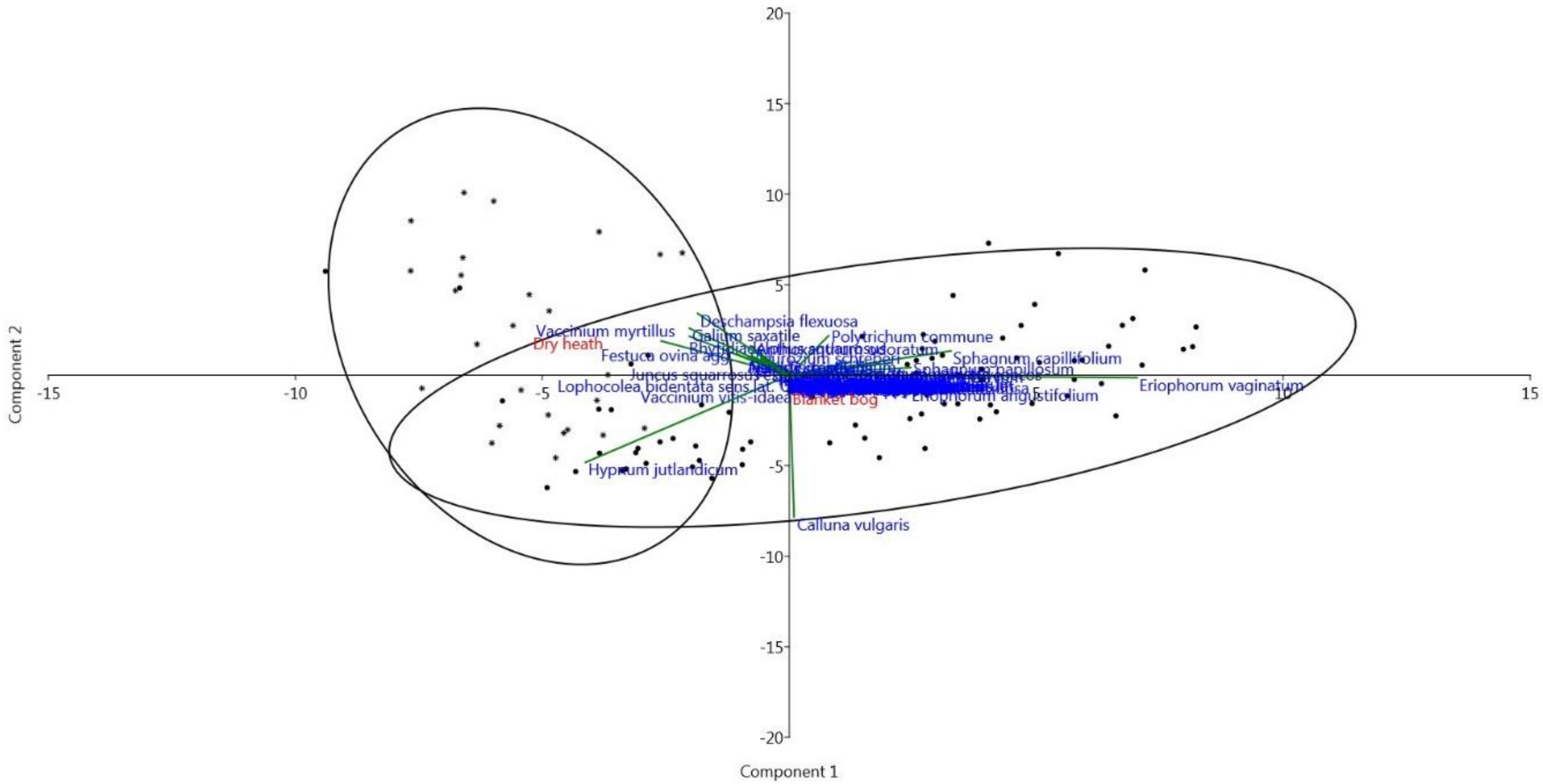

Figure 28: Principle Components Analysis illustrating how species and habitats are ordinated to the main axes of environmental change at Bowland. 95% Ellipses shown illustrating the overlap between bog and heath communities; the habitats share key species and degraded bogs have strong similarities with heaths.

