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Title: **Predicting the impacts of bioenergy production on farmland birds**

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Abstract

Meeting European renewable energy production targets is expected to cause significant changes in land use patterns. With an EU target of obtaining 20% of energy consumption from renewable sources by 2020, national and local policy makers need guidance on the impact of potential delivery strategies on the stocks and flows of ecosystem goods and services to ensure the targets are met in a sustainable manner. Within agroecosystems, models are available to explore consequences of such policy decisions for food, fuel and fibre production but few can describe the effect on biodiversity. This paper describes the integration and application of a farmland bird population model within a geographical information system (GIS) to explore the consequences of land use changes arising from differing strategies to meet renewable energy production targets. Within a 16,000 ha arable dominated case study area in lowland England, the population growth rates of 19 farmland bird species were predicted under baseline land cover, a scenario maximising wheat production for bioethanol, and a scenario focused on mix of bioenergy sources. Both scenarios delivered renewable energy production targets for the region (>12 kWh of renewable energy per person per day) but there was intra and interspecific variation in the predicted impacts of each on farmland bird populations. For example, the population growth rate across the 19 species for the baseline, maximised wheat production and mix of bioenergy sources scenarios were -0.0075, -0.0066 and -0.0086, respectively. Although further refinements are possible, the framework provides one of the first systematic attempts to spatially model the effect of policy driven land use change on the population dynamics of a comprehensive set of farmland birds. The GIS framework also facilitates its integration with other land use based ecosystem service models to explore wider synergies and trade offs arising from national or local policy interventions.

Highlights

- First GIS model to predict spatially the “local” impact of bioenergy policies
- Systematic model covers 19 farmland bird species.
- A 16,000 ha case study shows a synergy between bioenergy and farmland bird populations.
- Expanding arable crops increased bioenergy and reduced the decline of farmland birds.
- The model provides a method to determine the effects of policy driven land use change on biodiversity.

Keywords: farmland birds, ecosystem services, Geographical Information System, impact, land use, renewable energy

1. Introduction

Finite fossil fuel resources and the need to reduce greenhouse gas emissions have led to a global focus on increasing energy supplies from renewable sources. The European Union has set a target of obtaining 20% of energy consumption from renewable sources by 2020 (EC, 2009). The target set for the UK is 15%, which would be equivalent to renewable energy providing the equivalent of 4.6 kWh of electricity, 3.4 kWh of transport fuel and 3.7 kWh of heat per person per day (Burgess *et al,.* 2012). In 2011, the proportion of gross energy consumption from renewable sources was 13.4% within the EU27 but only 3.8% in the UK (EurObserv'ER, 2013). Realizing the 2020 targets will require a significant change in land use patterns at local, national, European (Rounsevell *et al,.* 2003) and even global scales. The recent revision of EU renewable energy policy (European Commission, 2012) in light of concerns over its impact on food production means that the long term implications for land use are unclear but in Britain, this may initially be an expansion or redirection of arable crops such as wheat and oilseed rape as first generation transport fuel production (Gallagher, 2008) and/or an expansion in the area under biomass crops, such as perennial grasses (e.g. miscanthus *Miscanthus giganteus*) and short rotation coppice (Burgess *et al,.* 2012; Committee on Climate Change, 2011).

Large scale, often policy driven, land use changes have the potential to cause unexpected and significant detrimental environmental impacts. In Europe, for example, this is perhaps best evidenced by significant declines in farmland biodiversity and deteriorations in soil, air and water quality over recent decades associated with agricultural intensification and land abandonment and driven to a great extent by the Common Agricultural Policy (Stoate *et al.*, 2001). There is also already evidence of unforeseen detrimental environmental impacts resulting from renewable energy policies. Rapidly increasing demand for biofuels, driven in part at least by EU policy (European Commission, 2006), have caused significant damage to biodiversity and ecosystem service provision through both direct and indirect land use change with impact reported in parts of South America and south east Asia in particular (e.g. Fargione *et al*., 2008; Fitzherbert *et al*., 2008). In implementing EU renewable energy policy it is crucial that we learn from these past mistakes and manage the delivery of renewable energy production targets in a sustainable manner (Petersen *et al.,* 2007). In particular this requires that renewable energy policies are integrated with other policies designed to manage issues such as food production and biodiversity conservation policies so that trade offs made between these potentially conflicting demands for finite land resources are sustainable (Murphy *et al,.* 2011). A key component of this is developing the capability to predict any potential detrimental environmental impacts of proposed land use and management changes so that appropriate prevention or mitigation actions can be identified and implemented where necessary.

Here we focus on the effects of policy driven renewable energy options on farmland biodiversity, using the impact on birds as a proxy for the consequences for wider biodiversity. Both the UK and other European governments have identified birds as indicators of biodiversity health and have adopted indices of population trends as headline indicators of sustainable development. More broadly, bird population trends have also been used as an indicator of continued biodiversity losses at a global scale (Butchart *et al,.* 2010). Hence the objective of this paper is to use a recently published modelling framework (Butler and Norris, 2013), integrated into a geographical information system (GIS), to predict the response of farmland bird populations to land use change scenarios associated with renewable energy production targets for a landscape in the UK.

2. Method

The modelling framework uses the concept of functional cover types to link land use to the population dynamics of farmland birds. In brief, structural land covers (e.g. wheat, grassland, woodland) are classified into functional land covers (e.g. foraging and nesting sites) according to their capacity to provide key resources. This approach provides a more mechanistic link between land use and population growth than more traditional habitat association models, it helps to reduce content specificity, and it facilitates the incorporation of novel land uses (Butler and Norris, 2013). The quantity, in terms of area, and quality, in terms of resource provision, of each functional cover type in a landscape effectively delimits the functional space available to a species. Functional space responses, linking land use to local population dynamics, have been modelled at a 1 km square scale for each of the 19 species included in the UK Farmland Bird Index (Butler and Norris, 2013). They were parameterized using bird abundance and habitat data collected from more than 600 1 km squares covered by both the Breeding Bird Survey (BBS) (Risely *et al,.* 2011) and Winter Farmland Bird Survey (WFBS) (Gillings *et al,.* 2008) (see Butler and Norris, 2013 for full details).

The first stage of our automated process used a GIS platform (ArcGIS version 9.3; ESRI Inc) to generate habitat data in the same format as used in the BBS and WFBS habitat surveys. In the second stage these habitat data are classified into functional space and used to predict farmland bird population trends. Full details of this process are provided below. A toolbox named “BirdMod” was developed to undertake these analyses, which can be installed and run on a standard computer. The script was developed using ModelBuilder and runs in Visual Basic or Python.

2.1. Case study area

The Marston Vale extends over about 16,000 ha in Bedfordshire in lowland England (Fig. 1a). Once currently consented urban developments are in place, the population density (3.1 ha^{-1}) and proportion of area allocated to agriculture (69%) and woodland (8%) will broadly reflect national values. However the area under crops and fallow (52%) is higher and the area under grassland (17%) is lower than the equivalent national means (30% and 37% respectively). The work presented here is part of a wider project exploring the interactions between renewable energy demand and supply, land use and the stocks and flows of ecosystem services and goods in the area (Burgess *et al.,* 2012; Howard *et al.,* 2012).

Land use across the Marston Vale was digitised using aerial photography from 2005 with polygons generated for each field, woodland, major road, watercourse, urban and commercial area (Table 1). This landscape configuration is hereafter referred to as *BASELINE*.

Figure 1 here

Aerial images from Google Earth^{TM} were used to assess the relative proportion of specific boundary types. Within ten randomly selected 1 km squares, all field boundaries were classified as either a) hedgerow with trees, b) hedgerow without trees, c) tree line with no hedge or d) no vertical structure; these classifications match those used to describe boundary features in BBS. The relative proportions of each boundary type across the ten squares were estimated to be 0.22, 0.30, 0.03 and 0.45 respectively and these values were used for the whole of Marston Vale in subsequent landscape structure assessments.

