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Exploring relationships between land use intensity, habitat heterogeneity and biodiversity to identify and monitor areas of High Nature Value farming

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ABSTRACT

Understanding how species richness is distributed across landscapes and which variables may be used as predictors is important for spatially targeting management interventions. This study uses finely resolved data over a large geographical area to explore relationships between land-use intensity, habitat heterogeneity and species richness of multiple taxa. It aims to identify surrogate landscape metrics, valid for a range of taxa, which can be used to map and monitor High Nature Value farmland (HNV).

Results show that variation in species richness is distributed along two axes: land-use intensity and habitat heterogeneity. At low intensity land-use, species rich groups include wetland plants, plant habitat indicators, upland birds and rare invertebrates, whilst richness of other species groups (farmland birds, butterflies, bees) was associated with higher land-use intensity. Habitat heterogeneity (broadleaved woodland connectivity, hedgerows, habitat diversity) was positively related to species richness of many taxa, both generalists (plants, butterflies, bees) and specialists (rare birds, woodland birds, plants, butterflies).

The results were used to create maps of HNV farmland. The proportion of semi-natural vegetation is a useful metric for identifying HNV type 1. HNV type 2 (defined as a mosaic of low-intensity habitats and structural elements) is more difficult to predict from surrogate variables, due to complex relationships between biodiversity and habitat heterogeneity and inadequacies of current remotely sensed data.

This approach, using fine-scaled field survey data collected at regular intervals, in conjunction with remotely sensed data offers potential for extrapolating modelled results nationally, and importantly, can be used to assess change over time.

1. Introduction

Agriculture has been a major driver of global environmental change and unprecedented biodiversity loss over the past century (Benton, Vickery, & Wilson, 2003; Firbank, Petit, Smart, Blain, & Fuller, 2008; Strohbach, Kohler, Dauberb, & Klimek, 2015). Agricultural intensification involves increases in external inputs (pesticide and fertilisers), land-use change, increases in field sizes and fragmentation and loss of semi-natural habitats; all of these have caused the decline of many different taxa (Billeter et al., 2008; Chamberlain, Wilson, Brown, & Vickery, 2001; Robinson & Sutherland, 2002). However, agriculture is important for food production; croplands and pastures cover 40% of the global land surface (Foley et al., 2005) and many species are dependent upon agricultural habitats (Benton et al., 2003). Therefore, biodiversity protection globally depends upon conservation in these human-dominated landscapes (Fahrig et al., 2011; Karp et al., 2012).

Evidence suggests that biodiversity can be increased by changing to low intensity land uses (Bignal & McCracken, 1996; Karp et al., 2012) or by changing landscape structure, e.g. increasing landscape heterogeneity and connectivity (Stein, Gerstner, & Kreft, 2014; Benton et al.,

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2003; Steffan-Dewenter, 2003). It may be more difficult to take land out of production because of farmer livelihoods and requirements for food (Fahrig et al., 2011). However, where agriculture depends on structural support payments, reductions in these could drive abandonment on marginal land (Renwick et al., 2013). Low intensity systems, for instance, semi-open habitats maintained through extensive grazing, are important for many priority species (Lubos Halada, Evans, Roma, & Petersen, 2011; Woodhouse, Good, Lovett, Fuller, & Dolman, 2005).

Landscape heterogeneity can moderate the negative effects of local land-use intensity (Perović et al., 2015). Increased compositional heterogeneity (diversity of habitat types) represents more niches which support more species, whilst configurational heterogeneity (number, size and arrangement of habitat patches) (Fahrig et al., 2011; Perović et al., 2015) increases the variability of microclimatic conditions and provides breeding sites (Stein et al., 2014; Benton et al., 2003), whilst increasing the ease with which species can move through the landscape and achieve viable metapopulations (Lawton et al., 2010). However, high habitat heterogeneity can have negative effects by increasing habitat fragmentation, at the expense of habitat specialists (Fahrig et al., 2011).

Agricultural landscapes vary widely in the degree of intensity of production and spatial heterogeneity, and by land ownership, historical and cultural practices, topography and soil type (Fahrig et al., 2011). To protect and maintain farmland biodiversity requires a framework for priority-setting. In Europe, the High Nature Value (HNV) farmland concept was introduced as *'areas in Europe where agriculture is a major (usually the dominant) land use and … supports or is associated with either a high species and habitat diversity, the presence of species of European concern or both*' (Andersen et al., 2003). Thus 'the preservation and development of HNV farming systems' is a strategic priority for EU member states and contributes to targets for halting biodiversity loss by 2020, so subsidies are prioritised to HNV areas (Brunbjerg et al., 2016). These tend to be marginal for farming with low productivity. They produce multiple ecosystem services such as carbon storage, clean water, and aesthetic landscapes.

Three HNV types are broadly recognised (Paracchini et al., 2008): Type 1-farmland with a high proportion of semi-natural vegetation; Type 2-farmland with a mosaic of low intensity agriculture and natural and structural elements, e.g. field margins, hedgerows, scrub, small rivers; Type 3- farmland supporting rare species or a high proportion of European or world populations (can occur at small scales in an otherwise intensively managed landscape).

The assumptions underlying the HNV types 1 and 2 definitions, that high species richness is associated with high habitat heterogeneity and low intensity land-use, are evidence-based (Stein et al., 2014); however, they have not been tested in all physical and cultural contexts and all scales of interest. To create a national HNV indicator, it is important to test these assumptions and to develop an understanding of fundamental ecological relationships, incorporating species diversity, to identify HNV areas. Species are sensitive to spatial and temporal scale, e.g. species with small area requirements can persist in highly fragmented habitat patches in agricultural landscapes too small to maintain species with larger ranges. Further, species have different functional traits (Perović et al., 2015) that influence responses to heterogeneity and drivers (e.g. land management, nutrient input). So, although there are studies that have used a single taxa as an indicator, biodiversity should be measured for a range of taxa (Fahrig et al., 2011), as a single species may not be a good predictor of other species groups (Billeter et al., 2008; Firbank et al., 2008).

