

# Scale-dependent habitat selection by wintering geese: implications for landscape management

Anne L. Harrison<sup>1</sup> · Nicky Petkov<sup>2</sup> · Daniel Mitev<sup>2</sup> ·  
Georgy Popgeorgiev<sup>2</sup> · Benedict Gove<sup>3,4</sup> · Geoff M. Hilton<sup>1</sup>

Received: 22 September 2016 / Revised: 2 August 2017 / Accepted: 2 September 2017 /  
Published online: 13 September 2017  
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**Abstract** The management of Arctic migrant geese is complex, because they frequently use landscapes under intensive human use, and are conflict species in multiple respects. Some populations are of high conservation concern, but they also cause agricultural damage, are quarry for hunters, and may be particularly sensitive to infrastructure developments. In Bulgarian Dobrudzha, large wintering populations of greater white-fronted geese *Anser albifrons* and red-breasted geese *Branta ruficollis* feed in agricultural land, and cause management dilemmas. We developed linear models to investigate fine- and meso-scale foraging habitat selection of geese foraging on winter wheat in the area, and used these models to make suggestions for zoning landscape use in order to reduce conflict and conserve geese. Habitat selection was scale-dependent. Geese selected fields that were near to major roosts and had low proximity to roads and tree-lines, which may be a proxy for hunting disturbance. We found some evidence for selection of wheat fields with high nutritional quality. Within fields, geese strongly avoided features which cause landscape ‘clutter’: power-lines, tree-lines and wind-turbines, but primarily over distances of less than a few hundred metres. Optimal management might involve encouraging goose populations to feed in areas close to roosts, by means of agri-environmental measures and creation of hunting-free refuges. This would allow efficient use of agri-environment funds, might reduce conflict with farmers, and would mean that infrastructure development—

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Communicated by Dr. Grzegorz Mikusinski.

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**Electronic supplementary material** The online version of this article (doi:[10.1007/s10531-017-1427-4](https://doi.org/10.1007/s10531-017-1427-4)) contains supplementary material, which is available to authorized users.

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✉ Geoff M. Hilton  
Geoff.Hilton@wwt.org.uk

<sup>1</sup> Wildfowl & Wetlands Trust, Slimbridge, Gloucestershire GL2 7BT, UK

<sup>2</sup> Bulgarian Society for the Protection of Birds, P.O. Box 50, 1111 Sofia, Bulgaria

<sup>3</sup> RSPB, RSPB Centre for Conservation Science, Sandy, Bedfordshire SG19 2DL, UK

<sup>4</sup> Present Address: Softlab, Julio A. Roca 695, Piso 1, Ciudad de, Buenos Aires, Argentina

notably wind farms—could be sited at greater distance from roosts with relatively minor impact on foraging habitat availability.

**Keywords** Red-breasted goose · White-fronted goose · Bulgaria · Zoning · Wind turbine · Agri-environment · Hunting · Conflict species

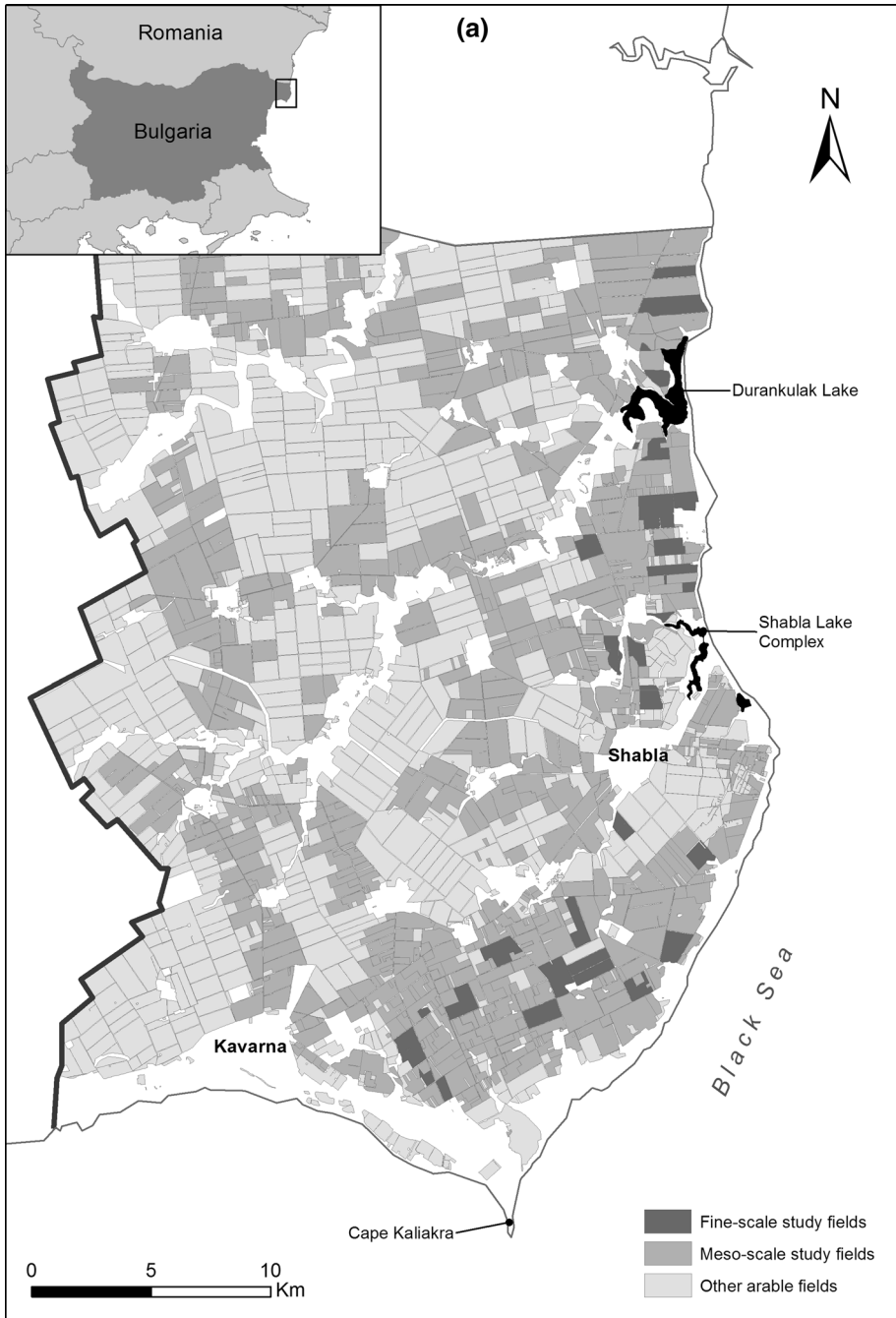
## Introduction

Arctic migrant geese form an important guild. In their arctic breeding grounds they are significant ecosystem components, being both important grazers (Jefferies et al. 2006) and a major prey item of vertebrate predators (Giroux et al. 2012; McKinnon et al. 2013). In their temperate wintering grounds they are important as a wildlife spectacle, and as quarry for hunters. In Europe and North America they are consumers of agricultural crops such as winter cereals and pasture grasses (Green and Elmberg 2014; Patterson 1991), although in east Asia they more frequently continue to use natural grasslands (Zhang et al. 2015, 2016). For all these reasons, goose management is a major concern of conservation, hunting and agricultural organisations: substantial resources have been devoted to efforts to restore diminished populations, maximise yield for hunters and minimise agricultural damage (Jensen et al. 2008; Klaassen et al. 2008; Madsen et al. 2014). However, these efforts may interact or produce conflict.