2.2. Future landscape scenarios

Two alternative scenarios representing different approaches to increasing land based renewable energy production within Marston Vale were constructed. These were principally defined to illustrate the application of BirdMod for exploring contrasting energy production scenarios and therefore represent plausible rather than optimal land use configurations. In each scenario, polygons classified as woodland, urban, commercial, transport, water or landfill stayed the same as in *BASELINE*. In the first, hereafter referred to as *MAXIMIZE*, all arable and grassland areas were assumed to be planted with wheat which, through the harvest of grain for bioethanol production and straw for heat, offers the greatest gross energy output (Burgess *et al*., 2012) (Fig. 1c). In the second scenario, hereafter referred to as *RESILIENCE*, the objective was to maximise renewable energy targets without an undue reliance on any individual renewable energy source (Grubb *et al.,* 2006). Similar areas of land were allocated to wheat, grass and barley as in *BASELINE* but a greater area was allocated to winter oilseed rape and small areas of miscanthus and short rotation coppice were introduced. As a consequence, the area of fallow land decreased and spring oilseed rape was lost from rotations (Fig. 1d). The land use allocation under *BASELINE*, *MAXIMISE* and *RESILIENCE* is summarised in Table 1. Using an existing framework for exploring trade offs between land use, renewable energy, food, feed and wood production (Burgess *et al.,* 2012), we calculated the capacity of *BASELINE*, *MAXIMISE* and *RESILIENCE* landscapes to meet a range of energy demand types within Marston Vale. Currently, the level of food production is greater than the local demand within Marston

Vale (see results and Table 2). We therefore also estimated energy output capacity for *BASELINE* under a scenario where, once local food demand is met, “surplus” wheat and oilseed rape are used for bioethanol and biodiesel production and arable straw and the non timber biomass of woodlands used for heating.

2.3. Predicting farmland bird trends from functional space availability

To mirror the BBS and WFBS habitat recording methodologies, calculations within the BirdMod toolbox were based on 1 km (100 ha) British Ordnance Survey grid squares overlain on the land use map. All squares containing less than 50 ha farmland, whether due to the extensive presence of other land use types (e.g. woodland or urban) or because the boundary of the Marston Vale bisected them, were excluded in accordance with original model parameterisation rules (Butler and Norris, 2013) (Fig. 2). Summer and winter habitat within the remaining squares under *BASELINE*, *MAXIMISE* and *RESILIENCE* were then quantified as follows:

2.3.1. Summer foraging and breeding habitat

Two transects (1000 m x 50 m), each subdivided into 200 m x 50 m sections, were overlain on each grid square (Figs. 2b and 2c). If a square overlapped the boundary of the Marston Vale but was retained in our analyses because the section falling inside contained more than 50 ha farmland (see above), the transects stopped at the boundary and the total number of complete 200 m sections may have been less than 10. The area of each land use type encompassed by each transect section was quantified, as was the proportion of each classified as “disturbed” or “undisturbed”; “disturbed” areas were defined as land within 50 m of an urban settlement or road (Figs. 2d and 2e). The length of any boundary features falling within each 200 m x 50 m section was also calculated.

If this was greater than 50 m, boundary characteristics were included in the classification of habitat features for that transect section. A set of habitat allocation algorithms (see Appendix A, Figs. A.1-A.3 in Supporting Information) was then applied to these data to assign primary and secondary BBS habitat classifications to each transect section. Boundary characteristics and polygon specific spring or autumn sowing date for cereals, were assigned using probability based number generators, underpinned by direct observation across Marston Vale and Defra Agricultural and Horticultural Census data for Bedfordshire (2005-2008 data: www.defra.gov.uk) respectively.

Figure 2 here

2.3.2. Winter foraging habitat

The digitized land use maps described above were built from spring and summer land use data. An additional habitat allocation algorithm (Appendix A, Fig. A.4), again underpinned where necessary by Defra Agricultural and Horticultural Census data for the region, was therefore used to backcast from these data to predict the WFBS habitat code for each polygon in the preceding winter.

2.3.3. Quantifying functional space availability

Butler and Norris (2013) identified the BBS and WFBS codes which defined six key functional space components: summer foraging cover as being of either high (SHQ) or low quality (SLQ); breeding cover of high (BHQ) or low quality (BLQ), and likewise for winter foraging cover (WHQ and WLQ). We used the same classifications and methodology to quantify functional space for each species in each square under *BASELINE*, *MAXIMISE* and *RESILIENCE* based on the BBS and WFBS classifications generated by BirdMod. For each species, the number of transect sections providing

BHQ and BLQ within each square, weighted by whether it was provided by the primary and/or secondary habitats, was divided by the total number of transect sections in that square and multiplied by 100 to estimate the total area (ha) of BHQ and BLQ available. This process was repeated to quantify the area of SHQ and SLQ available for each species in each square. Finally, the summed areas of polygons with WFBS habitats classified as providing WHQ or WLQ were calculated for each species in each square. Two energy crops, miscanthus and short rotation coppice, which are not currently present in Marston Vale, were introduced into the landscape in the *RESILIENCE* scenario. They were assigned BBS and WFBS codes for equivalent structural cover types and their contribution to the six functional space components for each species was assessed accordingly. For summer foraging and breeding cover, short rotation coppice was equated to a young woodland plantation with moderate shrub and field layer and to a farm scrub patch for winter foraging cover. Equivalent structural cover types in the current landscape were less apparent for miscanthus. For summer foraging and breeding cover, it was coded as an arable crop, but restrictions to its contribution to functional space were applied in line with the expected influence of the much taller, denser structure on food availability and perceived/actual predation risk for each species (Butler *et al.,* 2005; Whittingham and Devereux, 2008). Similarly, for winter foraging cover, miscanthus was broadly equated to a tall cereal crop but the structure of miscanthus crops over winter and its impact on resource availability were again taken into account when defining the quality of functional space provided (Sage *et al,.* 2006, 2010).

For each farmland bird species, high and low quality classifications of each functional cover type were mutually exclusive for any given polygon so the total area (i.e. high plus low quality) of breeding, summer foraging and winter foraging functional cover within a 1 km square could not exceed 100 ha. However, a polygon could potentially contribute to more than one functional cover type for each species so the area of functional space (i.e. breeding plus summer foraging plus winter foraging functional cover) within a square could exceed 100 ha.

Butler and Norris (2013) also showed that conspecific abundance in the surrounding landscape influences both population dynamics and the relationship between functional space and population dynamics. To account for this, they included a measure of conspecific abundance in the surrounding landscape, calculated as the distance weighted average of observed counts over a three year period for that species in all BBS squares, in their functional space models. To calculate the equivalent metric, we first calculated the average count of each species in each BBS/WFBS square based on the three years immediately prior to the year the digital photographs (i.e. 2002, 2003 and 2004) were taken; if a square was not surveyed in one or more of these years, records from the closest three years were used. We then calculated a weighted average of these counts for each species and each square based on the Euclidean distance between that square and each BBS/WFBS square. Parameter estimates for each species' functional space response were then applied to the functional space area and conspecific abundance data to calculate annual population growth rate (*pgr*) in each square. It is important to note that elements of the automation process described above are stochastic because random number generators underpin the assignment of particular habitat characteristics, such as spring or autumn sown cereals or boundary type, to each polygon when relative availability is dictated by set probabilities (Appendix A). We therefore repeated this process ten times and used the average *pgr* predicted for each species in each square in subsequent analyses.

The impact of the land use changes associated with each scenario on the *pgr* of individual species and the community as a whole (i.e. *pgr* averaged across all 19 species) was assessed using paired *t* tests, with each 1 km square under *BASELINE* paired with the corresponding square under *MAXIMIZE* and *RESILIENCE*. The average *pgr* across all species effectively represents the expected extent and direction of the annual change in the Farmland Bird Index for the study site under each scenario. The paired *t* test works under the assumption that the paired differences are independent and identically normally distributed. These assumptions were broken in the cases of turtle dove, yellow wagtail, corn bunting, rook, skylark and kestrel and Wilcoxon’s signed ranks test, a nonparametric method analogous to the paired *t* test, was used for these species instead.

3. Results

The daily energy demand per person within Marston Vale equates to about 80 kWh. Under *BASELINE* land cover patterns and prioritisation of food production, the output of heat and transport energy is assumed to be zero. If surplus food products were reallocated to energy production, it was estimated that *BASELINE* energy output could be increased to 11.3 kWh p^{-1} d^{-1}, comprising 4.9 kWh p^{-1} d^{-1} for transport fuel and 6.4 kWh p^{-1} d^{-1} for heating (Table 2). The combined value is similar value to the 2020 renewable targets, but it still only represents about 15% of the total energy requirement. Under the *MAXIMISE* scenario, conversion of all arable and grassland areas to wheat was calculated to increase potential production levels to 11.4 kWh p^{-1} d^{-1} of transport fuel and 9.6 kWh p^{-1} d^{-1} for heating (Table 2). The output of animal feed was also predicted to increase because of the formation of distillers grains in bioethanol production. Under the *RESILIENCE* scenario, the transport fuel availability was marginally greater than under *BASELINE*, because of the greater area of oilseed rape, and the area of miscanthus and short rotation coppice contributed to an increase in the available energy for heating.

