JNCC Report
No: ####

Earth Observation to produce indices of habitat condition and change
JNCC Ref. C14-0171-0901

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May 2015

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ISSN 0963 8901
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This report should be cited as:

Summary

The research reported here sought to test if the principles used in the National Forest Inventory (NFI) to monitor the habitat resource (forest) through Earth Observation (EO) might be extended to a wider suite of habitat types. The NERC Centre for Ecology and Hydrology (CEH) was asked to focus the selection of habitat types and review the understanding of how EO data could aid the identification of changed land use and management. CEH was also asked to draw up a plan for a practical test of how the project findings could be carried out. The approach comprised five steps, which are described within the present report.

Step 1 (Report Section 2.1): Appraisal of relevant extant and ongoing projects that have reviewed EO based techniques for condition monitoring of specific habitats.

Step 2 (Report Section 2.2): Comprehensive assessment of condition measures as they are applied to all UK habitats, both at a Broad and Priority scale (see Appendix 4 and Summary Table 3). CEH identified those habitats for which existing data are most detailed, and where knowledge of the mechanisms of habitat change and their causes are best understood, and thus where EO-derived measures appeared most relevant.

Step 3 (Report Sections 3.1, 3.2 and 3.3): Examination of detection of change by EO at a broad scale across the UK through both passive and active approaches, followed by a systematic appraisal of the condition measures identified in Step 2.

Step 4 (Report Sections 3.4 and 3.5): The project then described how a system might operate in practice, using a theoretical example for monitoring grassland condition, based upon the readiness of each method and whether parameters required calibration/validation.

Step 5 (Report Section 4): A detailed outline is included for a practical test to be conducted on the application of the project findings. Four pilot studies are considered, each reviewed in terms of relevant EO variables and condition measures, together with their readiness for application.

Key issues and conclusions

Mapping habitats and changes from one habitat to another is a different activity from determining and monitoring the changes in condition of a habitat. Consequently the Earth observation approaches available to carry out the latter are likely to be different from the approaches developed for the former. A variety of EO approaches are elaborated and summarised in Section 3.3 including Tables 3.3.1 and 3.3.2 and in greater detail in a separate Excel Workbook).

Those condition measures for which there is a clear potential to apply EO approaches and where the use of EO should be tested are:

- productivity (amount of live plant material);
- productivity (sward height);
- extent of dead material;
- presence of linear features; and
- presence of problem species.
Those condition measures for which EO approaches already exist and which should be relatively easy to adopt and implement are:

- extent of bare ground;
- extent of burning;
- percentage woody cover; and
- extent of water.

Those condition measures for which EO is unlikely to deliver reliable estimates are:

- vegetation composition (positive indicator species); and
- vegetation composition (graminoid/forb ratio).

There is a strong case for developing and testing a 3 stage condition monitoring system:

Stage 1: consists of a less spatially detailed and thus quick but effective search for evidence of change in condition.

Stage 2: delivers, where a change has been detected, a more spatially detailed and quantitative evaluation of the type of change.

Stage 3: samples and validates the measured changes.

Delivery of stage 1 and 2 require different approaches using different types of EO data, whilst Stage 3 involves field work. The variety of EO approaches available is limited by the type of EO data available at the moment and in the future. Very high (<1m to 2m) to high (5m to 10m) spatial resolution imagery (optical or radar) is important to deliver Stage 2, while the ability to build time series of imagery (annually, monthly or daily) is important to deliver Stage 1.

Many EO approaches discussed in this report involve a vegetation index that is based on one or two visible bands and/or one Near-infrared band (Appendix 1). This focus derives from the limited amount of spectral bands that are currently available at very high (< 1m to 2m) to high (5m to 10m) spatial resolution.

A theoretical example is worked out for monitoring grassland habitat condition where Stage 1 and Stage 2 of the monitoring system are elaborated using the vegetation index NDVI. As part of Stage 1, the example demonstrates the difference between using a map-to-image and image-to-image approach for change detection. The example also highlights outstanding questions which have to be resolved before such a system can be made operational:

1. Is the vegetation index, when used at medium (25m to 30m) to coarse (250m to 1km) spatial resolution, sensitive enough to detect change in condition?
2. Can the vegetation index be used to distinguish clearly the main condition measures (extent of bare ground, woody cover, dead material, and productivity (amount of life plant material) within a given grassland type?

For several of the condition measures (extent of water, extent of woody cover, extent of bare ground, productivity (vegetation height), linear features) there is a clear potential for using radar data. This potential needs to be tested.

Validation to establish the accuracy or the consistency of the estimated condition measures is important. Accuracy (bias and precision) is established by comparing the EO derived condition measures with independently collected (field work) observations. Consistency (precision) is established by evaluating repeat estimates that are acquired independently for the same sample or site using the same method or an ensemble of methods.

To help further evaluate the elaborated EO approaches in a systematic manner, a set of attributes has been identified and defined that enables JNCC and CEH to consider the
readiness (availability of EO data across time and across the UK; time required for implementation; amount of staff training required) and feasibility (staff resources required; data volume involved; cost of data; and pre-processing level of data at which it is available) of the approaches. A framework to help to assign readiness and feasibility scores to EO approaches was not fully developed in this report, but could usefully be developed further.
## Glossary of abbreviations used within this report

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AATSR</td>
<td>Advanced Along-Track Scanning Radiometer</td>
</tr>
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<td>AP</td>
<td>Aerial Photography</td>
</tr>
<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission and Reflection Radiometer</td>
</tr>
<tr>
<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
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<tr>
<td>CART</td>
<td>Classification And Regression Tree</td>
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<tr>
<td>CASI</td>
<td>Compact Airborne Spectrographic Imager</td>
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<tr>
<td>CEH</td>
<td>Centre for Ecology and Hydrology</td>
</tr>
<tr>
<td>CHRIS</td>
<td>Compact High Resolution Imaging Spectrometer</td>
</tr>
<tr>
<td>CSM</td>
<td>Common Standards Monitoring</td>
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<tr>
<td>Defra</td>
<td>Department for Environment, Food and Rural Affairs</td>
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<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
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<tr>
<td>DMC</td>
<td>Disaster Monitoring Constellation</td>
</tr>
<tr>
<td>DSM</td>
<td>Digital Surface Model</td>
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<tr>
<td>DTM</td>
<td>Digital Terrain Model</td>
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<tr>
<td>EA</td>
<td>Environment Agency</td>
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<tr>
<td>EBONE</td>
<td>European Biodiversity Observation Network</td>
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<td>ECN</td>
<td>Environmental Change Network</td>
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<tr>
<td>(E)TM</td>
<td>(Enhanced) Thematic Mapper</td>
</tr>
<tr>
<td>EO</td>
<td>Earth Observation</td>
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<tr>
<td>EU</td>
<td>European Union</td>
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<tr>
<td>EUNIS</td>
<td>European Nature Information System</td>
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<tr>
<td>EWS</td>
<td>Extra Wide Swath mode</td>
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<tr>
<td>FEP</td>
<td>Farm Environment Plan</td>
</tr>
<tr>
<td>FPAR</td>
<td>Fraction of Absorbed Photosynthetically Active Radiation</td>
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<tr>
<td>GPP</td>
<td>Gross Primary Production</td>
</tr>
<tr>
<td>HH</td>
<td>Horizontal - Horizontal wave mode</td>
</tr>
<tr>
<td>HICO</td>
<td>Hyperspectral Imager for the Coastal Ocean</td>
</tr>
<tr>
<td>HyMap</td>
<td>Hyperspectral imaging sensor</td>
</tr>
<tr>
<td>ILESAS</td>
<td>Institute of Landscape Ecology of the Slovak Academy of Sciences</td>
</tr>
<tr>
<td>IRS</td>
<td>Indian Remote Sensing</td>
</tr>
<tr>
<td>Irstea</td>
<td>Institut National de Recherche en Sciences et Technologies pour l’Environnement et l’Agriculture</td>
</tr>
<tr>
<td>IWS</td>
<td>Interferometric Wide Swath mode</td>
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<tr>
<td>JNCC</td>
<td>Joint Nature Conservation Committee</td>
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<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
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<tr>
<td>LCM</td>
<td>Land Cover Map</td>
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<tr>
<td>LiDAR</td>
<td>Light Detection And Ranging</td>
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<tr>
<td>MCA</td>
<td>Multi Camera Array</td>
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<tr>
<td>MEOW</td>
<td>Making Earth Observation Work</td>
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<tr>
<td>MERIS</td>
<td>MEdium Resolution Imaging Spectrometer</td>
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<tr>
<td>MNDWI</td>
<td>Modified Normalised Wetness Index</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate-resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MSI</td>
<td>Multi-Spectral Instrument</td>
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<tr>
<td>NDMI</td>
<td>Normalised Difference Moisture Index</td>
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<tr>
<td>NDVI</td>
<td>Normalised Difference Vegetation Index</td>
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<tr>
<td>NERC</td>
<td>Natural Environment Research Council</td>
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<tr>
<td>Acronym</td>
<td>Full Form</td>
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<tr>
<td>NIR</td>
<td>Near Infrared</td>
</tr>
<tr>
<td>NPP</td>
<td>Net Primary Production</td>
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<tr>
<td>NPV</td>
<td>Non-Photosynthetic Vegetation</td>
</tr>
<tr>
<td>NVC</td>
<td>National Vegetation Classification</td>
</tr>
<tr>
<td>OBIA</td>
<td>Object-based image analysis</td>
</tr>
<tr>
<td>OLI</td>
<td>Operational Land Imager</td>
</tr>
<tr>
<td>OS</td>
<td>Ordnance Survey</td>
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<tr>
<td>RGB</td>
<td>Red Green Blue</td>
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<tr>
<td>RPAS</td>
<td>Remotely Piloted Aerial System</td>
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<tr>
<td>RS</td>
<td>Remote Sensing</td>
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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
<tr>
<td>SAVI</td>
<td>Soil Adjusted Vegetation Index</td>
</tr>
<tr>
<td>SMAP</td>
<td>Soil Moisture Active Passive</td>
</tr>
<tr>
<td>SMOS</td>
<td>Soil Moisture and Ocean Salinity</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite Pour l'Observation de la Terre</td>
</tr>
<tr>
<td>SSSI</td>
<td>Site of Special Scientific Interest</td>
</tr>
<tr>
<td>STB</td>
<td>Science Technology Board</td>
</tr>
<tr>
<td>SWIR</td>
<td>Shortwave Infrared</td>
</tr>
<tr>
<td>UAV</td>
<td>Unmanned Aerial Vehicle</td>
</tr>
<tr>
<td>VH</td>
<td>Vertical - Horizontal wave mode</td>
</tr>
<tr>
<td>VI</td>
<td>Vegetation Index</td>
</tr>
<tr>
<td>VIS</td>
<td>Visible</td>
</tr>
<tr>
<td>VV</td>
<td>Vertical - Vertical wave mode</td>
</tr>
<tr>
<td>WV</td>
<td>Wave mode</td>
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1 Background to study, report structure and approach

Background - the research question

The project reported here arose from a long-term programme of research commissioned by JNCC and Defra to make the range of Earth Observation (EO) techniques more useful for public policy and for an integrated and well-founded approach to the management of land and natural resources i.e. Making EO Work for UK Biodiversity (MEOW). The specific purpose of this project was to help to understand the potential and feasibility of using parameters calculated from EO data to detect changes that can occur in habitats that may be significant enough to affect ecosystem function or biodiversity value.

Environmental policy and instruments in the UK include a broad range of land interventions that act to affect either landscape features or habitats and their condition in order to achieve specific biodiversity or ecosystem service outcomes. These interventions include, amongst others, nitrate vulnerable zones, catchment sensitive farming, Nature Improvement Areas, SSSI's (and other designated areas) and agri-environment schemes (AES e.g. Higher Level Stewardship). Such policies are intended to provide environmental goods and services and their success depends on a framework of regular monitoring, often using condition assessment (e.g. conducted under Common Standards Monitoring, Robertson & Jefferson 2000). Where such interventions involve grant aid, it is vital that the efficacy of the management be assessed, not least to ensure the proper use of public money. Not only does monitoring indicate the condition of a habitat but it should provide timely warning of any change in condition or habitat that might compromise the biodiversity value of the site.

At present, much of this monitoring is conducted on the ground by field survey but frequently augmented by manual aerial photography interpretation. The resources (money, time and people) involved in these monitoring campaigns mean that it is highly desirable to find other approaches that are complementary, rapid and truly indicative of habitat condition and change. Thus JNCC and Defra are looking to assess whether automated processing of remote sensed data can help target fieldwork, and thus reduce the amount necessary, as well as potentially providing relevant measures of change over landscapes, regions and even countries.

Following this theme and as a model approach, the Forestry Commission runs the National Forest Inventory (NFI), which contains an operational system that uses EO data to assess changes in quality of woodland habitats in order to locate woodland loss. Thus, for the whole UK, tri-annual processing of high resolution satellite data produces outputs that are relevant at a site scale and also for elaborating a national picture of change in the woodland resource. The NFI is based on existing accurate mapping of the stock of woodlands, such that there is a baseline where remotely-sensed data can indicate change within an automated framework.

The second phase of MEOW was published in 2014 (Medcalf et al.) and included some findings on how EO data could be used to detect factors that have an impact upon habitat condition. Those changes that are likely to be detectable include altered vegetation productivity, wetness, woodiness of the vegetation, vegetation structure, amount of bare ground, presence/size of linear features, conversion of natural habitat to built structures and eutrophication. MEOW Phase 2 was complemented by the development of the Crick Framework (http://jncc.defra.gov.uk/page-6281) which provided information on the potential for using EO methods to map the extent of certain habitat types. The present project seeks to move the approach forward so that soon the Crick Framework can be populated with information on the use of EO methods to assess habitat condition.
The research approach

Specifically, JNCC and Defra sought to test if the principles used in the NFI could be extended to a wider suite of habitat types. Given the limits of time available for this project (ca 11 weeks) it was acknowledged at the outset that a comprehensive analysis of this subject area was impossible and CEH were instead commissioned by JNCC to narrow down the selection of habitat types to be considered in more detail. CEH was required to categorise how these habitats could change, and at what rate, and how currently condition and change were assessed. The project was to review the understanding of how EO data could aid the identification of changed land use and management. Further, the project should plan how relevant EO data could be systematically analysed and what data would be required for such a system. Finally, CEH was asked to draw up a plan for a practical test of how the project findings could be carried out, possibly concentrating on a group of habitats such as grasslands as a pilot.

From the project outset, CEH focussed on those EO techniques with clear, immediate and successful application across large areas (e.g. wide swath satellite-borne systems), although other types of EO data would be considered. The project approach could be divided into five steps, which are described in Sections 2-4 of the current report.

**Step 1** (Report Section 2.1): An appraisal of relevant extant and ongoing projects that have reviewed EO based techniques for condition monitoring of specific habitats, so as to minimise duplication of effort. Further attention to this topic occurs in Section 3 of the report as the application of EO techniques to specific condition measures is developed.

**Step 2** (Report Section 2.2): CEH performed a wide-ranging assessment of condition measures as they are applied to all UK habitats, both at a Broad and Priority scale. Through iterative discussions within the CEH team, between CEH and JNCC and through further examination of the literature, the project assembled a summary of those EO measurements that are the most likely to pick up changes in habitat condition, as this is required by the conservation agencies (see both Appendix 4 and Summary Table 3). CEH identified those habitats for which existing data (mapped extent, habitat quality etc) are most detailed, and where knowledge of the mechanisms of habitat change and their causes are best understood. Thus habitats were assessed where potential for application of EO-derived measures appeared most profitable.

**Step 3** (Report Sections 3.1, 3.2 and 3.3): It is vital to know whether EO could detect change at a relevant scale and how EO might be tailored toward particular measures of condition and of change, seeking all the time to find methods that were widely applicable across a range of condition measures. Thus CEH firstly examined the detection of change at a broad scale across the UK through both passive and active approaches. Then working systematically through the condition measures appraised in Step 2, the project describes the applicability of EO techniques in a structured report, drawing where necessary on examples from current and recent research. In all, some 15 different condition measures are assessed, with an overview of the approaches provided in Section 3.3. EO options were assessed for their effectiveness, their practicality and their readiness to be applied now or in the near future.

**Step 4** (Report Sections 3.4 and 3.5): The next part of the report described how a system might operate in practice, using a theoretical example for monitoring grassland condition. Using habitat change measures that showed high readiness, the report describes how each EO-derived parameter can be calculated and whether the parameters require either calibration or validation.
Step 5 (Report Section 4): Finally a detailed outline is given for a practical test to be conducted on the application of the project findings. Four pilot studies are considered, each reviewed in terms of relevant EO variables and condition measures, together with their readiness for application. Three issues were to be resolved for each pilot study: a) practicality of the methods; b) errors on consistency in the estimates; and c) the operational processing chain. Working through the example of grassland habitat condition, the report describes broad-brush (national) approaches and those at a detailed local scale, together with consideration of the timing of EO data in relation to the stage (phenology, management etc) in the vegetation. Following examination of site selection, field data and validation, the report concludes by reviewing candidate sites for field-based calibration and validation.
2 Earth observation: habitat mapping, condition and change – recent studies and recommendations

The main objective of the present project is to identify practical methods for using EO to monitor change within previously mapped habitats and to assess condition of the habitat. To that end previous studies and reviews that focus primarily on mapping habitat are of less immediate relevance. However, two key sources were searched in some detail, as they do contain valuable material with importance for understanding the capacity of EO techniques to provide insights into habitat change and especially to those measures that are standardly used in condition assessment by JNCC and the country agencies. Firstly a very recent review of the possibilities and limitations of remote sensing in habitat mapping was conducted by Irstea as part of the MS.MONINA project (Corbane & Deshayes 2013). The main recommendations from this review and a summary of relevant papers and approaches that this work includes are set out in Section 2.1. The second key up-to-date source is the MEOW Phase 2 report (Medcalf et al. 2014), which also focuses primarily on mapping. However, this report (and related literature) does pay some attention to monitoring and measures of condition (e.g. section 6.5) and any salient points specifically from that work are clearly cited below in Section 2.1 (labelled MEOW). Section 2.2 then goes on to discuss how these sources were combined with an appraisal of methods of assessing habitat condition and habitat change in order to prioritise the EO techniques most relevant and useful for broad application and development.

2.1 Relevant points from recent projects

2.1.1 Overall recommendations

The Corbane & Deshayes review focussed on the possibilities and limits of remote sensing for mapping natural habitats, but within the context of monitoring the extent and quality of Natura 2000 habitats of interest (e.g. Annex 1 of the Habitats Directive). The review recognised that EO techniques have been extensively used in conservation due to their capacity to generate varied ecologically valuable measurements e.g. land cover and the biophysical properties of ecosystems. More importantly for the present project, EO can detect both natural and anthropogenic changes within habitats and at the landscape scale, though examples at the site level are much more frequent than at the regional and national scales. This evaluation of methods for mapping habitats and communities allows an understanding of the capacity of EO to detect changed extent in a habitat.

