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Identifying effective approaches for monitoring national natural capital for policy use.

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Abstract

In order to effectively manage natural resources at national scales national decision makers require data on the natural capital which supports the delivery of ecosystem services (ES). Key data sources used for the provision of national natural capital metrics include Satellite Remote Sensing (SRS), which provides information on land cover at an increasing range of resolutions, and field survey, which can provide very high resolution data on ecosystem components, but is constrained in its potential coverage by resource requirements.

Here we combine spatially representative field data from a historic national survey of Great Britain (Countryside Survey (CS)) with concurrent low resolution SRS data land cover map within modelling frameworks to produce national natural capital metrics.

We present three examples of natural capital metrics; top soil carbon, headwater stream quality and nectar species plant richness which show how highly resolved, but spatially representative field data can be used to significantly enhance the potential of low resolution SRS land cover data for providing national spatial data on natural capital metrics which have been linked to ecosystem services (ES). We discuss the role of such metrics in evaluations of ecosystem service provision and areas of further development to improve their utility for stakeholders.

Keywords: National natural capital metrics, satellite remote sensing, field survey, habitats, modelling, decision making.

Introduction

Even those individuals who rarely step out of the city are entirely reliant on nature to supply their fundamental needs, i.e. breathable air, food, water, energy and shelter. Scientists have been highlighting the threat that globally degrading ecosystems pose for the environmental and economic sustainability of human systems (Daily & Ehrlich 1992, Arrow 1995). This has resulted in the emergence of the term ‘natural capital’ (NC) which casts natural resources such as those described above into an economic term ‘capital’ in order to ensure that nature is valued alongside other forms of capital which contribute to wellbeing. NC underpins the provision of services to humans (Ecosystem Services (ES)).

In the UK, the government set up an independent body, the Natural Capital Committee (NCC) in 2012, to advise the UK Government on how to value nature and to ensure England’s ‘natural wealth’ is managed efficiently and sustainably. Global interest in valuing NC is reflected by the large numbers of businesses signing up to the natural capital coalition’s natural capital protocol (Natural Capital Coalition 2016).

Projects like TEEB (TEEB 2010) have highlighted the importance of both measuring and monitoring Earth's natural resources over time, in order to enable their effective and sustainable management. The importance of biodiversity in supporting the functioning of ecosystems has led to it being both a key target for monitoring and a political focus for action (Cardinale *et al.* 2012). For example, EU legislation to protect the environment focuses on improving the status of ecosystems and their biodiversity. Monitoring biodiversity alone fails to capture the multitude of ways in which nature supports human wellbeing, there is therefore a need to provide NC metrics which help us to link NC assets (such as species, ecological communities and freshwater) to each other and to the natural processes which underpin ecosystem functions and service production (Natural Capital Committee 2014; Maes *et al.* 2012). All EU countries have thus been tasked with mapping ES at a country level (European Commission 2011) by 2014. Done well, this is a substantial and complex challenge for science and society, but will provide essential information for policy makers and actors seeking to manage resources effectively (Maes *et al.* 2012). A key part of the challenge is the collection and transformation of robust data on ecosystems into metrics at scales which can influence decision makers (Grêt-Regamey *et al.* 2014). There have been relatively few attempts to carry out ecosystem service mapping focused on national scales (TEEB 2010; Hedden-Dunkhorst *et al*. 2015) including; England (Dales *et al.* 2014); Spain (Ministerio de Agricultura, Alimentación y Medio Ambiente 2014); Luxemburg (Liquete & Kleeschulte 2014 and Becerra-Jurado *et al.* 2015); Germany (Rabe *et al*. 2016). The work by Dales *et al.* (2014) in the UK focused on the use of proxy measures of land cover linked to look up tables associated with land cover types (Burkhard *et al.* 2009, 2012) to provide measures for ES provision. Other methods used in Spain, Luxembourg and Germany (Ministerio de Agricultura, Alimentación y Medio Ambiente 2014, Liquete & Kleeschulte 2014; Becerra-Jurado *et al.* 2015; Rabe *et al*. 2016) also used satellite based land cover information to provide information on the extent and locations of different habitat types. The use of habitat monitoring in this way has been identified as a potentially effective way of linking NC assets to service provision (Mace *et al.* 2015). However, work by Eigenbrod *et al.* (2010) has shown that attempts to provide measures/maps of NC relating to ES provision may suffer as a result of being based primarily on coarse proxy measures such as land cover. The difference between 'habitat' and 'land cover' may therefore be critical in the identification of methods and metrics which are appropriate for reporting on NC.

Habitats provide a pragmatic link between efforts to conserve populations of individual species and more integrated approaches to landscape-level management (Bunce *et al.* 2013). As well as including species and ecological communities, habitats reflect interactions between these and their relationships with natural processes. In contrast, land cover is typically information derived from interpretation of spectral imagery from SRS for large areas, including national extents (Morton *et al*. 2011). The recent launch of the Sentinel satellites and huge steps in data capacity and processing are likely to increase the potential for SRS data to go beyond land cover to more detailed interpretation of habitats and improved NC monitoring (particularly at local to regional scales) in the future. However, given the difficulties encountered in defining habitats consistently (even in the field) (Bunce *et al*. 2013), there will always be a role for field survey both for detailed monitoring of habitats, as well as for monitoring (the majority of) species and sub-surface soil and water. 'Habitat monitoring' as put forward by Mace *et al*. (2015), therefore implies the need to go further than merely providing information on land cover.