The mean predicted annual *pgr* across all 19 species for *BASELINE* was -0.0075 ± 0.0066 (Table 3). This represents an annual decline in farmland bird populations of 0.75%. The *MAXIMIZE* scenario was predicted to result in a significantly slower mean rate of decline across the 19 species (-0.0066 ± 0.0045; paired *t* test: t = -2.28, n = 142, $p < 0.05$). By contrast, changing from *BASELINE* to the *RESILIENCE* scenario was predicted to lead to a significantly greater rate of decline (-0.0086 ± 0.0059; paired *t* test: t = 5.22, n = 142, $p < 0.01$). This suggests that the Farmland Bird Index would continue declining under each scenario but the rate of decline would be slowest under

MAXIMISE (Table 3). The above values are the mean predicted *pgr* values across all 142 1 km squares; some individual squares showed positive values, and some showed much larger negative values (Fig. 3). The range of values across the squares were -0.07 to 0.08 for *BASELINE*; -0.13 to 0.09 for *MAXIMISE* and -0.08 to 0.08 for *RESILIENCE*.

Figure 3 here

3.1. Results for individual species

When averaged across all squares, ten species were predicted to have a negative *pgr* under each scenario whilst eight species were predicted to have a positive *pgr* under all three landscape configurations (Table 3, Appendix B Fig. B.1). Only *Falco tinnunculus* (kestrel) showed a change between negative and positive growth rates depending on the scenario.

Under *MAXIMIZE*, two species (*Streptopelia turtur* - turtle dove and *Carduelis carduelis* - goldfinch) were predicted to have significantly lower *pgr* than that predicted for *BASELINE* ($p<0.01$ in both cases but this did not involve an overall change in the direction of population trajectory for either). Sixteen species were predicted to have significantly higher *pgr* under *MAXIMIZE* than under *BASELINE* ($p<0.01$ in all cases) and, for one species (*Falco tinnunculus* - kestrel), this resulted in an overall change from a declining to an increasing population trajectory (Table 3). There was no significant change in the predicted *pgr* of starling between *BASELINE* and *MAXIMIZE*. Changing from *BASELINE* to *RESILIENCE* led to significant declines in the predicted *pgr* of twelve species ($p<0.05$ in all cases) and significant increases in the predicted *pgr* of two (*Motacilla flava* - yellow wagtail and *Columba palumbus* - woodpigeon, $p<0.05$

in both cases). For no species did the change in land use result in a switch in the overall direction of predicted population trajectory.

Maps of spatial patterns in *pgr* across Marston Vale under each scenario for three exemplar species are presented in Fig. 4. Equivalent maps for the remaining 16 species are available in Fig. B.2. Again, it is evident from Table 3 and Fig. 4 that there is considerable spatial variation at the 1 km scale in predicted *pgr* for individual species, with the extent varying between species and landscape configurations.

Figure 4 here

4. Discussion

This paper describes the first use of a functional space model to predict the spatial effect of policy driven land use change on the population growth rates of a comprehensive set of farmland bird species in a specific area. Engel et al (2013) describe the use of a habitat suitability model to predict the effect of bioenergy-related land use change but it is restricted to one species: skylark (*Alauda arvensis*). Mouysset et al (2012) use an intra-specific competition model and a scenario approach to predict the spatial and temporal impact of different policies and agricultural systems on the abundance of 34 bird species across France, but they did not model the effects of specific crops and the bird population results are not presented spatially.

The second innovation of this study is that it was completed alongside an assessment of the effects of the same land use changes on the level of food, animal feed, fibre, and bio-energy production as more fully reported by Burgess et al (2012). This integration of farmland bird, fuel, food, feed, and fibre assessments for a common set of scenarios for a single area can serve as a prototype of the kind of model integration that is needed to allow policy makers to predict the economic and environmental impacts of different land use policies.

The results indicate that the strategy adopted to deliver the UK's land based renewable energy targets can affect both gross bioenergy production and farmland bird population trends. Each of the three scenarios examined could deliver, in the context of the Marston Vale, 2020 renewable energy production targets for transport fuel and heat (Table 2), albeit at a cost to food production. Predicted gross energy levels were higher under *MAXIMISE* (21 kWh p^{-1} d^{-1}) than *RESILIENCE* (12.3 kWh p^{-1} d^{-1}) which was marginally greater than that for *BASELINE* (11.3 kWh p^{-1} d^{-1}). In terms of farmland birds, the highest mean *pgr* across the 19 species was predicted under *MAXIMISE* (-0.0067), compared to -0.0075 under *BASELINE*, and -0.0087 under *RESILIENCE*. Although the model predicted large changes in the pgr of individual species in response to the different land use scenarios, the effects on the pgr of the farmland bird community as a whole was surprisingly small. Mouysset et al (2012), who modelled farmland bird populations in France, also reported that a greater level of arable cropping would result in a marginally higher farmland index than the status quo, although the absolute trend would still be downwards. The reason for the predicted positive response to a larger arable area is that this increased the functional space for many farmland bird species, and the effect of the loss of grassland (assumed to be intensively-managed) was assumed to be minimal. If the grass was extensively-managed then the response may have been different (Mouysset et al, 2012).

One advantage of using a model which includes a range of bird species is that it highlights that although a particular scenario, i.e. *MAXIMISE*, is predicted to provide the highest gross energy and the slowest decline in overall farmland bird populations, it also highlights potential negative impacts for particular species. For example the *MAXIMISE* scenario, with a large arable area, was predicted to have the greatest negative effect on the turtle dove (*Streptopelia turtur*) population. Browne and Aebischer (2004) also identified that turtle doves in lowland England showed a preference for non-cereal areas. Mouysset et al (2012) also note the importance of the trophic level of the farmland bird species. An increase in the arable area can increase the number of granivorous species, but result in a substantial decline in the mean trophic level, i.e. there are fewer species at higher levels in the food chain. In addition the *MAXIMIZE* scenario creates a potentially volatile portfolio of a single renewable energy production type, where failure of the wheat crop (through for example disease) could result in near-total collapse of overall bioenergy and food production.

Interestingly, the reallocation of post harvest products to energy production once food demand had been met under *BASELINE* was predicted to deliver broadly equivalent levels of energy output to *RESILIENCE*, without the added detrimental impacts on farmland birds. It is important to note that our calculations for this reallocation scenario did not take into account factors such as the likely reduction in soil carbon and nutrient levels, and hence long term crop yields, associated with annual removal of straw. However, whilst they are therefore likely an oversimplification of long term effects, these analyses serve to highlight the potential contribution of alternative strategies, beyond direct changes in land use, for meeting renewable energy production targets.

The modelling framework presented here provides a method for quantifying the potential impacts of different land use scenarios on one aspect of biodiversity: farmland birds. Each species has different functional space requirements, so the predicted overall impacts of the two scenarios varied across the 19 farmland bird species modelled. Spatial analyses showed that there was also substantial intraspecific variation in predicted impact of each scenario across Marston Vale; many species exhibited positive predicted annual *pgr* in some squares even if their population trend across Marston Vale was predicted to be declining overall and *vice versa* (Fig. B.1). Furthermore, it was evident that the extent of this intraspecific variation differed between scenarios. These intra and interspecific differences within and between scenarios can be attributed to the type and number of habitat types that contribute to functional space, and the absolute and relative abundance of those habitats in each square under each scenario. For example, a species that relies on a limited number of habitats could show low spatial variation if that habitat type is very dominant or very rare in the landscape but high spatial variation if that habitat is more patchily distributed across the landscape. This is demonstrated by the generally reduced levels of spatial variation across species under *MAXIMIZE* as a consequence of the simplified cereal dominated landscape.

Whilst providing a detailed discussion of the response of individual species to each scenario is not the main focus of this paper, the contrasting responses to *RESILIENCE* and *MAXIMIZE* may appear somewhat surprising and thus deserve further discussion. Under *MAXIMIZE*, all arable and grassland areas were planted to wheat. Whilst this greatly reduced the overall heterogeneity of the landscape, it led to substantial increases in the predicted area of over winter stubble because it was assumed the existing 9:1 ratio of winter sown to spring sown wheat observed in Marston Vale would be maintained; in line with existing WFBS data, 50% of these over winter stubble areas were also assumed to be “weedy”. The species predicted to have higher *pgr* under *MAXIMIZE* compared to *BASELINE* tended to be those for which the quantity and/or quality of winter foraging functional cover has been identified as a key determinant of population dynamics (Butler and Norris, 2013; Gillings *et al.,* 2005). In contrast, those species for which over winter stubbles do not contribute to winter foraging functional cover availability or for which population dynamics are not driven by this component of functional space tended to fare less well under this scenario.

Under *RESILIENCE*, the areas assigned to each crop did not change substantially from *BASELINE*. However, there were reductions in the area of fallow and spring sown oilseed rape and two novel crops, miscanthus and short rotation coppice, were introduced in their place. Under our land use categorization, fallow effectively represents set aside, which has a high biodiversity value and contributes to the functional space of many farmland bird species (Firbank *et al.,* 2003; Gillings *et al.,* 2010; van Buskirk and Willi, 2004). The reduction in set aside, and its replacement with two crops whose structural characteristics were predicted to contribute little to the functional space of many of the farmland specialists included in the Farmland Bird Index (Anderson *et al.,* 2004; Sage *et al.,* 2006, 2010), resulted in the decline in the mean *pgr* of the 19 studied farmland birds.