However the review noted that EO approaches remained poorly exploited for habitat condition and outlined four key types of obstacle to the use of EO in habitat monitoring:

A. Application of EO influenced by varied quality of input variables, variability of resolution (spectral, spatial and temporal) and availability of both suitable remote sensing data and ancillary data to ensure transferability between sites.
B. Costs of imagery and other geospatial data have often been high until recently, together with the technical expertise required to handle the imagery/data.
C. Crucially the absence of a simple relationship between habitats and biophysical parameters such as land cover (Groom et al., 2005) i.e. habitat classes do not equate with land cover classes – see guidance in EUNIS system.
D. The absence of clear definitions of the habitat types (see Natura 2000 Interpretation Manual for EU28), with numerous issues reported on the possibilities of mapping Annex 1 habitat:
   a. Many habitats form part of a dynamic system and often co-occur in mosaics;
   b. Many biotopes overlap;
c. Habitats and communities defined using a variety of descriptive approaches and at different levels of detail and precision across the EU. [In the UK, methods based upon Broad/Priority Habitats coexist with those based on the NVC or locally-set categories].

For the purposes of condition assessment and monitoring, we generally require more attributes to be detected/measured than simply the correct species/community/habitat – please consult the tabulation of broad habitats against measures of condition and change, originally submitted as a working document and here included as Appendix 4.

Remote sensing can be integrated with field data to improve the precision of each approach or make data collection more efficient (Gerard et al., 2012). EO techniques have been applied to mapping life form, cover, structure and leaf-type but much less so to the identification of individual species. The correspondence between such physiognomic vegetation classes and detailed habitat types is not simple, needing field information and expert interpretation. The Corbane & Deshayes review (2013) advocates a rigorous sampling strategy that trains the classifier, allowing the monitoring of significant phenological or habitat change, and suggests the establishment of permanent sampling plots for ground-truthing and a dedicated validation framework.

2.1.2 Evaluation of habitats, species and sensors

Overwhelmingly, the Corbane & Deshayes review deals with mapping of habitat/community units but some approaches have application to habitat change and condition assessment.

- Cites 2 key reviews of the application of remote sensing to ecology and nature conservation (Kerr and Ostrovsky 2003; Turner et al. 2003).
- Three most readily detected/measured environmental parameters: primary productivity (e.g. via NDVI), climatic variables and habitat structure. Coarser measures of productivity have been applied to grasslands and examples of biomass determination using Radar in grasslands were documented and reviewed.
- MEOW showed that a combination of LiDAR and NDVI provided a good measure of overall productivity, allowing the differentiation of coarse (fertile, weedy etc) vegetation from short swards etc.
- Several studies have demonstrated the capacity of EO to map the distribution of relatively detailed habitat types and vegetation communities although this is more straightforward in coarse habitat mosaics than the finer grain of many habitats requiring condition assessment.
- The level of discrimination may be insufficient for the requirements of condition assessment unless procedures similar to those outlined in MEOW (Medcalf et al. 2014) for assessing single species stands are followed.
- The more powerful examples deal with Mediterranean communities, but also with Boreal types and locally for EUNIS habitat categories. For the UK situation, work using the automatic classification of aerial photos in moorland achieved discrimination of seven dominant land cover classes (Chapman et al. 2009).
- The appraisal of microwave remote sensing found evidence for the use of Radar in detecting soil moisture changes, and thermal sensors also have potential to be useful.
- Examples whereby calcareous grassland was successfully distinguished from mesotrophic pastures but lines of trees confounded with hedgerows.
- Noted the work of Lucas et al. (2011) in successfully mapping as many as 105 sub-habitat types (nominal resolution of 5 m) in Phase 1 survey of Wales, partly through establishing links with the broader biophysical characteristics of dominant species.
- Worth noting the relationship between plant phenology and spectral response e.g. during flowering and early seed, senescent, and early emergence. Studies of saltmarshes
show that the best period to discriminate key species is during the flowering and early-seed stages, although there is significant variation in spectral reflectance within a single species.

- Some alien invasive species (e.g. spurges of the *Euphorbia esula* s.l. group; *Heracleum mantegazzianum* etc) possess visually detectable and distinctive features at certain times of the year, allowing AP-based approaches to locate major infestations.

- For problem species in grasslands and heathlands, MEOW found that high resolution EO (RPAS) might be used after ground truthing, comparing known occurrence of such vegetation in a reference site with imagery to calibrate the EO images (Figure 6.45 of Medcalf et al. 2014). Thus:
  - *Phragmites australis* (reed) can be assessed hyperspectrally and via Radar & LiDAR, HSRes and AP, thus (according to MEOW Phase 2) a) “Reedbeds were classifiable when LiDAR “leaf-on” date data is available within the image stack”; b) “LiDAR or other high resolution DSM (such as from the UAS) is needed to identify some habitats successfully, for example reedbeds and saltmarsh creeks”; and c) “detailed DSMs from LiDAR or UAS (derived from the RGB sensor) increased the amount of information that could be extracted about the habitat presence, extent and condition (e.g. allowed identification of reedbeds).”
  - *Urtica dioica* (stinging nettle) areas could be identified from the results of a classification of ultra-fine UAS imagery.

*Woodland and other treed habitats*

- At least for forest/woodland cover, the Corbane & Deshayes review concludes that aerial photography may often provide “the most suitable combination of high spatial resolution, stereo coverage, image scales, film and camera options, versatility and cost”.
- Mapping undesirable (e.g. sycamore) and desirable tree species (e.g. ash) in England proved successful; using neural networks, classification accuracies were obtained of 83% and 94% respectively within a 400 ha forest using aerial imagery (Foody et al. 2005).
- Hyperspectral imaging may have potential to identify a species through the unique spectral signature of one of its components. Thus fine and continuous spectral scanning of vegetation should allow detailed description of chlorophyll content, nitrogen, water content, lignin etc. i.e. features related to plant phenology and health, stress and senescence. Hence there are some links to habitat condition measures as practised by the UK country agencies. However, this approach requires detailed calibration against ground-based survey (MEOW, Medcalf et al. 2014).
- As of 2013, there were only four hyperspectral sensors in orbit: Hyperion, CHRIS, HJ-1A and HICO and most space agencies have augmenting this array as a priority. The proposed combination of sensors will orbit in a continuum, with a temporal resolution of ≤5 days, with consequently much greater power in monitoring changed extent.
- Hyperspectral sensors have aided monitoring of riparian forests (high biodiversity or limited extension) where multispectral sensors are less applicable.
- However, temporal monitoring of forests is as yet not possible with these current hyperspectral platforms (aircraft- or satellite-borne). Hyperspectral data are much more sensitive to two measures of forest stand structure (age and average height) than to species diversity. Instead, the review described how the use of spectrometers is “surrogated to the coupling of hyperspectral knowledge to other remote sensing images at a coarser spatial and spectral resolution (e.g. MODIS, ASTER or Landsat)”.
- Studies of tree colonisation of montane grasslands in France (airborne hyperspectral sensor) managed to identify 12 tree species in the landscape at 90% precision, but with some confounding with other objects in the landscape. For this type of study, multi-seasonal data give much better results than the midsummer hyperspectral data.
Multi-echo or full waveform LiDAR allow forest biomass and timber volume to be scanned in forests, which has some peripheral relevance to habitat condition, together with basal area, mean stem diameter, canopy height and density. Corbane & Deshayes (2013) concluded that the knowledge and techniques required to process LiDAR data for forestry applications is not sufficiently developed for direct application by nature conservation agencies i.e. what is the import of the relationship between LiDAR signal and forest properties? Multispectral imaging can be effectively complemented by radar-derived information or LiDAR to provide information on stand composition and on stand structure respectively. Research suggests that a greater variety of individual tree species may be distinguished if one combines hyperspectral imagery and LiDAR.

Grassland

As with woodlands, use of multispectral remote sensing in grassland has proceeded through vegetation indices correlated to plant biophysical parameters and biomass. Higher resolution multispectral sensors (e.g. Quickbird) have been used to derive relationships with fine-scale plant species richness in semi-natural grasslands (Hall et al. 2012), clearly relevant to some condition measures. MEOW broadly discussed the detection of grassland species richness in section 6.4. Within grasslands, and indeed other habitats, soil moisture and soil temperature were detectable in the SWIR/NIR bands (NDWI – Normalised Difference Wetness Index). Red-edge wavebands have been indicated as most sensitive to grass biomass and thus to grazing levels; hence to standard condition measures. In their review, Corbane & Deshayes (2013) asserted that sensors such as WorldView-2 could provide a chance to detect grazing pressure and also to distinguish the impact of agricultural improvement on grasslands. Hyperspectral data are well suited to measuring grassland properties via their greater spectral/ spatial resolution and provide insights into LAI, chlorophyll, water and dry matter contents. Species composition is critical in distinguishing priority habitats and communities, and also in assessing condition. Various authors cited by the Corbane & Deshayes review (2013) have found that the spectral characteristics of some species of semi-natural grasslands are related to floristic composition. Hyperspectral imaging used in combination with radiative transfer models has been used to assess LAI, which correlates well with grazing intensity. A few other projects have studied the relationship between hyperspectral EO data and biomass production of mixed grasslands. This body of research confirms the importance of having multi-temporal spectral and biomass measurements, particularly at the start of the growing season, in order to acquire a fuller range of biomass and seasonal variability. SAR/LiDAR can indicate biophysical heterogeneities of grasslands (inferring species richness), and hence distinguishing native and improved grasslands.

Heathland

Generally fewer studies of EO and heathland than of forest or grassland and although at their most typical, various heath communities can be distinguished from spectral data, they represent part of a continuum and within-heath variation dictates the need for high spatial resolution data. Spanhove et al. (2012) combined a classification of dominant vegetation classes with advanced modelling, demonstrating the potential of hyperspectral remote sensing to derive information relevant to the conservation status of heaths, even for relatively fine-scale criteria.
Calluna age classes may require multiple imagery through the growing season, although some studies have successfully assessed age structure using sub-pixel unmixing analysis of hyperspectral data followed by a decision tree classification.

Radar imagery has been used to detect fire scars (Millin-Chalabi et al. 2014) and classify heathland types (Thoonen et al. 2013).

Airborne LiDAR is generally used in conjunction with multi-spectral or hyperspectral imagery where a LiDAR derived vegetation height model is used to locate the trees within the heathlands.

MEOW found that Lowland heath can be mapped at the landscape-scale, with wet and dry types often (but not always) distinguishable using contextual data. LiDAR improves the identification of all heath types (reducing confusion with scrub) and high resolution imagery improves both the delineation of boundaries and description of mosaic areas. For the mapping of heath habitats, OS MasterMap was used combined with very high resolution aerial imagery (colour infra-red photography), high resolution satellite imagery (Geoeye) and LiDAR. Very high resolution UAS aerial imagery and UAS DSM also contributed. The relative proportions of dwarf shrub and graminoid cover could be achieved through the differing structures i.e. long upright leaves vs woody vegetation. Mapping heaths with extensive Ulex europaeus may be problematic and MEOW suggested that multi-spectral EO could be used to develop rules to distinguish dense stands, whilst individual bushes might be classified using high resolution data from the UAS.

Wetland – freshwater and saline

Mapping wetland with EO methods has tended to use the optical spectrum: aerial photography, Landsat and SPOT images.

Working in the Camargue, Poulin et al. (2010) used multi-season SPOT-5 data in harness with ground survey to assess the predictive power of the satellite imagery in modelling various indicators of reed structure, some relevant to reedbed condition assessment: height, diameter, density and cover of green/dry stems. Landsat data may be more effective than SPOT data tracing shrub invasions of wet meadows.

In Australian studies, Landsat has been shown to be probably useful in characterising vegetation density, vigour and moisture status, but not effective in defining species composition.

Use of very high resolution optical sensors (e.g. IKONOS, Quickbird or aerial photography) can measure small features e.g. strips of vegetation along watercourses and aquatic vegetation of water bodies.

In wetlands, radar images have been used to detect surface water and highlight variation in surface moisture of bare or poorly vegetated ground. Mostly based on SAR data, the resultant detailed maps of water surfaces are crucial in monitoring the seasonal dynamics of wetlands.

Radar data are also useful for assessing vegetation structure, and related to soil moisture, surface roughness and the presence or absence of standing water. Timing and duration of flooding as well as changes in water depth can be detected. Where tidal wetlands have annual halophytes as their main cover, the very high resolution TerraSAR-X band has potential use.

The Corbene & Deshayes review (2013) concluded that: “The potential of SAR imagery for the discrimination of several vegetation types in wetlands still needs to be properly assessed given the recent increase in the types of frequencies (X, C, P and L bands), the spatial resolutions and the polarisations (single, dual, quad) currently available” and “a possible optimal solution could be found in the integration of SAR data with other types of sensors”.

LiDAR data have been used in wetlands to generate DEM, gain information on object-height, as well as separating vegetation types via structural features. When combined
with SAR and optical data, LiDAR gridded elevation information has been used to estimate water levels. In conjunction with aerial photos, LiDAR data have great potential for fine-scale mapping of mires.

- LiDAR data significantly improves vegetation mapping accuracy and helps to quantify the 3D structure of vegetation through an expert-generated decision tree algorithm, defining patches dominated by reedmace, sedges and reed. Reed health can be mapped in four categories: healthy, stressed, ruderal and die-back. However, the use of LiDAR may be limited by the difficulty in penetrating very dense reed stands.

**Summary tables:**

The tables below, taken from the 2013 Corbane and Deshayes review and the resultant paper (Corbane et al. 2015) provides an overall comparison of the various remote sensing techniques dealt with in their discussion of habitats. Summary Table 1 summarises the use and relevance of different sensors to parameters related to increasing levels of organisation (individual, population, community, landscape). In that table, Corbane and Deshayes (2013) use the term “conservation status” (marked *) to indicate the various designations given to sites (their populations and communities) under European biodiversity protection law, and thus the capacity of EO techniques to assess sites in comparison with others of known quality.

Summary Table 2 takes this approach further, citing the numerous literature sources marshalled by the review project and expanding its detail. Note that columns 1 and 3 (distinguishing very high spatial resolution from coarse spatial resolution combined with very high temporal resolution) are exchanged in the table structure between the two versions. In this table the applicability of various EO techniques are evaluated with regard to distinguishing broad physiognomic types and then in distinguishing variation within each of four broad physiognomic types: forests, grasslands, heathlands and wetlands.

Although both tables deal with sensor-types individually, combinations of sensors can be deployed to improve overall information gained and its utility.
Summary Table 1  Evaluation of suitability of Remote Sensing Sensor (from Corbane, C. and Deshayes, M. (2013): Legend: The different signs/shading indicate the degree of suitability of the sensor to the identification of the given parameter:

<table>
<thead>
<tr>
<th>[From Table 9 (page 55) of Corbane, C. and Deshayes, M. (2013)]</th>
<th>TYPE OF REMOTE SENSING SENSOR</th>
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<tbody>
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**Summary Table 2**: Evaluation of sensor suitability for the characterisation of natural habitats (based on Lichter et al. (2014) & reproduced from Corbane et al. 2015). Various remote sensing techniques (sensors & resolution) are compared for mapping both between broad physiognomic types (Level 1) and within these types (Level 2). Source references for evaluation table listed with main references. The degree of sensor suitability is indicated as follows:

<table>
<thead>
<tr>
<th>Level 1. Distinction between broad physiognomic types: grass, shrub, tree</th>
<th>Level 2. Distinction within the physiognomic type Forests</th>
<th>Level 2. Distinction within the physiognomic type Grasslands</th>
<th>Level 2. Distinction within the physiognomic type Heathlands</th>
<th>Level 2. Distinction within type Wetlands. Note: Wetlands are not a physiognomic type per se but are various physiognomic types that have adapted to the continuous or temporary presence of water</th>
</tr>
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<tbody>
<tr>
<td><strong>Low spatial resolution and very high temporal resolution (e.g. MODIS, AVHRR)</strong></td>
<td><strong>Deciduous/Coniferous/Mixed forest</strong></td>
<td><strong>With multi-seasonal imagery: Distinction between heath types</strong></td>
<td><strong>Seasonal imagery allows mapping the spatial extent of seasonally submerged wetlands &amp; some vegetation species</strong></td>
<td><strong>Seasonal imagery allows mapping the spatial extent of seasonally submerged wetlands &amp; some vegetation species</strong></td>
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<td><strong>Medium to high spatial/temporal resolution (e.g. Landsat, IRS, SPOT)</strong></td>
<td><strong>Broad types Foody &amp; Hill, 1996; Brown de Colstoun, 2003, dominant species using multi-temporal imagery (Walter et al., 1995)</strong></td>
<td><strong>With multi-seasonal imagery: Grassland types with different levels of agricultural improvement</strong></td>
<td><strong>Seasonal phenological variation can discriminate the evergreen Calluna vulgaris from the deciduous Vaccinium myrtillus</strong></td>
<td><strong>Seasonal vegetation species</strong></td>
</tr>
<tr>
<td><strong>Very high spatial resolution (e.g. IKONOS, Quick-Bird, GeoEye, WorldView-2, Pleiades)</strong></td>
<td><strong>Tree species classification (Immitzer et al., 2012), differentiation of structure &amp; age classes (Johansen et al., 2007), multi-temporal (Key et al., 2001)</strong></td>
<td><strong>With multi-seasonal imagery: Distinction between marshy vegetation &amp; some vegetation species (Back, 2003; Davranche et al., 2010), freshwater swamp vegetation (Harvey &amp; Hill, 2001), functional wetland types (MacAlister &amp; Mahasay, 2009)</strong></td>
<td><strong>Detection of riparian vegetation species (Belluco et al., 2006), shallow, submerged vegetation (Dogran et al., 2009)</strong></td>
<td><strong>Detection of riparian aquatic macrophyte species (Typha Phragmites, Scirpus) (Scheidt &amp; Skidmore, 2003; Rosso et al., 2005; Belluco et al., 2006; Jollineau &amp; Howarth, 2008)</strong></td>
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<tr>
<td><strong>Hyper spectral (e.g. HyMap, CASI, Hyperion)</strong></td>
<td><strong>(besides open water &amp; bare soil) (Fürster et al., 2010a,b)</strong></td>
<td><strong>Seasonal imagery allows mapping the spatial extent of seasonally submerged wetlands &amp; some vegetation species (Back, 2003; Davranche et al., 2010), freshwater swamp vegetation (Harvey &amp; Hill, 2001), functional wetland types (MacAlister &amp; Mahasay, 2009)</strong></td>
<td><strong>Detection of riparian vegetation species (Belluco et al., 2006), shallow, submerged vegetation (Dogran et al., 2009)</strong></td>
<td><strong>Detection of riparian aquatic macrophyte species (Typha Phragmites, Scirpus) (Scheidt &amp; Skidmore, 2003; Rosso et al., 2005; Belluco et al., 2006; Jollineau &amp; Howarth, 2008)</strong></td>
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<tr>
<td><strong>Laser scanning (LIDAR)</strong></td>
<td><strong>(Garcia et al., 2011)</strong></td>
<td><strong>Detection of floristic gradients (Schmidtlein &amp; associated ground species distributions</strong></td>
<td><strong>Only if types differ in structure or density</strong></td>
<td><strong>To be combined with multispectral/hyper spectral imagery for mapping forest species</strong></td>
</tr>
<tr>
<td><strong>Active microwave sensors (e.g. SAR)</strong></td>
<td><strong>(besides open water) (Kasischke et al., 1997)</strong></td>
<td><strong>Assessment of forest parameters (stand density, height, crown width, crown length) (Li et al., 2013), species distributions</strong></td>
<td><strong>Separation between natural grasslands &amp; improved pastures in Quad polarisation (Price et al., 2002b), mowing intensity via swath detection</strong> (Schuster et al., 2011)</td>
<td><strong>To be combined with multispectral imagery. High precision LiDAR-derived digital terrain map is used to build relationship between wetland vegetation species &amp; associated ground elevation. This may enhance the understanding of characteristics of different wetland vegetation species (Prisloe et al., 2006)</strong></td>
</tr>
</tbody>
</table>
2.2 Ranking the measures of condition in terms of Earth Observation

The initial phase of the present research comprised a definition and review of those habitat groups that would be amenable for more focussed work on the applicability of EO techniques. A major part of this phase was an evaluation of each priority habitat in terms of measures of ecological and hydrological variables that were relevant to condition assessment i.e. the identification and characterisation of relevant measures of change. To that end, CEH examined the condition assessment criteria for all priority habitats, tabulating the requirements for good condition under the Common Standards Monitoring (CSM: Robertson & Jefferson 2000) or Farm Environment Plan (FEP: Natural England 2010) systems and proposing a classification of relevant measures of change. This framework was first presented (as an Excel workbook), which JNCC augmented with the classification under the Crick Framework and with a prioritisation as to the immediate importance of each habitat for further review. A simplified version of this workbook is attached to this report as Appendix 4.