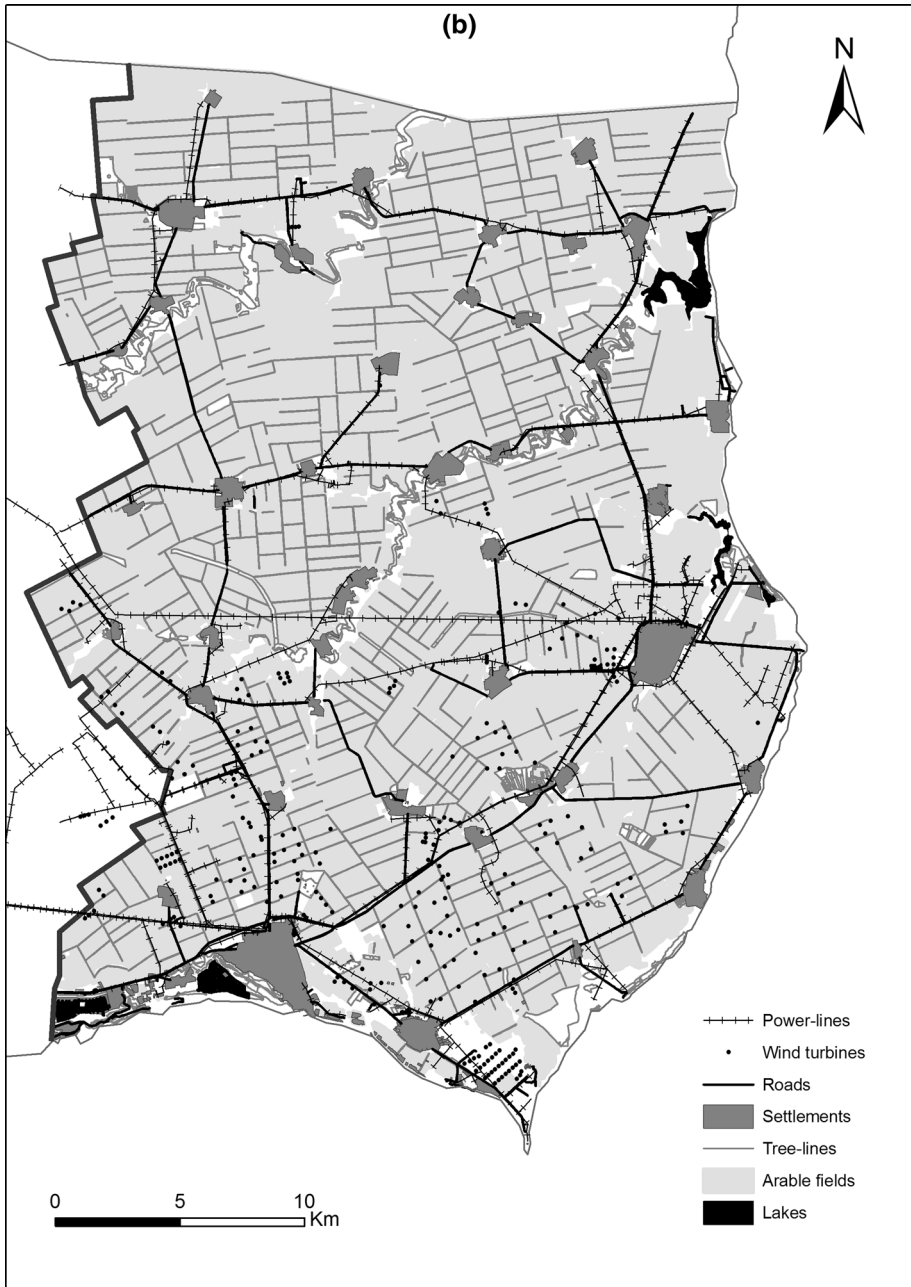
A prime example of this concerns the large populations of greater white-fronted goose *Anser albifrons*, red-breasted goose *Branta ruficollis* and greylag goose *Anser anser* that winter on the northern and western Black Sea coast (primarily Bulgaria, Romania and Ukraine) and are frequently concentrated in the Bulgarian Dobrudzha area (Fig. 1a). Several groups have a significant stake in these goose populations, but have different goals. Farmers are concerned about losses caused by geese eating green shoots of winter wheat, but also by damage caused to fields by hunters in cars. Legal hunting of white-fronted geese provides a source of employment and income (from permits) to people in the region, as well as recreational opportunities. Investors (and governments) wish to develop infrastructure in the region, with rapid growth in wind turbine installation (and associated access roads) in particular. Conservationists and the eco-tourist industry are concerned to maintain the status of these populations—in particular the globally Vulnerable red-breasted goose (Wetlands International 2016)—in the face of multiple pressures.

Policy responses to these goals have included a moratorium on all new wind farms in the region in the national action plan for energy from renewable sources 2011–2020 (Bulgarian Ministry of Environment and Water 2012) and a pilot agri-environment that encourages farmers to grow appropriate crops and compensates them for goose damage to those crops (Ministry of Agriculture and Foods 2015). However, neither policy was informed by firm evidence regarding the spatial scale of and interactions between birds, infrastructure and agriculture. Integrated spatial planning may offer more efficient solutions to these conflicts, by suggesting zoning of activities—not all of which are mutually exclusive. However, this requires a strong evidence-base. Here we apply foraging habitat selection models for wintering geese in Bulgarian Dobrudzha, and use these to develop a framework for spatial planning.

The environmental factors associated with animal abundance are commonly scale-dependent (Mayor et al. 2007, 2009; Orians and Wittenberger 1991). Wintering geese roost communally overnight on waterbodies, then make a commuting flight, often of several km (Johnson et al. 2014) to agricultural fields in which they forage on vegetation for the

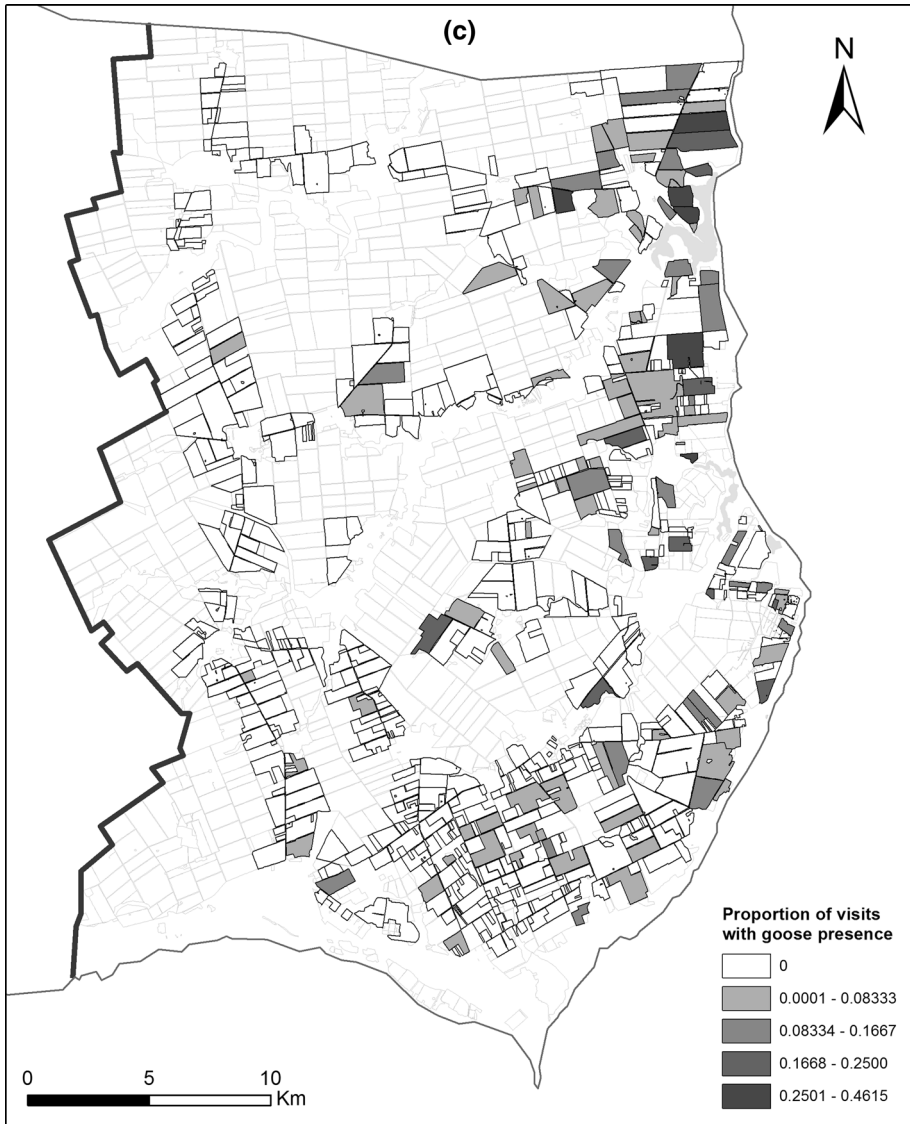


**Fig. 1** Map of the study area in Dobrudzha, Bulgaria, showing **a** arable fields in the study area, and study fields for meso-scale and fine-scale fieldwork; **b** distribution of key explanatory variable features in the study area; **c** Observed frequency of goose occurrence by field from meso-scale transect survey