As discussed above, our analyses assume that the management of crops for bioenergy is the same as for food. If, for example, it becomes evident that crop management practices, such as rates of agrochemical application or sowing and harvesting dates, change as a result of switching from management for food to management for renewable energy, the habitat allocation algorithms used to quantify functional space would need revision.

Our calculations of functional space in each 1 km square are also dependent on a number of assumptions. These include the categorization of boundary features based on a subsample of squares, the use of agricultural census data to infer winter crop cover types, and the use of the national WFBS data to assign proportions of weedy and non weedy stubbles. In any modelling exercise, assumptions are needed and we believe that the assumptions we have made are broadly representative and that there is no directional bias. If more site specific data were available for the above, the habitat allocation algorithms could be readily adapted to accommodate them. Note that assumptions relating specifically to the development of the functional space models are discussed in detail elsewhere (Butler and Norris, 2013).

Our assessment of the biodiversity impacts of each scenario is based on the predicted response of the Farmland Bird Index species, with any inferences of the effects on wider farmland biodiversity based on the broadly accepted assumption that bird population trends are indicative of wider biodiversity health (Gregory *et al.*, 2003). It is worth noting that whilst a decrease in the cropped area of an agricultural landscape may decrease the functional space for farmland species it may also increase the opportunities for more generalist species or those specialised to other ecosystems. For example, whilst short rotation coppice is likely to reduce the functional space for farmland specialists such as skylark and lapwing, which require more open vegetation, it can provide functional space for species associated with scrubland and early succession forests (Sage *et al.*, 2006). Such observations suggest that a full assessment of the biodiversity impacts of land use change needs more than a focus on solely farmland species whilst, where relevant, taking into account both local and national conservation priorities.

This study and others (e.g. Ekroos and Kuusaari, 2011; Robinson *et al.,* 2001; Schweiger *et al.,* 2005) highlight that the impacts of land use change on biodiversity will be species and context specific. The results of our assessment of the impacts of each scenario on farmland bird population dynamics therefore relate specifically to their implementation in the current landscape of Marston Vale. Although there are substantial areas of lowland England with similar wheat and oilseed rape dominated agricultural landscapes to which our results are likely to be broadly applicable, the response of the farmland bird community to these land use scenarios in other regions needs to be assessed on a case by case basis. The example presented here serves to emphasize the need for modelling frameworks that can accommodate such context specificity and which can be used to highlight the potential consequences of proposed land use changes at a range of spatial scales including field, farm and landscape.

The application of our approach is not limited to renewable energy based land use change and developing a GIS based framework facilitates the integration of BirdMod with other land use based models for a range of ecosystem services (e.g. Burgess *et al.,* 2012; Carver *et al.,* 2011; Smith *et al.,* 2010; Kareiva *et al.*, 2011). However, we recognize that there are still limitations which we intend to address in the future. Importantly, BirdMod requires a digitized version of the land uses within the study area as input data. Digitization of all the parcels within the area where the model is to be applied can be time consuming and may prove impractical for managers and researchers. Moreover, there is always an intrinsic error in the identification of structural land use types from aerial photography assessment. One option is to modify BirdMod and the underlying functional space responses to use input data from a national data source such as the Land Cover Map derived from the UK Countryside

Survey (Morton *et al*., 2011) to describe structural parcels and the boundary characteristics. However this in turn creates new inaccuracies and uncertainties because of the way in which land cover maps are developed and their spatial and temporal resolution is likely to limit the quantification of the functional space delivered by, for example, linear features. Furthermore, functional space models have so far only been developed for farmland bird species but previous work (Butler *et al.*, 2009) suggests that it should be possible to quantify functional spaces for other taxonomic groups and ecosystems and to develop the equivalent models.

5. Conclusions

Meeting UK and European renewable energy production targets is likely to lead to substantial changes in land use patterns at a range of spatial scales over the coming years. A variety of contrasting land use strategies could be employed to deliver these targets and the approach selected will determine the resultant impact on the stocks and flow of ecosystem goods and services, including biodiversity. Whilst there are an increasing number of tools to describe the interactions between land use and food, feed, fibre and fuel production, it has proved more difficult to develop tools to describe the effects on biodiversity; developing the capability to model context dependent biodiversity responses to land use change is therefore fundamental to the development of the evidence base needed to guide policy implementation decisions. We believe BirdMod, and the wider conceptual framework that underpins it, offers that capability and, as a consequence, that it could play a key role in ensuring renewable energy policy is delivered in a sustainable manner.

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Table 1. Assumed area for each land use type in Marston Vale, under *BASELINE* conditions (assuming consented development takes place), a *MAXIMIZE* scenario (focused on meeting renewable energy targets from wheat), and a *RESILIENCE* scenario (focused on meeting renewable energy targets from a range of crops)

Land use	Area (ha)		
	BASELINE	*MAXIMISE*	*RESILIENCE*
Wheat	4150	10745	4150
Grass	2596	0	2596
Winter oilseed rape	1209	0	1752
Fallow	984	0	315
Other spring crop	693	0	693
Barley	455	0	455
Crop	392	0	392
Spring oilseed rape	263	0	0
Bare soil	3	0	3
Miscanthus	0	0	193
Urban	1844	1844	1844
Commercial areas	372	372	372
Transport	279	279	279
Landfill	235	235	235
Woodland	1232	1232	1232
Woodland screening	186	186	186
Short rotation coppice	0	0	196
Water body	351	351	351
Other	853	853	853
Total	16097	16097	16097

Table 2. Equivalent per capita demand in the UK for energy, food, feed and timber, the renewable energy targets for 2020, the capacity for the current land use in the Marston Vale (*BASELINE*) to meet those demands assuming prioritisation of use for food or energy, and the corresponding outputs for a scenario maximising the wheat area and bioethanol production (*MAXIMISE*), and a *RESILIENCE* scenario. The output is expressed in terms of equivalent energy per person per day (kWh p^{-1} d^{-1}). The methodology for determining the values is described by Burgess *et al*. (2012)

Form of demand	Current demand	Renewable target (2020)	Output capacity			
			BASELINE prioritise food	*BASELINE prioritise energy*	*MAXIMIZE*	*RESILIENCE*
Electricity	15.0	4.6	0.0	0.0	0.0	0.0
Transport fuel	34.0	3.4	0.0	4.9	11.4	5.1
Heat	31.0	3.7	0.0	6.4	9.6	7.2
Energy subtotal	80.0	11.7	0.0	11.3	21.0	12.3
Food	1.9		9.4	1.9	1.9	1.9
Animal feed	5.6		4.2	7.3	9.9	7.3
Timber	4.4		0.9	0.9	0.9	0.9

Table 3. Mean and standard deviation (s.d.) of the predicted square level *pgr* values under each land use scenario for each of the 19 species considered and the community as a whole (i.e. *pgr* averaged across the 19 species). Species are listed according to predicted mean *pgr* for *BASELINE*. Results for the square level paired t test or Wilcoxon's signed ranks test in the case of turtle dove, yellow wagtail, corn bunting, rook, skylark and kestrel, are also indicated (* $p<0.05$ and ** $p<0.01$). The paired mean difference and associated s.d. together with the test statistic for each of the comparisons is given in Appendix B, Table B.1. All values are in *pgr* * 10^3 to reduce the number of decimals being reported.

