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Use of remote sensing to produce a habitat map of Norfolk

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ABSTRACT

Information on the extent, location and condition of semi-natural habitats is essential to deliver the national targets to achieve the UK commitment to Biodiversity 2020 (Defra, 2011). This strategy aims to halt overall biodiversity loss by 2020 and move towards a position of net gain. In order to achieve this, both local and national bodies need detailed information on the habitats present over their entire area.

Remote sensing provides opportunities for cost-effective, rapid and repeatable habitat mapping. This paper presents a method used to produce a seamless habitat map of the county of Norfolk, UK, of sufficient detail to inform land management decisions. Key aspects of the method were the development of parallel classification systems using different input data combinations and a long-term, volunteer-based map validation and update procedure. The habitat classification method utilised multiple earth observation platforms characterised by differences in spatial resolution, spectral range and season of image capture. The combinations of image data used were very important for the success of the analyses. The classification process was guided by ecological principles and local knowledge, along with targeted ground-truthing to guide class associations, confirm underlying ecological processes and to assess accuracy, and map revision.

The study found that automated methods of analysis were most effective when classifying habitats characterised by distinctive dominant cover species, or groups of dominant species. The methods were least effective at identifying habitats defined by the presence of low growth-form species at low frequency or where they form understorey vegetation; in such cases field checking is vital to confirm the habitat class assignment.

This scale of mapping can be used in combination with targeted, sustainable field survey effort to provide the level of information needed by decision makers to support Biodviersity 2020 targets and a wide range of other policy needs. The map has already been adopted by a wide range of organisations and finding application in such areas as Green Infrastructure, Living Landscape and habitat suitability modelling.

1. Introduction

Habitat maps are used by many organisations for monitoring the extent and quality of habitats. Monitoring over time allows loss of habitat to be identified, allowing the vulnerability of habitats and associated species to be assessed and identifying any requirement to mitigate to ensure no net loss. Conservation bodies use habitat data for management and restoration planning, but legislative factors also create a requirement for collecting and updating such data.

The UK National Planning Policy Framework places requirements on local authorities to map habitats and evidence a number of key biodiversity aspects, including ecological networks and Green Infrastructure. In England local authorities, government agencies and conservation charities are working together to deliver the national 'Biodiversity 2020: A Strategy for England's Wildlife and Ecosystem Services' objectives (Defra, 2011), which aim to halt overall biodiversity loss by 2020 and move towards net gain. This strategy is devised to deliver on commitments within the EU Biodiversity Strategy (European Union, 2011), including through legislation, such as the Habitats and Birds directives, and in the overarching international commitments under the Convention on Biological Diversity (CBD).

Remote sensing can be used to make rapid assessments of large areas of land, for relatively low cost compared to traditional field survey. Continuous habitat mapping by field survey is too expensive and logistically difficult to undertake on a regular basis, and therefore the high repeat times and increasing volume of archive data make remote sensing an attractive data collection method.

Remote sensing techniques have already been shown to provide benefit to national and regional-scale conservation and biodiversity initiatives (Nagendra et al., 2013; Rose et al., 2015). Remote sensing has been used successfully in monitoring habitat extent and condition, identifying land use changes (e.g., Lucas et al., 2011; Kindu et al., 2013; Regos et al., 2015), feeding into analyses of ecosystem function and service provision (Rose et al., 2015) and species distribution modelling (Broughton et al., 2013). The challenge is to identify a methodology that is repeatable and creates sufficiently detailed products for decision-making purposes.

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The methodology presented here uses object-based image analysis (OBIA). OBIA is a method of image analysis used in conjunction with image segmentation, and is an efficient method of habitat analysis (Lucas et al., 2007).The method works on the principle of grouping similar image pixels together and assessing them as a single 'object' (Burnett and Blaschke, 2003).

Two crucial considerations for meaningful remote sensing analyses are the scale of observations (Burnett and Blaschke, 2003; Karl and Maurer, 2010) and their timing. In general, smaller image pixel sizes facilitate more detailed classifications (Nagendra, 2001), but only if the sensor captures information in an appropriate spectral band range (Gao, 1999). In OBIA, the image segmentation parameters are customised to create objects at an appropriate scale for assessment.

Observation timing can be particularly important for habitat mapping, where discrimination between habitats can be improved if the date of image acquisition coincides with plant phenological stages (Ouyang et al., 2011). Therefore, ecological knowledge of the habitats present in the landscape to be classified is key, during both the image selection process and the data analysis.

The number of images available is often restricted by sensor repeat times, quality issues such as cloud cover or data cost. However, where multi-date images are available, it can be possible to discriminate between habitats that were formally spectrally inseparable, by detecting their phenological divergence (de Colstoun et al., 2003; Nagendra et al., 2013). Adopting an intra-annual time series approach has been effective in detecting small-scale grassland habitats (Schuster et al., 2015), an approach which could be applicable to landscapes of predominantly agricultural character but diverse management regime, where the semi-natural habitat landscape component is relatively small and fragmented.