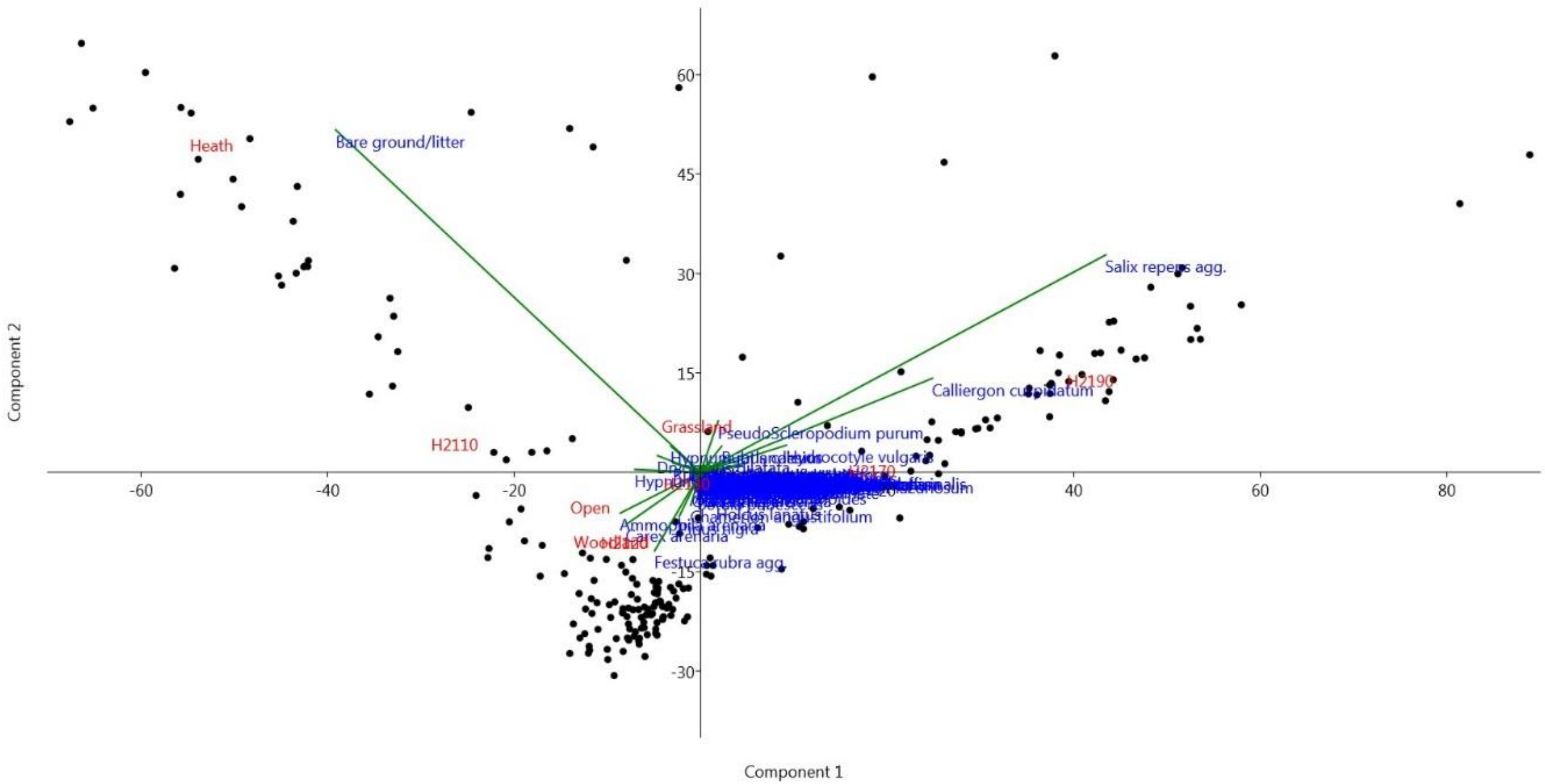

Figure 29: Principle Components Analysis illustrating how species and habitats are ordinated to the main axes of environmental change at Ainsdale Sand dunes. 95% Ellipses not shown for clarity. The close grouping of many species highlights the close relationships and transient nature of sand dune communities.