The challenges of identifying possible methods for producing NC metrics (and other closely related variables) and the associated monitoring which would be required has been the focus of a number of publications, many of which are summarised in Pettorrini *et al.* 2016). Skidmore *et al.* (2015) advocate the benefits of using SRS, particularly for global scale, cross-border monitoring of vegetation, but stress the importance of close working between ecologists and users of remote sensing in optimising the potential of such data. The GEO BON Ecosystem Service Working Group (Tallis *et al.* 2012) have produced a conceptual framework for monitoring trends in ES globally, which is based on numerical modelling combining SRS and field-based monitoring with national statistics data. Many of the concerns about the appropriateness of SRS metrics for ecosystem service (ES) supply or NC monitoring outlined in Pettorrini *et al.* (2016), relate to interpreting the complexity of relationships between potential measures and ES supply. This relates to a range of SRS metrics which go beyond land cover; including measures such as Net Primary Productivity (from NDVI data) and Land Surface Temperature and Equivalent Water Thickness (Pettorrini *et al.* 2016). Key concerns surround how SRS metrics can be linked to ES supply at appropriate scales. The challenge is to produce metrics at national scales which relate to SRS metrics but provide us with more useful information about the factors influencing those metrics and hence subsequent ES supply.

The recognised need for robust NC metrics which can provide information on the factors influencing NC at national scales points to the need for aligned nationally representative field and SRS survey. Here we combine spatially representative field data from a historic national survey of Great Britain (Countryside Survey (CS)) with concurrent high resolution SRS land cover map data within modelling frameworks to produce national NC metrics which provide a ‘measure’ of nature at a national scale. We describe below the field survey design and aligned SRS product which enable this approach together with examples of modelling approaches which have been used for the production of metrics. The metrics demonstrate the potential breadth of metrics which a combined field/SRS approach can enable, and include metrics describing; water quality, bee nectar plant richness and soil carbon. Water quality in headwater streams is an important indicator of the provision of clean water for drinking, household use and recreation. Bee nectar plant richness (here) indicates the resource available in the most extensive habitats across GB for wild bee populations which (aside from managed honeybee colonies), are the most important pollinators of crop monocultures (Klein *et al.* 2007). Soil C/organic matter storage is important for a wide range of regulating services including mitigation of flooding and climate change. We discuss the constraints and opportunities for the use and evolution of these methodologies and how they fit with policy requirements for information to assist with the effective management of NC for ecosystem service provision.

Materials and Methods

The dataset which we used to generate NC metrics was the GB Countryside Survey (CS). The survey structure (described below) is integral to its use for the provision of national NC metrics.

Countryside Survey

CS is a country-scale, long term national monitoring project which has taken place five times: in 1978, 1984, 1990, 2000 and 2007. The relevance of the survey to policy as a means of 'Accounting for Nature' (Haines-Young *et al.* 2000) was recognised soon after the initial survey resulting in government support for all of the following surveys. The last three surveys incorporated both SRS and field survey data and in 2007 habitats in both parts of the survey were described according to UK Broad Habitat definitions (Jackson 2000). Both the field and SRS surveys map habitats on a common Ordnance Survey Mastermap framework.

Field survey

The field survey was designed to provide national estimates of metrics relevant to natural resources (Norton *et al.* 2012), based on a randomly stratified sample of 1km squares (591 in 2007). The stratification of GB into the Institute of Terrestrial Ecology (ITE) land classes which underlie CS, was based on soil, geology and climate variables (Figure 1) (Bunce *et al*. 1996); each land class was sampled in relation to its extent. Within each of the sample squares complete habitat and landscape feature mapping and a set of integrated sampling protocols results in the collection of data representative of each of the ITE land classes for the extent and condition of habitats, landscape features, vegetation, soils and freshwater. Sampling protocols, detailed on countrysidesurvey.org.uk, include: vegetation plots associated with habitat and feature types, soil sampling in some plot types and sampling of headwater streams and ponds for macrophytes and invertebrate fauna.

SRS survey

Land Cover Map (LCM) 2007 is a map of GB habitats based primarily on combined summer and winter satellite data acquired by the Landsat-TM5, IRS-LISS3 and SPOT-4 AND SPOT-5 sensors covering a 3 year period between 2005 and 2008 (Morton *et al.* 2011). Habitats were classified into individual parcels based on information from generalised digital cartography refined with image segments.