**Fig. 1** continued

majority of the day, typically walking between foraging patches. We can therefore conceptualise habitat selection decisions as a two-level hierarchy: an initial decision about the field in which to forage, which dictates the flight from roost to a foraging site, and a second



**Fig. 1** continued

decision about where to feed once within the chosen field. The choice of field may itself be made according to characteristics of the field, but also of the landscape around the field. The drivers of habitat selection may differ according to spatial scale, and we examine goose habitat selection at two scales which reflect this putative hierarchical decision-making. First, we examine within-field goose distribution (hereafter ‘fine-scale habitat selection’), as measured by dropping density, as a function of local habitat variables. Second, we examine among-field selection (hereafter ‘meso-scale habitat selection’) using goose count data. We note however, that in the real world, spatial scale does not vary

discretely, and this conceptual two-level hierarchy probably simplifies the reality of goose habitat selection.

Arctic migrant geese are flocking, open-country foragers in winter, apparently preferring a wide view in order to detect and escape by flight from predators (Kear 2005). They feed variously on arable crops and grassland, and have been shown to select profitable foraging patches in terms of nutritional quality and availability of preferred vegetation (Hassall and Lane 2005; Owen et al. 1977; Vickery et al. 1994). In areas where they are hunted, geese may also be sensitive to human disturbance, so may avoid foraging in areas which they perceive high disturbance risk (Bregnballe et al. 2004; Madsen 1998). We therefore examine the fine- and meso-scale distribution of geese in relation to three main putative factors: avoidance of obstructions, or ‘clutter’ in the landscape; selection of high quality food patches; and avoidance of human (primarily hunting) disturbance. We consider the findings in light of the conflicts that exist in the study area, and the potential to resolve them through zoning land use.

## Methods

### Study system

The study area was the coastal strip of Bulgarian Dobrudzha, which comprises the foraging area for major goose populations wintering at the coastal roost lakes of Shabla and Durankulak (some geese roost on the adjacent Black Sea) (Fig. 1a). The inland boundary of the study area was set at ca. 22 km inland, which approximates the maximum foraging range observed for geese during this study (separate GPS telemetry observations). The study period comprised the winters 2011/12 and 2012/13. The study birds comprise part of the Pontic–Anatolian flyway population of greater white-fronted goose, and most of the world population of red-breasted goose; both populations migrate from arctic Russia to winter along the northern and western shores of the Black Sea coast between Ukraine and Greece. These are joined by much smaller numbers of residents/short-range migrants from the Black Sea and Turkey population of greylag geese. Co-ordinated roost counts indicate that total goose numbers in the study area in recent years have peaked at around 300,000 individuals (Kostadinova and Dereliev 2001). Substantial numbers typically build up in early December and main departure is in late February/early March, but goose numbers in the area fluctuate greatly, both within and between years: the birds appear to be highly mobile, shifting north and east along the flyway in response to mild weather, and south and west in response to cold weather (Kostadinova and Dereliev 2001; AEWIA Red-breasted Goose International Working Group unpublished data).

The study area is a low altitude coastal plain, with arable agriculture as the dominant land use. During the study period, the agricultural fields in the study area were predominantly cultivated with winter cereals (wheat *Triticum aestivum*, barley *Hordeum vulgare*), sunflower *Helianthus annuus*, rape *Brassica napus*, and maize *Zea mays* in rotation. Very small patches of other crops such as alfalfa *Medicago sativa* were present. In the first study winter, rape crops failed badly in autumn 2011 due to unusual weather conditions and were severely stunted by the time of goose arrival and mostly ploughed in during early spring. Consequently, in the second study winter, very little rape was grown. At the time of goose arrival into the area, maize stubbles were present, but these were usually ploughed by early January.

### Fine-scale habitat selection

We examined fine-scale habitat selection during February 2012 and January–February 2013 by undertaking dropping counts within study fields which geese were known by prior observation to have used for foraging (Fig. 1b).

Study fields were selected from fields in which geese had been observed foraging during the previous 2–3 weeks, and had ceased to use for the previous 3–5 days. In order to provide a range of values to assess goose displacement by wind turbines, we stratified the fields by the density of wind turbines within a 2 km radius (high, medium, low and nil turbine density) and selected approximately equal numbers of fields at random from within each stratum. Sampling points within fields were pre-defined using a systematic grid with a random origin, placed across the field.

At each point, all goose droppings were counted within a circle of 1 m radius. Geese produce droppings at short intervals (every few minutes while actively foraging), which may remain visible for at least 2–3 weeks, depending on the amount of precipitation, and hence dropping densities provide a good indicator of cumulative goose-use over recent weeks (Madsen and Boertmann 2008). Where a field was too small to allow 20 points at  $\geq 50$  m separation, we eliminated it from the study, since it was not possible to generate robust data for analysis. Where a field was large enough for this minimal sampling, we sampled 20–30 points, at spacing  $\geq 50$  m. Each field was sampled only once, though some very large fields were visited on successive days in order to complete the sampling. The mean size of visited fields was 64 ha ( $N = 39$ ,  $SD = 46$  ha,  $min = 4$  ha,  $max = 197$  ha).

### Meso-scale habitat selection

We assessed meso-scale habitat selection by evaluating the frequency of goose presence in a large set of fields within our study area that were repeatedly visited through two winters (Fig. 1a). A series of road transects were traversed twice weekly (except during extreme weather conditions) by car between 11 December–11 March in winter 2011/12 and 12 December–4 March in 2012/13. These transects comprised the great majority of the extra-urban surfaced roads in the study area. Observer teams stopped at pre-determined intervals along the routes to count geese in visible fields. In order that true absences could be determined, we pre-identified, for each transect, the set of fields that were visible to the observers from the stopping points.

In each study field on each visit, the number of geese present was counted. Effectively all observed goose presence was in winter cereal fields (see below). Although use of maize stubbles was anecdotally observed during the period immediately after goose arrival in early winter, this had effectively ceased by the time fieldwork commenced. Hence for further habitat selection analysis, we included only winter cereal fields. Although the transect routes were identical in the two winters, the fields in which winter cereals were present differed between years because of crop rotation. 267 winter cereal fields covering 15,400 ha were included in the 2011/12 survey and 489 fields covering 17,458 ha were included in the 2012/13 survey, at an average of 15.9 surveys per visited field. This was equivalent to 40 and 45% of the total estimated area of winter cereals in the study area in the two study winters respectively (estimated by calculating Normalised Difference Vegetation Index (NDVI) for each field using a RapidEye level 3a (2011/12) and a Landsat 8 (2012/13) image, and ground-truthing with known fields to distinguish winter wheat from other field types). Only fields for which 10 or more censuses were conducted were included

in analysis, leaving 214 fields in 2011/12 and 420 in 2012/13. Among these retained fields, the mean number of censuses per field per winter = 18.1, and 35 and 39% coverage respectively of the area of winter cereals in the study area.