Through discussions between CEH and JNCC, and through internal review with colleagues, the project team simplified the measures of change into more generalised categories, presenting them in a table that summarises their application to particular broad habitats – see Summary Table 3. This tabulation allowed a ready ranking of potential measures in terms of their broad applicability to habitats of interest. Very many measures applied in condition assessment were within the general category of vegetation structure and composition, asking questions as to whether the extent of the habitat had changed [17 examples1], whether the zonation of habitats had altered [6 examples] and/or what the productivity of the habitat was, for example in terms of vegetation height or evidence of grazing and browsing [15 examples]. More specific measures focussed on the cover of shrubs and trees [13] or dwarf shrubs [3]; or of herbaceous cover e.g. positive indicator species [17], “problem species” [15] or bryophytes [2]. The graminoid:forb ratio [5] and tussock structure [2] were used in grasslands. Other measures less directly related to vegetation included the extent of bare ground [14], including linear features [3] and the cover of litter and other dead material [8], amongst which the extent of burning [3] was important on heaths and moors. Finally, a few measures related to aquatic habitats and landscape. Thus the extent of water [5], its turbidity [2], quality and temperature [2] were employed in still and flowing water-bodies. Landscape, topography and mapping [5] measures are occasionally important, with the presence of structures [5] and microtopography [3] more rarely used. This section develops the use of these condition measures and comments upon their utility partly through reference to the review of key literature sources notably the MEOW Phase 2 report (Medcalf et al. 2014) and Corbane and Deshayes (2013) (see section 2.1).

2.2.1 Vegetation structure and composition

Most of the measures employed in condition assessment for habitats may be broadly placed here, though the review of these individual variables suggested that many are not worth pursuing for EO as they require detailed floristic/taxonomic assessment (presence/absence of indicator species and quantification) and are thus most amenable to field-based appraisal. Some further literature review may indicate that some may be pursued. Most of the useful measures cited would require high spectral resolution.

1 In section 2.2, numbers in square brackets without any further clarification refer to the number of times that a particular condition measure is employed across the full range of broad habitats.
2.2.1.1 General measures of structure/composition:

A. Has the extent of the habitat feature changed?
This is one of the three most often employed measures of habitat condition. High resolution EO could potentially be used. For habitat mapping, JNCC etc would need to be able to distinguish the target habitat from all others and the use of EO would depend on the Broad/Priority Habitat and the extent of fieldwork which takes place as ground-truthing – see the Crick framework. For this (and zonation), the EO approaches would include high resolution aerial photography (AP), with LiDAR for detailed topography (and tree height distribution and density of canopy).

B. Zonation (e.g. altered, evidence of dynamic situation)
This variable comprises a variant of the latter i.e. can EO demonstrate that a particular distribution (succession) of habitats has changed and are all stages still present (if necessary)? Some zones may be more or less identifiable, and there may be some dependence on productivity. Thus using the same approaches as for habitat extent, one could employ high resolution EO to ascertain whether previously mapped zones (habitats) remained or had moved. Utility of EO would be influenced by the width of zones (i.e. by the spatial resolution of the technique). For example one could create a grid in a buffer zone around a lake, or in relation to the main gradient of succession, and use that grid to check for evidence of a dynamic situation (see section 3 of this report).

C. Productivity (e.g. vegetation height, evidence of grazing/browsing)
This measure is also used in very many condition assessments, but the fine detail required may be less amenable to EO than to field-based appraisal, especially where the condition assessment requires assessment of vegetation height to an accuracy of ±10-20 cm, especially within grasslands. Coarse measures of biomass determination using Radar in grasslands may be made. A combination of LiDAR and NDVI may provide a good measure of overall productivity but this does not correspond simply with the height ranges used in condition assessments. At least four measures were identified where EO could contribute to assessing this variable. Firstly, measuring weed cutting in rivers may be done via RPAS (Remotely Piloted Aerial System) on specific streams/rivers, examining the stage-level. The productivity (height) of mountain willow scrub may be amenable to LiDAR and stereoscopy, but note that this habitat has very limited extent. Most importantly and broadly applicable, there is a need to assess the extent to which grassland height may be accurately detected using LiDAR/Radar. Finally, herbicide damage may be detected through fluorescence, though there are doubts as to whether there are as yet any sensors that will deliver this.

2.2.1.2 Specific measures of structure/composition – woody vegetation:

The cover of shrubs and trees is one of the six most widely used condition measures. Consideration of the use of EO may be dealt with in 4 categories: woodland/scrub, heaths, hedges and species-specific measures.

Firstly, Forest Research has shown the use of LiDAR to demonstrate the age classes in woodland and canopy cover. With regard to the special “woodland” type of orchards, it will be possible to detect with high resolution EO if fruit trees are planted in a regular arrangement. Scrub and tree invasion of herbaceous habitats could be detected using AP and a grid (see under zonation above), LiDAR and texture analysis as practised in studies of Salisbury Plain (Redhead et al. 2012). The linear “woodland” of the riparian tree zone might also be detected through high resolution EO e.g. tree cover (LiDAR) linked to information on stock access/bare soil obtainable with RPAS (i.e. disruption of canopy cover).
Secondly, dwarf shrub cover is only locally relevant but in heath and moorland habitats is a vital measure of condition. MEOW Phase 2 reviewed the approaches applicable to such habitats (see section 2.1). The relative proportions of dwarf shrub and graminoid cover could be achieved through the differing structures i.e. long upright leaves vs woody vegetation.

Thirdly, measures on hedgerows are presently the subject of PhD study by Lyndsey Graham (Newcastle University) of ground-based LiDAR. EO may contribute but the uncertainty is high in national assessments. Condition assessment is likely to require high resolution data (e.g. LiDAR) and DSM for hedgerow height, width and gappiness (though this may need some field boundary ancillary data).

Lastly, some specific shrub taxa are cited in condition assessment. *Salix repens* cover could be assessed on dunes through use of LiDAR and comparison of summer and winter imagery. Although *Ulex europaeus* is spectrally distinct, there are problems with mapping its extent (see section 2.1).

2.2.1.3 Specific measures of structure/composition – herbaceous vegetation:

Along with extent, the presence of certain positive indicator species is the most widely applied condition measure. In probably the majority of cases this variable needs field assessment in order to be measured adequately. However, some aspects are amenable to EO usage (see commentary on productivity above and in section 2.1).

Grasslands

Grassland condition may be examined by EO in terms of species richness, phenology and structure, as well as grass margins to arable land. Previous reviews do not deal with the graminoid:forb ratio (including specific levels of forb cover) *per se* but rather focus on species-richness. Thus grasslands with a high proportion of forbs can be detected by EO data and the precise type of grassland (calcareous, acid etc) inferred with reference to contextual geology data. The timing of greening of grasslands is a key measure to distinguish more improved (generally fertilised) grasslands from relatively natural swards. The presence of tussocks [2] in arable margins and in other grasslands may be assessed through a visual approach. EO could be applied in the special case of grass margins to arable land by using a targeted search within arable fields and high spatial resolution imagery captured at the right time of year to distinguish forb rich swards from tilled land (similarly annual cover in arable margins could be distinguished through an AP time series). Finally, measuring vegetation emergent from gries on limestone pavement could be attempted via LiDAR and 3-D spectroscopy, with pattern recognition (though requiring very high resolution e.g. RPAS data).

Single species

Many other measures of vegetation structure and composition are applied to condition assessment, often requiring data on particular species, with varying degrees to which EO can be applied. Most of these measures deal with "problem" species, though in some cases the species are key elements of the habitats. Thus, in both bogs and dunes, the cover of bryophytes needs to be assessed; for bogs dehydrated *Sphagnum* might be linked to soil moisture measures (see below) and detected through fine scale NIR (airborne and temperature).

Problem species in the UK include *Aizoaceae* (sea-cliffs), bracken, dock, nettle, reed, rhododendron (see above), rush, thistle etc. High resolution EO (RPAS) might be used after ground truthing and, since these very competitive species can occur in dense stands
and produce abundant litter (e.g. nettles), such features may be detectable through EO imagery.

Particular attention in condition assessment is paid to the following:

- **Pteridium aquilinum** (bracken) can be readily detected through visual inspection of imagery from different seasons, measuring the extent of living/dead *Pteridium*.
- **Phragmites australis** (reed) can be assessed hyperspectrally and via Radar & LiDAR, HSRes and AP (see Section 2.1).
- **Juncus effusus** (soft rush) – there is a need to ascertain whether it does indeed have a "black hole effect" in LiDAR (Gerard et al. 2012). The Crick Framework spreadsheet states that “Detailed DTM may help with structural features such as rushes” in lowland fens.
- **Urtica dioica** (stinging nettle) may be one of the agriculturally favoured problem species where EO could play a role.
- **Spartina anglica** (Common Cord-grass) colonising open flats would be straightforward to detect, but invasion into extant marsh is more difficult (vegetation height, roughness?).
- **Molinia caerulea** (Purple Moor-grass) becomes a negative condition indicator when very tussocky and overwhelmingly dominant, producing thick litter. LiDAR/NDVI may be applied when reconnaissance ground survey has confirmed/indicated the height differential.
- **Impatiens glandulifera** (Himalayan Balsam or Policeman’s Helmet) stands have been detected through the pink masses of its flowers in RBG, augmented by MCA RPAS imagery, the latter allowing young growth (pre-flowering/seeding) to be identified and thus targeted management.
- Although some other alien invasive species possess visually detectable and distinctive features at certain times of the year, such convenient attributes are not found in all species perceived as pests or problematic, and thus this approach has limited potential.

### 2.2.2 Abiotic aspects related to vegetation structure and composition

The non-living elements of the habitat structure are more generally amenable to assessment through EO techniques.

#### 2.2.2.1 Extent of bare ground

High resolution EO could potentially be used (NDVI), for example looking at relative measures of change (from imagery always taken at same time of year). The approach would be comparable to that outlined above for zonation. Sub-types of bare ground include ditching, peat erosion, arable margins and paths across scree:

- Ditching could be detected through newly exposed soil and manual examination of AP etc.
- Peat erosion might be found via height data (e.g. LiDAR or radar interferometry) to detect shrinking peat level or volume.
- Arable margin condition could be assessed through timing/duration that ground is bare.
- Paths across scree may require identification of linear features and using airborne LiDAR/Radar to detect rock/stone size in scree and texture.

The presence of linear features (paths, diggings, ditches etc) is an occasional condition measure that could potentially be found with high resolution EO.

#### 2.2.2.2 Extent of dead material
Litter and dead timber extent [8] are an important secondary measure of condition in several habitats. In wooded habitats, the live trees themselves may prevent EO finding the dead timber (even if present). There is a need to test and calibrate NDVI vs litter in order to be surer as to what the imagery means in terms of litter cover. As discussed under grasslands above, greenness, greening and NDVI may be useful, specifically in terms of trends in NDVI.

A particular variant of the dead vegetation measure is provided by the extent of burning. Here a time series, with baseline prior to the fire is useful as well as micro-topography and a vegetation map. Relevant EO approaches include TM, DTM (at a frequency that identifies Sphagnum areas), measurement of failure to revegetate by July/August (as an indication of damage to peat/moss), together with absence of vegetation (thermal signature - SWIR). The impact of fire on the heath (for example, asking whether it has been excessive?) may be best achieved in the second year post-fire, looking at wet and dry peat, and assessing productivity and surface roughness.

2.2.3 Aspects related primarily to water and water-regime

Most of the measures described here refer to open fresh water, with some attention to saturated soils and marine situations.

The extent of water is a special instance of the habitat extent measure. EO can be used, with the relevant resolution dependent on size. However, current EO techniques are not effective for detecting water bodies where they are covered by a vegetation layer, such as where rivers and streams are shaded by riparian trees etc. Extent of water may be assessed in terms of area and depth. The use of Radar on the water surface could detect the extent of open water and its temporal variation (through a time-series) – such a time series is especially important in seasonal water-bodes such as dune slacks and aquifer –fed naturally fluctuating water-bodies.

The quality of the water is employed in condition assessment through turbidity, water chemistry and water temperature.

A. Turbidity may relate to suspended sediment, chlorophyll A etc, and be measured through NDVI. However, this approach would require sensors with Landsat resolution and many water bodies in the UK are too small to be monitored with sensors such as MERIS or Sentinel-3, where ideally the water-body should be at least 1km in diameter. There is a concern that data may be sporadic. Sentinel-2 will provide improved capabilities over Landsat since it includes specific bands for water and it will provide more frequent imagery, which is needed for monitoring lakes as they are highly dynamic.

B. Algal growth could be detected via NIR for Chlorophyll A. Manual interpretation of AP time series may be required to distinguish temporary impact of storm-caused erosion/runoff, and thus the imagery depends on weather conditions. However, one could look for an anomaly against a 10 year average of the same month to see whether changes in turbidity etc were “one-off events”. Channels in imagery of 681-705 nm give a good correlation with Total Suspended Solids.

C. Water quality as measured by pH, pollution etc may be inferred in terms of turbidity and Chlorophyll A (as above). EO might be used dependent on the type of algae (benthic, suspended etc) present and such usage is currently being tested at CEH Lancaster. High resolution EO could potentially be used but would need to be temporally frequent and Sentinel-2 data will provide new capabilities in this area.
D. Water temperature [2] can be detected through thermal sensors (RPAS-related *i.e.* Remotely Piloted Aerial System, a preferable term to Unmanned Aerial Vehicle (UAV)). There are questions of spatial resolution and this approach would need calibration.

Soil moisture and soil temperature are detectable in the SWIR/NIR bands (via NDWI – Normalised Difference Wetness Index) though they need to be calibrated with regard to recent rainfall events, and are relevant to wetlands, including wet grassland. A modified index (MNDWI) uses the green band in place of the NIR band, and is useful for distinguishing water, moist soil and moist vegetation. These variables can be related to measures of bare ground and burnt areas - can we distinguish wet areas and burnt areas in a heath/moor? A 20-30m resolution may be good enough to reveal concerted drainage effort lowering water-tables. These methods can be calibrated and validated using soil moisture data from the *Countryside Survey* (CS – coordinated by CEH). CEH Lancaster (Clare Rowland, Emma Tebbs) currently plan to test the Normalised Difference Moisture Index, applied to Landsat imagery and calibrated using CS data, as a way to map soil moisture across the UK.

Assessment of marine shallow-submerged biotope structure and composition would essentially follow an approach similar to that outlined for zonation *i.e.* assessing sediment vs rock vs algae vs sedentary *Mollusca/Annelida*. This would probably be done at low tide using EA CASI.

### 2.2.4 Landscape, topography and mapping

Though not widely used in condition assessment, the 3 remaining groups of measure are quite amenable to use of EO techniques:

1. **Landscape mapping** - EO could potentially be used. In the case of the context of ponds, superimpose an EO derived habitat map on an up-to-date Land Cover Map (LCM) [EBONE – Gerard *et al.* 2012]
2. Presence of structures could be detected by visual interpretation of AP. One would need to assess the significance of artificial surfaces, and the signal would vary with the type of structure. The Environment Agency do identify in-river structures, removing them from the processed imagery. The structures can be seen with high resolution EO (RPAS) supported with OS data.
3. **Topography** can be assessed via LiDAR (including micro-topographic variation), automated analysis of stereo pairs of airborne or satellite high spatial resolution imagery, or radar interferometry.
**Summary Table 3:** Relevance of differing measures of condition to particular broad habitats (distilled from Workbook of 4th February 2015)

*Note:* for measures shaded: green see section 3; blue (mapping); white (water) and salmon-pink (not reviewed in Section 3)

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<th>Generic measure of change in condition</th>
<th>Rivers &amp; streams</th>
<th>Standing open waters</th>
<th>Arable &amp; horticultural</th>
<th>Boundary &amp; linear features</th>
<th>Broadleaved, mixed &amp; yew woodland</th>
<th>Coniferous woodland</th>
<th>Acid grassland</th>
<th>Calcereous grassland</th>
<th>Neutral grassland</th>
<th>Improved grassland</th>
<th>Dwarf shrubheath</th>
<th>Fen, marsh &amp; swamp</th>
<th>Bogs</th>
<th>Montane habitats</th>
<th>Inland Rock</th>
<th>Supra-littoral rock</th>
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3 The potential of EO approaches

From the review process described in the previous section, we can identify a range of sensors and their established use in mapping habitats and in assessing other ecological attributes of habitats and vegetation. This section reviews the availability and practicability of a range of EO options that might be deployed for assessing habitat condition and habitat change i.e. the options elaborated took into consideration the EO data that are expected to be readily available now and in the future:

1. Aerial photos (Visible and Near Infrared, <1m)
2. Multi-Spectral:
   - SPOT (VIS, NIR, SWIR, 5m to 20m)
   - Landsat: (E)TM, OLI (VIS, NIR, SWIR, 25m)
   - Sentinel 2: MSI (VIS, NIR, SWIR, 10m to 60m);
   - Sentinel 3: MERIS (VIS, NIR, SWIR, 300m)
   - Terra and Aqua: MODIS (VIS, NIR, SWIR, 250m, 500m, 1km)
3. Radar:
   - Sentinel 1: SAR C-band (resampled to 20m standard; interferometric wide swath mode, IWS - VV and IWS - VH);
   - Terra-SAR X and COSMO sky med: SAR X-band (25cm, 3m & 6m resolution; Multiple polarisation available)
4. Airborne LiDAR

The spatial resolution of the EO data is the main driver determining its use (Table 3.1).