HNV farming is the only Common Agricultural Policy (CAP) impact indicator for which there is no common methodology explicitly provided at the European union (EU) level. Each Member State uses data and methodologies suited to their prevailing bio-physical characteristics and farming systems, and based on the highest quality and most appropriate data available, including for instance, landscape elements (hedgerows) and indicator species (particularly birds and plants) (Klimek, Lohss, & Gabriel, 2014; Morelli, Jerzak, & Tryjanowski, 2014; Brunbjerg et al., 2016).

There have been attempts to create a system for identifying HNV farmland consistently across Europe using various approaches, including land cover, farming system, protected areas and species (Andersen et al., 2003; Beaufoy, Baldock, & Clarke, 1994). Most European-scale approaches lack the spatial and temporal resolution necessary for national and regional application (Lomba et al., 2014).

Even at national and regional scales it can be difficult to obtain data at high resolution on landscape elements, farming intensity, management practices (Strohbach et al., 2015) and biodiversity. Coarser, spatially continuous, remotely sensed data may be available but do not provide the detail of finely resolved data (Wood et al., 2018), for instance, small biotopes and hedgerows cannot be easily detected by remote sensing, and data are not necessarily available at the appropriate frequency to monitor change. Where biodiversity data are available they are often sampled data such as the bird surveys carried out for common bird monitoring in the UK (Harris et al., 2018) which cover selected sites but make it difficult to produce continuous maps (Strohbach et al., 2015).

Here, we develop methods to integrate fine-scaled, sampled data (for biodiversity, landscape heterogeneity and structure) with coarser, spatially continuous data from remote sensing (Boyle, Hayes, Gormally, Sullivan, & Moran, 2015; Klimek et al., 2014) to enable extrapolation outside of the sampled sites. This study is at a national scale (Wales) and uses data collected as part of the monitoring project (GMEP; Glastir Monitoring and Evaluation Project) designed to detect the impacts of the Glastir agri-environment scheme (the main scheme by which the Welsh Government pays for environmental goods and services funded by the EU's Rural Development Programme (RDP).

This study: i) explores the relationships between elements of land-use intensity, habitat heterogeneity and species diversity (using a range of taxa) to support the use of metrics to identify HNV types 1 and 2; ii) uses the results of those analyses to identify key explanatory variables that could be used to scale up nationally from fine-scaled analysis of field survey samples and iii) maps High Nature Value farmland in Wales.

2. Materials and methods

2.1. HNV indicator

The development of an HNV indicator was discussed in a consultation process with a range of partners and stakeholders in Wales comprising the Centre for Ecology & Hydrology (CEH), British Trust for Ornithology (BTO), Royal Society for the Protection of Birds (RSPB), National Farmers Union (NFU), Natural Resources Wales (NRW) and the Welsh Government (WG). The consultation considered the concept of HNV, definitions, criteria and which metrics were of primary interest to the community and for which there were relevant data. We chose not to make the assumption that certain types of farming system are automatically of High Nature Value. Instead we used more objective, quantitative methods suited to the prevailing bio-physical characteristics of the area. The definition of farmed land used is quite broad, it includes arable, improved and neutral grasslands and semi-natural habitats (e.g. acid grassland, bog, heath) that are grazed. It excludes urban, coniferous forest and large areas of woodland (although we have considered broadleaved woodland connectivity). A large extent of Wales was considered to be farmed land although it is not farmed intensively.

2.2. Fine-scaled data

To explore these relationships, we used data from the Glastir Monitoring and Evaluation programme (GMEP). The methodology is based on that of Countryside Survey (Smart et al., 2003; Norton et al.,

Table 1
Variables used in analysis.

Diversity metrics		Habitat structure metrics (Fine-scaled analysis)		Habitat structure metrics used for All Wales analysis (significant variables from previous analysis)	
Plants	Total species richness (Mean per plot per 1 km)	**Habitat heterogeneity**	Habitat diversity (Shannon index)	**Habitat heterogeneity**	Habitat diversity (Shannon index) LCM (Land Cover Map)
	Ancient woodland indicator species (Mean per plot per 1 km)		Habitat patch size (mean area of habitat in 1 km)		
	Wetland indicators (Mean per plot per 1 km)		Wetland connectivity		Wetland connectivity LCM
	Plant habitat indicators (mean per plot per 1 km)		Broadleaved woodland connectivity		Broadleaved woodland connectivity LCM and NFI
Pollinators	Butterfly species richness		Length of hedgerows		Woody linear feature density
	Woodland Butterfly species richness		Length of lines of trees		
	Bee diversity		Total length of Inland water (streams and rivers)		
	Hoverfly diversity				
	rare invertebrate species richness	**Land-use intensity**	% semi-natural habitat	**Land-use intensity**	% semi-natural habitat in 1 km LCM
Birds	Woodland bird species richness		% Improved land		% Improved land in 1 km LCM
	Farmland bird species richness		Sward height		
	Rare bird species richness		Total number sheep		
			Total number pigs		
	Upland bird species richness		Total number horses		
		Soils	% rare and occasional soils		
			Soil diversity		

2012), with some methodological differences (Emmett and the GMEP team, 2014). Over 4 years, 300 x 1 km squares were sampled, half of these were based on a stratified random sample by land class (e.g. geology and soils), and the other half a random sample weighted towards Welsh government priorities for options within Glastir. Within each 1 km squares, a series of measurements were taken. The metrics used are outlined in Table 1.