Common name	**Scientific name**	***BASELINE***		***MAXIMIZE***		***RESILIENCE***	
		$\overline{X}$	s.d.	$\overline{X}$	s.d.	$\overline{X}$	s.d.
Turtle dove	*Streptopelia turtur*	-71.36	63.01	-134.57^{**}	3.29	-80.48^{**}	57.03
Yellow wagtail	*Motacilla flava*	-62.08	2.07	-60.27^{**}	1.26	-61.49^{**}	1.85
Starling	*Sturnus vulgaris*	-56.63	7.80	-56.37	7.61	-56.17	7.73
Corn Bunting	*Miliaria calandra*	-44.48	7.67	-36.69^{**}	7.02	-46.04^{**}	7.41
Linnet	*Carduelis cannabina*	-34.59	5.54	-30.72^{**}	5.49	-35.52^{**}	5.38
Yellowhammer	*Emberiza citrinella*	-29.04	11.61	-22.79^{**}	10.98	-29.99^{**}	11.46
Rook	*Corvus frugilegus*	-24.96	5.83	-24.33^{**}	5.62	-25.05	5.85
Stock dove	*Columba oenas*	-19.30	13.46	-13.34^{**}	13.05	-19.47	13.47
Skylark	*Alauda arvensis*	-16.43	6.97	-12.32^{**}	4.06	-19.02^{**}	6.52
Lapwing	*Vanellus vanellus*	-1.03	7.76	-0.62^{*}	7.62	-1.38^{*}	7.84
Kestrel	*Falco tinnunculus*	-0.64	7.36	5.83^{**}	6.37	-1.21^{*}	6.80
Greenfinch	*Carduelis chloris*	3.98	13.57	7.46^{**}	12.0	2.24^{**}	13.03

					4		
Whitethroat	*Sylvia communis*	14.63	5.26	14.86**	5.34	14.17**	5.24
Goldfinch	*Carduelis carduelis*	15.88	2.11	15.31**	1.58	15.30**	1.85
Reed bunting	*Emberiza schoeniclus*	16.19	2.46	19.34**	2.46	16.01**	2.49
Woodpigeon	*Columba palumbus*	22.00	4.84	25.67**	3.10	22.32*	4.55
Grey partridge	*Perdix perdix*	27.59	7.17	34.20**	7.32	27.19	6.93
Jackdaw	*Corvus monedula*	32.81	32.16	44.64**	36.13	33.44	32.85
Tree sparrow	*Passer montanus*	84.80	17.99	98.03**	15.30	80.52**	17.58
All species		-7.51	6.56	-6.67*	4.49	-8.66**	5.98

Fig. 1. Land use maps of the Marston Vale (2009): (a) location of the Marston Vale (b) *BASELINE*, (c) *MAXIMIZE* and (d) *RESILIENCE* scenarios.

Fig. 2. The different steps run within BirdMod to quantify habitat availability prior to reclassfication into functional space: (a) location of the 1 km x 1 km squares within the Marston Vale, (b) example of the location of the 200 m x 50 m transect sections (red lines) within each square, (c) distance between parallel transects, (d) detail of the different land uses identified on one of the transects showing the disturbed (red dots) areas and (e) table summarising the land uses for the selected transect as estimated by BirdMod. Grey cells show squares that have been excluded from the analysis (e.g. area of farmland is <50 ha).

Fig. 3. Mean annual *pgr* across the 19 bird species for the (a) *BASELINE*, (b) *MAXIMIZE* and (c) *RESILIENCE* scenarios. Positive and negative values were coded using a blue and red coloured scale, respectively. The range and the breaks for each of the scales were determined to enhance visualisation.

Fig. 4. Spatial variation in predicted annual *pgr* across Marston Vale for three exemplar species. Positive and negative values were coded using a blue and red coloured scale, respectively. The range and the breaks for each of the scales were determined to enhance visualisation. See Fig. B.2 for equivalent maps for the other 16 species.

Fig. A.1. Primary habitat allocation algorithm applied when the first tier of classification (P-L1) was FARMLAND. B is the total length of hedges within the 1 km square; D is the total area of disturbed habitat within the transect section; RAND() is a randomly generated number between 0 and 1, with the associated subscript number identifying the tier within the four level hierarchical BBS habitat code structure; P-L1, P-L2, P-L3 and P-L4 represent the four primary habitat levels; and WHT, OSR, CRP and FLW are the land uses coded as specified in Table 1.

Fig. A.2. Primary habitat allocation algorithm applied when the first tier of classification (P-L1) was WOODLAND, WATER or HUMAN. B is the total length of hedges within the 1 km square; D is the total area of disturbed habitat within the transect section; RAND() is a randomly generated number between 0 and 1, with the associated subscript number identifying the tier within the four level hierarchical BBS habitat code structure; P-L1, P-L2, P-L3 and P-L4 represent the four primary habitat levels; and TR,CM, LD, OTH and URB are the land uses coded as specified in Table 1.

Fig. A.3. Secondary habitat allocation algorithm applied. B is the total length of hedges within the 1 km square; D is the total area of disturbed habitat within the transect section; RAND() is a randomly generated number between 0 and 1, with the associated subscript number identifying the tier within the four level hierarchical BBS habitat code structure; P-L1, P-L2, P-L3 and P-L4 represent the four primary habitat levels; S-L1, S-L2, S-L3 and S-L4 represent the four secondary habitat levels; and WHT, OSR, CRP and FLW are the land uses coded as specified in Table 1.

Fig. A.4. Winter habitat allocation algorithm applied. GRS, WDL, WSC, OSR, CRP, BRL, WHT are the land use (LU) classes as coded in Table 1; RAND() is a randomly generated number between 0 and 1, with the associated subscript number identifying the tier within the three level hierarchical WFBS habitat code structure; W-L1, W-L2 and W-L3 represent the three winter habitat levels.

Fig. B.1. Box plot (median, quartiles and non outlier range) of the predicted annual *pgr* for each species and scenario. Species are coded as: CB - corn bunting; GO - goldfinch; GE - greenfinch; GP - grey partridge; JD - jackdaw; LP - lapwing; LN - linnet; RB - reed bunting; RO - rook; SK - skylark; SG - starling; SD - stock dove; TS - tree sparrow; TD - turtle dove; WH - whitethroat; WO - woodpigeon; YW - yellow wagtail; YH - yellowhammer.

Fig. B.2. Spatial variation in predicted annual *pgr* across Marston Vale for 16 species not included in Fig. 4. Positive and negative values were coded using a blue and red coloured scale, respectively. The range and the breaks of the scale were determined to enhance visualization.

Appendix A. Algorithms applied for primary and secondary habitat classifications.

BBS classifies primary and secondary habitats in each transect section. The algorithms used to replicate this classification are summarized in Figs. A.1 and A.2 for the primary habitat and Fig. A.4 for the secondary habitat. These algorithms were implemented in an Excel platform and followed the guidelines for the UK Defra Agricultural and Horticultural Census data 2005-2008 (www.defra.gov.uk).

The primary habitat is defined by four levels named P-L1, P-L2, P-L3 and P-L4. P-L1 is classified into *WOODLAND*, *FARMLAND*, *HUMAN* or *WATER* based on the dominant land use identified in the digitized polygons from the aerial photography as described in the methodology section. Each of the P-L1 classes follows a different set of habitat allocation algorithms to identify P-L2, P-L3 and P-L4 (Figs. A.1 and A.2).

Similarly, the secondary habitat also has four levels coded (S-L1, S-L2, S-L3 and S-L4), with classification based on the sequence of habitat allocation algorithm in Fig. A.3. The stochastic component in the model is introduced by the RAND() variable, where RAND represents a randomly generated numbers between 0 and 1, independently identified for each tier of habitat classification.

Fig. A.4 summarizes the algorithm applied to each winter land use classification of each polygon larger than 0.3 ha. Winter habitat is defined by 3 levels (i.e. W-L1, W-L2 and W-L3). Polygons with any other summer land use type classification than these included in Fig. A.4 were not assigned a winter habitat code as only farmland habitats were recorded in Winter Farmland Bird Survey.

Appendix B. Response of individual species to the three land use configurations.

Table B.1. Results from the paired t-test analysis. $\overline{X}$ refers to the mean paired difference between the *BASELINE* and *MAXIMIZE* (M) scenarios or the *BASELINE* and *RESILIENCE* (R) scenarios, with positive values indicating a higher predicted annual *pgr* and negative values a lower predicted annual *pgr*. "s.d." and "test results" stand for the standard deviation of the mean paired difference and the t-values from the t-test (n=142, df=141). For the case of turtle dove, yellow wagtail, linnet, reed bunting, woodpigeon and tree sparrow, the "test results" show the outputs of the Wilcoxon's signed-ranks test (n = number of signed ranks and z = z-ratio). All the mean and standard deviation are in *pgr* * 10^3 to reduce the number of decimals being reported.