## Explanatory variables

Data was gathered on eleven explanatory variables, though not all were used in both fine-scale and meso-scale models (Table 1). These variables aimed to capture three broad factors that were hypothesised to influence goose distribution: first, avoidance of landscape features that create ‘clutter’; second, selection of profitable foraging patches; third, avoidance of human disturbance (especially hunting activity). We recognise that these factors probably interact. Selection of low disturbance, low clutter foraging patches may indirectly contribute to the profitability of these patches, because such sites might permit greater foraging time, lower vigilance and/or fewer disturbance events. Further, avoidance of landscape clutter and avoidance of disturbance are clearly linked, particularly in the case of the variables *Tree-line proximity* and *Visibility*. We hypothesise that avoidance of hunting disturbance would result in avoidance of tree-lines (which can provide cover for hunters) and selection for areas with wide visibility; however, these variables may also be important even in the absence of hunting, because they influence the risk of predation.

The fine-scale study was predicated upon studying distribution of geese within fields which they were already known to have used, and the variables *Previous crop*, *NDVI* and *Roost proximity* did not vary in meaningful and/or measureable ways within-fields, so we modelled the influence of these variables associated with profitable foraging sites at meso-scale only. Two nuisance variables were also included in the meso-scale models: *Field area*, on the basis that larger fields provide a greater total amount of food and are therefore more likely to support frequent goose use (Zhang et al. 2015); and *Winter* (categorical two-level variable), on the basis that absolute goose numbers in the study area differed between the two winters of the study.

*Previous crop* (i.e. the crop grown in the previous agricultural year) was determined by direct fieldwork observation. In winter cereal fields during the study period, sunflower (66% of fields) and maize (22%) dominated as the previous crop, with small amounts of

**Table 1** Explanatory variables used in fine- and meso-scale goose habitat selection models, showing the main factors that we hypothesise influence goose distribution

Explanatory variable	Avoidance of human disturbance	Avoidance of landscape clutter	Selection of profitable foraging areas	Used in fine-scale models	Used in meso-scale models
Settlement distance	+			+	+
Road proximity	+			+	+
Visibility	+	+		+	+
Tree-line proximity	+	+		+	+
Wind turbine proximity		+		+	+
Power-line proximity		+		+	+
NDVI			+		+
Previous crop			+		+
Roost proximity			+		+



wheat, rape and ‘previous crop unidentified’ (12% in total). Following data exploration, we merged values into a two-level categorical variable: maize vs all other previous crops. The other explanatory variables were derived from GIS layers of their distribution in the study area.

The detailed derivation of explanatory variables from landscape features is described in Electronic Supplementary Material S1. In brief, *Settlement distance* was calculated as the distance (m) to the edge of the nearest settlement (Fig. 1b). We used viewshed analyses to estimate the *Visibility* of the landscape to geese at sampling locations. We calculated average NDVI for each field using RapidEye level 3A and Landsat 8 satellite imagery (acquired in April 2012 and May 2013 respectively; 5 and 30 m resolutions respectively) by taking the average value from pixels lying within the field footprint. To estimate the influence of wind turbines, power-lines, tree-lines, and roads on geese, we calculated for each feature an index which combined information about the number of these elements in proximity to the sample location, and their distance from the sample location. For fine-scale analysis, this involved inverse distance weighting of all features within a 2 km radius of the sampling point, and for meso-scale analysis this involved simpler calculation of the number of features within fields and in buffers around them.

## Analysis

All GIS data handling was performed using ESRI ArcGIS 10.3 (ESRI 2011). All statistical analysis was conducted in R 3.20 (R Development Core Team 2008).

Wintering geese are highly aggregated in the landscape, and our response variables had a high proportion of zeros. We therefore used package *glmmADMB* (Fournier et al. 2012) to build models that accounted for zero inflation and overdispersion. We tested models with and without zero inflation, and using both negative binomial and Poisson distributions. At both spatial scales, comparison of model AICs indicated that zero inflated negative binomial models performed best.

Consequently, at the fine spatial scale, we built zero inflated negative binomial generalised linear mixed models (ZINB, see Zuur et al. 2009), while for meso-scale analysis we built zero inflated negative binomial general linear models (ZIB); in both cases a log-link function was used.

Covariate explanatory variables were standardised and centred (mean = 0, SD 1) prior to analysis. We used Pearson correlations to test for collinearity among the scaled and centred explanatory variables. Where large correlations existed ( $r > 0.4$ ), we modified the model selection procedure such that each collinear variables could be present separately, but they could not both be present in the same model.

We used k-fold ( $k = 10$ ) cross-validation to investigate our models’ predictive power. We calculated the mean of the ten Pearson correlations between observed and predicted values for the validation data.

For both fine-scale and meso-scale models, model diagnostics indicated some model misspecification. Possibly the inclusion of two-way interactions would resolve the problem, but although it is reasonable to hypothesise that there may be interactions between explanatory variables in this system, the complexity of the models would lead to problems of convergence and interpretation. In addition, we elected explicitly to model the zero-inflated and overdispersed nature of the response variables, which prevented us from simultaneously modelling potential residual spatial autocorrelation (in both sets of models), and temporal autocorrelation (in the meso-scale model), since to our knowledge such

procedures are not currently available. These diagnostics indicate that some caution is required in model interpretation.

Although both dropping counts and goose counts do distinguish between the different main goose species present in the study area, response variables in our models were based upon combining values for all goose species. Both of the two commoner species co-occur in fields to a very large extent, even down to the very local scale, and the occurrence of one species in a field is very likely influenced by the occurrence of the other. Separate habitat selection models for each species are likely to lead to very similar and non-independent conclusions.

### *Fine-scale habitat selection*

We modelled goose-use of sampling points as a function of the variables *Turbine proximity*, *Power-line proximity*, *Tree-line proximity*, *Road proximity*, *Settlement distance* and *Visibility* (Table 1). A zero inflated negative binomial GLMM was developed using each sampling point as an observation, and the number of goose droppings as the response variable. Sampling points were nested within discrete fields, so we declared *Field* as a random intercept in all models, which effectively captures the between-field variation in the total amount of goose-use due to factors which are relatively invariable within fields, plus nuisance variables such as the number of geese in the overall study area at the time of sampling and rate of dropping deterioration (consequent upon recent weather).

Correlograms of standardised model residuals indicated significant autocorrelation among points that were less than ca. 200 m apart, but the effect was very modest, with the Moran correlation coefficient between points that were 0–200 m apart  $< 0.2$ .

There was just one version of the *Settlement distance* variable. For the remaining five variables, there were multiple versions, calculated using different spatial scales/decay rates (see Electronic Supplementary Material S1). The first step in the modelling process was to select in turn the best fitting version for each of these variables. For each variable, we ran a set of full models containing all six explanatory variables. The models within each model set differed only in having a different version for the variable of interest. For each variable we selected the optimal version which produced the lowest AIC within its model-set.

Following this variable selection procedure, we used AIC to select the top models from among a full candidate model set that comprised the previously selected optimal version for each variable.

A full model of the form:

$$\text{Dropping count} \sim \text{Settlement distance} + \text{Turbine proximity} + \text{Power-line proximity} \\ + \text{Road proximity} + \text{Tree-line proximity} + \text{Visibility} | \text{random intercept} = \text{Plot name}$$

was run using Maximum Likelihood. All possible main-effects combinations of these explanatory variables were modelled ( $N = 64$ ), retaining the random intercept throughout. A top model set with  $\Delta\text{AIC} < 2$  was selected, and model averaging was used to generate coefficients and their confidence intervals.

### *Meso-scale habitat selection*

We modelled field selection by geese using zero inflated negative binomial general linear models. The response variable was the number of positive goose counts, with the number

of censuses conducted as an offset; this we take to indicate the relative strength of goose selection of each available field.