<table>
<thead>
<tr>
<th>Habitat mapping</th>
<th>Rapid change detection</th>
<th>Local condition monitoring</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial photos (Visible and Near Infrared)</td>
<td>Aerial photos (Visible and Near Infrared)</td>
<td>SPOT (VIS, NIR, SWIR, 5m)</td>
</tr>
<tr>
<td>SPOT (VIS, NIR, SWIR, 5m to 20m)</td>
<td>Landsat: (E)TM, OLI (VIS, NIR, SWIR, 25m)</td>
<td>Landsat: (E)TM, OLI (VIS, NIR, SWIR, 25m)</td>
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<tr>
<td>Sentinel 2: MSI (VIS, NIR, SWIR, 10m to 60m)</td>
<td>Sentinel 2: MSI (VIS, NIR, SWIR, 10m to 60m)</td>
<td>Sentinel 2: MSI (VIS, NIR, SWIR, 10m)</td>
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<tr>
<td>Sentinel 3: MERIS (VIS, NIR, SWIR, 300m)</td>
<td>Terra and Aqua: MODIS (VIS, NIR, SWIR, 250m, 500m, 1km)</td>
<td>Sentinel 1: SAR C-band (resampled to 20m standard, interferometric wide swath mode, IWS - VV and IWS - VH)</td>
</tr>
<tr>
<td>Sentinel 1: SAR C-band (resampled to 20m standard, interferometric wide swath mode, IWS - VV and IWS - VH)</td>
<td>Terra-SAR X and COSMO sky med: SAR X-band (25cm, 3m &amp; 6m resolution; Multiple polarisation available)</td>
<td>Terra-SAR X and COSMO sky med: SAR X-band (25cm, 3m &amp; 6m resolution; Multiple polarisation available)</td>
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<tr>
<td>Airborne LiDAR</td>
<td>Airborne LiDAR</td>
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</tbody>
</table>

With the above EO data options in mind this evaluation:
1. assesses the data types’ feasibility in terms of the spatial and temporal resolution required to detect relevant habitat change and condition;
2. evaluates each option in terms of its expected effectiveness in detecting a given change and its practicality;
3. evaluates the shortlisted EO based techniques in terms of their ability to detect variables clearly relevant to change in a range of habitats; and
4. for each EO derived parameter, establishes not only how it can be calculated and used but also whether there is a need for calibration or validation, and how that might be achieved.

The description of these assessments of feasibility and practicality follows an essentially constant structure. The approach is described with its aims and any need for ancillary data, and identifies any requirements or caution that must be exercised with the approach. Where the approach can be illustrated through practical examples, these are reported. The evaluation concludes with a bullet-point summary, listing the type of EO data the approach uses (including any optional types), describes the conditions (temporal, atmospheric etc) under which the approach can be used (also required) and discusses any sources of uncertainty in applying the approach.

There are two main parts. The first part looked into approaches that would be suitable for a broad brush change detection across the country. The second part looked into the more detailed approaches that are designed to confirm the changes observed using a broad brush approach and establish the extent and type of change.

3.1. Broad brush change detection (unknown change detected)

- **Automated**, direct observation, baseline required, multiple dates, one or multiple data type, ancillary data could prove useful.

**Aim**: to look for evidence of a change in a broad brush manner across the country. Omission errors should be minimised. The change map is designed to guide more detailed investigations that confirm the change has occurred and establish the extent and type of change. The key is to find a method that (i) will highlight real (and persistent) changes, (ii) is suitably sensitive to provide an early warning of change and (iii) is not confused/affected by natural within and between year variations and dynamics of a habitat. Introducing information on precipitation, surface and/or air temperature and/or soil moisture (as times series of spatial data) may in some cases help separate real change from natural short to medium term variations.

Two generic approaches are relevant here: (1) a map-to-image comparison and (2) an image-to-image comparison. In a map-to-image comparison, the starting point is that the existing map layer would already contain information about the condition of the habitat. The change detection is carried out by **evaluating the absolute EO data values against a pre-existing EO value scale of condition** and so establish whether the condition has changed and how. Here, most of the method development will focus on establishing a robust EO value scale of condition for a particular habitat. In an image-to-image comparison, the **evaluation of relative changes in EO data values against a pre-defined threshold** determines if a change has occurred. If different types of changes are possible, this method will not allow for the attribution of change. Using relative changes inherently includes the EO data value of the preceding time point which tells us about the condition of the habitat at that time.
point. Here, the method development will focus on establishing the minimum threshold value that represents a real change.

All methods identified below are of the image-to-image comparison type. A map-to-image comparison is elaborated further below as part of a working example for grassland habitats (i.e. section 3.3).

Caveat: It is not certain that any of the approaches suggested below will detect subtle changes in condition characterised by e.g. changes in % cover of bare ground, woody vegetation, or changes in productivity.

3.1.1 Passive (VIS, NIR, SWIR and Long Wave)

The EO signal that is being compared could be (i) the reflectances of a selection of spectral bands available (e.g. single value - pixel, average or standard deviation of multiple values – object); and (ii) a vegetation index (VI) (See Appendix 1), or EO derived variables (e.g. cover class, surface temperature, phenology metrics, fractional indices).

There are several options available for consideration:
1. Compare a chosen day, month or period of one year with the same day, month or period of another year.
2. Compare a chosen day, month or period of one year with the same day, month or period from many preceding years.
3. Compare a whole year against a whole preceding year.
4. Compare a whole year against many preceding years.

A fifth option may be possible, whereby images gained just a short time apart, possibly as a series, might be compared with the aim of revealing the direction of change

Option 1: Compare a chosen day, month or period of one year with the same day, month or period of another year.

Figure 3.1.1: Example of a 2 dimensional feature space, showing the distance and angle measures that could be used to compare pixel or object reflectances from 2 time points. The change in reflectance values shown could for example be the
result of a shift from a very productive grass with low litter cover (i.e. a high NIR reflectance and low Red reflectance) to a less productive grass with high litter cover (i.e. a slight drop in NIR reflectance and high Red reflectance).

- Use an angle or distance between time points of a pixel or cluster of pixels (object) placed in a spectral feature space to determine change (see Figures 3.1.1 and 3.1.2). The alarm is triggered when the distance or angle exceeds a pre-defined threshold.

Figure 3.1.2: Spectral distance: A worked example from Clare Rowland (CEH) of how the spectral distance calculated between the (E)TM imagery of 1990 and 2007 for segments of the LCM identified areas of change. The 1990 and 2007 imagery are summer-winter composites of RED, NIR and SWIR bands creating a 6 dimensional feature space. The spectral distance calculated could be the Euclidean or Mahalanobis distance.

- Use NDVI differencing. The alarm is triggered when a pre-defined threshold is exceeded.
Figure 3.1.3: NDVI differencing: An example from Mitchard et al. 2009 where NDVI differencing is used to find areas of shrubs and trees encroaching on semi-arid grasslands. Left shows a histogram of the NDVI difference values acquired for a region in Cameroon and the thresholds used to determine when a change has occurred. The values which are larger than 1.2 standard deviations away from the mean (i.e. zero = no-change) are mapped as changed. Right: the resulting change maps. Higher (positive or negative) difference values are interpreted as higher (increases or decreases) of % woody cover.

The diagrams in Figure 3.1.3 (from Mitchard et al. 2009) show a worked example for NDVI differencing. Here a ratioed NDVI difference measure is used to detect changes in woody cover in a savannah environment: \( \frac{NDVI_t - NDVI_{t-1}}{NDVI_t + NDVI_{t-1}} \). The Landsat (E)TM image dates were chosen to represent the driest part of the dry season period, to enhance the difference in greenness between the herbaceous and woody vegetation. The years were determined by the availability of cloud free imagery (see Appendix 2).

- **EO data**: Medium to coarse spatial resolution VIS and NIR; **Optional**: SWIR
- **Also required**: Date, month or period of the year match between years. If no atmospheric correction has been applied, carry out a between year image normalisation to remove differences in overall illumination conditions (e.g. apply a linear regression model derived from 25 known invariant targets (Mitchard et al. 2009). There are also simple dark object subtraction-based atmospheric correction methods that could be used e.g. Chavez (1988; 1996) and methods for removing the spatially varying effect of haze on the imagery (e.g. haze optimised transform (HOT: see Zhang et al. 2002)). These methods do not require the identification of invariant targets.
- **Uncertainty**: The use of thresholds requires a calibration procedure. Establish a measure of uncertainty through a set of comprehensive case studies with validation exercise, representing regions that are defined by the landscape and tiles of imagery. To help determine a suitable threshold an omission/commission ratio should be defined a priori. To reduce uncertainty consider implementing an ensemble of change detection methods. Ensembles of methods could also be used to quantify uncertainty when no other options for validation are possible. This approach could also help identify outlier methods (i.e. a method that consistently delivers different results from the other methods).

**Option 2**: Compare a chosen day, month or period of one year with the same day, month or period from many preceding years.

- Use the z-score, a dimensionless quantity that indicates how many standard deviations an observation (x) is above or below the mean: \( z = \frac{x - \mu}{\sigma} \) (Zhang et al. 2005). An example where a Z-score is used is in (Mitchard et al. 2009). This approach requires the availability of EO data from several or many years, preceding the year of interest.
Figure 3.1.4: An example time series of NDVI extracted for two pixels (crosshair and arrow). The time-series clearly shows the time-point (2005) when the ‘arrow’ pixel changed from forest to crop while the ‘cross hair’ pixel remained a forest throughout the whole period. In this case, a Z-score would have reliably identified the change as it occurred. The date of the single date NDVI image is a day in 2013. The change (2005) is visible in the 2001-13 MODIS 500m time series shown. The shape of the time series changes substantially. (Source: unpublished internal work by CEH)
Figure 3.1.5: A contrast of the evolution of the NDVI of each year for a pixel representing a woodland in the UK against the average behaviour observed over a 10 year period (mean and stdev) at that same location. Although there are occasions where individual values exceed a NDVI + stdev or NDVI – stdev threshold, it is clear that in reality no significant changes occurred. (Source: Gerard et al, 2013)

Figure 3.1.6: An example of the z-score calculated for a day in spring (day 97), comparing the MODIS NDVI of day 97 of a single year with the average and stdev calculated for day 97 of all 12 years. Here the Z-score was used to observe between year variations in the timing of leaf flush. For the purpose of detecting persistent changes in condition, it will be important to take into account between year seasonal variation. The white areas on the map represent areas with no data. Cloud cover is the main cause of data loss. (Source: Gerard et al, 2013)
In each year there are 46 8-day periods, however due to cloudiness, haze or snow, an NDVI value may not be available for a particular 8-day period in the 10-year record. Figure 3.1.7 shows, for each 250m pixel, the number of 8 day periods within a season for which there are 6 or more years of good quality historical data (red = 1 – 3, green = 4 – 6, blue = 7-10(max)). Broadly, areas to the South and East which are less affected by rainfall and cloud cover have the largest number of historical periods available for the analysis.

- **EO data:** Medium to coarse spatial resolution VIS and NIR; **Optional:** SWIR
- **Also required:** Date, month or period of the year match between years. If no atmospheric correction has been applied, carry out a between year image normalisation to remove differences in overall illumination conditions (e.g. apply a linear regression model derived from 25 known invariant targets (Mitchard et al. 2009)).
- **Uncertainty:** The use of thresholds requires a calibration procedure. Establish a measure of uncertainty through a set of comprehensive case studies with validation exercise, representing regions that are defined by the landscape and tiles of imagery. To help determine a suitable threshold an omission/commission ratio should be defined *a priori*. To reduce uncertainty, consider implementing an ensemble of methods, although there will remain the issue of different timings of leaf burst.

**Option 3. Compare a whole year against a whole preceding year**

This approach is similar to Option 1 except that the availability of a time-series of observations representing a whole year allows for the calculation of an integral (area below the curve) or an annual average which can than subsequently be compared.
Option 4. Compare a whole year against many preceding years.

This approach is similar to Option 2 except that the availability of a time-series of observations representing a whole year allows for the calculation of an integral (area below the curve) or an annual average which can than subsequently be compared.

- **EO data:** Time series of medium to coarse spatial resolution VIS and NIR; **Optional:** SWIR
- **Also required:** Remove bad quality observations from time series.
- **Uncertainty:** The use of thresholds requires a calibration procedure. Establish a measure of uncertainty through a set of comprehensive case studies with validation exercise, representing regions that are defined by the landscape and tiles of imagery. To help determine a suitable threshold an omission/commission ratio should be defined *a priori*. To reduce uncertainty, consider implementing an ensemble of methods. Poor quality data may be identified by reviewing the quality layer of the MODIS (or other) data products. Pixels with cloud, haze, smoke, snow or water are flagged in this quality layer. Another quality test is to remove outliers from the time-series. Many use interpolation to clean up the time series. CEH recommend that JNCC (1) do not use any pixels which do not have enough data points within a year; and (2) use the non-interpolated time-series. The success of this approach should be tested.

Comparing these four options, option 1 would be practical with moderate-resolution sensors such as Landsat and Sentinel-2 but the other three options would probably require MODIS-type sensors in order to provide sufficiently frequent images to produce time series or to be able to look at the same date for multiple years.

### 3.1.2 Active (X, C, S, L-band)

The description here is based in part on personal communication from Alistair Lamb, Airbus-Astrium. There are two types of radar derived measure that are available for comparison:

1. The ‘Amplitude’ or backscatter of a wave. The temporal comparison of backscatter values is analogous to how such comparison would be done with optical data. Aggregation of per pixel signals to a land parcel object will produce an average backscatter value which can be evaluated through time for evidence of change. For evaluating vegetation structure changes a cross polar panel is required (*i.e.* VV + VH polarisation). This cross polar response is very sensitive to vegetation structure (*i.e.* volume scattering).

2. The coherence and phase shifts between interferometric pairs of data. The time between the observation pair should be kept to a minimum as the assumption is that no change has occurred within that period (*e.g.* \( T = May \ 12 \ 2012 \) and \( T+1 = May \ 22 \ 2012 \)).
A change from low to high coherence of land parcel (between interferometric pair of year 1 and interferometric pair of year 2) could for example represent an increase in bare ground (high coherence) / decrease of vegetated areas (low coherence).

Both types of measure can be implemented with Sentinel-1 (C-band) but nobody has tested this yet. They have been shown to work with TerraSAR-X (X-band).

Similar to passive VIS, NIR and SWIR, for active radar the alarm is triggered when a pre-defined threshold is exceeded. The same options for comparing measures are available for consideration:

1. compare a chosen day, month or period of one year with the same day, month or period of another year.
2. compare a chosen day, month or period of one year with the same day, month or period from many preceding years (it should be noted that radar is not affected by cloud, thus making the measurement of each of these 4 options easier than with optical data).
3. compare a whole year against a whole preceding year.
4. compare a whole year against many preceding years.

- **EO data:** High to medium spatial resolution radar (L, S, C or X band) cross polarised or interferometric pairs. Time series are required for options 3 and 4.
- **Also required:** For interferometry accurate co-registration of the paired observations is very important.
- **Uncertainty:** The use of thresholds requires a calibration procedure. Establish a measure of uncertainty through a set of comprehensive case studies with validation exercise, representing regions that are defined by the landscape and tiles of imagery. To help determine a suitable threshold an omission/commission ratio should be defined *a priori*. To reduce uncertainty, consider implementing an ensemble of methods.

### 3.2 Evaluation of approaches by measure of habitat condition

#### 3.2.1 Extent of habitat feature: Condition Measure 1

- **Automated,** direct observation, no baseline required, single or multiple dates, one or multiple data types, sometimes ancillary data is required.

**Aim:** produce area extent of the habitat feature

This measure is used in the condition assessment of 90% of broad habitats – only arable and rivers/streams are not thus assessed and is best delivered through the production of a local, regional or national habitat map. For possible approaches, please refer to the recommendation made by the MEOW report (Medcalf et al 2014).

- **Uncertainty:** Omission and commission from correspondence matrices produced by comparing habitat map with a reference field survey. The field survey should have a sample design that is developed to minimise bias and enhance the precision of the estimates acquired from the resulting correspondence matrix. Olofsson *et al.* (2013, 2014) contain guidelines for good practice and examples. The variance of the estimated extent (class proportion) can be derived from the correspondence matrix (Walsh & Burk 1993).
3.2.2 Productivity: Condition Measure 3

- **Automated**, indirect or direct observation, no baseline required, single or multiple dates, one data type.

**Aim:** For herbaceous habitats, determine (i) the sward height (cm), (ii) amount of live plant material (leaves and flowering shoots), (iii) type of management (grazing or mowing). For woody habitats determine (iv) browsing damage to the vegetation.

3.2.2.1 Sward height in cm

Given that standard condition assessments require such precision, the only option is to aim for very precise direct estimates of height derived from LiDAR or possibly radar. Plants need to grow a certain height before their canopy starts to interact with the LiDAR or radar signal. The main challenge will be to determine whether the signal to noise ratio of the LiDAR or radar signal will be sufficient to reliably and consistently estimate sward height with cm precision. Although there are some examples demonstrating potential (Figures 3.2.1 and 3.2.2 below), both options will need testing thoroughly.

For example, LiDAR biases in height can be up to 10 cm for grasses and herbs (Hopkinson et al. 2005), but these results will vary with LiDAR system. The digital surface model (NEXTMAP) derived from 5m airborne radar has a precision of 1.5m and has so far mainly been used to detect woody vegetation. It is clear that for sward height the radar waveband selection will be crucial. For example, C-band (3.75-7.5cm wavelength) is not very good at discriminating between shrub, trees, hedgerows, and bushy crops, while reeds are very visible in X-band (2.5-3.75 cm waveband) (personal communication Alistair Lamb, Airbus-Astrium). Schuster et al. (2015) have shown how a time-series of high spatial resolution X-band radar (i.e. TerraSAR-X) can be very effective in mapping grassland types. The X-band would pick up changes in sward height and structure observed throughout the growing season.
**EO data**: very high spatial resolution LiDAR (< 1m) or high spatial resolution radar (X-band); **Optional**: full waveform LiDAR, time-series.

**Also required**: Calibration using in situ height observations. To test the feasibility one would need to collate detailed in situ observations to compile average sward height against which the LiDAR or radar (relative) sward height classes are compared. This exercise may be sufficient to establish an empirical approach that will work in most cases. Validation (when monitoring) could consist of a more crude in situ checking.

**Uncertainty**: Validation through comparison with in situ height observations.

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**Figure 3.2.1**: A fringe of reed as seen in the field (top) and by a full waveform airborne LiDAR (bottom). Red pole indicates the 2.2 m height measurement of the reed patch in the field. The brown dots are the LiDAR measurements which gave an average of 2.9 m height estimate. (Source Mücher et al. 2012)
3.2.2 Amount of live plant material in swards and browsing damage to the vegetation in woody habitats (dwarf shrublands and woodlands)

This would be an indirect approach where the RED, NIR and SWIR bands, often in the form of a Vegetation Index, are used to determine the amount of green, healthy vegetation present. There exists a large amount of published work linking VIs with NPP, GPP and biomass. Often the integral under the VI curve of one growing season (or one year) is used. However for regions where there is frequent cloud cover, methods that require few time points should be sought. CEH (Emma Tebbs) recently showed that good regressions could be achieved between NDVI and grassland productivity (site based Annual NPP) with single date Landsat 8 OLI and Landsat TM imagery acquired during spring or autumn (see Figures 3.2.3 and 3.2.4). The method uses ground truth data from Wales for calibration and the plan is to extend this method to the whole of the UK using data from CEH's Countryside Survey. The regression results were relatively better for the spring image than for the autumn image.

The masking out of shade should form part of a standard pre-processing procedure. Spectral unmixing is an option that could be considered. However, an issue with spectral unmixing is that for the N components in which one is interested, one requires N-1 independent spectral bands. When working at very high or high spatial resolution one quickly runs out of bands to use and ends up with the same bands used by the VI. In addition one needs to identify pure end-members. For dead material (i.e. litter or Non-
Photosythetic Vegetation (NPV)) this may be tricky as one always looks at a % cover (even when working at m resolutions). Nonetheless, the approach could be tested.