Natural capital mapping approaches using field survey and LCM

The basic premise underlying the approaches to developing NC metrics described here was that the representativeness of data collected in the field survey made it possible to extrapolate modelled results from the sampled 1km squares to the national scale using LCM2007 habitat information and other relevant national spatial data (e.g. digital terrain modelling, (DTM) weather data, deposition data etc.). LCM provided the national map of habitats; the field survey provided nationally representative condition data from vegetation plots which describe habitats. Using data from LCM2007 and the field survey, alongside detailed spatially comprehensive covariate datasets (as detailed in Table 1, below), it was possible to use statistical model-based analysis to predict values for NC metrics (Norton *et al.* 2016; Henrys *et al.* 2015) at national scales.

We produced data for three NC metrics (water quality, nectar plant richness and top soil carbon concentration) to demonstrate the potential breadth of NC data which can be provided by combining SRS and field datasets with statistical modelling approaches. For more details on the modelling approaches and more discussion on their efficacy in relation to each of the metrics below please see Norton *et al.* (2016) and Henrys *et al.* (2015) as referred to below. Details on field protocols associated with each of the metrics are available at www.countrysidesurvey.org.uk

Water quality

CS freshwater sampling was focused on providing a snapshot of the condition of headwater streams; the smaller tributaries that carry water from the upper reaches of a catchment to the main channel of the river. Headwaters occur in approximately 60% of the CS survey squares. In each CS square containing a headwater stream surveyors sampled macroinvertebrates using a kick sample method modified from Murray-Bligh (1999). Data for two survey years (1998 and 2007) were used in the water quality model. They include: a) an index for measuring the biological quality of rivers using selected recorded families of macroinvertebrates as biological indicators (Biological Monitoring Workers Party (BMWP) score) and b) an expected ‘reference’ macroinvertebrate community at a stream or river site calculated using specifically developed software - the River Prediction and Invertebrate

Classification System (RIVPACS). The predicted community (b), based on sampled attributes of the stream/river at each site, was then compared to the measured stream community (a) for each site to provide an observed/expected (o/e) ratio which for an un-impacted site will be close to one. As degradation, associated with human impacts increases, the observed index value fails to meet expectations and the value of the ratio falls below one. Boosted Regression Tree (BRT) (Elith *et al.* 2008) models in R (R Core Team, 2016) were used to identify explanatory variables that account for trends in the o/e BMWP scores at the $1km^2$ scale. The models comprised the observed BMWP score (Box-Cox transformed, lambda 0.628) data as the response variable and 10 explanatory variables (Table 1, column 1) as the potential predictors. The best-fit models were determined by adjusting values of two model parameters (tree complexity and the learning rate) until model predictive deviance was minimized without data overfitting. The models were initially trained on a sub-set of the CS 1km squares and tested on the remainder before being extended to the national scale at the $1km^2$ scale. Model performance was evaluated based on the proportion of the deviance explained (pseudo R^2), the Pearson correlation coefficient (c) and the root mean square error (RMSE) between fitted and observed data. Residuals were examined using histograms and Shapiro-Wilk tests to test whether predictions follow normal distributions and to confirm model assumptions were met. The 10 explanatory variables in both models were generated for all prediction areas.

In order to produce predicted o/e BMWP values for the unmonitored sites, expected values for BMWP (predicted) were required and these were generated using the 45 ITE land classes as a base. The expected BMWP scores from the CS data (data derived from RIVPACS using real, sampled environmental attributes at each site) were averaged for each land class. This value was used as the predicted expected BMWP values for the randomly generated river sampling site in each unmonitored grid square. Predicted o/e values were calculated by dividing the predicted observed (from BRTs) by the predicted expected (average scores for ITE land classes). Based on the fitted model a map of predicted water quality for each 1km square containing streams/rivers of Strahler order 1, 2 or 3 was produced together with a plot of RMSE.

Bee nectar plant species

In the field survey the presence of plant species was recorded in vegetation plots which sample habitats within the stratified random sample of squares across Great Britain. Mean counts of distinct bee nectar producing plant species (Carvell *et al.* 2006) were calculated for the 2*2m vegetation plots within each square. Generalised Additive Mixed Models (GAMM's) (Lin *et al.* 1999) in MGCV package (Wood 2004) in R (R Core Team, 2016) were fitted to bee nectar plant species counts matched with explanatory variables, recorded at either plot or 1km square level (Table 1, column 2). Generalised Additive Mixed Models are an extension of the generalised linear model framework where complex error structures can be included to account for any dependence structure present in the data (similarly to mixed effects models) and non-linear smoothly varying relationships between response variables and covariates can also be incorporated (similarly to generalised additive models). These covariates were determined *a-priori* according to expert knowledge and scientific understanding informed by joint work on pollination (Baude *et al.* 2016). A Poisson error structure with log link function was assumed and a random component (square) was included in the model to account for replicate plots within squares (see Henrys *et al.* 2015). Having fitted the model, Moran's *I* statistic was used to assess whether there was evidence of spatial auto-correlation in the residuals. In this case, fitting spatially explicit covariates, easting and northing, in the model to capture the large scale spatial variation was sufficient and no further spatial terms were required. Model selection was based on minimising Akaike information criterion (AIC), whilst RMSE was also calculated to examine model fit. Based on the fitted model a map of predicted species counts and a map of RMSE were produced for GB.