The Crick Framework was developed for the project 'Making Earth Observation Work for UK Biodiversity', commissioned by the Department for Environment, Food and Rural Affairs (Defra) and Joint Nature Conservation Committee (JNCC) (Medcalf et al., 2011, 2013). It is a rapid method of assessing data requirements for identifying different habitat types using earth observation (EO), to inform decision makers wishing to commission such studies, but who lack technical expertise in remote sensing image analysis.

Norfolk was an ideal study site for a trial of the Crick approach as it contained both intensive agricultural areas and a wide range of Annex 1 and BAP priority habitat types, some of which are highly fragmented, representing a test of the resolution capacity of EO data. The county also had a very active community willing to be engaged in providing support and updating of the map; this level of support was crucial during the development phase, and to ensure longevity of the final product.

2. Methods

2.1. Study area

A pilot-stage classification had been previously produced for two areas within the Norfolk Broads and northwest coast (Medcalf et al., 2013). The study area for upscaling this work was the county of Norfolk, UK, comprising a total area of 55,740 km^2 (Fig. 1). West Norfolk is characterised by large-scale arable farming on rolling landscape, punctuated by areas of grassland, grazing marsh and distinctive human-influenced woodland and heath, with a continental European climate. East Norfolk includes the Broads region, containing a large wetland network created from dug-out peat, bordered by woodlands and a large area of grazing marsh. The Norfolk coastal belt comprises a mosaic of habitats, including salt marsh, grazing marsh, sand dune, maritime cliff and heathland.

2.2. Data used

Three categories of data sets were used in the analysis: optical (satellite images, aerial photography), topographic and supporting vector data sets. The optical data comprised SPOT (Système Pour l'Observation de la Terre), IRS (Indian Remote Sensing), Landsat-5, RapidEye and DMC (Disaster Monitoring Constellation) satellite images and a multi-date colour infrared (CIR) aerial photography mosaic. Topographic information such as elevation, slope and aspect was derived from a GeoPerspectives Digital Terrain Model (Infoterra Ltd and Bluesky International Ltd). Vector data sets comprised MM (MasterMap®, Ordnance Survey) and hand-digitised cloud masks for the June and July Landsat scenes. Further details of the data sets are provided in Table 1.

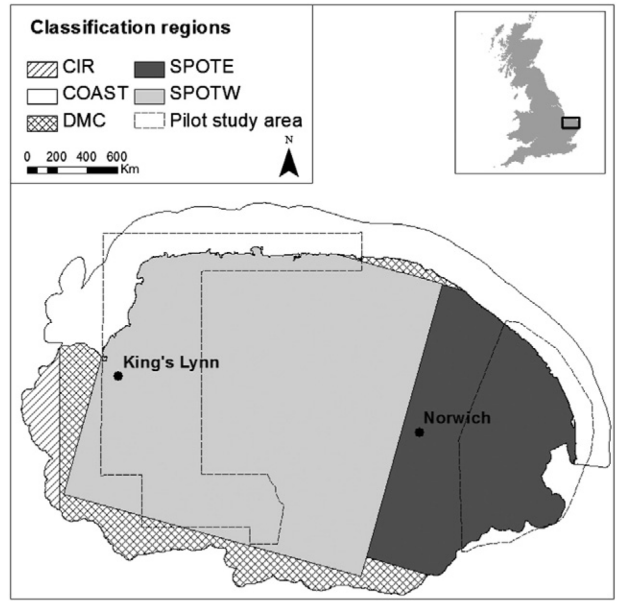

Fig. 1. Norfolk study region divided into five classification regions according to image availability.

2.3. Image processing

Three pre-processing stages were applied to the satellite images: registration (converting to OSGB36 coordinate system), radiometric correction (converting pixel values to reflectance) and atmospheric correction (correcting image values for atmospheric effects such as water vapour). Image registration was carried out in ERDAS Imagine 11.0 (ERDAS, Inc) using the Geoperspectives DTM. Radiometric and atmospheric corrections were carried out in ENVI 4.7 (ITT Visual Information Solutions). Atmospheric correction was undertaken using the FLAASH tool.

2.4. Rule-base development

Image and vector layers were imported into eCognition Developer 8 (Trimble, Germany GmbH), for multi-scale image segmentation, and development of a hierarchical rule-based classification.

Image segmentation parameters were optimised on a habitat-by-habitat basis through the adoption of a multi-stage segmentation–classification–re-segmentation approach. Segmentation parameters such as scale and compactness were modified to create larger, more regularly-shaped objects from which to classify habitats such as arable and improved grasslands, before re-segmenting to produce small irregular objects from which to classify scrub. The effectiveness of class rule thresholds was sensitive to the segmentation parameters; the size and shape of an object determines the number and location of pixels included, which in turn determines the overall object values.

Spectral classes for the classification were chosen to reflect Annex 1/BAP habitats as far as possible. A list of habitats known to be present within the study region was provided by Norfolk Biodiversity Information Service (NBIS), and field visits in 2012 were used to gather initial rule