Figure 3.2.3: The relationship between Annual NPP and Thematic Mapper derived NDVI values for 297 grassland habitat plots (Source: Emma Tebbs – CEH)

Figure 3.2.4: Thematic Mapper derived NDVI - Annual NPP relationship extrapolated beyond the survey squares. Area shown is SE Wales. (Source: Emma Tebbs – CEH)
If single date observations are used, the timing of the observations will be critical. Figure 3.2.5 shows how for an improved grassland site at North Wyke farm, which was surveyed in late August 2014, % cover of litter has a stronger relationship with NDVI than biomass clippings (= GPP). Alternatively one may use MODIS data to check which point in the growing season the Landsat image covers and then apply a correction. To compare NPP maps produced using this method from one year to the next, it will be necessary to recalibrate the relationship for each year with more ground truth data.

**Figure 3.2.5**: Left: % cover of litter versus NDVI; Right: Biomass (kg/ha) versus NDVI. The data are for an improved grassland site at North Wyke farm and were collected from 1 m² samples placed 12.5 m apart along two parallel transects. The NDVI was derived from reflectance observation collected using a CROPSCAN field radiometer. Source: Anita Shepherd (Rothamsted Research) and France Gerard (CEH).

Figure 3.2.6: Preliminary work by Clare Rowland (CEH) demonstrates the within-habitat variability in moisture (NDMI – same as NDSWIR or NDWI) and greenness (NDVI)
For the purpose of habitat condition assessments, regional and habitat specific relationships between VI and ‘productivity’ will have to be established which may require further refining to take into account other spatial (e.g. moisture) and temporal variables (e.g. management, weather) (see Figure 3.2.6 above.)

- **EO data:** Very high to high spatial resolution VIS and NIR; **Optional:** time-series; SWIR. The launch of the Sentinel-2 satellite will mean that more frequent imagery will be available which will make methods based on area under the NDVI curve more feasible.
- **Also required:**
  - Test/confirm effectiveness of VI in distinguishing different levels of productivity.
  - Calibration with *in situ* observation.
  - Timing of VI observations has to be consistent between years: *i.e.* same period within the growing season. This can be done by evaluating time-series of VI between years using imagery available at higher temporal frequencies, but coarser spatial resolution (*e.g.* MODIS).
  - Normalisation of VI between years and between *e.g.* adjacent images/photos or along airborne image scan to deal with variations in atmospheric/illumination conditions, image quality). Example of between years normalisation procedure for VI from (Mitchard *et al.* 2009) is shown in Figure 3.2.10. The alternative is to carry out an atmospheric correction.
- **Uncertainty:** Validation through comparison with *in situ* productivity observations

### 3.2.2.3 Type of management (grazing versus mowing) in swards

Time series of VI show distinct patterns which can be linked to different management practices. The key will be to prove that these patterns are consistent and exclusively linked to management practices. It is likely a regional and habitat specific approach will be required.
Figure 3.2.7: An example for grasslands in Slovakia, showing how time-series of VI could potentially highlight different management practices in swards. Source: EBONE project, author Andrej Halabuk (ILESAS).

A time-series of high spatial resolution X-band radar (i.e. TerraSAR-X and Sentinel-1) may also be an effective option (Ali et al. 2013; Schuster et al. 2015). Phenological assessment could usefully work with a detailed inventory. To some extent, one can generalise the rate of change of NDVI to indicate grazing/cutting but gappiness (due to cloud) of a typical time-series would be the major problem.

Figure 3.2.8: Example of how time-series of TerraSAR-X data (left) and 250 MODIS NDVI data (right) can detect a grazing/mowing event in an Alpine shrubland; (Source: Ali et al. 2013). Note: CEH Lancaster (Dan Morton & Emma Tebbs) are working on a project which uses Sentinel-1 data in a similar way to examine time-series in arable crops.

- **EO data**: Time series of high to medium spatial resolution VIS and NIR or high spatial resolution X-band radar; **Optional**: SWIR
- **Also required**: Test/confirm effectiveness of time-series of VI or X-band radar in distinguishing different management practices.
- **Uncertainty**: Validation through comparison with in situ observations

3.2.3: **Presence/absence**: Condition Measure 4, 8, 10, 19 (Problem species; Altered zonation; Evidence of dynamics; Structures; Presence of Tussocks)

- **Manual**, direct observation, no baseline required, single date, one data type, no ancillary data required.

  **Aim**: produce a table showing (number of times) a feature (a species, zone or dynamics stage, a structure, a tussock) is present or absent within the habitat.

  For more detail (i.e. number of times): divide habitat into pre-defined equal area windows, polygons.
Interpret presence/absence within each window.

Example table:

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<td>Z5</td>
<td>Yes</td>
<td>Yes</td>
<td>yes</td>
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- **EO data**: Very high to high spatial resolution VIS; Optional: NIR, stereo, hyperspectral.
- **Also required**: Manual interpretation protocol.
- **Uncertainty**: a measure of interpretation consistency through independent repeat interpretation of subsample, although this is very labour intensive.

3.2.4: **Percentage (%) cover**: Condition Measure 5, 6, 7, 8, 9, 12, 16 (Bare ground; Vegetation structure & composition (shrub and tree cover; Extent of dead material; Altered zonation; Extent of water; Extent of burning; Vegetation structure & composition (dwarf shrub cover))

- **Manual**: direct observation, no baseline required, single date, one data type, no ancillary data required.

Aim: produce a table or bar chart showing % cover of a zone, dynamics stage or bare ground present or absent within the habitat.

Overlay habitat with a grid of points. Precision (spatial) is determined by the interval between points. For more detail divide habitat into pre-defined equal area windows, polygons.

Interpret the points: identify which zone/dynamic stage is under the point or for a particular cover type (e.g. bare ground) identify if the point is hitting that cover type or not.

% cover of cover type (a zone, a dynamic stage) = number of points hitting cover type (a zone, a dynamic stage)/ total number of points.

Example chart:
3.2.5 Extent of bare ground: Condition Measure 5

- **Automated**, direct observation, no baseline required, single date, one data type, no ancillary data required

**Aim**: produce % cover of bare ground present or absent within the habitat. Precision (spatial) is determined by the pixel resolution of the imagery used.

For more detail divide habitat into pre-defined equal area windows, polygons. Calculate a Vegetation Index (NDVI, NDVI-GR that is suitable for VIS imagery only): \[ NDVI = \frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}}; \text{NDVI-GR} = \frac{\text{Green}-\text{Red}}{\text{Green}+\text{Red}}. \]

Place 'water' (NDVI \(_w\) < 0), 'urban fabric' (NDVI \(_{urb}\) \(\approx\)0), 'bare ground' and 'vegetation' (0 \(<\text{NDVI}_{bgr} < \text{NDVI}_{veg}\)) on a NDVI scale through calibration.

EO data: Very high to high spatial resolution VIS; Optional: NIR, Stereo pairs, hyperspectral.

Also required: Manual interpretation protocol.

Uncertainty: a measure of interpretation consistency through independent repeat interpretation of subsample. Power test to establish required density of points. There is a key difference in the approaches described here and for presence/absence of problem species. In section 3.2.3, one merely asks the interpreter to assess whether any of the features are present within the grid or polygon, and the output is a qualitative yes/no table. In dealing with percentage cover data (3.2.4) the interpreter has to assess every single point, and the output is a number (% cover).
Alternatively, introduce a mask (habitat map, or manual) that removes other features present within the habitat which can be confused with bare ground in VI signal (non-vegetated surfaces: roads, buildings, bare rock). Apply a pre-defined threshold (defined through calibration) to produce a binary map (‘bare’ – ‘not bare’).

- **EO data:** Very high to high spatial resolution VIS or VIS and NIR; **Optional:** high spatial resolution panchromatic imagery to pan-sharpen the VI bands (e.g. Hill et al. 2007), and so enhance the spatial resolution of the VI.

- **Also required:**
  - Test to confirm general effectiveness of VI in separating exposed peat from surroundings. Develop and test generic method to separate bare soil from urban fabric.
  - Timing of VI observations has to be consistent between years: *i.e.* same period within the growing season. This can be done by evaluating time-series of VI between years using imagery available at higher temporal frequencies, but coarser spatial resolution (e.g. MODIS).
  - Normalisation of NDVI between years and between *e.g.* adjacent images/photos or along airborne image scan to deal with variations in atmospheric/illumination conditions, image quality. Example of between years normalisation procedure for NDVI from Mitchard *et al.* (2009) is shown below.

- **Uncertainty:** Pareto measure (Boschetti *et al.* 2004, see Appendix 3) to establish impact of pixel resolution on estimates; Validation exercise to evaluate the % cover of bare ground from VI threshold (*e.g.* *in situ* or compare with manual grid point method). The derivation of the Pareto measure is outlined in Appendix 3.
The NDVIIs from the 1986 TM and 2006 ASTER images were calibrated to the 2000 (E)TM+ image using linear regression models derived from 25 known invariant targets (i.e. their land cover type and appearance did not change in any of the three images). These targets were drawn from water bodies, grasslands, and dense tropical forest. This process should have removed most remaining calibration problems between the different sensors and atmospheres, and is as successful as absolute radiative correction (Coppin et al. 2004).

3.2.6 Percentage (%) cover of woody vegetation: Condition measure 6, 16
(Vegetation structure and composition – shrub and tree cover; Vegetation structure and composition – dwarf shrub cover)

- **Automated**, direct observation, no baseline required, single date, one (or two) data type, may require ancillary data.

**Aim:** produce a table showing % cover of woody vegetation within the habitat.

For more spatial detail divide habitat into pre-defined equal area windows, polygons. A variety of **options** are available: Determine a significant difference between neighbouring pixels or parcels in (1) height (LiDAR or stereo), in (2) image reflectance and texture using very high spatial resolution VIS, (3) image reflectance using high to medium spatial resolution VIS, NIR, SWIR in (4) radar backscatter.
Figure 3.2.11: Example of a woody cover layer derived from combining the NEXTMAP digital surface model (based on airborne Radar) with TM derived NDVI (Source Emma Tebbs, CEH).

Option 1: Height (LiDAR, radar or stereo pair)

This option is likely to work for all habitats. Produce or use a Digital Surface Model derived from LiDAR, Radar or stereo pair. Apply a predefined height threshold to separate woody vegetation from other vegetation. If there are elevated features present which are not woody vegetation, a mask will have to be created and applied. This can be done using NDVI imagery to separate out tall vegetation from other tall features in the landscape (see Figure 3.2.11).
Figure 3.2.12: source Hill et al. 2006

**For woodland habitats,** the derivation of a woodland canopy density score based on the density of LiDAR returns reaching the ground could provide more subtle changes in woodland structure, e.g. Hill, et al. 2006 (see Figure 3.2.12). The use of Sentinel 2 is described under Option 3 (medium spatial resolution imagery).

- **EO data:** High resolution LiDAR, Radar or stereo pair
- **Also required:** A mask of non-woody elevated features
- **Uncertainty:** The height precision of the digital surface models achieved from LiDAR (and stereo pairs) is generally very high. Sources of uncertainties will be the spatial resolution of the original observations and areas of very dense vegetation under which the elevation of the terrain is estimated through interpolation. Use correspondence matrix derived from comparison of outputs with *in situ* survey or manual interpretation of very high resolution imagery using traditional tracing or grid point method.

Option 2: Image reflectance and texture using very high to high spatial resolution VIS and NIR

**For grassland habitats,** use, for example, the (or a variant of the) method developed by (Redhead, 2012 #1763): Carry out a supervised classification of very high spatial resolution image consisting of (1) the first component of PCA of blue, green, red bands; (2) the red band; (3) the Haralick mean texture of the red band (Haralick *et al*., 1973) derived from a 9x9 moving window.

Caveats:
- Shadow on the imagery from topography is a major source of confusion. An initial mask is recommended – ideally something to be done before any other analyses are attempted.
- The approach proved very effective on Salisbury Plain (Redhead *et al*. 2012), but it should be tested in habitats with show more within habitat heterogeneity.
- Other options, such as re-running a segmentation within objects to detect if there are any “new” features in the image, may also be effective.

**For woodland and heath habitats**
- Use a manual approach described to quantify % cover.
- Use a variant of the approach described to quantify % cover of bare ground using NDVI or NDVI-GR.
- Use the approach developed by Hill *et al* (2007): pan-sharpen RED and NIR bands with corresponding panchromatic layer to then produce a high spatial resolution NDVI (e.g. 2.5m). Apply a lower and upper threshold to the panchromatic band and an upper threshold to the NDVI to produce the woody cover map.

**For fens, marsh & swamp and bogs,** the soil moisture in these habitats is expected to be generally higher than in grasslands, woodland and heathland. It is not clear if the approaches listed for grassland, woodland and heathland will perform better or worse in a wetland environment. This should be tested. An example of the spectral signatures of wetlands and other land cover classes is given by Ozesmi and Bauer 2002 (see figure and...
text from this paper reproduced below). Woody vegetation (i.e. Forest) in this example has a higher NIR reflectance than wetland suggesting it could be distinguished from the wetland.

- **EO data**: Very high to high resolution VIS and NIR.
- **Also required**: Observations should be timed to maximise the difference in VIS band reflectance and/or VI between woody and non-woody vegetation (e.g. late summer).
- **Uncertainty**: Pareto measure (Boschetti *et al.* 2004; Mallinis & Koutsias 2012, see Appendix 3) to establish impact of pixel resolution on estimates; use correspondence matrix derived from comparison of outputs with in situ survey or manual interpretation of very high resolution imagery using traditional tracing or grid point method).

**Figure 3.2.13**: Ozesmi and Bauer 2002

Option 3: **Image reflectance using medium spatial resolution VIS, NIR and SWIR**

The availability of a SWIR channel will increase the mapping accuracy of woody cover. There exists a vast amount of literature that focuses on mapping woody or forest cover as part of a land cover or habitat map using medium resolution imagery. When the aim is to produce a within pixel % woody cover estimate the following options could be considered:

- Use the approach by Hansen *et al.* (2013). A random forest or CART model is trained to produce % woody cover classes (gradient). A range of per-band metrics derived from time-series (6 year stretch) of medium resolution EO imagery (Landsat TM) are fed into the CART. Many of the metrics used by the CART are phenology metrics so the time-series is required to build up 16 day to monthly observations and thus capture the annual cycle. The CART is trained with samples of visually interpreted high spatial resolution imagery. The training samples could be delivered using the manual grid point approach. This method has also been implemented with MODIS imagery.
• Use *a posteriori* probability measures of a maximum likelihood classifier to derive % woody cover as described in Hill *et al.* (2007) – see Figure 3.2.14 below.

• Use multispectral data and the spectral unmixing method to separate a ‘woody’ end-member from everything else (e.g. Gonzales-Alonso *et al* 2007 used this to separate burned areas from everything else).

- **EO data:** Medium resolution VIS, NIR and SWIR.
- **Also required:** Observations should be timed to maximise the difference in VIS band reflectance and/or VI between woody and non-woody vegetation (e.g. late summer).
- **Uncertainty:** Use correspondence matrix derived from comparison of outputs with *in situ* survey or manual interpretation of very high resolution imagery using traditional tracing or grid point method).

![Figure 3.2.14](image.png)

*Figure 3.2.14:* An example showing how a posteriori probability measures could be converted into within pixel % cover, Source: Hill *et al.* 2007
Option 4: Active radar (X, C, S, L-band)

Radar is well suited for mapping woody cover. However the level of detail and accuracy at which it will deliver woody cover is determined by the spatial resolution and the waveband (Table 3.2.1).

Table 3.2.1 Frequency and wavelength of radar bands

<table>
<thead>
<tr>
<th>Band</th>
<th>Frequency</th>
<th>Wavelength</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>1–2 GHz</td>
<td>15–30 cm</td>
</tr>
<tr>
<td>S</td>
<td>2–4 GHz</td>
<td>7.5–15 cm</td>
</tr>
<tr>
<td>C</td>
<td>4–8 GHz</td>
<td>3.75–7.5 cm</td>
</tr>
<tr>
<td>X</td>
<td>8–12 GHz</td>
<td>2.5–3.75 cm</td>
</tr>
<tr>
<td>K</td>
<td>18-26.5 GHz</td>
<td>1.1-1.7 cm</td>
</tr>
</tbody>
</table>

The following summarises the main points from personal communication with Alistair Lamb (Airbus – Astrium): When using radar data acquired during ‘leaf on’ the X-band, has the shortest waveband of the range and responds to the top surface of the vegetation canopy (i.e. the backscatter looks like a grainy photo). X-band has sufficient detail to observe loss of individual trees in a tropical forest selective logging case. The DeCover 2 project (http://www.de-cover.de/public/RSS_Keuck.pdf) demonstrated how multi temporal TerraSAR X could be used to map woody/non-woody cover (overall accuracy 70.1%) but was not suitable for determining within pixel woody cover % levels.

C-band penetrates deeper into the canopy and changes polarisation. So here using the cross polarisation component in the signal will be beneficial. C-band does not really distinguish between leaf-on and leaf-off. C-band will pick up ‘bushy vegetation’ but is not very good at discriminating between shrub, trees, hedgerows and bushy crops (e.g. rape seed). C-band can be used as a change alert tool across a forest canopy, in terms of a deviation from expected backscatter response (Ryan et al. 2012; Mitchard et al. 2013).

L-band, with the longest wavelength, penetrates deeper into the canopy and bounces back from trunks, branches and ground surface. L-band will distinguish forests from shrubby cover.

- **EO data**: High to medium resolution radar (X, C or L-band); **Optional**: Multi-temporal.
- **Also required**: Initial calibration with in-situ data.
- **Uncertainty**: Use correspondence matrix derived from comparison of outputs with in situ survey or manual interpretation of very high resolution imagery using traditional tracing or grid point method).

3.2.7 Extent of dead material: Condition Measure 7

- **Automated**, direct observation, no baseline required, single date, one data type, no ancillary data.

**Aim**: produce a table showing % cover of dead material within the habitat.

For more detail divide habitat into pre-defined equal area windows, polygons.
For grassland habitats there is strong evidence that the reflectance is influenced by dead plant material (i.e. litter) across the VIS, NIR and SWIR spectrum (see Figure 3.2.15). There is also a real possibility that a distinction can be made between litter and bare soil (Figure 3.2.16) using the VIS, NIR or SWIR part of the spectrum.

**Figure 3.2.15:** Left: Changes in simulated canopy reflectance when the fraction of litter in a grassland canopy increases from 0% (green line) to 100% (red line); source (Asner, 1998 #1604). Right: Preliminary field radiometry results, showing a link between fraction of litter and NDVI (source: Anita Shepherd (Rothamsted Research) and France Gerard (CEH)).

**Figure 3.2.16:** VIS-NIR (0.5–1.1 μm) and SWIR (1.3–2.4 μm) spectral reflectance of dry (dashed lines) and wet (solid lines) soils and litter types (Source: Nagler et al. 2000).

- Use a VI threshold to separate bare ground from vegetation (showing varying degrees of litter content): e.g. Place 'water' (NDVI\(_w\) < 0), 'urban fabric' (NDVI\(__{urb}\) = 0), 'bare ground', litter and vegetation' (0 <NDVI\(_{bgr}\) < NDVI\(_{litter \& veg}\)) on a NDVI scale through calibration. Use a regression model between the VI and % litter to estimate % litter from the VI.
Use multispectral data and the spectral unmixing method to separate the 'litter' end-member from everything else (e.g. {Gonzalez-Alonso, 2007 #1771} used this to separate burned areas from everything else).