Top Soil Carbon

Top soil carbon (C) (hereafter called soil C) was measured in five random vegetation plots in each 1km square in CS to a depth of 15cm (Norton *et al.* 2012, Reynolds *et al.* 2013). The co-location of soil C measures with a range of other soil, vegetation and habitat measures provides a unique data source for a full integrated assessment of soil C status in GB. Carbon concentration was estimated based on loss-on-ignition for a total of 2614 cores across the 591 squares surveyed in 2007 (Reynolds *et al.* 2013).

Generalised additive mixed models (GAMMs), as described above, were fitted to topsoil C concentration matched with potential explanatory variables, recorded at either plot or 1km square level (Table 1, column 3). Rather than assume a specific distribution for the soil C concentrations, a bootstrapping procedure of resampling survey squares was adopted to robustly estimate the associated variance. The bootstrapping was run once the structure of the final model had been chosen. Once again model residuals were examined for evidence of spatial autocorrelation using Moran's *I* statistic and model selection was made by AIC whilst also examining the RMSE for the fitted models. Having selected the final model structure, for each resample of the bootstrapping, a GAMM was fitted with random intercepts included, corresponding to unique squares. Predictions across GB were obtained for each fitted model and the mean value for each 1km grid cell was plotted together with the RMSE (Henrys *et al.* 2015); no cell was mapped if it did not contain at least a 50 % cover of one of the broad habitats sampled by CS).

Results

Sampled field survey data, LCM habitat information and a range of national spatial covariates were used in different statistical modelling approaches to produce mappable national NC metrics.

Water quality

The models that showed the best explanatory power indicated that the 10 predictor variables shown in Table 1, column 1 were significant predictors of o/e BMWP. Percentage of woody cover and degree of topographical slope were the most influential drivers of observed BMWP values at the 1km^2 scale. The predicted o/e BMWP values at the national scale showed a strong south-east/north-west pattern with higher water quality in western and northern areas (where land use is less intensive) and lower water quality in the more arable eastern and southern areas of England (Figure 1a). Model fit (RMSE) is mapped in Figure 2a.

Bee nectar plant species

Explanatory variables influencing bee nectar plant richness included locational, habitat and weather variables, alongside N deposition (which negatively impacted on species richness) (Table 1, column 2). As for water quality, the results showed a strong south-east/north-west pattern, but in contrast show higher NC (numbers of bee nectar producing plant species) in the more continental lowlands of the south-east compared to lower measures in the wetter, uplands of the north-west (Figure 1b). Model fit (RMSE) is mapped in Figure 2b.

Top soil carbon

Figure 1c shows high soil C in the upland peaty soils in the north and west, low C on the predominantly arable soils of the east of England and the far-east of Scotland and intermediate levels for the more grass-dominated landscapes of the west of GB. As with bee nectar plant richness, explanatory variables include both locational, habitat and weather variables (Table 1, column 3) but with sulphur deposition as a positive indicator due to slowing of organic matter decomposition in response to the high rates of acidic deposition experienced in many parts of GB. Model fit (RMSE) is mapped in Figure 2c.

Overview

High level comparisons of the natural capital metrics at national scales indicate that soil carbon and water quality show broadly similar patterns, so where one is high, so is the other. In contrast, bee nectar plant species is more often low where soil carbon and water quality are high.

Discussion

This work aimed to build on and refine existing approaches for mapping NC at national scales in GB and to highlight the value of integrated field and SRS monitoring data. The value of CS data (field and SRS) in relation to the rising agenda of ES both in the UK and across Europe (Braat & de Groot 2012) was apparent as we planned for the last survey, and soon after the survey, CS was used to produce a number of publications relating to ES provision (Norton *et al.* 2011; Robinson *et al.* 2011; Maskell *et al.* 2013; Henrys *et al.* 2014; Norton *et al.* 2015). The CS legacy of continuing relevance to policy (begun in the 1986 survey) was also reflected in the extensive use of CS in the UK National Ecosystem Assessment (NEA) (2011).

The ongoing challenge of detailing how ecosystem service provision depends on NC assets is an important one which provides challenges at multiple scales (Maes *et al*. 2012, 2013; Martínez-Harms & Balvanera, 2012; Schägner *et al.* 2013; Grêt-Regamey *et al.* 2014). For policy makers, data on NC, how it is changing over time and what that means for the provision of ES is vital for making resource decisions at national scales (Balvanera *et al.* 2001; Braat & de Groot 2012). Several of the publications regarding the use of CS data for ecosystem service assessments (Norton *et al.* 2011; Henrys *et al.* 2014; Norton *et al.* 2015) acknowledged that CS data is only part of the equation, the part that relates to NC rather than to the services provided. Evaluation of ES provision at national scales from the NC measured in CS requires a complex process of linking NC assets to multiple ES provision through available evidence (Braat & de Groot 2012; Maes *et al.* 2013, Shägner *et al.* 2013). This process is currently underway as part of continuing work on the development of appropriate metrics (see '*Next steps'*, below).