*NDVI* was nested within *Winter*, because different weather conditions and hence agricultural practice meant that mean and variance of *NDVI* differed between-years, whereas we expected goose response to *NDVI* to be relative to the *NDVI* of other fields available at the same time. *Power-line proximity* and *Road proximity* were positively correlated, and so models were only permitted to contain one or neither of these two variables, but not both. We then used Maximum Likelihood to model all possible combinations of fixed effects, selected a top model set with  $\Delta\text{AIC} < 2$ , and used model averaging to generate coefficients and their confidence intervals. Correlograms of standardised model residuals indicated no significant residual spatial autocorrelation.

## Results

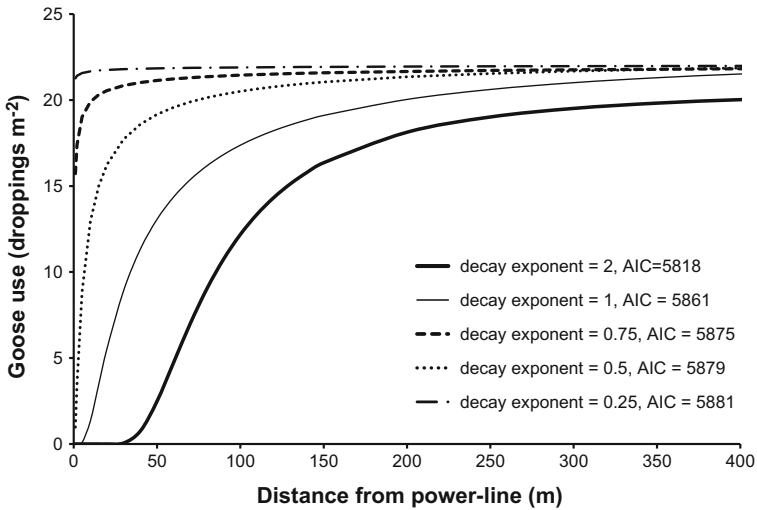
### Fine-scale habitat selection: within-field dropping counts

The locations of sampling fields are shown in Fig. 1a. We sampled 891 points in 39 fields. The mean dropping count at points was 16.8 (range = 0–243; SD = 26.2; median = 8). Zero dropping counts made up 32% (N = 282) of samples. For *Turbine proximity*, *Power-line proximity* and *Tree-line proximity*, the best fitting version of the variable, as measured by AIC of full models containing all other explanatory variables was with a decay exponent of two, while for *Road proximity*, the best version was with a decay exponent of 0.25. For *Visibility*, the proportion of visible pixels within a 1500 m radius of the point was the selected as the best version of the variable. Figure 2 illustrates how the different decay exponents gave different response curves to the features that are avoided by foraging geese: note that the selection of the optimum decay exponent is itself subject to some uncertainty, which propagates into the subsequent models.

High goose-use was associated with low proximity of wind turbines, power-lines and tree-lines (Tables 2, 3). There was weak evidence of an association with areas of high surrounding visibility. There was no evidence for avoidance of roads or settlements. All of the top models contained the *Turbine proximity*, *Power-line Proximity* and *Tree-line Proximity* variables and the confidence limits of the parameter estimates for these variables did not approach zero. *Power-line proximity* had the largest parameter estimate, followed by *Tree-line proximity* and then *Turbine proximity*. *Visibility* was included in the second-best model, but with a small effect size, and 95% CIs that overlap zero. *Road proximity* was in the third best model and *Settlement distance* was not included in the top model set; neither of the latter two variables were informative.

Figure 3 shows that there is effectively complete goose avoidance at distances of less than ca.80 m for turbines, ca.40 m for power-lines and ca.10 m for tree-lines, whereas goose abundance adjacent to roads is >95% of the maximum modelled abundance (assuming the absence of any other avoided features). For wind-turbines, modelled abundance reaches 50% of the modelled maximum at ca.200 m distance, whereas for power-lines it is ca.90 m and for tree-lines it is ca.25 m.

K-fold cross-validation indicated that the mean Pearson correlation coefficient between observed and predicted values in the validation data-sets was 0.65.



**Fig. 2** Modelled effect of choosing different decay exponents on the modelled relationship between goose abundance and proximity to power-lines. Curves based on coefficients from a zero inflated negative binomial GLMM using dropping-count as a response. The decay exponent for the influence of power-lines was allowed to vary between 0.25 and 2, while retaining the remaining five fine-scale explanatory variables at their optimal decay exponent. Predicted dropping-count for each decay exponent is calculated by assuming a scenario in which a single power-line segment is present at the specified distance

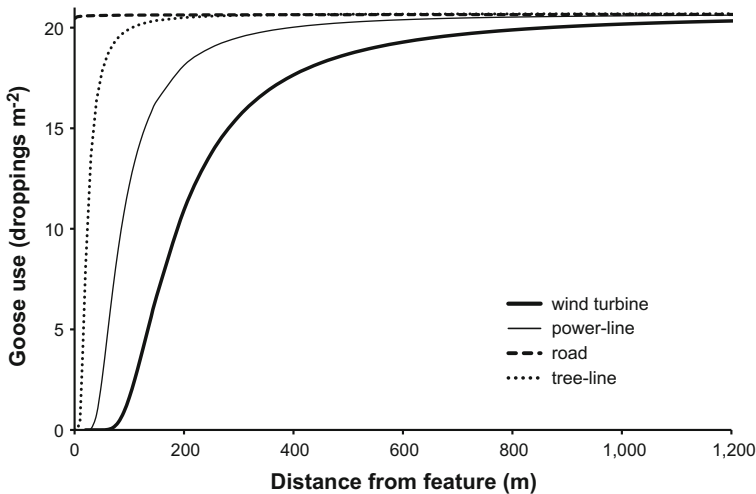
**Table 2** Top model set for fine-scale habitat selection by geese in Bulgarian Dobrudzha

Model rank	df	ΔAIC	weight	Power-line proximity	Tree-line proximity	Turbine proximity	Visibility	Road proximity	Settlement distance
1	7	0.00	0.51	+	+	+			
2	8	1.16	0.29	+	+	+	+		
3	8	1.86	0.20	+	+	+		+	

Based on zero-inflated negative binomial GLMM's. Showing all models with ΔAIC < 2. + indicates explanatory variable included in the model

**Table 3** Fine-scale habitat selection model coefficients, confidence intervals and relative importance

Fixed effects	Relative importance	Coefficient (with shrinkage) (95% CI)	P
Intercept	1	2.15 (1.83, 2.47)	<0.0001
Power-line proximity	1	-3.00 (-3.72, -2.29)	<0.0001
Tree-line proximity	1	-1.62 (-2.31, -0.94)	<0.0001
Turbine proximity	1	-0.35 (-0.58, -0.11)	0.004
Visibility	0.29	0.009 (-0.035, 0.098)	0.35
Road proximity	0.20	-0.0089 (-0.25, 0.16)	0.67
Settlement distance	0	-	-



**Fig. 3** Modelled effect of landscape features on goose abundance, based on fine-scale models. Curves based on coefficients from a zero inflated negative binomial GLMM using dropping-count as a response and raw values of all six explanatory variables. Predicted dropping-count for each feature type respectively is calculated by assuming a scenario in which a single feature (i.e., a single wind turbine, or 250 m segment of power-line, road or tree-line) is present within a 2 km radius

### Meso-scale habitat selection

Geese were never detected in stubbles or fallow fields during the study period. Only 37 fields contained rape (35 of which were in winter 2011/12) and geese were detected in two of these (5%). Geese were detected at least once in 18% (115/634) of surveyed cereal fields, but more than once in only 7% of fields (maximum detections in a field = 7) (Fig. 1c). Statistical analysis focused on winter cereal fields only. Examination of diagnostic plots indicated that two rather extreme outlying high values for *Roost proximity* may have been unduly influential and these were removed for final analyses.