2.2.1. Biodiversity

2.2.1.1. Plant species. A series of up to 50 vegetation plots sampling different features were located within each 1 km squares (Smart et al., 2003). Linear features (watercourses, hedges and field boundaries) and areal features (fields, unenclosed land and small semi-natural biotope patches) were sampled. Linear plots were 1 m × 10 m laid out along a feature. Area plots were randomly placed (2 m × 2 m), while a series of targeted plots sample small habitat patches and habitats of conservation value. In each vegetation plot, a list was made of all vascular plants and the more easily identifiable bryophytes. Response variables calculated from the vegetation plot data for each 1 km squares include: mean number of total plant species per plot, mean number of ancient woodland indicator species per plot (Kimberley, Kirby, Whyatt, Blackburn, & Smart, 2013), mean number of wetland species per plot and mean number of species indicating high quality habitats. The latter was created from a list of plant indicator species taken from the Common Standards Monitoring guidance for Sites of Special Scientific Interest (JNCC, n.d) and refined in consultation with the Botanical Society of the British Isles from a list of axiophytes ('worthy' plants indicative of habitats of high conservation value). The mean number of wetland species per plot was calculated using this list for wetland habitats only. The ancient woodland indicators were identified in a separate list collated from discussions with woodland experts.

2.2.1.2. Birds. The bird surveys were carried out by BTO. The survey protocol operated at the same spatial scale (1 km squares) as the national BTO/JNCC/RSPB Breeding Bird Survey (BBS), but involved more intensive fieldwork in space and time (Emmett and the GMEP team, 2014). The surveys consisted of four visits to each square, equally spaced through mid-March to mid-July. On each visit, the surveyor walked a route that passed within 50 m of all parts of the survey square to which access had been secured, taking up to 5 h. All birds seen or heard were recorded on high-resolution field maps using standard BTO activity codes. Bird data were summarised to calculate the number of woodland bird species in a 1 km survey square (species-specific maxima across all four visits), and the same for farmland birds, upland birds and rare birds. There are defined species and habitats of principal importance to conservation in Wales that are known as 'Priority' or Section 7 species and habitats (Wales Environment act) and the rare birds are taken from that list (A1). The woodland bird index and the farmland bird index are well-established for reporting at national level in the UK and mainland Europe (Gregory et al., 2008).

2.2.1.3. Pollinators. Butterfly Conservation organised the survey of pollinators focused on three main pollinator groups: butterflies (*Lepidoptera: Rhopalocera*), bees (*Hymenoptera: Apoidea*) and hoverflies (*Diptera: Syrphidae*). Butterflies were recorded to species level, whilst bees and hoverflies were recorded as groups (A2) based on broad differences in morphological features associated with ecological differences. Shannon diversity indices were calculated using the number of bee and hoverfly groups recorded, to account for evenness. A 2 km transect route was taken through each 1 km square survey (following the UK Butterfly Monitoring Scheme, Brereton, Cruickshanks, Risely, Noble, & Roy, 2011), all butterflies within a 5 m box are recorded while walking a fixed route at a steady pace under a set of pre-determined weather conditions and at a set time of day (known as 'Pollard walks', Pollard, 1977). Hoverfly and bee groups were also counted simultaneously along the same transects. Pollinator metrics used in this analysis include bee species diversity index, hoverfly diversity index, butterfly species richness, woodland butterfly species richness and species richness of rare invertebrates (Section 7, Wales Environment act, n.d).

2.2.2. Habitat heterogeneity

2.2.2.1. Habitat diversity. Habitat areas (> 20 m × 20 m) were mapped and classified in the GMEP field survey onto hand held computers using the Broad and Priority Habitat classification (Jackson, 2000). Shannon's diversity index was calculated to take into account the number of Broad habitats and the dominance among them (Firbank et al., 2008).

2.2.2.2. Habitat patch size. Mean area of habitat per 1 km squares was calculated from field survey mapping data.

2.2.2.3. Linear features. Linear features (< 5 m wide, minimum length 20 m) recorded include the length of managed hedgerows, unmanaged lines of trees, streams and ditches in each 1 km square.

2.2.2.4. Connectivity of woodlands and wetlands. Habitat connectivity is a function of the number and size of habitat patches and how close together they are; this was estimated from the habitat maps recorded by the field survey team. We considered Euclidean distance (distance in metres between the edges of each habitat patch) and least-cost methods, and used least-cost for fine-scaled data. Least-cost paths were calculated as a function of the landscape occurring between two habitat patches, using expert judgement of the ease of movement of a generic broadleaf woodland or wetland species to assign weightings to each habitat (Jackson et al., 2013). Linear features containing woody components were included with the assumption that species associated with broadleaf woodland could move along linear features as easily as they could move within woodland.

The Probability of Connectivity (PC) metric was calculated, using the Conefor program (Saura & Torné, 2009), between all broadleaf woodland patches to measure woodland connectivity and between all wetland patches for wetland connectivity. The model was parameterised with a dispersal distance of 200 m. This was scaled so that the square with the highest PC metric had a value of 1.

2.2.3. Land-use intensity

The proportion of improved land (improved grassland and arable) was calculated from the habitat maps recorded by the field teams. Semi-natural land was defined as all Broad Habitat types excluding improved grassland, arable and horticultural, coniferous woodland and urban. The sward height of all appropriate land cover types was recorded by surveyors and the mean sward height per square averaged over the number of land parcels was calculated. Data on livestock from the June Agricultural census at holding (farm) scale were provided by the Welsh government. These data were overlaid onto the field survey squares and the total number of pigs, sheep and horses per 1 km squares were calculated as metrics.