The particular challenge in this study was to provide national measures of NC which can improve on basic land cover proxies, such as those used in Dales *et al.* (2014). The modelled data produced here are better able to characterise NC at national scales because they include condition information on NC as well as an indication of the variables which influence both presence and condition. CS provides a unique opportunity to produce these metrics because of its national spatially representative design and integrated monitoring approaches (including SRS). In recent years SRS has received a great deal of attention for its potential to monitor aspects of NC, in particular, biodiversity (Petrou *et al.* 2015; Pettorelli *et al.* 2015). The sheer volume of papers supporting this possibility indicate a need to both emphasise the value of the innovative technologies which make remote earth observation possible and to validate the research approaches which explore those technologies.

In contrast, field survey, though widely acknowledged as absolutely fundamental to the effective use of SRS data (Gillespie *et al.* 2008; Xie *et al.* 2008) suffers from being a long established and apparently resource intensive activity. Recently SRS and field survey combined have been shown to provide an effective method for monitoring relevant to NC and ES at 'local' scales (Martínez-Harms *et al.* 2016; Lawley *et al*. 2016). In Australia, a similar approach has been used to characterise habitat condition using field based reference data, but lack of representative field data at national scales there resulted in the use of synthetic data (Harwood *et al.* 2016). Inevitably, scale is an issue for country level sampling and GB is a small country in comparison with Australia. However, size does not preclude the adoption of parsimonious but effective sampling approaches, to enable the production of national NC metrics. Approaches using standardised protocols, (like the GB Countryside Survey), have been identified as particularly important for biodiversity rich countries where there is an urgent need to monitor ecosystems and anthropogenic impacts upon them (Stephenson *et al.* 2017). Key criteria to enable this include: 1) an underlying stratification of the landscape at a national scale based on (relatively) static biophysical variables, 2) statistically robust sample sizes of randomly located sampling units within the stratification, 3) concurrent field and SRS surveys and 4) commonality of habitat definitions across field and SRS data.

Whilst the concept of ‘Natural Capital’ was not extant in 1978 when CS began, the survey was designed to measure the state and condition of GB across multiple ecosystem components and this ‘enlightened’ approach is now proving to be highly relevant to the modern concept of assessing natural capital. The NC metrics presented here are viewed as the most robust available at a national scale for England, whilst also covering Scotland and Wales. User friendly versions of the three metrics reported here and a wider set of metrics, developed using these approaches for the government’s adviser for the natural environment in England (Natural England), appear in documented form on a publicly accessible website (Natural England 2016). This policy use acknowledges the value of data that goes beyond quantifying the spatial distribution of land cover types to provide a better understanding of the condition of the resource and the factors known to impact on it. This, in turn, will enable better links to be made between the land cover and ecosystem service provision. It should be noted that CS is a ‘snapshot’ survey, which, whilst providing valuable data on some elements of NC may not be appropriate for all natural capital measures pertinent to ES provision, for example, the soil carbon or land extent on which crop or animal production (provisioning services) depend are recorded in CS but the resulting provision of ‘food’ is better sourced from other data sources. The process of identifying which NC data can best inform on ES delivery remains ongoing both for CS and more broadly (see '*Next steps'*, below) and will help to ensure that CS data is used as fully as possible.

Combining data from both spatially representative highly resolved field survey, high resolution national coverage SRS and other national spatial datasets overcomes issues of imprecision from using SRS data alone (Rhodes *et al.* 2015). Whilst imprecision of SRS may be overcome by using different forms of SRS (such as light detection and ranging (LiDAR) and digital cameras mounted on unmanned aerial vehicles (UAV's) for recording presence of some features (e.g. streams, hedges, individual trees) these may be currently impractical at national scales in terms of data processing requirements and/or visibility of particular features. Similarly, whilst the potential use of SRS for habitat condition measures has been highlighted (Petrou *et al.* 2015; Pettorelli *et al.* 2015), its use is constrained by the scale of observations and the requirement for field survey validation. For the metrics reported here, field mapped habitat information and field sampled vegetation, soil and water are currently essential.

The modelling approaches used to produce metrics represent particular points in time and identify potential environmental drivers and the variables which relate to the field measures, using correlative approaches. They do not identify the causal pathway between drivers of change and measured variables but rather provide predictions of NC metrics at a national scale (Henrys *at al.* 2015). The quality of the predictions is reliant on the availability of national data of sufficient spatial extent and quantity to provide a good fit between modelled NC metrics and the factors impacting on them. The use of statistical modelling approaches means that models can be produced with associated information on model fit to data as shown in figure 2 a-c (see also Henrys *et al.* 2015) which is valuable for those wishing to use them for land use decision making. In all cases, where predicted values are high, RMSE is also high. In the examples provided here it is notable that the water quality predictions are heavily influenced by the ITE Land Classes, causing rather distinct border lines blue western part vs. northern and eastern areas. The approaches taken here (and resulting models) will continue to evolve in response to; 1) improved data on explanatory variables including the availability, resolution and processing capacity relating to RS data, and 2) the use of other national NC datasets.