The top model set ( $\Delta AIC < 2$ ) included seven models and included all explanatory variables except *Power-line proximity* (Table 4). *Plot area*, *Road proximity*, *Tree-line proximity*, *Roost proximity*, *Winter* and *NDVI* were included in all top models and their effects were significant in the averaged model (Table 5).

The largest effects were a positive association between goose occurrence and *Roost proximity*, and a positive association between goose occurrence and *Field area* (Fig. 4). There was a weak (though significant) negative association between goose occurrence and *Road proximity* and *Tree-line proximity*. There was a weak positive association between *NDVI* and goose occurrence, but this was significant only in winter 2011/12. Goose occurrence was substantially higher in *Winter 2011/12*. There was some indication of higher goose occurrence where maize was the previous crop (the variable was included in the top six models), but this was non-significant. *Visibility*, *Settlement distance* and *Power-line proximity* were uninformative.

For the meso-scale model, K-fold cross-validation indicated that the mean Pearson correlation coefficient between observed and predicted values in the validation data-sets was 0.43.

**Table 4** Top model set for meso-scale habitat selection of geese in Bulgarian Dobrudzha

Model rank	df	$\Delta AIC$	Weight	Field area	Road proximity	Tree-line proximity	Roost proximity	Winter	NDVI	Previous crop	Turbine proximity	Visibility	Settlement proximity	Powerline proximity
1	12	0.00	0.24	+	+	+	+	+	+	+	+			
2	13	0.30	0.21	+	+	+	+	+	+	+	+	+		
3	11	1.25	0.13	+	+	+	+	+	+	+	+		+	
4	13	1.39	0.12	+	+	+	+	+	+	+	+	+		
5	12	1.50	0.11	+	+	+	+	+	+	+	+	+	+	
6	14	1.77	0.10	+	+	+	+	+	+	+	+	+	+	
7	12	2.00	0.09	+	+	+	+	+	+	+	+	+		

**Table 5** Model-averaged coefficients for variables in the top model set for meso-scale habitat selection of geese in Bulgarian Dobrudzha

Explanatory variable	Relative Importance	Coefficient (without shrinkage) (95% CI)	Coefficient (with shrinkage)	P (with shrinkage)
Intercept	1	−3.12 (−3.69, −2.55)	−3.12 (−3.69, −2.55)	<0.0001
Field area	1	0.44 (0.26, 0.62)	0.44 (0.26, 0.62)	<0.0001
Road proximity	1	−0.37 (−0.70, −0.041)	−0.37 (−0.70, −0.041)	<0.027
Tree-line proximity	1	−0.41 (−0.67, −0.14)	−0.41 (−0.67, −0.14)	0.003
Roost proximity	1	0.75 (0.52, 0.95)	0.74 (0.52, 0.95)	<0.0001
Winter (2012/13)	1	−1.77 (−2.38, −1.16)	−1.77 (−2.38, −1.16)	<0.0001
NDVI (2011/12)	1	0.48 (0.18, 0.79)	0.48 (0.18, 0.79)	0.002
NDVI (2012/13)		0.26 (−0.36, 0.88)	0.26 (−0.36, 0.88)	0.42
Previous crop (not maize)	0.91	−0.44 (−0.88, −0.006)	−0.40 (−0.89, 0.08)	0.10
Turbine proximity	0.76	−0.28 (−0.61, 0.05)	−0.21 (−0.58, 0.16)	0.26
Visibility	0.51	0.15 (−0.068, 0.38)	0.078 (−0.14, 0.30)	0.48
Settlement distance	0.22	0.090 (−0.13, 0.31)	0.020 (−0.11, 0.15)	0.76

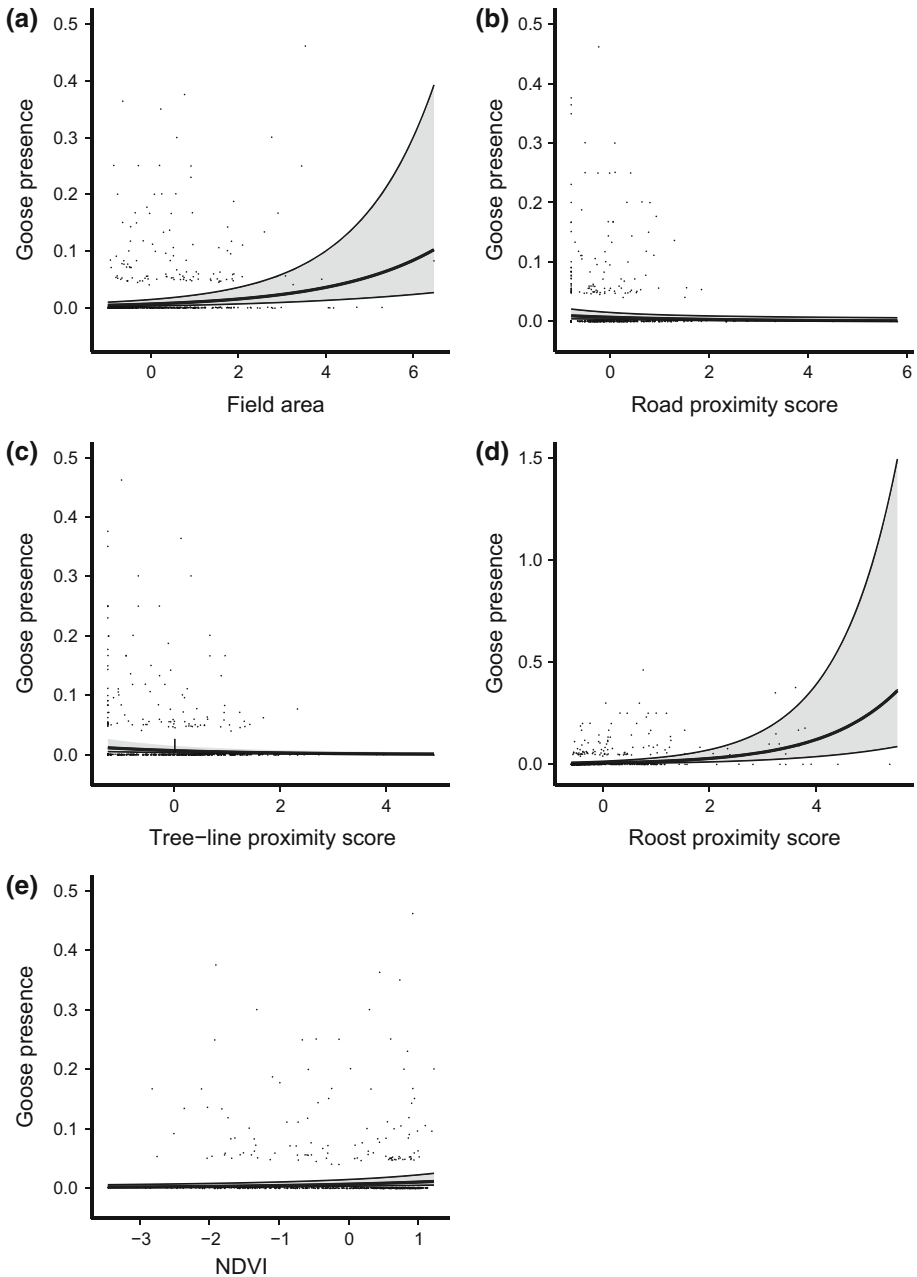
## Discussion

We have demonstrated that habitat selection in wintering geese in Bulgarian Dobrudzha is influenced by all the main factors initially proposed: avoidance of landscape clutter, foraging profitability, and avoidance of human disturbance. The modelled relationships provide a tool for landscape planning in an area with multiple stakeholders. However, it is also clear that the influence of these factors upon goose distribution varies by spatial scale, and that confining the analysis to a single spatial scale would have led to very different conclusions.