Common name	**Scientific name**	Paired $\overline{X}$ (M)	s.d. (M)	Test results (M)	Paired $\overline{X}$ (R)	s.d. (R)	Test results (R)
Turtle dove	*Streptopelia turtur*	63.20	64.03	*n=139, z=10.11*	9.11	26.94	*n=139, z=3.48*
Yellow wagtail	*Motacilla flava*	-1.81	2.09	*n=138, z=8.56*	-0.58	1.39	*n=120, z=4.26*
Starling	*Sturnus vulgaris*	-0.25	3.29	-0.93	-0.45	3.23	-1.68
Corn Bunting	*Miliaria calandra*	-7.78	5.48	*n=142, z=10.04*	1.56	2.83	6.59
Linnet	*Carduelis cannabina*	-3.87	2.86	-16.11	0.92	1.74	6.28
Yellowhammer	*Emberiza citrinella*	-6.24	6.17	-12.05	0.95	2.43	4.65
Rook	*Corvus frugilegus*	-0.62	1.24	*n=142, z=5.35*	0.09	0.76	*n=140, z=0.10*
Stock dove	*Columba oenas*	-5.95	7.45	-9.521	0.17	3.46	0.61
Skylark	*Alauda arvensis*	-4.10	6.41	*n=142, z=6.63*	2.58	4.70	6.55
Lapwing	*Vanellus vanellus*	-0.41	2.26	-2.158	0.35	1.69	2.45
Kestrel	*Falco tinnunculus*	-6.47	7.91	*n=141, z=8.69*	0.57	3.37	2.01
Greenfinch	*Carduelis chloris*	-3.47	5.80	-7.13	1.73	4.08	5.06
Whitethroat	*Sylvia communis*	-0.23	0.62	-4.41	0.45	1.39	3.90
Goldfinch	*Carduelis carduelis*	0.57	1.16	5.88	0.58	1.31	5.28
Reed bunting	*Emberiza schoeniclus*	-3.15	2.13	-17.65	0.17	0.65	3.23
Woodpigeon	*Columba palumbus*	-3.67	3.96	-11.02	-0.31	1.74	-2.17

Grey partridge	*Perdix perdix*	-6.60	5.91	-13.31	0.39	3.54	1.31
Jackdaw	*Corvus monedula*	-11.83	19.27	-7.31	-0.62	4.93	-1.51
Tree sparrow	*Passer montanus*	-13.22	15.69	-10.04	4.27	12.60	4.04
All species		**-0.84**	**4.38**	**-2.28**	**1.15**	**2.63**	**5.22**

Figure 1

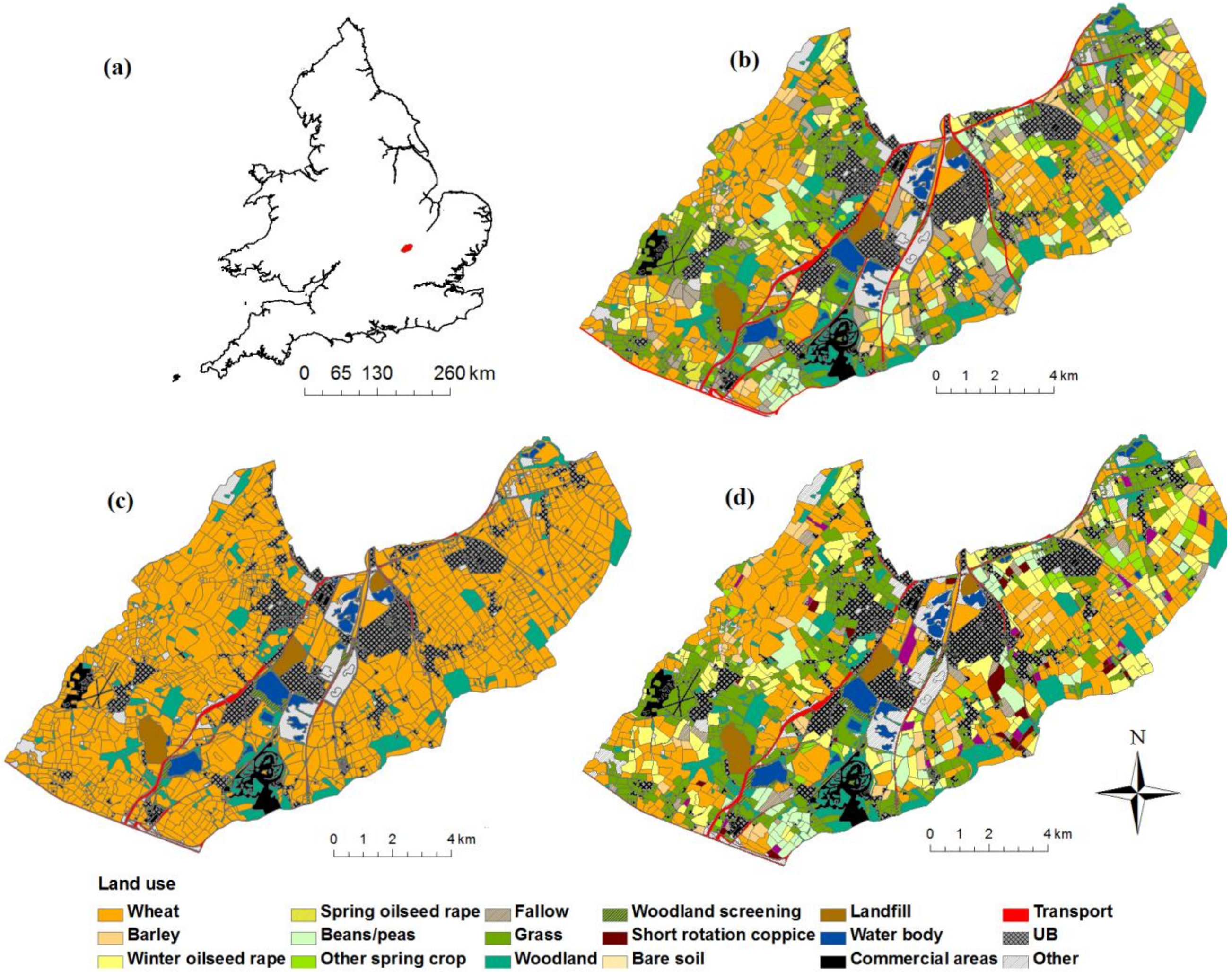
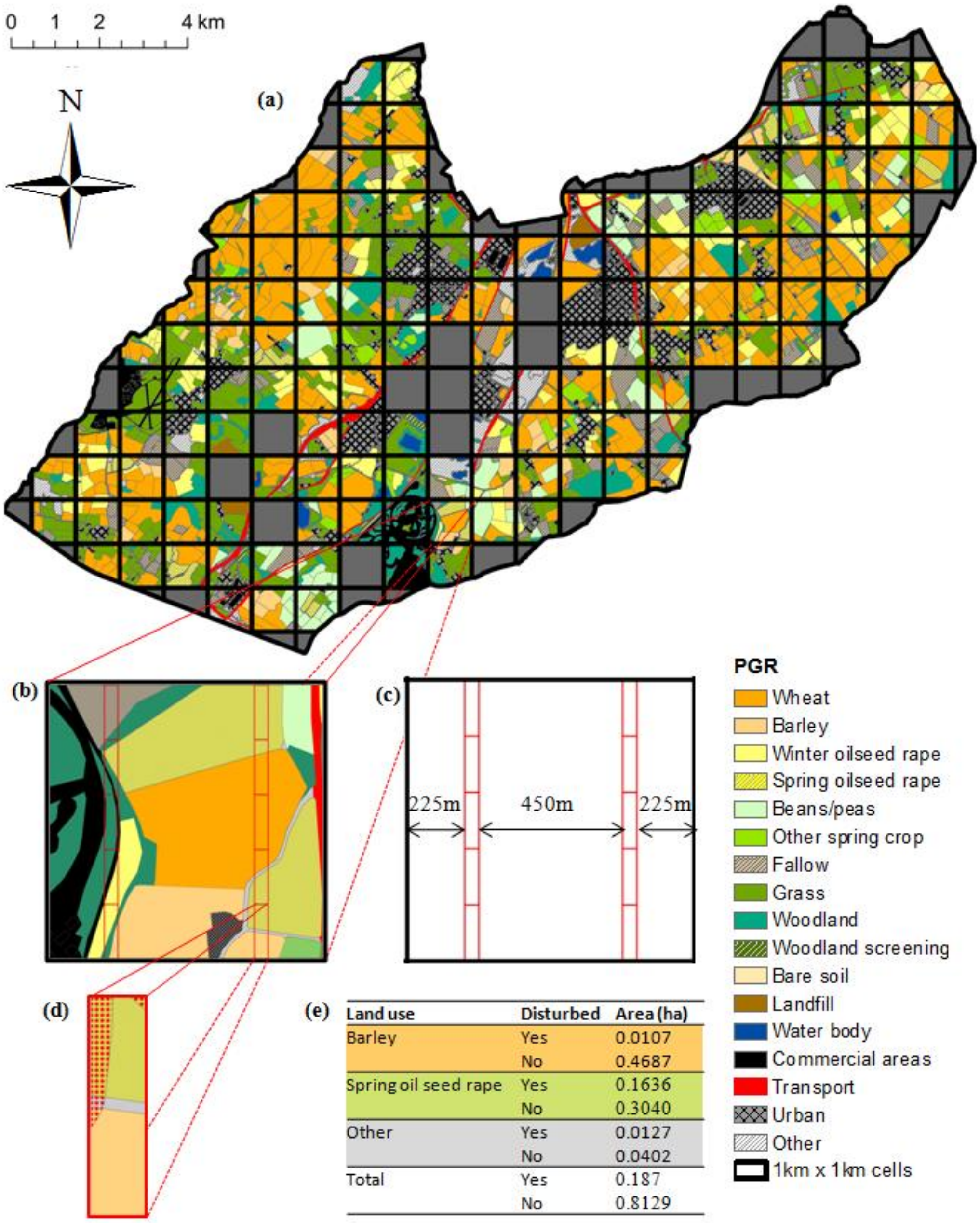
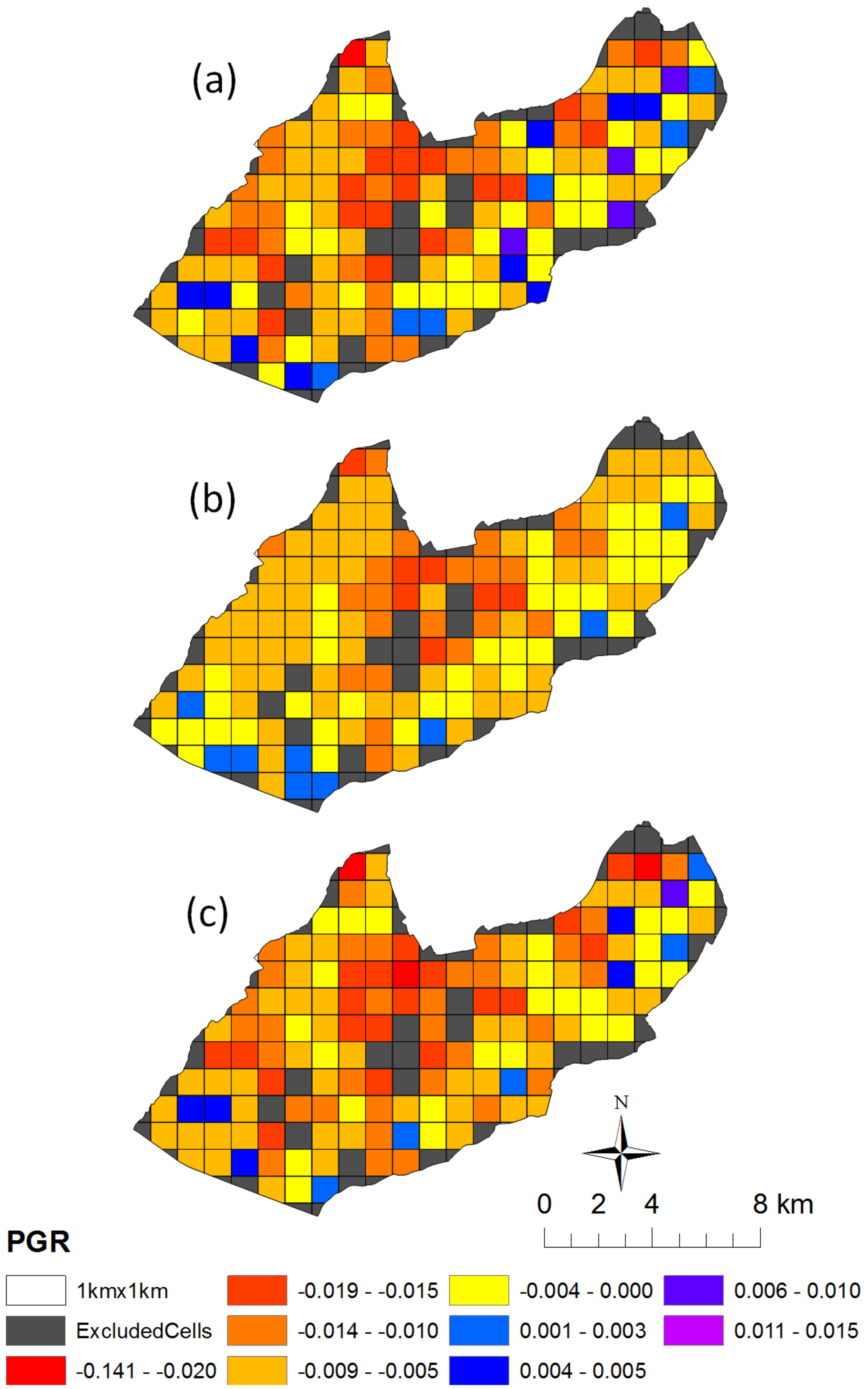