**EO data:** Very high to high resolution VIS and NIR.

**Also required:**
- Observations should be timed to represent the period when litter cover is expected to be the highest.
- Test/confirm effectiveness of VI in separating 'litter' from 'bare' and 'green vegetation'.
- Timing of VI observations has to be consistent between years: *i.e.* same period within the growing season. This can be done by evaluating time-series of VI between years using imagery available at higher temporal frequencies, but coarser spatial resolution (*e.g.* TM, MODIS).

**Uncertainty:** Use correspondence matrix derived from comparison of outputs with *in situ* survey or manual interpretation of very high resolution imagery (*e.g.* RPAS) using traditional tracing or grid point method.

**EO data:** High to medium spatial resolution VIS, NIR and SWIR; **Optional:** Hyperspectral

**Also required:**
- Observations should be timed to represent the period when litter cover is expected to be the highest.
- Test/confirm effectiveness of spectral unmixing in determining % 'litter'.
- Timing of observations has to be consistent between years.

**Uncertainty:** Use correspondence matrix derived from comparison of outputs with *in situ* survey or manual interpretation of very high resolution imagery (*e.g.* RPAS) using traditional tracing or grid point method. As discussed in section 3.2.2.2, spectral unmixing is an option that could be considered and again the issue with spectral unmixing is that for the N components in which one is interested, one needs N-1 independent spectral bands. [See section 3.2.2.2]. Despite these caveats, the approach could be tested.

*For woody vegetation habitats,* litter is expected to have very little impact on the spectral reflectance of the habitat (Asner *et al.* 1998) and use of EO is unlikely to be successful.

### 3.2.8 Extent of water: Condition Measure 9

- **Automated,** direct observation, no baseline required, single date, one data type, no ancillary data.

**Aim:** produce a table showing % cover of water within the habitat.

For more detail divide habitat into pre-defined equal area windows, polygons.

For this condition measure radar should be the first choice. Radar (*i.e.* Synthetic aperture radar–SAR) is particularly effective for measuring moisture inundation and seasonal variations in water levels. Choice of polarisation matters: C-band VV data has mainly been used to study flooding in wetlands dominated by herbaceous vegetation. Originally, for monitoring flooding under forest canopies L-band was the preferred choice. However, more
recently C-band HH has been shown to work for mapping the extent of flooding in some temperate forests (e.g. Lang & Kasischke 2008). The ability of C-band HH data to detect flooding beneath the forest canopy varies according to site conditions including the biophysical character of forests.

- **EO data**: High or medium resolution radar (C or L band); **Optional**: Multi-temporal.
- **Also required**: If the water extent changes dynamically throughout the year, the observations should be timed to capture the minimum and maximum extent.
- **Uncertainty**: Pareto measure (Boschetti *et al.* 2004, see Appendix 3) to establish impact of pixel resolution on estimates; validation exercise to evaluate the accuracy of water extent (*e.g.* in situ survey or compare with manual interpretation using grid point method or traditional tracing).

### 3.2.9 Extent of burning: Condition Measure 12

- **Automated**, direct observation, baseline required, time-series (same time revisit each year), one data type, no ancillary data required.

Aim: produce a table showing % cover of burnt area within the habitat.

For more spatial detail divide habitat into pre-defined equal area windows, polygons; or produce burned patch size statistics. Two options available: determine a significant change between 2 time points in (1) reflected RED, NIR & SWIR spectrum; or in (2) radar backscatter.

**Option 1**: **Reflected VIS, NIR and SWIR spectrum**

Many approaches exist, all relying on a sudden change in the reflectance signal caused by the disappearance of vegetation and the exposure of soil. Mallinis & Koutsias (2012) reviewed the performance of 10 approaches (including an object based approach and VI thresholding) in a Mediterranean setting using 2 to 4 bands of a single date Landsat TM image. Accuracies achieved were high (> 90%) and the difference in outcome between approaches was not significant.

A common approach for global burnt area mapping relies on a reduction in VI after a burn event caused by the complete or partial but sudden removal of vegetation (see Table 3.2.2).

Both NDVI or NDSWIR (also referred to as NDWI or NBR (normalised burn ratio): \(\text{NIR-SWIR} / (\text{NIR+SWIR})\)) are suitable for this task, however NDSWIR has been shown to be more sensitive than NDVI (Figures 3.2.17 and 3.2.18 below). Using NDVI-GR could be an option but as far as CEH is aware, this has not been extensively tested. If recovery after a burn is slow (> 1 year) the recommended method to spot and map a burned area is to evaluate the VI difference between 2 time points: \(\Delta \text{VI} = \text{VI}_{t} - \text{VI}_{t-1}\), where \(\text{VI}_{t}\) is the (average) VI of a given month for year \(t\) and \(\text{VI}_{t-1}\) is the (average) VI of the same month for the previous year \(t-1\).
Table 3.2.2: Review carried out in 2010 by France Gerard summarising burnt area algorithms used at global or continental scale.

<table>
<thead>
<tr>
<th>Name</th>
<th>Area covered</th>
<th>Spectrum used</th>
<th>Temporal</th>
<th>Spatial</th>
<th>Spatial contrast</th>
<th>Temporal contrast</th>
<th>Number and type of threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLOBCARBON K1</td>
<td>global</td>
<td>NIR and Thermal</td>
<td>3 days</td>
<td>1km</td>
<td>yes</td>
<td>no</td>
<td>1 fixed (K&gt;15.5) and other complementary thresholds; a priori: original algorithm used bayesian formula (Piccoli 1998)</td>
</tr>
<tr>
<td>GLOBCARBON E1</td>
<td>global</td>
<td>4 spectral channels (ATSR-series)</td>
<td>3 days</td>
<td>1km</td>
<td>no</td>
<td>no</td>
<td>4 fixed thresholds: (1) RED0.67m &lt; 10%; (2) NDVI &lt; 0.4; (3) SWIR1.6m &lt; 20%; (4) NIR &lt; SWIR1 and (5) BT11m &gt; 350 K.</td>
</tr>
<tr>
<td>MODIS global burnt area</td>
<td>global</td>
<td>NIR and SWIR (MODIS)</td>
<td>1 day</td>
<td>500m</td>
<td>no</td>
<td>yes (moving through time series in daily steps)</td>
<td>(probability function based on deviation from predicted reflectance of BRDF model, sensor calibration and atmospheric correction errors)</td>
</tr>
<tr>
<td>L3JRC</td>
<td>global</td>
<td>NIR and SWIR (SPOT VEGETATION)</td>
<td>1 day</td>
<td>500m</td>
<td>yes</td>
<td>no</td>
<td>1 (based on average + 2*stdev of NIR of pixels in window); NIR and SWIR used for extra checks</td>
</tr>
<tr>
<td>CEH burnt area</td>
<td>Boreal forests</td>
<td>NIR and SWIR (MODIS) + Thermal anomalies (MODIS)</td>
<td>1 day (8 day composite of daily data)</td>
<td>500m; 1km</td>
<td>no</td>
<td>yes (differing between consecutive years in 8 day steps, i.e. 8 day composite)</td>
<td>1 (based on average - 1*stdev of NDSWIR difference of pixels showing thermal anomalies in window + forest mask)</td>
</tr>
<tr>
<td>HANS</td>
<td>Boreal forests in Northern America</td>
<td>RED and NIR (AVHRR) + Thermal anomalies (AVHRR)</td>
<td>1 day (10 day composite of daily data)</td>
<td>1km</td>
<td>no</td>
<td>yes (differing through time series in 10 day steps, i.e. 10 day composite)</td>
<td>(based on average + 1*stdev of NDVI difference of pixels showing thermal anomalies in window + forest mask)</td>
</tr>
<tr>
<td>Giglio et al. 2009</td>
<td>Siberia, USA, Africa</td>
<td>RED, NIR and SWIR (MODIS) + Thermal anomalies (MODIS)</td>
<td>1 day</td>
<td>500m; 1km</td>
<td>yes</td>
<td>yes (differing between 2 windows moving through time series - one following the other- each consisting of 10 cloud free days)</td>
<td>Several which vary with landcover conditional probability functions based on NDSWIR difference and trained by burned (pixels) and 'unburned' pixels identified using amongst others thermal anomalies spatial varying probability i.e. nearest to burned pixel increases probability</td>
</tr>
<tr>
<td>Gonzales-Alonzo et al 2007</td>
<td>A single fire event in Spain</td>
<td>15 spectral channels in RED and NIR (MERIS)</td>
<td>A single date post fire</td>
<td>300m</td>
<td>yes</td>
<td>no</td>
<td>1 fixed (from histogram of values expressing match of pixel spectrum with burnt end-member spectrum - ENVI tool)</td>
</tr>
</tbody>
</table>

Figure 3.2.17: A comparison between NDVI and NDSWIR demonstrates (in a boreal forest environment) the increased sensitivity of NDSWIR to differentiating disturbed from undisturbed woody vegetation (Source: George et al. 2006).
Figure 3.2.18: A comparison between NDVI and NDSWIR demonstrates (in a boreal forest environment) the increased sensitivity of NDSWIR to burned forested areas; (Source: Cuevas-González et al. 2009).

Any pixels or segments with a $\Delta VI >$ pre-defined threshold is mapped as a burn. The threshold is identified through training using known $\Delta VI$ of burned areas and un-burned areas (Figure 3.2.19). Over large areas, the threshold is expected to vary spatially (regionally) and will be a function of the within habitat cover heterogeneity.

Figure 3.2.19: Example of a threshold approach used to separate burned from unburned pixels (source Charles George and France Gerard- CEH)
Option 2: Active (X, C, S, L-band)

Detecting change using radar can be done through the 2 measurement types: (1) amplitude (backscatter) and (2) coherency and phase (from interferometric pairs). The same principles apply for burnt area mapping. Attributing the change to burning will require additional information such as thermal anomalies, a visual check using multi-spectral imagery, or possibly through the search of ‘burn shapes’ using a feature extraction procedure.

3.2.10 Presence of linear features: Condition Measure 14

- **Manual**, direct observation, no baseline required, single date, one (or two) data types, no ancillary data required.

**Aim:** produce statistics describing density of linear features present within the habitat (e.g. histogram of length, total length/total area ratio). Precision is determined by the pixel resolution of the imagery used.

For more detail divide habitat into pre-defined equal area windows, polygons.
Example chart:

- **EO data:** Very high to high spatial resolution VIS or VIS and NIR, **Optional:** Stereo pairs, LiDAR, hyperspectral.
- **Also required:** Manual interpretation protocol.
- **Uncertainty:** a measure of interpretation consistency through independent repeat interpretation of subsample.

- **Automated,** direct observation, no baseline required, single date, one (or two) data types, no ancillary data required

**Aim:** produce statistics describing density of linear features present within the habitat (*e.g.* histogram of length, total length/total area ratio). Precision is determined by the pixel resolution of the imagery used.

For more detail divide habitat into pre-defined equal area windows, polygons.

Main data type: used to spectrally differentiate between bare and other (see Measurement 3):

- Calculate a Vegetation Index (NDVI, NDVI-GR that is suitable for VIS imagery only).
- If only main data type is used: apply a threshold (pre-defined through calibration) to produce a binary map (‘bare’ – ‘not bare’).

Secondary data type: used to further enhance the linear feature detection and exploits the difference in height between the bare ground/exposed peat and soil and its surroundings (*i.e.* vegetation):

- Produce or use a Digital Surface Model produced from LiDAR or a stereo pair.
- If main and secondary data type are used: apply a threshold (pre-defined through calibration) that is function of surface height and NDVI to produce a binary map (‘bare’ – ‘not bare’).

Apply feature extraction procedure on binary map designed to detect linear features. Alternatively apply a feature extraction procedure directly on NDVI layer or combined NDVI - surface height layers.

Calculate length of features in GIS.
**EO data:** Data Type N°1: Very high to high spatial resolution VIS or VIS and NIR; Data Type N°2: Stereo pairs or LiDAR; **Optional:** high spatial resolution panchromatic imagery to pan-sharpen the VI bands, *e.g.* Hill *et al.* (2007); hyperspectral.

**Also required:**
- Timing of VI observations has to be consistent between years: *i.e.* same period within the growing season. This can be done by evaluating time-series of VI between years using imagery available at higher temporal frequencies, but coarser spatial resolution (*e.g.* MODIS).
- Normalisation of NDVI between years and between *e.g.* adjacent images/photos or along airborne image scan to deal with variations in atmospheric/illumination conditions, image quality). Example of between years normalisation procedure for NDVI can be found in Mitchard *et al.* (2009).

**Uncertainty:** Validation exercise to evaluate the linear feature statistic (*e.g.* *in situ* or compare with manual grid point method). Possibly, a variant of Pareto measure Boschetti *et al.* 2004; Mallinis & Koutsias 2012, Appendix 3) could be developed to establish impact of pixel resolution on estimates.

**Linear features: Hedgerows:** Although the methods applied to the presence of linear features also apply here, there are now initiatives which will improve the quality of the hedgerow database and allow EO to contribute to condition assessment. Thus Ordnance Survey will produce a digital hedgerow map on behalf of the UK Rural Payments Agency. Ongoing research at the University of Leicester (Kevin Tansey) and at CEH Lancaster (Paul Scholefield) is addressing EO estimation of hedgerow height, width and gappiness. However, at present many of the condition measures standardly used are outwith the capacity of EO.

### 3.2.11: Soil Moisture: Condition Measurement 20

- **Automated,** direct observation, baseline required, multiple dates, one (or two) data types, no ancillary data required

**Aim:** evaluate spatial and temporal changes in soil moisture within the habitat

- Use relative soil moisture products (*e.g.* Figure 3.2.20 below) derived from active radar and/or passive thermal signals ([https://ismn.geo.tuwien.ac.at/satellites/](https://ismn.geo.tuwien.ac.at/satellites/); [http://rs.geo.tuwien.ac.at/products/](http://rs.geo.tuwien.ac.at/products/)). Because soil moisture is dynamic in time it is advisable to work with a time series of observations that characterise the seasonal soil moisture dynamics and so allow for the detection of change in these dynamics. The use of metrics similar to the phenology metrics to establish sudden changes and trends could be an option.
- Alternatively a z-score approach could be used where a pre-defined threshold highlights anomalies from many preceding years’ average behaviour.
Figure 3.2.20: Example of the use of C-band SAR for determining the moisture saturation levels in a Siberian wetland landscape (Reschke et al 2012). Note how an area that was affected by fire shows high saturation levels.

- **EO data**: High to medium spatial resolution radar (C-, L-band).
- **Also required**:
  - Timing of the observations has to be consistent between years.
  - Test the sensitivity (and consistency of the sensitivity) of soil moisture products to in-situ observed soil moisture related condition changes.
- **Uncertainty**: Tests determining the sensitivity and consistency of this method will provide a good insight into the uncertainties. The impact of the spatial scale at which the soil moisture is observed on sensitivity and consistency will also have to be evaluated.

- Use surface temperature products as an indirect measure of relative soil moisture.
  - Use the signal from a thermal band as an indirect measure of relative soil moisture.

**Caveat**: Surface temperature has a daily temporal cycle. Surface temperature is influenced by a range of variables. Main variables are solar irradiation (i.e. time of day), air temperature (i.e. season), soil moisture and vegetation (land) cover.

- **EO data**: High to medium spatial resolution thermal signal.
- **Also required**:
  - Timing of the observations has to be consistent between years.
  - Test the sensitivity (and consistency of the sensitivity) of surface temperature products/thermal band to in-situ observed soil moisture related condition changes.
- **Uncertainty**: Tests determining the sensitivity and consistency of this method will provide a good insight into the uncertainties. The impact of the spatial scale at which the soil moisture is observed on sensitivity and consistency will also have to be evaluated.
3.2.12 Height of dunes, Evidence of dynamics in dunes: Condition Measure 15 (Topography)

- **Automated**, direct observation, no baseline required, single date, one data type, no ancillary data required

**Aim**: produce statistics describing height of dunes present within the habitat (e.g., number of maxima found, average height of maxima, number of minima found, average height of minima, average height). Spatial precision is determined by the pixel resolution of the imagery used. Height precision is determined by quality of the Digital Terrain Model.

For more detail divide habitat into pre-defined equal area windows, polygons, or identify individual dunes. Produce or use a Digital Terrain Model derived from LiDAR, stereo pair or radar. Use custom designed programs to locate individual dune formations and extract relevant height statistics, for example, methods used by Forestry Commission to locate individual crown in conifer forests ([http://www.geos.ed.ac.uk/~mscgis/05-06/s0570648/](http://www.geos.ed.ac.uk/~mscgis/05-06/s0570648/)) or methods developed to characterise mountain peaks (Podobnikar 2012).

**EO data**: LiDAR, Stereo pairs or radar.

**Also required**: Timing of observations (i.e., leaf off during winter) would improve the accuracy of the height measures.

**Uncertainty**: Possibly by looking at the range of values produced by an ensemble of automated methods that have been developed in the literature.

### 3.3 Gathering an overview of EO approaches

#### 3.3.1 EO approaches summary table

The large table (Excel spreadsheet) appended to this report sets out in detail, and for each condition measure, the spatial, temporal, spectral and sensor requirements of the EO approaches described in 3.1 and 3.2. Bound within the report are Tables 3.3.1 and 3.3.2, which summarise the EO data characteristics expected for proposed measurements and available EO Technology (sensor and payload). In the spreadsheet, the condition measures which were not considered in 3.2 are highlighted in orange. The table shows the importance of the very high (<1m to 2m) and high (5m – 10 m) spatial resolution EO data sources and the potential role radar (SAR-C band and SAR-X band) could play in a high proportion of cases. The codes in the boxes refer to spatial resolution (S), automated (A) or manual (M) and temporal frequency (T).

<table>
<thead>
<tr>
<th>&lt;1m–2m</th>
<th>5m-10m</th>
<th>20m-30m</th>
<th>70m-100m</th>
<th>250m-300m</th>
<th>500m</th>
<th>1km (8km)</th>
<th>12km-50km</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>S2</td>
<td>S3</td>
<td>S4</td>
<td>S5</td>
<td>S6</td>
<td>S7</td>
<td>S8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Single date</th>
<th>Multiple dates</th>
<th>Time-series</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>T2</td>
<td>T3</td>
</tr>
</tbody>
</table>

The combined requirements per approach are listed within the square brackets, for example [M;S1;T1] refers to a method that is automated (A) and that requires single date (T1) EO
data at a spatial resolution of <1 to 2m (S1). Symbols between round brackets, for example [A;S5;(T1+T3)] indicate a differencing method that requires a single date data set representing one year and a time series of data representing another year.

### 3.3.2 Readiness and feasibility scoring of EO approaches

To help further evaluate the elaborated EO approaches in a systematic manner, a set of attributes has been identified and defined that could help to gauge the readiness and feasibility of the approaches in further work.

The readiness of an approach relates to the time it would be likely to take to create a functional change detection process using the approach in question. It takes into account the availability of EO data across time and across the UK; the time required for implementation; and the amount of staff training required.

Feasibility considers the likelihood that the EO approach will ever yield useful results for detecting condition change, given adequate investment in development. It is a function of the staff resources required; data volume involved; cost of data; and the level of pre-processing that the required data has already undergone.