Next steps for NC mapping

Whilst the national NC metrics shown here and used in aligned approaches (see Baude *et al.* 2016) provide a valuable proof of concept and an improvement on previous approaches (Dales *et al.* 2014), research is continuing to explore the wider potential of the field and SRS elements of the CS dataset in relation to NC mapping. This reflects ongoing work across the spectrum of how NC information may be used in decision making (Ruijs & van Egmond 2017). Particular challenges include interpreting *change* in NC metrics over time. Field survey data has been widely used to investigate change in a wider range of ecological measures across the period of the survey (1978-2007) (Norton *et al.* 2012) in large part due to consistency of methodologies. In contrast, land cover maps have been in step with the technologies and data availabilities of their time. This has severely hampered the ability to interpret where differences (1990-1998-2007) are due to changing habitats and where they are due changing methodologies. Assessments of change in NC metrics using the approaches outlined in this paper may be constrained by this issue, (although it will be possible to assess the uncertainties associated with land cover mapping issues). Clearly, continued consistency of methodologies for both field survey and land cover mapping in an integrated monitoring approach are essential to enable continued assessment of change in NC metrics in the future. It is to be hoped that with the advent of much more regular and consistent Sentinel data, problems of SRS data inconsistency will become less of an issue.

Another area of research in terms of the applicability of such approaches includes an exploration of how to scale NC metrics, in particular, down to local levels. Whilst national scale metrics are relevant to national policy makers, those making decisions about management require data for their local patch. A number of studies show the relevance of integrated SRS/field survey monitoring approaches at a range of scales (Martínez-Harms *et al.* 2016 Lawley *et al*. 2016; Rabe *et al.* 2016). In an ideal world, the adoption of common approaches for monitoring across all scales, including habitat definitions, field sampling protocols (for both volunteer and professional surveys) and a common mapping framework, would facilitate co-ordinated monitoring across both local and national scales (Stephenson *et al*. 2017). Further research is investigating; a) how NC metrics are affected by the use of regional habitat information in place of LCM2007 and b) how data from citizen science (in particular species recording) can be integrated with professional survey effectively.

Naidoo *et al.* (2008) highlight the importance of moving beyond simplistic assessments of single ES to understanding synergies and trade-offs in their delivery. These examples indicate the potential for considering how different metrics relate to one another across space. Integrated analysis of NC metrics, to investigate the relationships between NC metrics at a single location, is an obvious next step forward for this research, especially given the co-location of multiple ecological measures in the field survey. Previous research has explored the interactions between ecological measures taken in CS squares (see Maskell *et al.* 2013) in the light of understanding the multiple roles of different elements of NC in metrics relevant to different ES. The analysis carried out by Maskell focused on CS squares only and did not take into account the covariates influencing NC metrics. Future analysis will need to consider how covariates impact differently on separate metrics and on how metrics interact with one another, for example, relationships between biodiversity metrics on land and soil/water.

Further challenges, which are the focus of current research, concern defining the relationships between NC metrics and ecosystem service production (Maes *et al*. 2012, Braat & de Groot 2012). This is particularly important for shaping future monitoring if it is to be used as part of ecosystem service assessment. Future monitoring approaches may need to balance the continuity of field and SRS measures against their relevance to national measures of NC relevant to ES delivery. This will rely on continued research, including interdisciplinary approaches, to identify the links between NC measures and ecosystem service delivery.

Conclusions

Policy makers and resource managers require evidence to support decision making around the management of natural capital. This need for evidence is a huge challenge for ecological science; we still have much to understand about how NC underpins ES delivery and, as ever, we have limited resources with which to monitor state and change. This work shows the potential for combining highly resolved multi-ecosystem component field data which samples representatively at a country level with high resolution whole-country SRS data to produce spatially explicit NC metrics. These data (alongside additional metrics) have been commissioned in an accessible form by the government's adviser for the natural environment in England who are keen to improve on previous approaches focused on land cover alone (Dales *et al.* 2016). Many of the next steps reflect the requirements of these stakeholders, in particular their recognition of what may be needed by more locally based resource managers and the need for assessing change in NC. Finally, this work emphasises the value of well-designed long term monitoring and the importance of ensuring its continuing support for effective NC management.

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Data archiving

Countryside Survey data is held in the NERC data centre, all datasets have DOI's.

Figure and table legend

Table 1 Model variables (response variable in grey) for the three natural capital models.

Figure 1.a) Predicted observed/expected Biological Monitoring Working Party (o/e BMWP) scores for all squares containing headwater streams (Strahler order 1-3) in GB (across the 1998/2007 surveys). Higher scores (blue colours) indicate higher water quality, areas with no colour do not contain headwater streams, (previously published in Norton *et al.* (2016)) b) Predicted counts of bee nectar producing plant species for 1km squares across GB. Higher scores (dark blue colours) indicate higher numbers of species, c) Predicted Carbon Concentration g/kg in topsoil 0-15 cm across GB. Higher scores (dark blue colours) indicate higher carbon concentrations. Images created in ArcGIS version 10.