(a)
0 65 130 260 km
(b)
0 1 2 4 km
(c)
0 1 2 4 km
(d)
0 1 2 4 km
N
Land use
Wheat
Barley
Winter oilseed rape
Spring oilseed rape
Beans/peas
Other spring crop
Fallow
Grass
Woodland
Woodland screening
Short rotation coppice
Bare soil
Landfill
Water body
Commercial areas
Transport
UB
Other

Figure 2

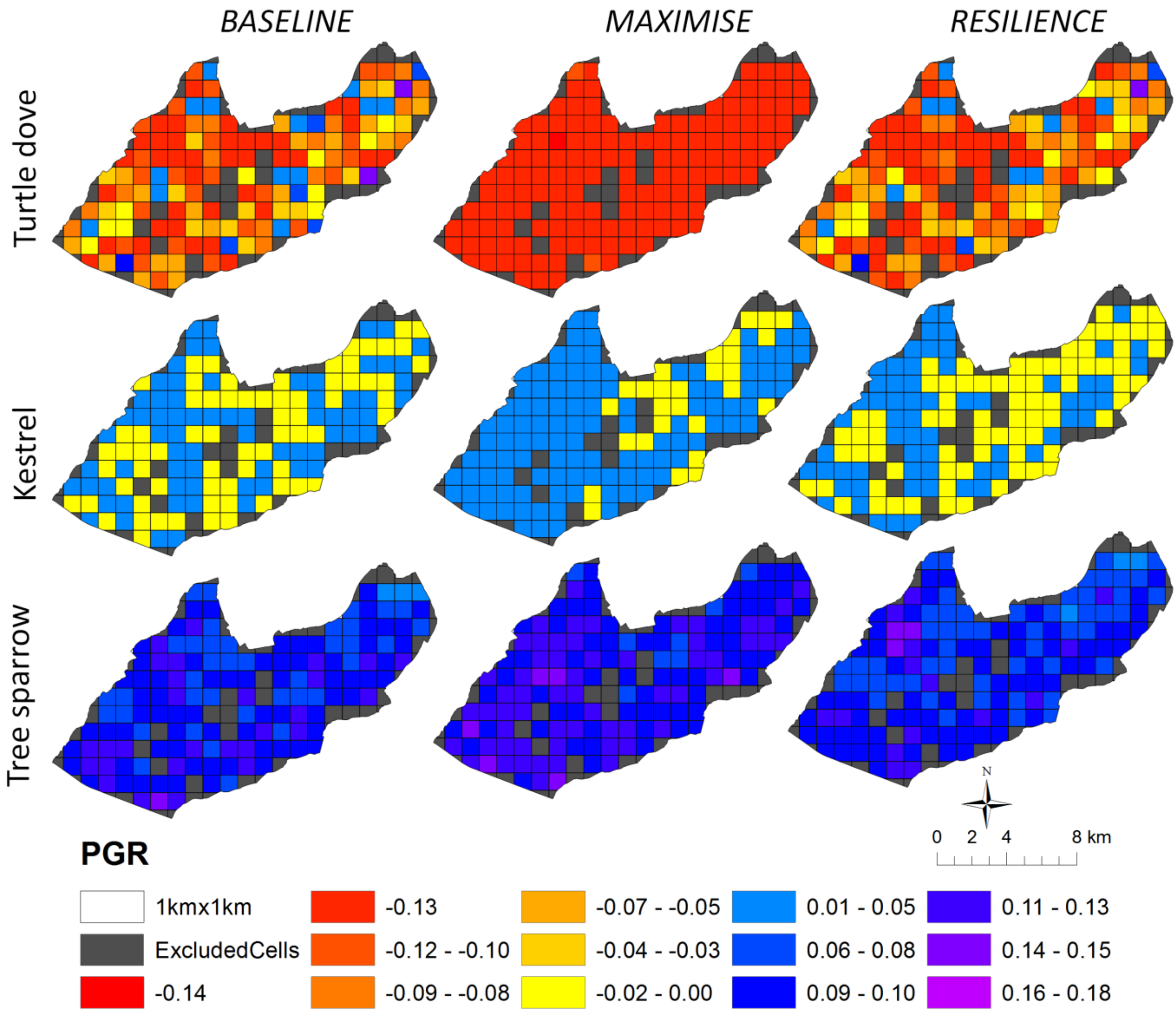


Land use	Disturbed	Area (ha)
Barley	Yes	0.0107
	No	0.4687
Spring oil seed rape	Yes	0.1636
	No	0.3040
Other	Yes	0.0127
	No	0.0402
Total	Yes	0.187
	No	0.8129