2.2.4. Soils

The soils of Wales are mapped as part of the soil survey of England and Wales (Avery, 1980). The National Soil Map (NATMAP) for Wales is available at reconnaissance scale (soil associations), 1:250,000 for all of Wales (NSRI, 2001). Maxwell et al. (2017) used 98 soil associations taken from the soil survey of England and Wales in an analysis to identify rare soils and to assess spatial patterns (soil diversity) across Wales and these data were used here. Soil diversity is measured using the Shannon diversity indices similarly to the calculation for habitat diversity (Maxwell et al., 2017).

2.2.5. Fine-scaled analysis

Generalised Additive Modelling (GAM) (Hastie & Tibishirani, 1990) in R (R core team, 2017) was used (with a Poisson distribution) to analyse interactions between species richness of biodiversity indicators and explanatory variables (Table 1). Spatial autocorrelation (SAC) was tested by extracting the model residuals and testing with Moran's I in R (using functions in the 'ape' library) (Dormann et al., 2007). Results suggested that there was SAC for some variables (birds, butterflies, bees: $p < 0.001$), so we accounted for SAC by specifying a spatially explicit model for the residual structure with the nlme package, which provides functions for spatial correlation structures (Dormann et al., 2007).

Multivariate analyses of the spatial relationships between biodiversity metrics and explanatory variables were undertaken using Canoco (Ter Braak & Smilauer, 2002). Data were collated at the 1 km squares resolution and all biodiversity variables per square were centred and standardised to zero mean and unit variance. The standardised response data result in all variables having the same centred standard deviation; hence, Redundancy Analysis (RDA) -a linear model- is appropriate to test the explanatory power of independent predictors of habitat diversity and spatial heterogeneity. Significant predictors were identified using Monte Carlo permutation tests (Leps & Smilauer, 2003).

2.3. National data; all 1 km squares in Wales

To scale up from the fine-scaled analysis of sample field survey squares requires data for every 1 km square in Wales. Using the significant explanatory variables identified in the RDA analysis above, the analysis was repeated using data from sources available at the national scale. The Land Cover Map 2007 (LCM2007; Morton et al., 2011) was used for some metrics: it is a vector based land cover map for the UK based on a spatial framework that uses national cartography products (OS MasterMap for Great Britain). LCM2007 was derived by classifying 30 m pixel size satellite data, with 23 classes based on Broad Habitats and validated against ground reference polygons distributed across the UK (Morton et al., 2011).

2.3.1. Habitat heterogeneity

2.3.1.1. Habitat diversity. Habitat diversity was calculated using the method described above but using the LCM2007 Broad Habitat classes rather than Field Survey data.

2.3.1.2. Woody linear features. The percentage cover of woody vegetation was calculated using airborne radar data (NEXTMap®), optical imagery from satellites and data from the National Forest Inventory. NextMap provides canopy height information at 5 m × 5 m spatial resolution and this dataset was used to identify 'tall' features in the landscape. Normalised Difference Vegetation Index (NDVI) imagery was used to separate vegetated from non-vegetated areas. NDVI was derived using data from the Landsat 8 Operational Land Imager (OLI), calibrated to reflectance and masked to remove cloud and cloud shadow. NDVI was calculated using:

$$NDVI = \frac{(Near\ infrared\ reflectance - Red\ reflectance)}{(Near\ infrared\ reflectance + Red\ reflectance)}$$

Larger areas of woodland were supplemented by the National Forest Inventory 2013 dataset to produce a woody features product with a binary (woody/non-woody) classification at 5 × 5 m spatial resolution (Tebbs & Rowland, 2014).

2.3.1.3. Connectivity. Wales was divided into ~20,000 1 km squares for which area and location of broadleaf woodland and wetland were assessed from LCM. Within the GMEP field survey squares the least-cost connectivity metric was compared to the Euclidean distance metric and there was a high significant correlation (r squared = 0.95, $p < 0.001$) so, for the all Wales dataset, Euclidean distances were used to reduce processing time. The pairwise distances and size of each fragment were used to calculate the probability of connectivity metric for each 1 km grid cell using Conefor software (Saura & Torné, 2009), as for the field data.

2.3.2. Land-use intensity

The percentages of semi-natural and improved land were calculated in the same way as above but using remotely-sensed LCM2007 data rather than field survey data.

2.3.3. National analysis

To compare the use of explanatory variables from fine-scaled field data with remotely sensed data, an RDA with the fine-scaled field survey biodiversity data as response variables, habitat heterogeneity, land-use intensity and soils (Table 1) as explanatory and the remotely sensed data as supplementary variables, was performed in CANOCO (Ter Braak & Smilauer, 2002). This analysis was for field survey squares only. Supplementary variables are added on the ordination diagram without influencing the positioning of the sites (scores), which are constrained by the explanatory variables alone (Fig. A2).

RDA including all squares in Wales was carried out in R (R core team, 2017; Oksanen et al., 2017) to enable the use of large datasets. To test the predictive power of the multi-variate analysis, an RDA was carried out with data from the first three years only (2013–2015, 225 1 km squares), using biodiversity metrics from the field survey as response variables and remotely-sensed habitat heterogeneity and land-use intensity data as explanatory variables. Data for all other non-GMEP squares in Wales were passively added to the ordination space using the remotely sensed explanatory variables only. Site scores for year 4 sites (75 squares) based on passively adding them using remotely sensed explanatory variables were extracted. Then the RDA described above was repeated including year 4 field data (2013–2016, 300 squares). Site scores for year 4 squares (75) were extracted from the results of this analysis and compared to the scores extracted from the previous ordination to validate the analysis.

Finally, the axis scores from the RDA of all field survey squares (300), with biodiversity response data and remotely sensed explanatory variables and all non-GMEP squares in Wales, passively added to the ordination space, were used to map the extent of HNV land in Wales.