CEH began developing a framework as part of this project to quantify the readiness and feasibility of different approaches using a scoring system. However, time constraints have limited its full development; to ensure accuracy and reliability of scoring, it is desirable to consult broadly with experts to gather a range of opinions, which was outside the scope of this project. Further development of such a framework could be a useful focus for future projects. Without a developed framework, this current project considers readiness and feasibility of EO approaches, but using more qualitative estimations, rather than a scoring system.
Table 3.3.1: EO data characteristics expected for proposed measurements

<table>
<thead>
<tr>
<th></th>
<th>&lt; 1m-2m</th>
<th>5m-10m</th>
<th>20m-30m</th>
<th>70m-100m</th>
<th>250m-300m</th>
<th>500m</th>
<th>1km (8km)</th>
<th>12km-50km</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIS</td>
<td>VI-GR* (bare, woody, burning)</td>
<td>VI-GR* (bare, woody, burning)</td>
<td></td>
<td>bare</td>
<td>bare</td>
<td>bare</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIS + NIR</td>
<td>VI-RN* (bare, woody, burning, productivity-life plant material, dead plant material, water); texture/shapes (linear features, problem species, woody, tussocks)</td>
<td>VI-RN* (bare, woody, burning, productivity-life plant material, dead plant material)</td>
<td></td>
<td>VI-RN* (bare, woody, burning)</td>
<td>VI-RN* (bare, woody, burning)</td>
<td>VI-RN* (bare, woody, burning)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIS+ NIR + SWIR</td>
<td>Wetness index (relative surface wetness, burning), multi-spectral (bare, woody, burning)</td>
<td>Wetness index (relative surface wetness, burning), multi-spectral (bare, woody, burning)</td>
<td></td>
<td>Wetness index (relative surface wetness, burning), multi-spectral (bare, woody, burning)</td>
<td>Wetness index (relative surface wetness, burning), multi-spectral (bare, woody, burning)</td>
<td>Wetness index (relative surface wetness, burning), multi-spectral (bare, woody, burning)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thermal</td>
<td>Relative surface wetness</td>
<td>Relative surface wetness</td>
<td></td>
<td>Relative surface wetness</td>
<td>Relative surface wetness</td>
<td>Relative surface wetness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long wave</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Soil Moisture</td>
</tr>
<tr>
<td>Stereo photos</td>
<td>DSM, DTM, woody, texture/shapes (linear features, problem species, woody, tussocks)</td>
<td>DSM, DTM, woody</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LiDAR</td>
<td>DSM, DTM, woody, sward height</td>
<td>DSM, DTM, woody</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X-band, 2.5-3.75cm</td>
<td>DTM, woody, burning, water, sward height</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C-band, 3.75-7.5cm</td>
<td>Woody, water, burning, soil moisture</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L-band, 15-30cm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Soil moisture, water</td>
</tr>
</tbody>
</table>

* VI-GR is a Vegetation Index based upon the bands green and red
* VI-RN is a Vegetation Index based upon the bands red and near infra-red
### Table 3.3.2: EO data characteristics of available EO Technology (sensor and payload)

<table>
<thead>
<tr>
<th>Category</th>
<th>&lt;1m – 1 m</th>
<th>2m-10 m</th>
<th>20m-30 m</th>
<th>70m-100 m</th>
<th>250m-300m</th>
<th>500m</th>
<th>1km (8km)</th>
<th>12km-50km</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>VIS</strong></td>
<td>HSR Satellite sensors, Airborne Camera, RPAS Camera</td>
<td>HSR Satellite sensors, Airborne Camera, Airborne Multi-Spectral, MSI on Sentinel 2, SPOT</td>
<td>(E)TM, OLI on Landsat8, MSI on Sentinel 2, SPOT, DMC</td>
<td>MODIS, MERIS</td>
<td>MODIS</td>
<td>MODIS, AVHRR, AATSR</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>NIR</strong></td>
<td>RPAS Camera</td>
<td>HSR Satellite sensors, Airborne Camera, Airborne Multi-Spectral, MSI on Sentinel 2, SPOT</td>
<td>(E)TM, OLI on Landsat8, MSI on Sentinel 2, SPOT, DMC</td>
<td>MODIS, MERIS</td>
<td>MODIS</td>
<td>MODIS, AVHRR, AATSR</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SWIR</strong></td>
<td>Airborne Multi/Hyper-spectral</td>
<td>(E)TM, OLI on Landsat8, MSI on Sentinel 2, SPOT</td>
<td>MSI on Sentinel 2</td>
<td>MODIS</td>
<td>MODIS</td>
<td>MODIS, AATSR</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Thermal</strong></td>
<td>RPAS</td>
<td>Airborne Thermal</td>
<td>(E)TM, TIRS on Landsat8</td>
<td>MODIS, AVHRR, AATSR</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Long wave</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>Stereo photos</strong></td>
<td>RPAS Camera, Airborne Camera</td>
<td>Airborne Camera</td>
<td></td>
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<tr>
<td><strong>LiDAR</strong></td>
<td>RPAS, Airborne</td>
<td>Airborne</td>
<td></td>
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</tr>
<tr>
<td><strong>X-band, 2.5-3.75cm</strong></td>
<td>Terra-SAR X and COSMO sky med</td>
<td></td>
<td></td>
<td>SAR C-band on Sentinel 1</td>
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<tr>
<td><strong>C-band, 3.75-7.5cm</strong></td>
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<tr>
<td><strong>L-band, 15-30cm</strong></td>
<td></td>
<td></td>
<td></td>
<td>SMAP</td>
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</tbody>
</table>
3.4 A worked out theoretical example for monitoring grassland condition

In line with the forest monitoring approach developed by the Forestry Commission the first step is to look for evidence of a change in a broad brush manner across the country. This change map is designed to focus the subsequent effort associated to the more elaborated and detailed approaches that are designed to confirm the change and establish the extent and type of change.

3.4.1 The vegetation index:

The grassland condition measures which EO could potentially deliver are:

- Extent of dead material (% litter) – through a VI threshold (late summer)
- Extent of bare ground (% ground) – through a VI threshold (spring)
- Productivity:
  - sward height – through radar (high spatial resolution, multi-temporal, X-band); or LiDAR
  - amount of live vegetation – through a regression between VI and GPP (spring or autumn),
- Presence/absence of problem species – through manual interpretation or texture analysis of high spatial resolution VIS (and NIR) imagery.
- % Woody cover – through a variety of methods some of which use a VI threshold (late summer) or a set of phenology metrics from a VI time-series (whole growing season).

For grasslands, the vegetation index (VI) is proving to be a very versatile EO variable. When each condition measure was elaborated separately, the VI was identified as a possible solution for 4 out of the 7 condition measures. This suggests that theoretically it should be possible to develop a scale of VI values for grasslands which could be used to not only detect substantial changes in a grassland through image-to-image comparison but also to monitor shifts jointly in productivity (shifts between acid, neutral and improved), % bare ground, % litter and % woody vegetation through a map-to-image comparison.

Depending on the spatial scale of the imagery we are considering the condition measures (productivity = improved, neutral or acid grassland, bare ground, woody vegetation, litter) could be treated as a distinct and discrete feature, that is identifiable on the image, or as a component that contributes to the overall VI value of a pixel (See Figure 3.4.1). So, depending on the spatial scale of the imagery, the VI signal will have to be handled differently.
For the first broad brush step, medium scale (20m to 30m) resolution imagery should be used. This means that the VI value could represent a mixture of cover types and that it will always be the result of a % contribution of productivity, litter, bare ground and woody vegetation present within a grassland pixel. Assuming the majority of the grassland pixels monitored are pure grassland pixels we can now consider two approaches: (1) a map-to-image comparison and (2) an image-to-image comparison.

The second more elaborated and detailed step, designed to attribute the detected change to specific measures of condition, is more likely to involve a (3) map-to-map comparison. Here the type of data that will be used will be very high to high spatial resolution imagery. Here, the grassland VI values will allow for the detection and mapping of distinct features of bare ground, woody vegetation or productivity, needed to establish/confirm the type and direction of change.

### 3.4.2 Implementing a map-to-image comparison

In a map-to-image comparison, the evaluation of absolute image reflectance values (in our example: VI values) would detect and attribute a change in a single step. The starting point is that the existing map layer would already contain information about the condition of the grassland. Evaluating the absolute image VI values against an existing pre-defined VI scale of condition would then allow us to establish whether the condition has changed and how.

Considering the generic spectral curves of the grassland variables associated to condition: bare, grass productivity, litter and woody vegetation, we could expect the absolute NVDI values to follow the pattern shown in Figure 3.4.2-Left. Looking at real NDVI values from a variety of sources and locations and at different time points we find the picture to be more complicated (Figure 3.4.2-Right).
Figure 3.4.2: Left: A theoretical pattern of NDVI values we could expect for the condition variables in grasslands. Right: Patterns of NDVI using real NDVI values from a variety of sources and locations taken at different times of the year.

Figures 3.4.2 and 3.4.4-3.4.6 shown below, highlight the issue of evaluating absolute NDVI values to indicate a change from one condition to another. Figure 3.4.2-Right hints at the complexity of the VI -grassland condition relationship. Each of the condition variable (productivity, % bare, % litter, % woody) will contribute to the VI value:

\[ V_{I_{\text{grass}}} = f (\text{grass productivity}, \% \text{ bare}, \% \text{ litter}, \% \text{ woody cover}) \]

The manner in which each individual variable alters the NDVI may be different:

\[ V_{I_{\text{grass}}} = f (f (\text{grass productivity}), f(\% \text{ bare}), f(\% \text{ litter}), f(\% \text{ woody cover})) \]

For example, for an improved grassland with a VI value of 0.9, an increase in the % cover of litter is likely to reduce the VI at a smaller rate than a same increase in % cover of bare ground. This relationship may be different in the case of an acid grassland or a wet grassland. The same changes in VI observed could also be attributed to either a reduction in productivity, an increase in litter content or an increase in bare ground. Finally, because the relative difference in VI between woody cover and grassland is likely to vary with grassland type and productivity, the rate of change in grassland VI with % woody cover is also likely to be very different.

We also know that the VI values are also affected by variables we are not interested in: e.g. soil type and moisture, leaf phenological cycle (which is determined by time and influenced by the weather and the local climate), the management, sensor view angle:

\[ V_{I_{\text{grass}}} = f (f (\text{grass productivity}), f(\% \text{ bare}), f(\% \text{ litter}), f(\% \text{ woody cover}), \text{ soil type}, \text{ soil moisture}, \text{ time}, \text{ management type}, \text{ sensor view angle}, \text{ atmospheric conditions}, \text{ co-registration error}) \]

At the moment we do not know to which of these variables the VI will be the most sensitive. This is important as we only need to include in the model the variables that will strongly alter the VI. We can also choose to reduce the impact of unwanted variables by introducing a correction (e.g. atmospheric correction, view angle correction, optimise co-registration) or making informed EO image choices. For example, choosing observations that were taken
with viewing zenith angles that are zero or close to zero; choosing observations that always represent the same stage of the growing season.

For the model to be effective in determining shifts in condition (in terms of productivity, % litter, % bare ground and % woody), it is important to establish that the VI is sensitive to changes in these condition variables (e.g. Figure 3.4.3). The literature suggests this is the case, but more often than not, when this is demonstrated the focus is on one or two variables. To establish a generic method that relies on the interpretation of absolute VI values all condition variables have to be considered in the model. The model could be an empirical regression model or a physically based radiative transfer model. In both cases, because of the large number of possible variable combinations, inversion is likely to be implemented through a look-up-table. Calibration to regional/local conditions will be required.

Nevertheless, there will be unwanted sources of variation in the VI which cannot be accounted for and so these will have to be treated as noise. This will reduce the effectiveness of the model’s predictions of the condition measures. At the moment it is not clear whether the signal-to-noise ratio will be large enough for the approach to be effective.

**Figure 3.4.3:** Example of a sensitivity analysis carried out using a radiative transfer model. The model was parameterised to represent a grassland. The sensitivity analysis was carried out on LAI, Leaf Chlorophyll content and Leaf water content. The changes observed across the spectrum, show how a VI would be affected by the LAI, chlorophyll content and leaf water content of the grassland (Source: S. Punalekar and A. Verhoef – University of Reading).
**Figure 3.4.4:** The relationship between Annual NPP and Thematic Mapper derived NDVI values for 297 grassland habitat plots (Source: Emma Tebbs – CEH) – see also Figure 3.2.3 in section 3.2

**Figure 3.4.5:** **Left:** % cover of litter versus NDVI; **Right:** Biomass (kg/ha) versus NDVI. The data is for an improved grassland site at North Wyke farm. The data were collected from 1 m² samples placed 12.5 m apart along two parallel transects. The NDVI was derived from reflectance observation collected using CROPSCAN field radiometer. Source: Anita Shepherd (Rothamsted Research) and France Gerard (CEH) - see also Figure 3.2.5 in section 3.2
3.4.3 Implementing an image-to-image comparison

In an image-to-image comparison, the evaluation of relative changes in the image reflectance values (e.g. VI values) compared against a pre-defined threshold would determine if a change has occurred. If different types of changes are possible, this method would not allow for an attribution of the change (i.e. the determination of the type of change).

In contrast with a map-to-image approach, where you are reliant on an a single absolute VI value to determine whether a change has happened, using relative changes in the VI allows for less sophisticated methods which have the potential to be as effective as the map-to-image approach. Using relative changes inherently includes the VI value of the preceding time point which tells us about the condition of that grassland at that time point. To detect a change, we only need to establish the minimum amount of change in VI that will represent a real change.

If the previous condition of the grassland was known, the direction of change (negative or positive) may provide a hint of the type of change to expect. For example, an increase in NDVI of a previously acid grassland could indicate an increase in productivity or shrub encroachment. A decrease in NDVI would suggest a higher litter content, a higher proportion of bare ground or the presence of water. The exact attribution of change is carried out through further image analysis, using additional and more spatially detailed EO data and/or different algorithms. This could then be verified through subsequent field surveying.

Similar to the map-to-image approach, there will be unwanted sources of variation in the VI which will have to be treated as noise (e.g. atmosphere, view angle). This will reduce the effectiveness of the change detection method. At the moment it is not clear whether the signal-to-noise ratio will be large enough for any approach to be effective.

There are several image-to-image comparison options available for consideration (see section 3.1 of the report):

1. compare a chosen day, month or period of one year with the same day, month or period of another year.
2. compare a chosen day, month or period of one year with the same day, month or period from many preceding years.
3. compare a whole year against a whole preceding year.
4. compare a whole year against many preceding years.

Figure 3.4.7 from Mitchard et al. (2009) demonstrates in more detail the use of VI differencing to compare a single image of one year with a single image of another year (i.e. option 1). Here a ratioed NDVI difference measure is used to detect changes in woody cover in a grassland savanna environment:

\[
\frac{NDVI_t - NDVI_{t-1}}{NDVI_t + NDVI_{t-1}}
\]

Negative NDVI differencing values were interpreted as a loss of woody cover, while positive values as a gain in woody cover. Manual image interpretation of very high spatial resolution imagery using the grid point approach was used to confirm the observed woody encroachment in the savannah.
invariant targets (i.e. their land cover type and appearance did not change in any of the three images).

The Landsat (E)TM image dates were chosen to represent the driest part of the dry season period, to enhance the difference in greenness between the dry herbaceous and green woody vegetation. The choice of years was determined by the availability of cloud free imagery. The impact of varying atmospheric conditions between images is reduced through a normalisation/calibration procedure (Figure 3.4.8). In this example, one image is normalised to the other by applying a linear regression model derived using the VI values of a number of known invariant targets: \( VI_{img1} = f(VI_{img2}) \). Other normalisation procedures exist, such as histogram equalisation, all of which are equally valid. The choice of procedure will depend on the imagery available and habitat under consideration.

3.4.4 Implementing a map-to-map comparison

In a map-to-map comparison, the evaluation of changes is based on the comparison of the condition measures derived from the EO data. In other words, the EO derived condition measure acquired for the year of the assessment is compared with the EO derived condition measure acquired for the preceding assessment years.

This approach is expected to dominate the second step of the monitoring, when very high spatial resolution imagery is used to attribute the type and direction of change. In this context the term ‘map’ in ‘map-to-map comparison’ should be extended with ‘statistics’ as in nearly all relevant approaches discussed in section 3.1, the condition measure is provided as a single value (or a table of values) that embodies the condition of the whole grassland habitat. In a GIS setup the condition measures would be listed as part of a habitat polygon attribute table. So, unless the condition measure is dependent on remembering the location of features within the habitat polygon, the spatial (i.e. ‘map’) aspect of the measure has become less relevant. Not having to worry about the exact location of features is particularly attractive as it removes the need to optimise co-registration between maps (EO Imagery).
4. Recommendations and proposal for a practical test

Four potential pilot studies have been identified for a practical test:
1. Monitoring grassland habitat condition
2. Monitoring dwarf shrubland and bog habitats
3. Monitoring the woody cover and bare ground in grassland, dwarf shrubland, bog, and fen, marsh & swamp habitats.
4. Monitoring the extent of water in grassland and fen, marsh & swamp habitats.

The reasoning behind the choice is as follows (see Table 4.1):

**Monitoring grassland habitat condition**

A single EO variable (i.e. Vegetation Index) is found to be relevant for a number of condition measures associated to grassland habitats (i.e. productivity, extent of woody cover (tree, shrub, dwarf shrub), bare ground and dead material). In addition, the delivery of two of these condition measures (i.e. woody cover and bare ground) is expected to be very feasible. There is potential for an approach that would incorporate all four condition measures and this should be investigated. The readiness of the approach is very low and so the pilot study will involve a substantial amount of research and development.

**Monitoring dwarf shrubland and bog habitats**

Two EO variables (i.e. Vegetation Index and SAR X-band or C-band backscatter) are found to be relevant for a number of condition measures associated to dwarf shrubland and bog habitats (i.e. extent of woody cover (tree, shrub, dwarf shrub), bare ground and burning). Moreover, the delivery of all of these condition measures is expected to be very feasible. Here the challenge will be the separation between bare and burned areas and so the available approaches have medium readiness, and scope for some research and development should be incorporated in the pilot study.

**Monitoring the woody cover and bare ground in grassland, dwarf shrubland, bog, and fen, marsh & swamp habitats**

Two EO variables (i.e. Vegetation Index and SAR X-band or C-band backscatter) are found to be relevant for the condition measures extent of woody cover and bare ground. Although the approaches to deliver these measures are likely to vary with habitat (i.e. grassland, dwarf shrubland, bog, and fen, marsh & swamp habitats), the delivery of the measures is expected to be feasible in most cases. Here the readiness varies from high for determining bare ground using the vegetation index, to medium for determining woody cover using the vegetation index, to low for determining both bare ground and woody cover from SAR. The amount of research and development required will vary accordingly.

**Monitoring the extent of water in grassland and fen, marsh & swamp habitats**

SAR C-band is expected to be very successful at delivering a measure of the extent of water. The readiness is high; the key here is to find out whether the 20m (Standard) resolution of the sentinel-1 SAR-C instrument will be sufficient or whether the higher spatial resolution modes will be required.
Table 4.1: Illustrating the reasoning behind the choice of pilot studies: green box = includes the cases discussed under grassland habitats; orange box = includes the cases discussed under dwarf shrubland and bog habitats; red box = includes cases discussed under woody cover and bare ground; and blue box = cases discussed under extent of water. [Based upon Summary Table 3 – see section 2].