Figure 3


(a)
(b)
(c)
N
0 2 4 8 km
PGR
1kmx1km
ExcludedCells
-0.141 - -0.020
-0.019 - -0.015
-0.014 - -0.010
-0.009 - -0.005
-0.004 - 0.000
0.001 - 0.003
0.004 - 0.005
0.006 - 0.010
0.011 - 0.015

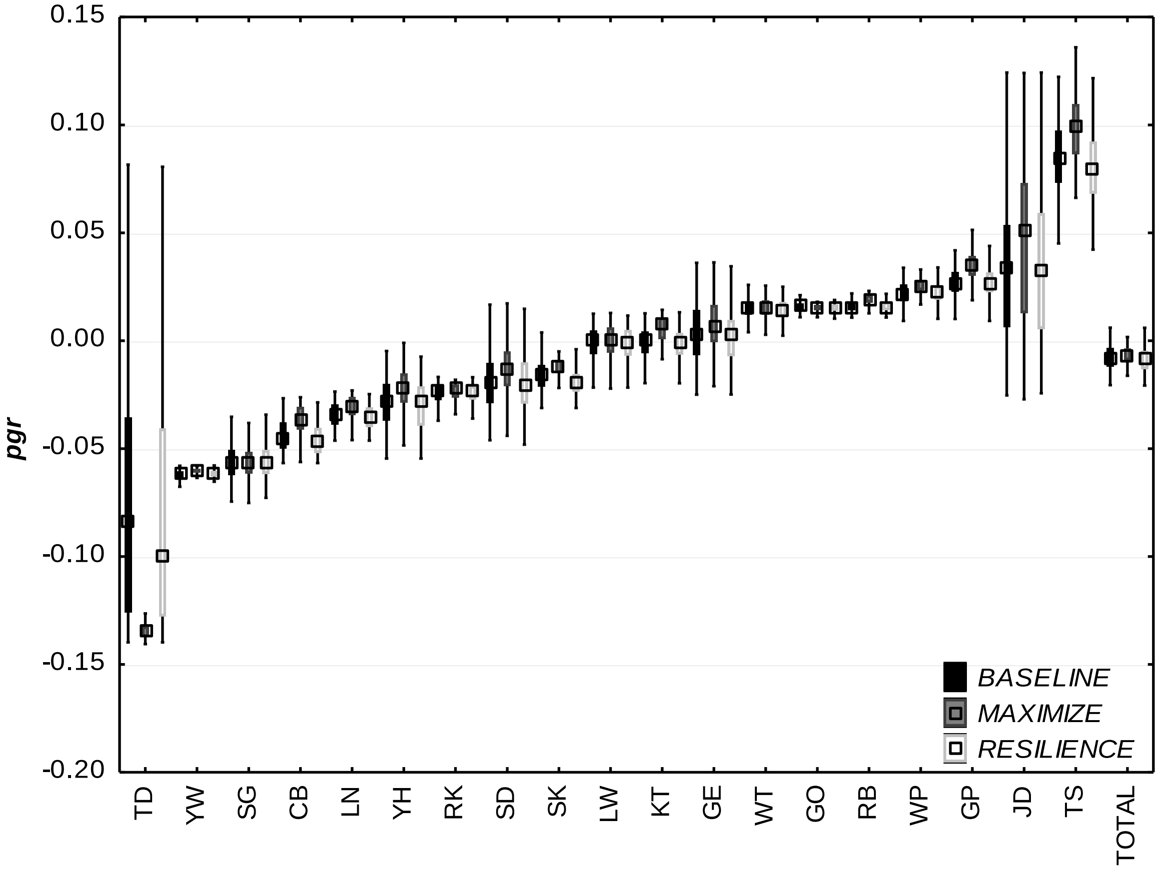
757 Figure 4



758

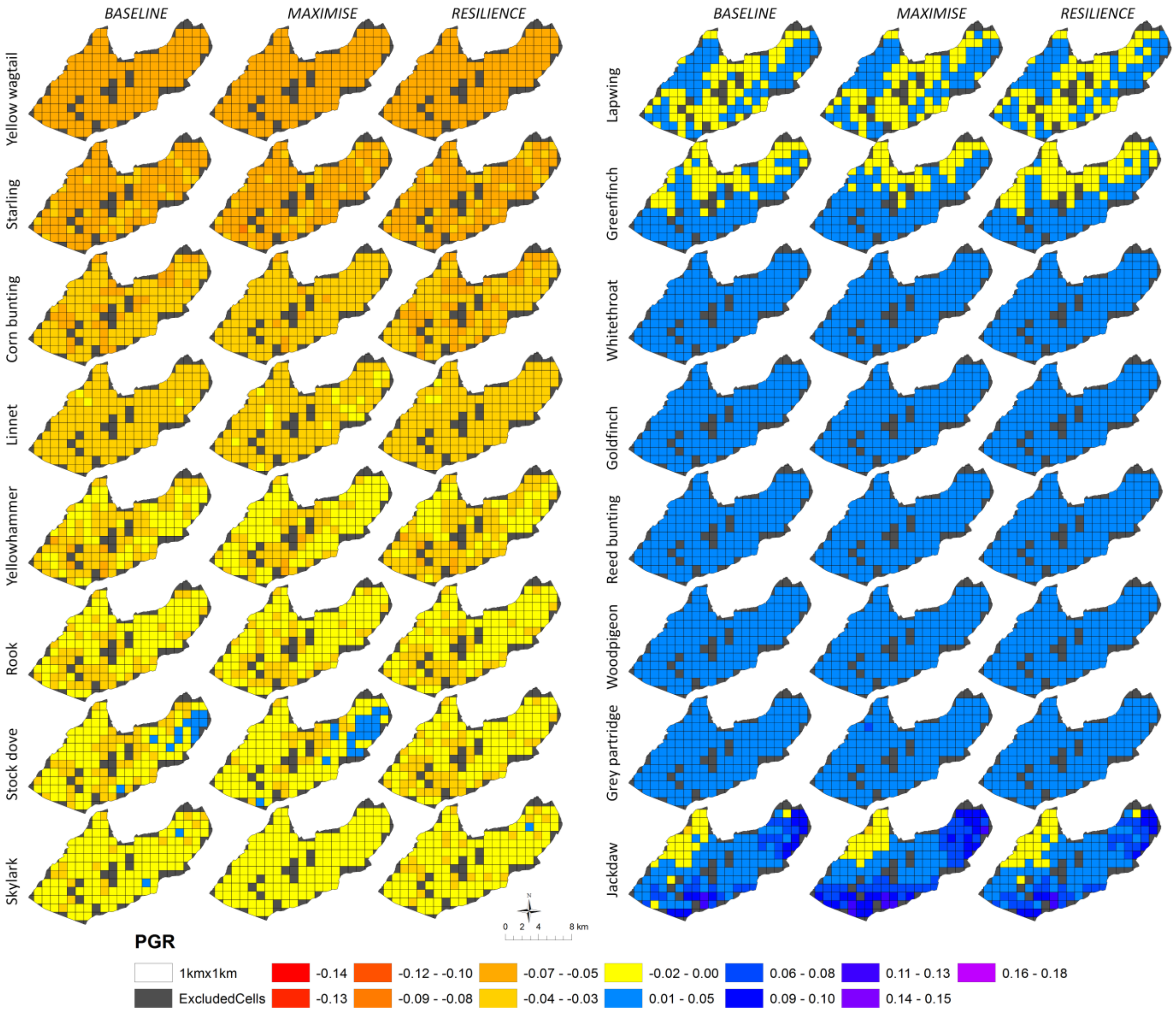
759

Figure B1



0.15
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
pgr
BASELINE
MAXIMIZE
RESILIENCE
TD
YW
SG
CB
LN
YH
RK
SD
SK
LW
KT
GE
WT
GO
RB
WP
GP
JD
TS
TOTAL

Figure B2


BASELINE
MAXIMISE
RESILIENCE
BASELINE
MAXIMISE
RESILIENCE
Yellow wagtail
Starling
Corn bunting
Linnet
Yellowhammer
Rook
Stock dove
Skylark
Lapwing
Greenfinch
Whitethroat
Goldfinch
Reed bunting
Woodpigeon
Grey partridge
Jackdaw
0 2 4 8 km
PGR
1kmx1km
ExcludedCells
-0.14
-0.13
-0.12 - -0.10
-0.09 - -0.08
-0.07 - -0.05
-0.04 - -0.03
-0.02 - 0.00
0.01 - 0.05
0.06 - 0.08
0.09 - 0.10
0.11 - 0.13
0.14 - 0.15
0.16 - 0.18