Figure 2 a) Root Mean Square Error (RMSE

Table 1

1	2	3
Biological Monitoring Working Party (BMWP) invertebrate taxa score – observed/expected[+]	Bee nectar plant richness	Topsoil (15cm) Carbon concentration
1) % Arable, 2) % Improved Grassland, 3) % Urban in 1km square from LCM	1) Broad Habitat from LCM	1) Broad Habitat from LCM
4) % woody cover along the stream within a 1km square (LCM)	2) Mean annual temperature	2) Growing degree days[++]
5) Slope[+++] - over a 1km length centred on the sampling site i.e. from a point 500 m upstream to a point 500m downstream	3) Mean monthly rainfall	3) Rainfall intensity[++++]
6) Altitude of sampling site[+++]	4) Altitude	4) Soil texture
7) Strahler stream order (1,2 or 3) [+++++]	5) Nitrogen deposition[*]	5) SO_4 deposition[*]
8) Easting and 9) Northing	6) Easting, and 7) Northing	6) Easting, and 7) Northing
10) Survey year		

[+] (Box-Cox transformed, lambda 0.628)

[++] Annual average growing degree days (day by day sum of the mean number of degrees by which the air temperature is more than 5.5 °C); obtained from the Met Office (2014) averaged for the six preceding years to each survey year.

[+++] Data obtained from PANORAMA data (a gridded Digital Terrain Model (DTM) with 50m post-spacing.

[++++] Rainfall intensity (mm day^{-1} on days of rain $\geq$ 1 mm) for each 5 km grid square in the UK; obtained from the Met Office (2014) averaged for the six preceding years to each survey year.

[+++++] Data obtained from the Intelligent River Network (IRN) for GB, https://data.gov.uk/dataset/ceh-digital-river-network-of-great-britain-1-50000

*Deposition data for each 5 km grid square in the UK was obtained from interpolated estimates calculated by the Fine Resolution Atmospheric Multi-pollutant Exchange (FRAME) model developed at CEH[22]. Due to data limitations the deposition values associated with the 1978, 1998 and 2007 surveys are from 1987, 1997 and 2005 respectively. Values (kg ha^{-1} yr^{-1}) for each 1km square were based on deposition estimates for the dominant broad habitat in each square.

Figure 1.