### Habitat selection by foraging geese

Meso-scale analysis—i.e. field selection—indicates a strong influence of foraging profitability and avoidance of human disturbance. Geese in Bulgarian Dobrudzha feed almost exclusively on winter cereals, and select strongly for fields close to large roosts. This is unsurprising, because short commuting flights result in lower flight energy expenditure. There was some evidence for selection of more profitable, nutrient-rich crops, as indicated by an association with NDVI in one of the study winters. They also avoid fields which have a high density of roads and tree-lines around them. These effects imply that human disturbance, particularly from hunters, might be a significant factor in field selection. In addition to shooting from hidden positions at dawn roost flights, hunters in Bulgarian Dobrudzha frequently drive cars around the area in search of foraging geese. They use tree-lines to provide cover in a flat, open, agricultural landscape.

Notably however, there is little evidence that field selection is affected by landscape clutter, i.e., objects such as wind turbines and power-lines, or visibility more generally.



**Fig. 4** modelled effect of explanatory covariates on frequency of goose occurrence in fields. **a** *Field area*; **b** *road proximity*; **c** *tree-line proximity*; **d** *roost proximity*; **e** *NDVI*. Line shows predicted values from a zero inflated negative binomial GLM  $\pm$  SE (shaded area). For each covariate, values for all other covariates were fixed at the mean values in the original data-set, winter was fixed at 2011/12 and previous crop was fixed as maize. Raw data (number of goose presences divided by number of counts) are shown as points



There was a positive association with field size, which might indicate selection for landscape openness, but in view of the absence of any effect of visibility per se, we suspect that the field area relationship may simply reflect the fact that large fields contain more foraging resource.

However, at fine-scale, we find very strong avoidance of turbines and power-lines, as well as avoidance of tree-lines. These results imply that within-field patch selection may be strongly driven by perceived predation risk, with geese selecting for areas with a clear view of approaching predators and few obstacles to escape flight. Large raptors are relatively abundant in the study area, and attacks on foraging goose flocks by peregrine *Falco peregrinus*, saker falcon *Falco cherrug*, northern goshawk *Accipiter gentilis* and white-tailed eagle *Haliaeetus albicilla* are regularly observed (Authors, pers. obs.). However, avoidance of power-lines and wind turbines may equally indicate a form of neophobia, a possibility which is supported by the suggestion that goose avoidance distance declines with time since wind turbine construction (Madsen and Boertmann 2008).

The model outcomes are broadly in agreement with previous work on goose winter habitat selection. For example, selection of areas close to roosts (Amano et al. 2006a; Vickery and Gill 1999), and avoidance of roads (Gill 1996; Keller 1991; Larsen and Madsen 2000; Madsen 1985), power-lines (Ballasus and Sossinka 1997; Larsen and Madsen 2000) and tree-lines (Amano et al. 2006a; Larsen and Madsen 2000; Madsen 1985) has been shown previously. Avoidance of wind turbines has previously been demonstrated in barnacle goose *Branta leucopsis*, bean goose *Anser fabalis*, greylag goose, pink-footed goose *Anser brachyrhynchus* as well as the greater white-fronted goose (Hötter et al. 2006; Kowallik and Borbach-Jaene 2001; Kruckenberg and Jaene 1999; Larsen and Madsen 2000). Reported displacement distances vary between studies, but typically there is an exclusion zone close to turbines where geese are absent and an area beyond where goose densities are reduced, the total area affected can be as little as 50 m or as much as 850 m from turbines. Our fine-scale analysis used a more complex metric for turbine influence than used in previous studies, combining information on both the number and proximity of all turbines near to the sampling location, rather than just the distance to the nearest turbine, and confirms a strong short-range avoidance.

Nevertheless, although fine-scale wind turbine avoidance was demonstrated, we also show that avoidance of power-lines and tree-lines can be important. The units by which we measure these linear features are 250 m segments (which may be contiguous), whereas turbines are discrete single entities, so comparing the coefficients for them is not particularly instructive. However, we show that geese are almost entirely excluded from the immediate vicinity of turbines, power-lines and tree-lines (but not roads), although turbine avoidance is somewhat more extensive. The great majority of tree-lines, power-lines and roads in the study area have been in situ for several decades, whereas wind turbines have largely been constructed in the last decade. Ultimately, avoidance of wind turbines and other landscape clutter by foraging geese—often referred to as displacement—can be interpreted as a form of habitat loss (Drewitt and Langston 2006). However, this loss may not be immutable if the birds are able to exploit the food resource under some circumstances, such as following habituation or during periods where alternative food resources are depleted. For geese, landscape clutter may also result in increased mortality through collision, although evidence to date suggests collision mortality is low (Rees 2012; Sugimoto and Matsuda 2011). Barrier effects may occur where wind turbines are situated on the route of commutes between goose roosts and foraging areas, or along migration corridors (Madsen et al. 2010). This may result in higher energy costs of travelling around the obstacles, or may deter birds from using traditional flight lines, but has been little

studied. This analysis extends previous work by explicitly considering the different spatial scales at which geese may make decisions about foraging location. Foraging habitat selection has been shown to be scale-dependent in many animal taxa (e.g., Ciarniello et al. 2007; de Knegt et al. 2011; Irvin et al. 2013), although rarely for geese (but see Guerena et al. 2014; Leopold and Hess 2013). Based on their daily foraging routine, it is tempting to suggest that our study populations make hierarchical habitat selection decisions: upon departing the roost in the morning, geese make a commuting flight and land in a chosen field to forage. Once on the ground within the field they select foraging patches mainly by walking. This two-step process whereby meso-scale habitat selection is made from the air and fine-scale habitat selection is made on the ground might promote between-scale variation in habitat selection (Kristan 2006). However, our statistical models may simply be failing to detect the meso-scale influence of wind turbines and power-lines due to the very strong influence of roost proximity and the fact that very few fields that are close to large roosts have wind turbines (see Fig. 1b). In addition, wind turbines in our study area tend to be rather widely spaced, while fields are typically large, meaning that fine-scale turbine avoidance does not preclude use of fields which have relatively high turbine proximity scores. The strong effect of road avoidance may have precluded the detection of a power-line effect, because these two variables were collinear, although this seems very unlikely: substitution of *Road proximity* by *Power-line proximity* in our final top model for meso-scale habitat selection resulted in an extremely weak power-line effect (coefficient = 0.0084, SE = 0.074, P = 0.91). We do caution that our models have relatively low predictive power, and there are indications that we have failed to model all relevant factors. We speculate that this may relate in large part to the effect of hunting disturbance on goose distribution in the study area. We used proximity of surfaced roads and tree-lines as proxies for hunting distribution, but these probably provide only a rough approximation of the spatial distribution of a factor that appears anecdotally to be significant in the study area. Obtaining better information on the spatial distribution of hunting would be a very valuable step forward.

Wintering geese typically fly from roost to feeding sites in flocks, and then forage on the ground in flocks. In these situations, patch-choice decisions made by individuals are potentially influenced by information about patch quality, costs and benefits of flocking and individual personality and fitness (e.g., Aplin et al. 2014). How these decisions aggregate into collective decision-making about fine- and meso-scale habitat selection by flocks is poorly understood (but see Amano et al. 2006b).

### Using models to support landscape management

The model outcomes lend themselves to management prescriptions. In particular we are able to suggest solutions to apparently competing land uses. The idea of zoning competing land-uses to provide optimal conservation outcomes is well established, but has generally been applied in the context of marine spatial planning (Boyes et al. 2007; Douvère and Ehler 2009; Kannen 2014; Kenchington and Day 2011; McWhinnie et al. 2015; Yates et al. 2015) or reserve design for protected species or habitats (Moilanen 2007), although see Cote et al. (2010) and Geneletti (2013) for examples of landscape-scale zoning in terrestrial areas. Here we consider a zoning approach in a largely unprotected terrestrial landscape, to resolve problems for conflict species. Although zoning has been used to manage the requirements for both hunting opportunities and conservation of quarry species (Fox and Madsen 1997), and to target agri-environment payments to minimise goose—farmer conflict (Jensen et al. 2008; Klaassen et al. 2008), here we consider how

conservation, hunting, agriculture and infrastructure development might simultaneously be accommodated in our study area.