3. Results

3.1. Fine-scaled analysis

3.1.1. Generalised Additive Models (GAM's)

The results of analyses of explanatory variables against species richness can be seen in Table 2 and supplementary Fig. A3a–A3e, where the GAM curve has been superimposed onto the raw data. There were no significant relationships with hoverflies. Adding a spatially explicit model to account for SAC did not affect many of the results. Bees were the group most influenced and some results were no longer significant when SAC was accounted for.

The proportion of semi-natural habitat was positively associated with plant habitat quality indicators, wetland specialist plants, rare invertebrates and upland birds. It was negatively related to butterflies, bees, total plant species richness, woodland butterflies and farmland birds. There were non-linear, unimodal relationships with ancient woodland plants, rare birds and woodland birds (Fig. A3a). There were inverse relationships with the proportion of improved land (Fig. A3b): for example, there were negative relationships for plant habitat indicators, wetland specialist plants, rare invertebrates, and upland birds.

Habitat diversity (Fig. A3c) was positively, linearly, related to total plant species richness, woodland birds and rare birds and unimodally to bees. There were no significant relationships with the other biodiversity indicators.

There were positive relationships with broadleaved woodland connectivity (Fig. A3d), for both generalists (butterflies) and specialists (woodland butterflies, birds & plants (slightly u-shaped) and rare birds). Rare invertebrates, upland birds and wetland and plant habitat indicators were negatively related to broadleaved connectivity. Farmland birds and total plant species richness were non-linearly (unimodally) related. There was no significant relationship with bees. The relationships between biodiversity and hedgerow length (Fig. A3e) were quite similar to broadleaved connectivity; the only differences were that total plant species richness, woodland plants and farmland birds were linearly positively related, rather than unimodal, and wetland indicator plants were not significantly related to hedgerows.

3.1.2. Multivariate analysis

The results of the multi-variate RDA analysis are shown in Fig. 1*a. axis* 1 and 2 explained 20% and 2.7% of the variation, respectively. Axis 3 (Fig. A1) explained 2.3% of the variation. There is a clear gradient between low intensity land-use (high proportion of semi-natural land - HNV type 1) and high intensity land-use (high proportion of improved land) which appears to roughly equate to Axis 1, with significant relationships to particular species groups. The other gradient appears to relate to habitat heterogeneity (bottom left to top right) with increasing habitat diversity, broadleaved connectivity, hedgerows and lines of trees on Axis 2. This aligns with HNV type 2. The discrimination of types 1 and 2 HNV was carried out by separately bisecting each of these principal gradients. Since all 1 km squares have a score on each axis, the result is a subset of squares that have the overlapping attributes of both type 1 and type 2 HNV. Thus the two types are not defined to be mutually exclusive when mapped across Wales.

In the analysis, the following variables were statistically significant (using Monte Carlo permutation tests to test the significance of regression) as predictors of biodiversity: broadleaved connectivity ($F = 22.4$, $p < 0.001$), % improved land ($F = 3.2$, $p < 0.01$), % semi-natural habitat ($F = 33.3$, $p < 0.001$), wetland connectivity ($F = 6.5$, $p < 0.001$), habitat diversity ($F = 4.6$, $p < 0.01$), hedgerow length ($F = 5.7$, $p < 0.01$), lines of trees ($F = 10.7$ $p < 0.001$) and inland water ($F = 4.4$, $p < 0.01$). The proportion of rare and occasional soils, soil diversity, the stocking density of sheep, pigs, horses, patch size and sward height were not statistically significant. Significant variables have been included on the ordination diagram (Fig. 1a).

The ordination diagram indicates that (as with the GAMs) a high proportion of semi-natural land was associated with species richness of plant habitat quality indicators, upland birds, wetland plants and rare invertebrates along with wetland connectivity. Broadleaved woodland connectivity was strongly associated with woodland birds, woodland plants, rare birds and total plant species richness. Hedgerow length was positively associated with farmland birds, woodland butterflies, total

Table 2

Results from GAM's (Poisson distribution) from fine-scaled field data, including spatially explicit model for residual structure; species richness as response variable against explanatory variables. (Dir = direction of relationship, + positive, − negative, ∩ unimodal, U u-shaped. ns = not significant. * $p < 0.05$, **$p < 0.01$, ***$p < 0.001$).

	Broadleaved connectivity		Hedgerow length		Habitat diversity		% semi-natural		% Improved land	
	F	Dir	F	Dir	F	Dir	F	Dir	F	Dir
Total Plant species richness	7.2***	∩	20.5***	+	4.3*	+	7.8***	−	16.2***	∩
Ancient woodland indicator plants	9.9***	∩	11.9***	+	ns		4.1**	∩	ns	
Plant Habitat indicators	4.3*	−/U	21.4***	−	ns		24.3***	+	58.5***	−
Wetland plants	18.6***	−	ns		ns		9.9***	+	ns	
Butterflies	16.7***	+	30.8***	+	ns		46***	−	47.6***	+
Rare invertebrates	12.5***	−	13.9***	−	ns		22.7***	+	18.4***	−
Bees	ns		ns		6.6***	∩	9.5**	−	ns	
Woodland Butterflies	10.8***	+	11.11***	+	ns		12***	−	5.9***	+
Hoverflies	ns		ns		ns		ns		ns	
Rare birds	93.7***	+	34.6***	+	22.8***	+	101.4***	∩	71.3***	∩
Farmland birds	9.4***	∩	17.4***	+	ns		18.2***	−	41.5***	+
Upland birds	3.9*	−	12.8***	−	ns		18.3***	+	11.4***	−
Woodland birds	97.7***	+	17.6***	+	15.9***	+	59.8***	∩	28.9***	∩