Appendix 3 – Frequency of habitat classes at Ainsdale

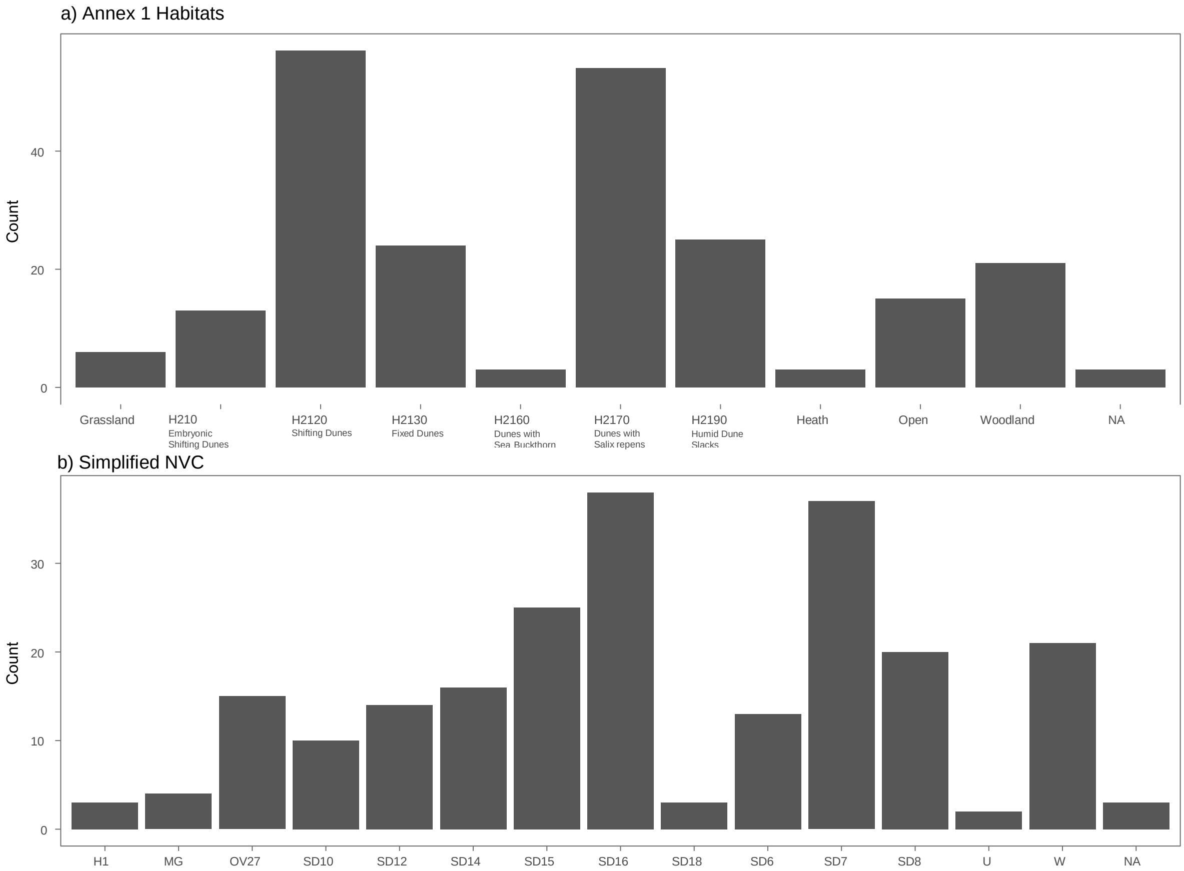

Figure 30: Count of habitat occurrence using NVC and Annex 1 classifications for Ainsdale dunes

Appendix 4 – Ainsdale Comparison of CASI and Sentinel-2 Predictions with Ecological Survey mapping