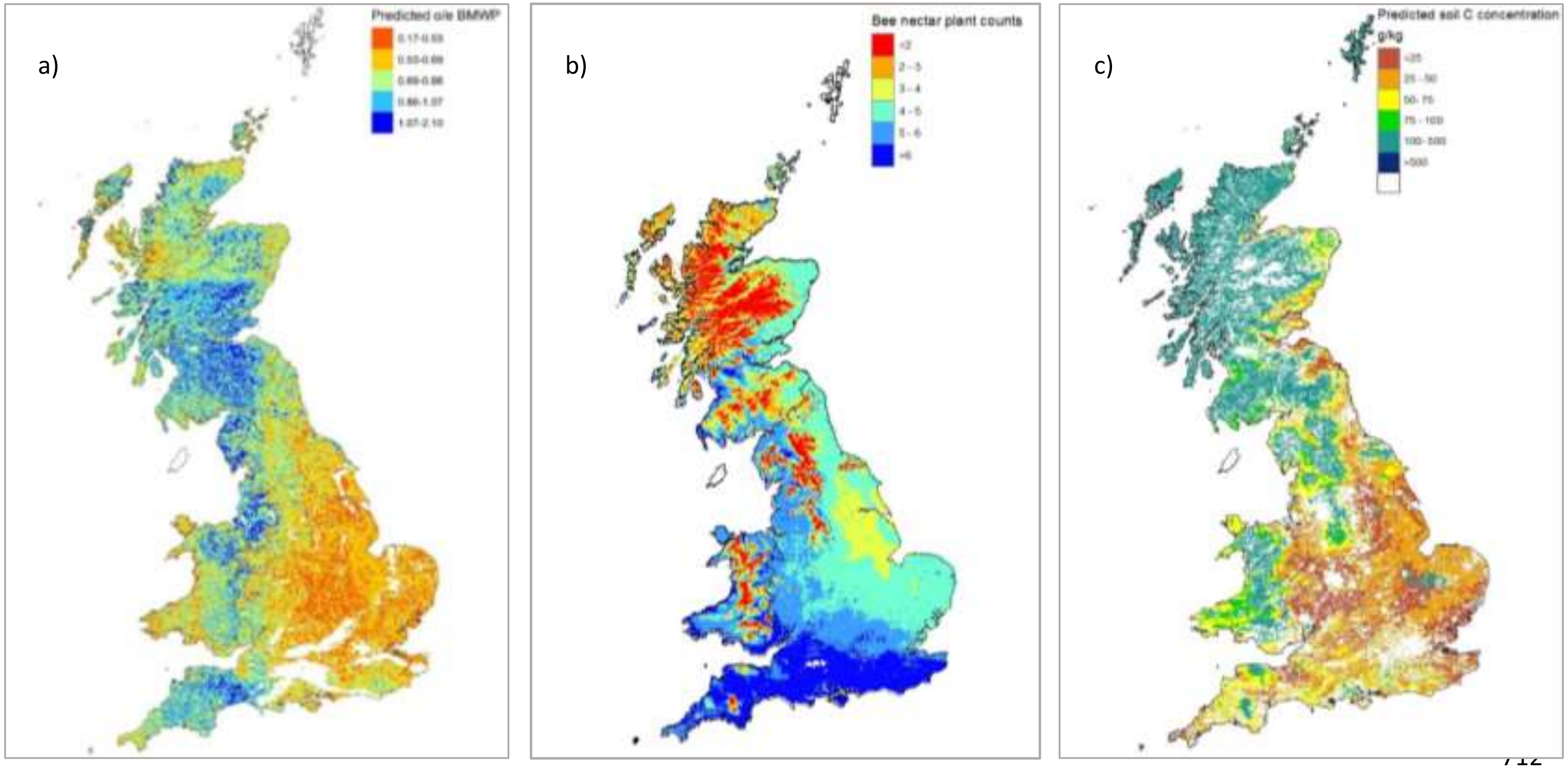
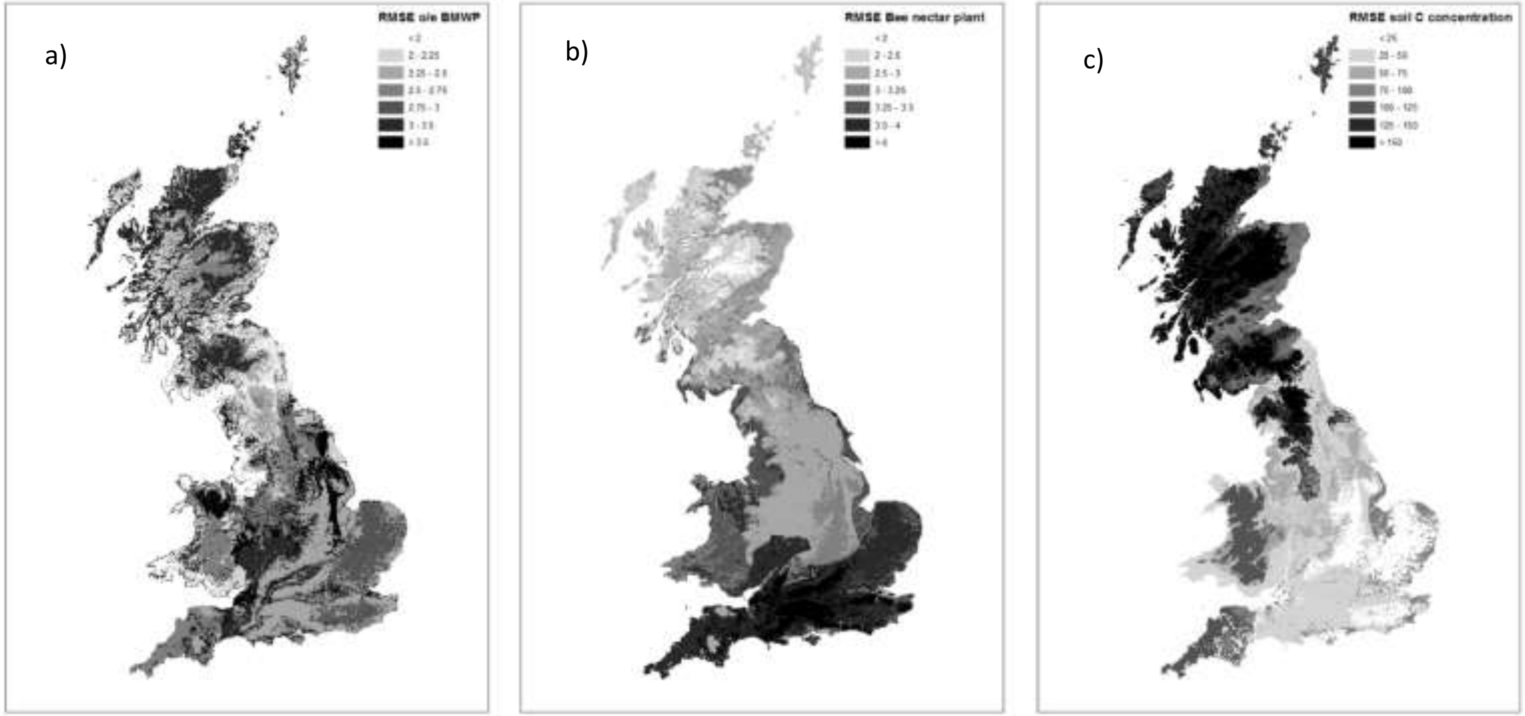

a)
Predicted o/e BMWP
0.17-0.53
0.53-0.69
0.69-0.86
0.86-1.07
1.07-2.10
b)
Bee nectar plant counts
<2
2 - 3
3 - 4
4 - 5
5 - 6
>6
c)
Predicted soil C concentration
g/kg
<25
25 - 50
50 - 75
75 - 100
100 - 500
>500

Figure 2


a)
RMSE o/e BMWP
b)
RMSE Bee nectar plant
c)
RMSE soil C concentration