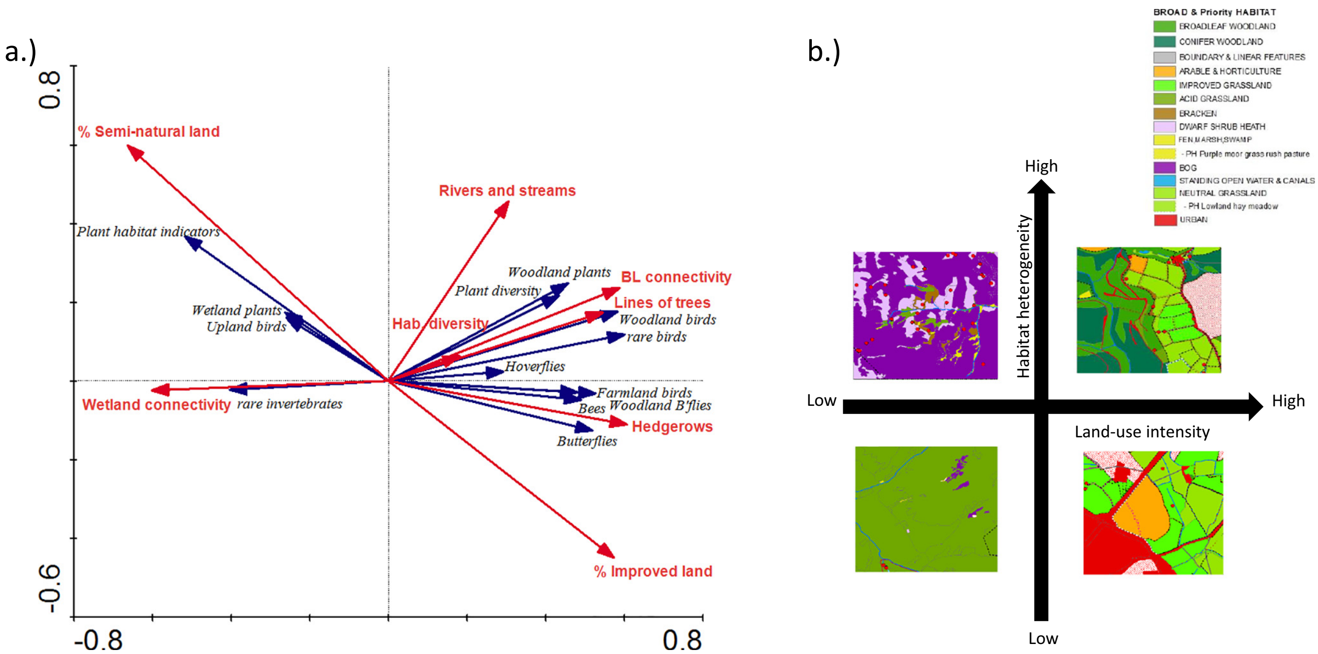

Fig. 1. a.) Ordination results from RDA b.) simplified version of ordination diagram with Habitat maps from 1 km squares to demonstrate different types of heterogeneity and land-use intensity. Top left: Low Intensity land-use/high habitat heterogeneity; top right: High Intensity land-use/high habitat heterogeneity; bottom left: low intensity land-use/low habitat heterogeneity; bottom right: high intensity land-use/low habitat heterogeneity.

butterflies and bees. Habitat diversity was strongly associated with woodland birds, rare birds and total plant species richness.

The association of explanatory variables and response variables enables classification into four quadrants that describe the types of 1 km squares that were found in the data (Fig. 1b). The types of square are represented using example 1 km square habitat maps from the field survey.

3.2. National analysis based on remotely-sensed data

The results of repeating the ordination of GMEP field data, including explanatory variables from remotely-sensed data, can be seen in Fig. A2. There were similar relationships with biodiversity variables regardless of whether they were derived data from field survey or remote sensing.

Fig. 2 shows the results of testing the prediction of axes scores from a subset of squares using two different methods (with biodiversity data and when passively added to the ordination using only explanatory variables). Fig. 2a shows a highly significant relationship between site scores on axis 1 (land-use intensity). The result for axis 2 (Fig. 2b) is not significant.

Axis site scores from the all Wales analysis have been extracted and categorised (based on the 20th percentile, commonly used to identify upper and lower proportions of distributions whilst not solely identifying the extremes) into 'High' (top 20 percentile), 'medium' (middle 60 percentile) and 'low' (lowest 20 percentile). These have been mapped across Wales (Fig. 3), to signify the distribution of Type 1 (% semi-natural vegetation) and Type 2 (habitat heterogeneity) HNV farmland. Fig. A4 shows boxplots of the distribution of the ordination axis scores across the categorised HNV classes. The maps suggest that