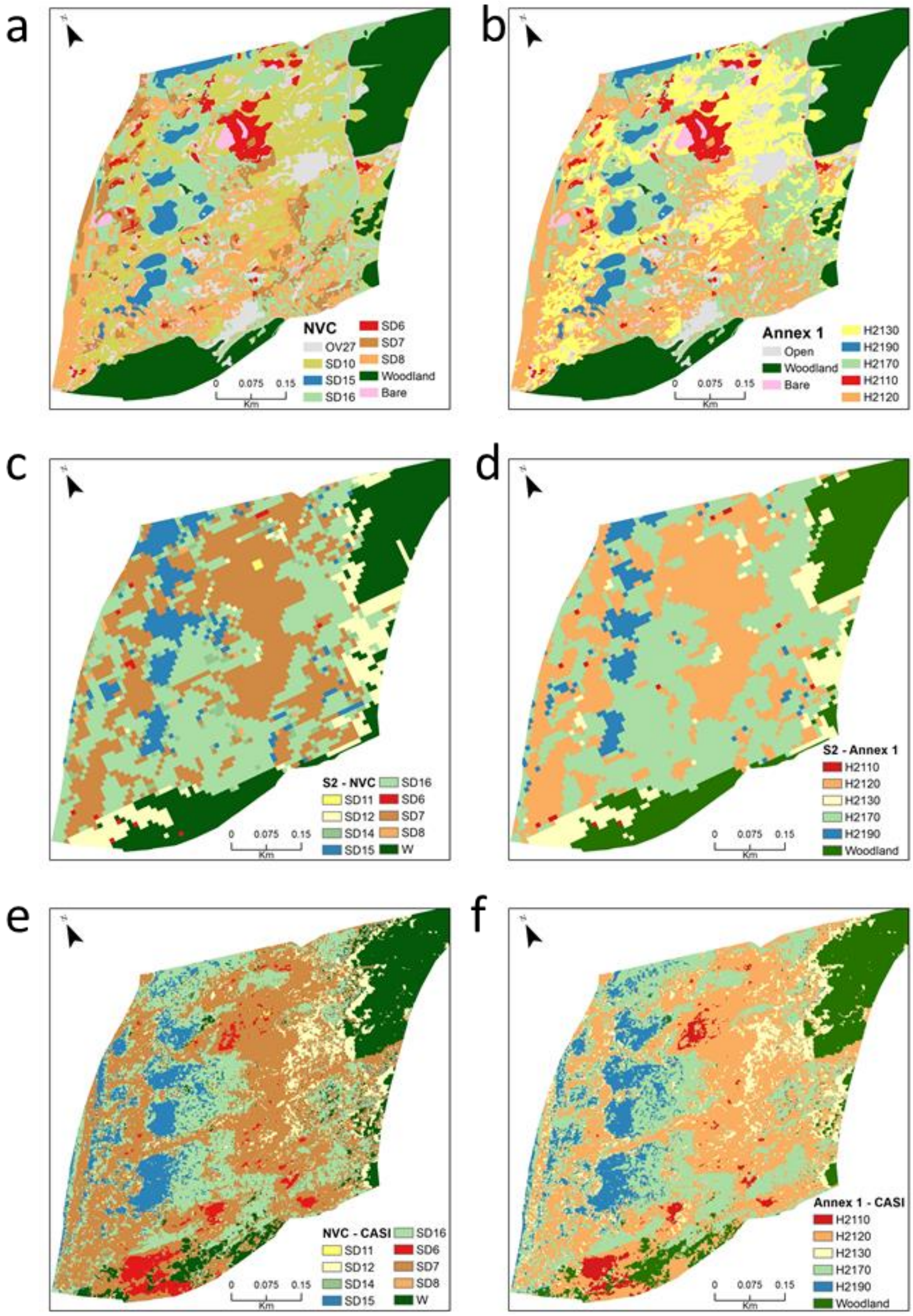

Figure 31 Comparison of the predicted maps against ground survey plots. A-B Ecological survey, C-D Sentinel-2 predictions, E-F CASI predictions.