<table>
<thead>
<tr>
<th>Generic measure of change in condition</th>
<th>Rivers &amp; streams</th>
<th>Standing open waters</th>
<th>Arable &amp; horticultural</th>
<th>Boundary &amp; linear features</th>
<th>woodland, mixed &amp; other woodland</th>
<th>Conifer woodland</th>
<th>Acid grassland</th>
<th>Coloumbrisol</th>
<th>Neutral grassland</th>
<th>Improved grassland</th>
<th>Mown / sward</th>
<th>Dead sward</th>
<th>Bogs</th>
<th>Fen, mire &amp; swamp</th>
<th>Mire habitat</th>
<th>Inland Rock</th>
<th>Superficial rock</th>
<th>Superficial sand</th>
<th>Upland rock</th>
<th>Upland sand</th>
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</tr>
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<td>Productivity (e.g. vegetation height, evidence of grazing/browsing)</td>
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<td>✓</td>
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<tr>
<td>Extent of dead material (e.g. litter, timber etc)</td>
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<td>Zonation (e.g. altered, evidence of dynamic situation)</td>
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<tr>
<td>Turbidity (e.g. suspended sediment, chlorophyll A)</td>
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</tr>
<tr>
<td>Vegetation structure &amp; composition (bryophytes, esp. Sphagnum)</td>
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<td>✓</td>
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<td>2</td>
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<tr>
<td>Water temperature</td>
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</tr>
</tbody>
</table>
Any of the pilot studies should be designed to resolve the following questions:

**Method:**
- Is the choice of EO data proposed adequate?
- Could an approach in line with the method developed by the Forestry Commission for forest monitoring work be used?
- Will a first broad brush method be sensitive enough to detect changes in condition?
- Can we make the broad brush method more sensitive by adding other EO data layers to our first EO data choice? Is the extra sensitivity gained worth the extra effort involved in adding more EO data layers?
- For the broad brush approach, what is an acceptable balance between omission and commission errors? Too many commission errors will result in too much effort devoted unnecessarily in the subsequent more detailed analysis to check and attribute the change in condition. Too many omission errors will result in too many habitats undergoing change not being identified.
- For the broad brush approach, what is a suitable revisit time? Can this be achieved across the UK taking into account the expected cloud cover?
- Can the subsequent more detailed local analysis be designed to monitor several habitats and/or condition measures jointly?
- For the detailed local analysis, what is a suitable revisit time and do all the habitats and/or condition measures have to be monitored at the same temporal frequency?
- For both the broad brush approach and the detailed local analysis, how do we calibrate? What is the most cost-efficient approach for calibration (i.e. what is the minimum calibration effort we can get away with without affecting the effectiveness of the method)?

**Error or consistency in estimates:**
- How accurate/consistent do the condition measures estimates have to be to enable adequate monitoring?
- What is the most cost-efficient approach for validation? How should we sample? How should we calculate accuracy/consistency? How precise do the accuracy estimates have to be?
- What are the main sources of error? How can we reduce the sources of error?

**Operational processing chain:**
- How many key steps are involved and what does the work flow between these steps look like?
- How long will each step take?
- What type or resources will be required in terms of hardware, software, person-months etc?

**Monitoring grassland habitat condition**

Following discussion, JNCC and CEH jointly decided to focus on grassland as the best candidate habitat for the pilot studies. Grasslands were preferable for two key reasons: 1) they are an important, extensive and varied group of habitats where condition assessment is vital and where habitat change may be relatively rapid; and 2) a wide range of EO-based techniques can be tested. One key question here (generated from the tabular summary in section 3.3) is: Is it possible to use a vegetation index (NVDI, SAVI or EVI) to monitor changes jointly in productivity (amount of life material), extent of woody cover (tree, shrub, dwarf shrub), bare ground and dead material or do we need other EO data sources or condition specific approaches to enhance the monitoring? Another question is: what other
EO parameters and/or approaches offer significant potential (e.g. changes in red band indicating scrub development) and would a combination of these EO parameters and approaches be a better option?

**Broad brush UK**

The potential of a gradation (scale) of vegetation index values related to the four condition measures forming the basis of the broad brush approach for grassland monitoring across the UK should be investigated. The focus should be on the use of medium spatial resolution (10m-30m) multi-spectral imagery ((E)TM, OLI, MSI or SPOT). The effectiveness of coarser (250m-300m) resolution imagery could also be evaluated. VI-differencing methods (image-to-image) should be compared against a look up table method (map-to-image). The look up table method is explained further in the worked out example for grassland condition.

The VI based options could also be compared against the spectral distance method (image-to-image) which allows for the full spectral range of a multi-spectral instrument to be used. The addition of sentinel-1 SAR-C data to any of the methods above should also be investigated (see Table 4.1).

The recommendation is to start with a VI–differencing approach, because it is the easiest to implement, and build up the complexity of the approach (i.e. move from the top left to the bottom right of Table 4.2) and evaluate the increase in accuracy achieved versus the increase in effort (complexity of method) involved.

**Table 4.2:** Overview of EO methods that could be tested for the broad brush UK wide detection of condition change. Each of the methods based on reflectance data have been elaborated in parts 3.1 and 3.4 of the report. For SAR, approaches are expected to be conceptually similar.

<table>
<thead>
<tr>
<th>Image-to-Image</th>
<th>Map-to-Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>VI-differencing (see 3.1.1)</td>
<td>Spectral distance (see 3.1.1)</td>
</tr>
<tr>
<td>VI-differencing (see 3.1.1) + SAR-differencing</td>
<td>Spectral distance (see 3.1.1) + SAR-differencing</td>
</tr>
</tbody>
</table>

**Detailed local:**

The potential of using vegetation index values, derived from very high spatial resolution (<1m – 2m) VIS-NIR imagery (e.g. Rapid-Eye, aerial photography) as the main or only EO data source to estimate the four condition measures in the detailed local analysis should be investigated. The effectiveness of high spatial resolution (5m-10m) imagery could also be investigated. The inclusion of other proven methods could be investigated, as well as the addition of TerraSAR-X.

The main outstanding methodological issues are:

1. how to estimate litter content or how to attribute changes in the EO signal to changes in litter content (instead of changes in productivity); and
2. how to combine condition measure specific methods (e.g. section 3) into a single cost effective workflow.

Comparing manual versus automated approaches in terms of cost effectiveness could be considered. The recommendation is to start with a vegetation index only approach, because it is easy to implement, and build up the complexity of the workflow by adding more data
layers and methods and evaluate the increase in accuracy achieved versus the increase in effort (complexity of method) involved.

**Timing:**
Grassland management (grazing, or mowing) will add another dimension to an already multivariate problem, so the timing of the monitoring will have to be when management is expected to have the least impact (e.g. spring time before any hay (or silage) cut). It is less easy to introduce such a control to deal with local variation in the timing of grazing.

**Table 4.3:** Example of how the EO methods could be combined and tested for detailed local condition monitoring. Each of the methods based on reflectance data have been elaborated in parts 3.2 and 3.4 of the report. For SAR, approaches are expected to be conceptually the same.

<table>
<thead>
<tr>
<th>Automated</th>
<th>Manual (see 3.2.4, 3.2.10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Pan-sharpened) VI threshold for bare ground, woody cover and shade (see 3.2.5, 3.2.6, 3.2.7) + VI – differencing for productivity and woody cover (see 3.2.2.2 and 3.1.1)</td>
<td>(Pan-sharpened) VI + VI - differencing</td>
</tr>
<tr>
<td>(Pan-sharpened) VI threshold for bare ground and shade (see 3.2.5, 3.2.6, 3.2.7) + VI – differencing for productivity (see 3.2.2.2) + texture analysis for woody cover (see 3.2.6)</td>
<td>(Pan-sharpened) VI + VI - differencing and Stereoscopic aerial photo pair (VIS, NIR)</td>
</tr>
<tr>
<td>(Pan-sharpened) VI for bare ground and shade (see 3.2.5) + VI – differencing for productivity (see 3.2.2.2) + (multi-temporal) SAR for woody cover (see 3.2.6) and productivity (see 3.2.2.1)</td>
<td>Stereoscopic aerial photo pair (VIS, NIR)</td>
</tr>
</tbody>
</table>

**Site selection:**
A site is defined as a parcel of land which is considered to contain a single grassland type (acid, neutral, calcareous, improved) and might, for example, correspond to a single management unit of a SSSI (a typical target of condition assessment). The selected sites for the pilot study should:

- Have a history of known and well documented changes in condition (a change in productivity, a change in bare ground cover, a change in woody cover, a change in litter content). This is important to enable the testing of the sensitivity of the broad brush approach.
- Represent the four broad types of grasslands found in the UK: acid, calcareous, neutral and improved grasslands. The improved grasslands are there to be used as a point of reference: high productivity, no woody cover, no bare ground, no litter (in spring), little change in condition expected.

The selected sites could also:
- If possible represent the expected regional variations in the UK taking into account the scene coverage of a Landsat (E)TM (OLI) scene (in future Sentinel-2 MSI scene).
- Include a gradation of soil moisture (see figure 4.1, illustrating the effect of soil moisture on the NDVI) and soil type (grassland type should cover this).
• Be chosen to represent varying parcel sizes (to test the impact of pixel size / parcel size ratio).

Field data:
To evaluate the performance of the broad brush approaches and the detailed local monitoring a comprehensive set of field measurements repeated in a consistent manner across all sites will have to be collected. The aim of the field data collection is to characterise the overall condition of the chosen grassland sites, so the sampling strategy (i.e. site = parcel of same grassland type) and measurement protocol should be designed to estimate best the extent of bare ground, woody cover, litter content and productivity (i.e. amount of live plant material) of the site. Existing data, collected from, for example, ECN sites or CS could potentially be used to deliver proxy estimates of the condition measurements.

Ideally a pair of sites should be found to allow for independent calibration and validation. However if this is not possible the same sites could be used to first develop a calibration for the methods and subsequently evaluate the performance of the methods. This should be pointed out clearly from the start with a caveat that accuracies achieved will be artificially high.

![Figure 4.1](source: Todd & Hoffer 1998)

Calibration
The aim is to develop an operational calibration procedure designed to re-adjust the parameters of the chosen method/model to allow for both between-year variability and regional variability. Ideally we would like to be able to reduce the calibration efforts as the monitoring progresses in time. In other words, the pilot study should investigate whether it is possible to improve the fit of the chosen method/model to regional/local conditions continuously by informing it with a build-up of a reducing number of observations over time. The approach for calibration will be different depending on whether the chosen method relies
on determining condition based on relative EO values or absolute EO values. The pilot study should compare methods in terms of the additional efforts associated to the corresponding calibration. Between-year variability can be reduced through normalisation procedures. The pilot study should evaluate the benefits of using normalisation procedures to reduce the amount of effort going into field-based calibration.

Not all reference data used for calibration will require field based observation. The pilot study should look into alternative and more effective ways of collecting the reference data. For example, the manual interpretation of very high spatial resolution imagery may provide % bare ground and/or woody cover estimates that are sufficiently reliable for use in calibration and validation. The use of time series of coarse resolution VI may be an effective way of minimising the effect of between-year variability in terms of the onset of the growing season.

**Validation:**

The aim here is to develop an operational validation procedure that will add estimates of error or consistency in the derived condition measures every time the habitat is monitored and so establish confidence in the observed changes. The types of data collected for the validation procedure are often the same as those collected for calibration. The key point is that the validation and calibration datasets are independent. The pilot study should consider validation through field surveying or independent EO based procedures (e.g. manual interpretation or possibly even ensembles of methods).

**Candidate sites for field-based calibration and validation**

Some approaches to calibration and validation of individual EO parameters are mentioned in section 3.2. At a more general level, both Countryside Survey (CS - Carey et al. 2008; Wood et al. 2015) and the Environmental Change Network (ECN, see http://www.ecn.ac.uk/) have been used to calibrate some EO approaches. Thus, CS was used to calibrate the Land Cover Map (Morton et al. 2011). CEH Lancaster has subsequently developed this approach and taken these analyses further as part of a project examining the validity of using LCM as part of a screening tool for Biodiversity Offsetting (Norton et al. 2014).

Other CEH activity has investigated how RPAS imagery (through the MEOW project) and aerial photography (Wood et al. 2015) could be used for mapping Countryside Stewardship squares. However, in these cases the approach focussed more on habitat extent (see section 3.2.1. of this report) rather than on other measures of condition. Ongoing CEH work in the Pennines (Moor House) and other ECN sites is using daily photographs to assess the timing of greening up for both heather moorland and upland acid grassland. This work has the potential to investigate productivity indices, provided it is associated with vegetation sampling.

Overall, Countryside Survey has proven capacity to demonstrate spatial variation in plant communities and habitat types, as the survey includes many plots of the same habitats throughout the UK. ECN complements this approach by providing better temporal resolution due to the more frequent and regular measurements at the same locations. Thus ECN aligned with EO should provide a better grasp of how habitats change over time (e.g. seasonally) and CS aligned with EO could help establish variability in vegetation types over space (and to a lesser extent time – across the survey period).

Together CS and ECN might provide a context within which to interpret the practical test and pilot studies described above. Thus the ECN sites might have particular advantages for the
calibration and/or validation of the EO approaches advocated above, since they are recorded frequently to standard protocols and have been established over 20 years. ECN could therefore provide directly comparable field data over the lifespans of many EO sensors. In that regard ECN has a distinct advantage over Countryside Survey where the interval between ground surveys is at least 7 years and has been much longer. CS, however, has the advantage of better spatial coverage and more replication of target priority and broad habitats. Practically, ECN may provide the best option, but its limited range of sites should be augmented with other field sites with a consistent and well-documented history of both ecological change (possibly in response to management for biodiversity) and monitoring of the vegetation. Such supplementary sites might come from those registered with the Ecological Continuity Trust, including long-term experiments managed by CEH and others such as Tadham Moor (Somerset), Somerford Mead (Oxford), Cockle Park (University of Newcastle) and, of course, the Park Grass and Broadbalk experiments at Rothamsted.
5. References


CORBANE, C. & DESHAYES, M. 2013. Possibilities and limits of remote sensing for mapping natural habitats. IRSTEA literature review as part of the MS-Monina project


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## Appendix 1: NDVI and other vegetation indices

**Table A1.1:** Vegetation indices that have been investigated to look at vegetation condition

<table>
<thead>
<tr>
<th>Index</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI (Rouse <em>et al.</em> 1974)</td>
<td>$\frac{NIR - Red}{NIR + Red}$</td>
</tr>
<tr>
<td>Red-edge Green NDVI (Buschmann &amp; Nagel 1993)</td>
<td>$\frac{RedEdge - Green}{RedEdge + Green}$</td>
</tr>
<tr>
<td>Green NDVI (GNDVI) (Gitelson &amp; Merzlyak 1996)</td>
<td>$\frac{NIR - Green}{NIR + Green}$</td>
</tr>
<tr>
<td>Red-edge index (NDRE) (Barnes <em>et al.</em> 2000)</td>
<td>$\frac{NIR - RedEdge}{NIR + RedEdge}$</td>
</tr>
<tr>
<td>Chlorophyll Green Model (CGM) (Gitelson <em>et al.</em> 2005)</td>
<td>$\frac{NIR}{Green} - 1$</td>
</tr>
<tr>
<td>Chlorophyll Red-edge Model (CRM) (Gitelson <em>et al.</em> 2005)</td>
<td>$\frac{NIR}{RedEdge} - 1$</td>
</tr>
<tr>
<td>Red-edge NDVI</td>
<td>$\frac{RedEdge - Red}{RedEdge + Red}$</td>
</tr>
<tr>
<td>NDSWIR (Gerard <em>et al.</em> 2003)</td>
<td>$\frac{NIR - SWIR_{1600nm}}{NIR + SWIR_{1600nm}}$</td>
</tr>
<tr>
<td>Wetness Index NDWI <em>(Goa, 1996)</em></td>
<td>$\frac{NIR - SWIR_{1200nm}}{NIR + SWIR_{1200nm}}$</td>
</tr>
</tbody>
</table>
Appendix 2: Influence of cloud cover on data availability

Figure A2.1: Cloud free data availability for MERIS imagery as a percentage of the total number of days for each year from 2005 to 2010 (above) together with a 6 year mean availability for the total period (right). Source: Final PHAVEOS report to STB – project No 130517 by Astrium GEO-Information Services.
Appendix 3: Pareto boundary

Boschetti et al. (2004) proposed to use the Pareto Boundary as a means to help understand whether the limited accuracy of a low spatial resolution map is given by poor performance of the classification algorithm or by the low resolution of the remotely sensed data that had to be classified. The development or improvement of EO classification algorithms is being driven by the need to reduce the classification error. The Pareto boundary identifies the residual omission and commission errors (derived using a confusion matrix) that cannot be avoided in any way. Figure A3.1a illustrates this. The coarse resolution EO imagery would never reproduce the small detail of the ‘truth’ layer representing the landscape at a higher spatial resolution. Along the Pareto boundary the reduction of the omission and the commission errors become two partially conflicting objectives (Figure A3.1d). This method is only applicable to hard classifiers. In Boschetti et al. (2004) it is demonstrated for a binary map. For a general case (> 2 cover classes), the analysis has to be repeated for each class, collapsing all the other classes into the background.

**Figure A3.1:** Figures: Source Boschetti et al. 2004. The procedure for generating the Pareto boundary starting from the high resolution reference (i.e ‘truth’) map and calculated for a pre-defined lower resolution which generally represents the resolution(s) of the EO imagery used to produce the land cover map(s); (a) The pre-defined low-resolution grid is overlaid on the high-resolution reference map; (b) The percentage cover of the class of interest is computed for each low-resolution grid cell; (c) Thresholds, varying from (0 to 100) are applied on the percentage cover to generate a set of low-resolution binary maps. Each of these maps represents a possible solution; (d) Each of these solutions is compared against the original reference map to produce the corresponding omission and commission errors (from the confusion matrix), which, when plotted and joined up, form the Pareto boundary.
Figure A3.2: Figure: Source Boschetti et al. 2004. The performance of a classification algorithm or accuracy of a map, expressed in terms of omission and commission error (point A in plot), can now be put within the context of the spatial resolution of the EO imagery used. The Pareto line (dashed black line) represents the omission/commission error related to the spatial resolution of the imagery, while the area right and above the line but left and below point A represents the residual error associated to the classification procedure used.

Pareto was implemented by Mallinis & Koutsias (2012) to compare the performance of a selection of burnt area mapping algorithms whilst taking the spatial resolution into account (Figure A3.3).

Figure A3.3: Figures: source Mallinis & Koutsias (2012)
Left: The increase in omission and commission errors caused by an increase in pixel size (in meters) demonstrated through the Pareto boundary for a binary map (burned/not burned) of a site in the Mediterranean. The Pareto boundary determines, by means of a very high spatial resolution reference dataset (meter resolution), the maximum user and producer's
accuracy values (i.e. minimum omission and commission errors) that could be attained by a lower spatial resolution map (e.g. 10m to > 1000m) (Boschetti et al. 2004).

**Right:** Example of how Pareto boundary enables an objective comparison of mapping methods (dots in figures), taking pixel size (30 m) and the structure of the landscape being mapped into account. The best performing mapping methods are those that lie the closest to the pareto line. The three plots refer to three test sites (Parnitha, Kassandra and Alex/Poli).

The abbreviations refer to the mapping method used: Spectral unmixing (SMA); Neural networks (NN); Logistic regression (LOG); Maximum likelihood (ML); Thresholding of vegetation indices – Normalised burn ratio (NBR); IHS transformation (IHS); Principal component analysis (PCA); Classification and regression trees (CART); Object-based image analysis (OBIA); Support vector machines (SVM).