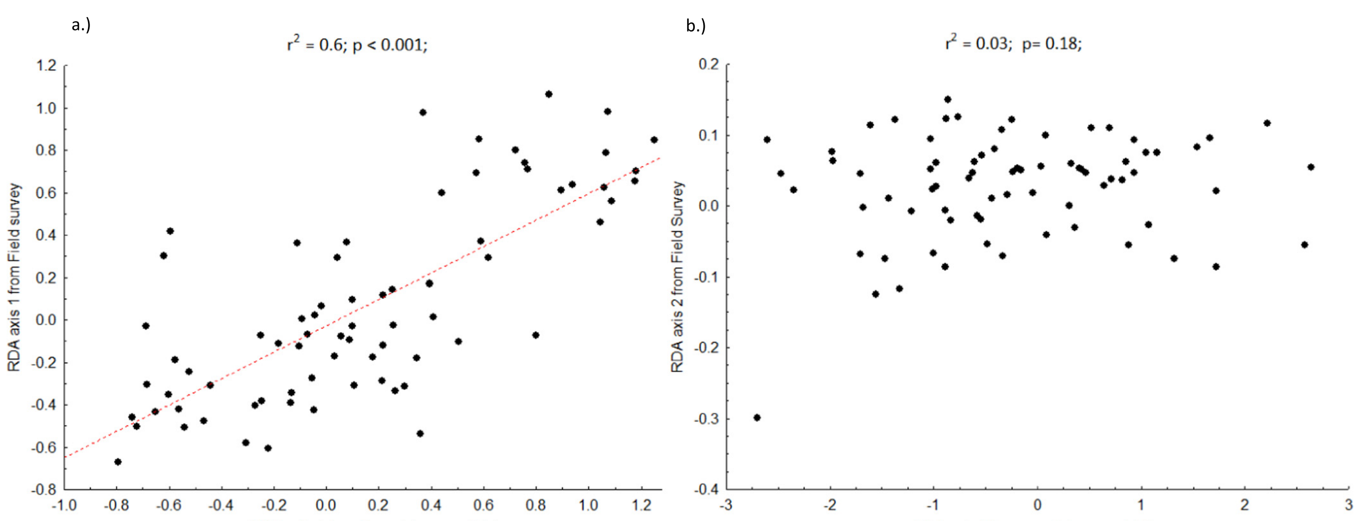

Fig. 2. Test of analysis for 75 1 km squares from year 4, comparing results from RDA where survey squares were added passively using remotely sensed environmental variables only with results from an RDA including field survey biodiversity data. a.) axis 1: land-use intensity b.) axis 2: habitat heterogeneity.

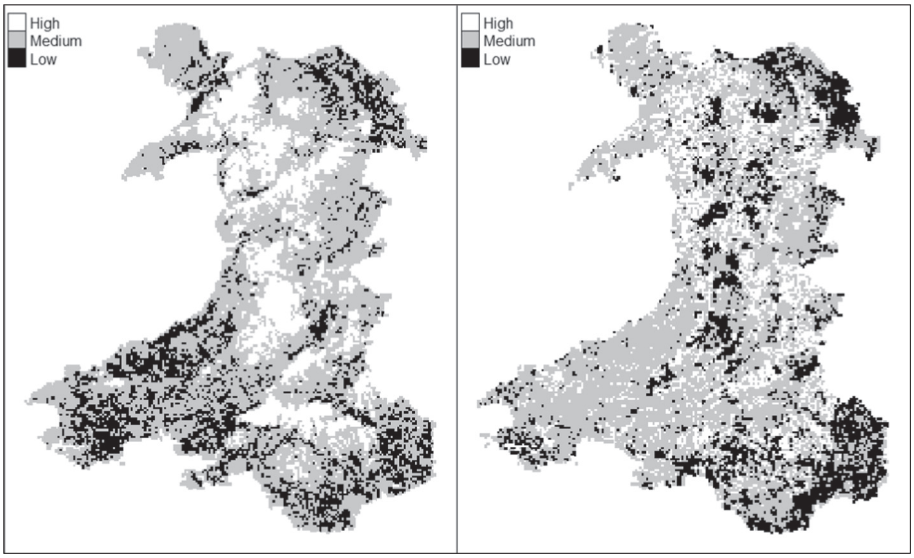

Fig. 3. Maps of High Nature Value farmland in Wales a.) Type 1 land-use intensity (percentage of semi-natural land) and b.) Type 2 Habitat heterogeneity.

approximately 35% of the land in Wales is in the upper percentile for HNV Types 1 and 2 combined.

4. Discussion

Conservation of farmland is important for mitigating biodiversity decline (Kleijn, Rundlöf, Scheper, Smith, & Tscharntke, 2011). Identifying areas of High Nature Value spatially enables targeting of conservation actions and farming subsidies (Klimek et al., 2014). In this study, land-use intensity and habitat heterogeneity were clearly identified as two major gradients acting upon species diversity in Wales at the spatial scale of 1 km. They also form the criteria for classification of HNV farmland. Our results therefore provide a uniquely detailed and large-scale test that supports the two hypothesised relationships that define Types 1 and 2 HNV.

4.1. Relationships between land use intensity and biodiversity

In Wales, there are large areas of semi-natural, extensively grazed land composed of heathland, semi-natural grassland, bog and purple moor grass rush pasture (Blackstock, Howe, Stevens, Burrows, & Jones, 2010) and ffridd (a transitional habitat of unimproved grassland, shrub heath, bracken and scrub; Woodhouse et al., 2005) and these areas are important in a European context (Russell et al., 2011). They are associated with many habitat-specialist species and are valued for their aesthetic, cultural and functional importance (Vickery et al., 2001). This includes upland birds, rare invertebrate species, plants indicative of high conservation value habitats and wetland plants (all of which were significant in this study). It might have been expected that butterflies would be positively related to semi-natural habitat (a number of habitat specialists are only found in such habitats). However, this was not the case. Pollinator surveys were conducted in July and August to coincide with peak butterfly abundance, this is after the main flight period of some Welsh habitat specialists. Also, most habitat specialist butterflies that fly during the survey period have restricted ranges in Wales (e.g. High Brown Fritillary, *Argynnis adippe*).

Higher land-use intensity was associated with farmland birds, bees and butterflies, reflecting positive responses of farmland-associated species to a degree of active management. Also, higher land-use intensity tends to be in lowland environments, which have a more benign climate, associated with greater numbers of species. Wales is not as intensively farmed as some countries: there are no large areas of arable, field size is not large and there are often hedgerows and linear habitats, which may explain why species richness among these groups is not lower at higher intensity. In an analysis of all of Great Britain, the relationship between land-use intensity and species richness was unimodal (Maskell et al., 2013). In Wales, land-use intensity is low to medium in comparison to the UK as a whole so it sits on the left and middle of centre of the unimodal curve rather than to the right.

4.2. Relationships between habitat heterogeneity and biodiversity

Habitat heterogeneity is a desirable cultural landscape quality (Swetnam, Harrison-Curran, & Smith, 2017), regardless of benefits for species diversity. However, both compositional and configurational heterogeneity are positively related to many taxa in landscapes in Wales: habitat specialists (woodland birds, butterflies and plants, rare birds, farmland birds) and generalists (plants, bees and butterflies). There is supporting evidence from the literature: species groups differ in response to environmental heterogeneity (Fahrig et al., 2011). Bees require several different and sometimes also very specific habitat types to persist in a landscape (Billeter et al., 2008). The diversity of butterflies has been shown to be related to small-scale habitat heterogeneity (Weibull, Bengtsson, & Nohlgren, 2000). Habitat diversity enables source populations in semi-natural elements to spill over to intensively managed fields (Holland & Fahrig, 2000; Smart et al., 2006). Bird species' preferences vary, both with respect to the scale of the heterogeneity and responses to specific levels of heterogeneity (Aue, Diekötter, Gottschalk, Wolters, & Hotes, 2014; Siriwardena, Cooke, & Sutherland, 2012; Pickett & Siriwardena, 2011). There is evidence that bird taxonomic and functional diversity can increase within HNV farmland in relation to land-use composition and increased configurational heterogeneity (Morelli, 2018).

Woodland varies in extent, condition and distribution across the Welsh landscape (Russell et al., 2011). Where woodland patches have contracted or become isolated, connectivity of woody linear features is important to maintain viable populations of many taxa. Hedgerows, whilst not providing all of the conditions for woodland habitat specialists, can provide some of the required conditions needed, e.g. for shelter, food, microclimate and soil. Hedgerow habitat and woody structures in open landscapes significantly increase the number of bird species, by increasing ecological niches, particularly benefiting generalist woodland birds (Aue et al., 2014; Hinsley & Bellamy, 2000; Morelli et al., 2014). Some species, e.g. skylark and lapwing, are negatively influenced by hedgerows (Hinsley & Bellamy, 2000). In this study, there were positive relationships between hedgerows and rare, woodland and farmland birds.

4.3. Estimating the area of High Nature Value farmland

Indicators specifying the amount of land under High Nature Value farming in Wales and how it changes over a specified time period (context and impact) are important. Any methodology needs to be spatially precise and sufficiently frequent to detect change (Lomba et al., 2014). It has been possible in some countries to collate the 'best' data available to map HNV farmland as a one-off, but it may not be practicable to repeat this at regular intervals.

In this study, we propose using disaggregated fine-scaled data to build models that can include remotely sensed data to provide continuous coverage (Klimek et al., 2014; Boyle et al., 2015). The surveys for data collection can be repeated over set time periods to analyse change. When remotely sensed explanatory variables were jointly analysed alongside field survey data there was a high degree of correlation between them suggesting that there is potential to use remotely sensed data as a surrogate for field survey.

Applying this process will be helped by the large volumes of freely available, medium resolution (< 30 m pixel size) satellite data provided by Landsat-8 and Sentinels 1 and 2. These data will lead to more frequent production and updating of EO products, for example the UK Land Cover Map is moving to a three-year repeat cycle, from an approximately 10 year repeat cycle. The increase in the availability of high resolution data from Sentinel-1 and Sentinel-2 is also leading to a wider range of routinely-derived EO-products for the UK, including vegetation productivity (Tebbs, Rowland, Smart, Maskell, & Norton, 2017). Developments such as these are likely to increase our ability to map HNV and changes in HNV in the future.

The testing of the method in the validation analysis demonstrated that the percentage of semi-natural/improved land was a very useful metric for identifying HNV type 1 farmland. However, for habitat heterogeneity and HNV type 2 farmland, although the initial RDA analysis identified some interesting patterns in the species data, the analysis using only remotely sensed explanatory variables to add squares passively did not predict the species richness of the survey squares as well. This may be because multiple explanatory variables were used, rather than one simple indicator, and because of complex relationships between biodiversity and habitat heterogeneity.

There are issues with remotely sensed data. Although some habitats can be identified fairly accurately from satellites, e.g. woodland, other habitats (e.g. grasslands, bogs and heath) cannot be classified accurately (Morton et al., 2011; Wood et al., 2018). Vegetation structure can also be difficult to capture remotely: small biotopes (< 20 m) which particularly in intensive landscapes may contain valuable biodiversity, will often be below the minimum mappable size of products derived from satellite data (Wood et al., 2018). This may impact on measures such as habitat diversity. Rhodes, Henrys, Siriwardena, Whittingham, and Norton (2015) found that high-resolution field data generated more reliable models of predicted local population responses to land-use change than lower resolution, remotely sensed data. Further finely scaled analysis at a field level and improvements in remotely sensed data may be necessary to clarify these relationships and to increase explanatory power of the models (Klimek et al., 2014).

4.4. Summary

A high proportion of semi-natural land is associated with high biodiversity of habitat specialists and species indicating areas of high conservation value. This metric can be derived from coarse, remotely sensed data to predict and to map High Nature Value type 1 farmland.

Habitat heterogeneity is associated with increased diversity of generalist and specialist species groups and interesting relationships were found between broadleaved woodland connectivity, habitat diversity, lengths of hedgerows/lines of trees and field survey biodiversity data. The complexity of these relationships and the inadequacies of current remotely sensed data make it more difficult to replace fine-scaled analysis with simple surrogate metrics. Estimation of extent and spatial configuration of HNV type 2 requires further work to refine the method and to create better metrics.

The approach described here, using fine-scaled field survey data collected consistently at frequent intervals in association with remotely sensed data offers a great deal of potential for extrapolating modelled results nationally and also of ensuring repeatability of the analysis to assess change over time, and could usefully be applied to enhance the identification and monitoring of HNV in other European countries.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2018.12.033.

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