Very strong selection of fields close to larger roosts is a key finding. Further concentrating the goose population into areas close to roosts, would facilitate efficient zoning of different land uses. For example, if agri-environment funding to encourage appropriate winter cereal cultivation and provide compensation for grazing damage (see Petkov et al. 2017) were focused around the key roost lakes, it would help ensure that good quality habitat is provided in the optimal location, while minimising goose-farmer conflict and ensuring efficient use of financial resources (Jensen et al. 2008; Madsen et al. 2014). Agri-environment funding could be further streamlined by deploying it preferentially in fields that are relatively unaffected by the landscape features that are avoided by geese. We suggest that if (hunting) disturbance were minimised in fields near to roosts, then foraging may be further concentrated into such areas (see Madsen 1998 for an example of redistribution of geese to roosting areas where hunting disturbance was experimentally reduced). Earlier work indicates that avoidance of tree-lines and roads would diminish in areas where hunting disturbance is reduced (Fox and Madsen 1997) due to habituation. Management to focus goose grazing in areas close to roosts would then reduce the conservation impact of infrastructure development—such as wind turbines and associated power-lines and access roads—if these were sited further away. Conversely, if infrastructure is developed in sites that are close to roosts, our models suggest that it would have the combined effect of reducing habitat suitability and increasing access to fields by hunters, creating increased disturbance. Detailed examination of how legitimate hunting interests could be accommodated in the area is beyond the scope of this paper, but we note that hunting from fixed points tends to create fewer disturbance impacts (Fox and Madsen 1997) and suggest that consensus selection of such points and provision of suitable access and facilities may be worth exploring.

This work provides important qualitative messages for management. Quantitative examination of the predicted impact of future scenarios, specifically the deployment of new wind turbines, is fully explored in a separate paper (Harrison et al. in prep.) in a similar manner to Larsen and Madsen (2000). However, these assessments are based upon a static, statistical, population-based model of bird responses to habitat. Individual-based Modelling provides a mechanistic approach that, while data-hungry, is perhaps better suited to modelling dynamic wildlife response to future landscape change scenarios (Amano 2012; Stillman and Goss-Custard 2010; Stillman et al. 2015). This technique has, for example been used to address the impact of future land-use change (Nabe-Nielsen et al. 2010), and to facilitate landscape-planning and wildlife conflict management (Heinonen et al. 2014; Stillman et al. 2010; Wood et al. 2014). In our study system, there are key uncertainties that hinder predictions. A more complete understanding of management options for geese in Bulgarian Dobrudzha would be gained by using measures of the food consumption rates and bio-energetics of individuals to estimate how much habitat is required to sustain the population, how individual fitness responds to changes in habitat suitability, and hence how the population might respond to future change (Inger et al. 2006).

**Acknowledgements** This study formed part of the project ‘Conservation of the Wintering Population of the Globally Threatened red-breasted goose (*Branta ruficollis*) in Bulgaria’, funded by the LIFE + Programme of the European Commission (LIFE 09/NAT/BG/000230). We are grateful to fieldworkers Thomas Amphlett, Brian Anderson, Ivalio Asenov, Yana Barzova, Brid Colhoun, Matt Collis, Yalchin Dereliev, Georgi Gerdzhirov, Aiden Hatibov, Richard Hazell, Mihail Iliev, Ivan Ivanov, Rebecca Kane, Valentin Katrandziev, Brittany King, Radoslav Moldovanski, Stoyan Nikolov, Pencho Pandukov, Anton Stamenov,

Anna Staneva, Mladen Vasilev and Alexander Zarkov. Emma Teuton (RSPB) provided GIS advice and support. Adam Butler (Biomathematics and Statistics Scotland) provided statistical advice. Peter Cranswick, Kevin Wood and Baz Hughes provided advice during manuscript preparation.

## References

- Amano T (2012) Unravelling the dynamics of organisms in a changing world using ecological modelling. *Ecol Res* 27:495–507
- Amano T, Ushiyama K, Fujita G, Higuchi H (2006a) Foraging patch selection and departure by non-omnivorous foragers: a field example in white-fronted geese. *Ethology* 112:544–553
- Amano T, Ushiyama K, Moriguchi S, Fujita G, Higuchi H (2006b) Decision-making in group foragers with incomplete information: test of individual-based model in geese. *Ecol Monogr* 76:601–616
- Aplin LM, Farine DR, Mann RP, Sheldon BC (2014) Individual-level personality influences social foraging and collective behaviour in wild birds. *Proc R Soc B*. doi:10.1098/rspb.2014.1016
- Ballasus H, Sossinka R (1997) The impact of power lines on field selection and grazing intensity of wintering white-fronted- and bean geese *Anser albifrons*, *A. fabalis*. *J Ornithol* 138:215–228
- Boyes SJ, Elliott M, Thomson SM, Atkins S, Gilliland P (2007) A proposed multiple-use zoning scheme for the Irish Sea. An interpretation of current legislation through the use of GIS-based zoning approaches and effectiveness for the protection of nature conservation interests. *Mar Policy* 31:287–298
- Bregnballe T, Madsen J, Rasmussen PAF (2004) Effects of temporal and spatial hunting control in waterbird reserves. *Biol Conserv* 119:93–104
- Bulgarian Ministry of Environment and Water (2012) [Statement on Strategic Environmental Assessment for the national action plan for energy from renewable sources 2011–2020]. [http://www3.moew.government.bg/files/file/Industry/SEA/Statements\\_EO/Stanovishte\\_EO\\_1-2-2012.pdf](http://www3.moew.government.bg/files/file/Industry/SEA/Statements_EO/Stanovishte_EO_1-2-2012.pdf) (in Bulgarian)
- Ciarniello LM, Boyce MS, Seip DR, Heard DC (2007) Grizzly bear habitat selection is scale dependent. *Ecol Appl* 17:1424–1440
- Cote P, Tittler R, Messier C, Kneeshaw DD, Fall A, Fortin M-J (2010) Comparing different forest zoning options for landscape-scale management of the boreal forest: possible benefits of the TRIAD. *For Ecol Manag* 259:418–427
- de Knegt HJ et al (2011) The spatial scaling of habitat selection by African elephants. *J Anim Ecol* 80:270–281
- Douvere F, Ehler CN (2009) New perspectives on sea use management: initial findings from European experience with marine spatial planning. *J Environ Manag* 90:77–88
- Drewitt AL, Langston RHW (2006) Assessing the impacts of wind farms on birds. *Ibis* 148:29–42
- ESRI (2011) ArcGIS desktop: release 10. Environmental Systems Research Institute, Redlands
- Fournier DA, Skaug HJ, Ancheta J, Ianelli J, Magnusson A, Maunder M, Nielsen A, Sibert J (2012) AD model builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. *Optim Methods Softw* 27:233–249
- Fox AD, Madsen J (1997) Behavioural and distributional effects of hunting disturbance on waterbirds in Europe: implications for refuge design. *J Appl Ecol* 34:1–13
- Geneletti D (2013) Assessing the impact of alternative land-use zoning policies on future ecosystem services. *Environ Impact Asses* 40:25–35
- Gill JA (1996) Habitat choice in pink-footed geese: quantifying the constraints determining winter site use. *J Appl Ecol* 33:884–892
- Giroux MA, Berteaux D, Lecomte N, Gauthier G, Szor G, Bety J (2012) Benefiting from a migratory prey: spatio-temporal patterns in allochthonous subsidization of an arctic predator. *J Anim Ecol* 81:533–542
- Green AJ, Elmberg J (2014) Ecosystem services provided by waterbirds. *Biol Rev* 89:105–122
- Guarena KB, Castelli PM, Nichols TC, Williams CK (2014) Spatially-explicit land use effects on nesting of Atlantic Flyway resident Canada geese in New Jersey. *Wildl Biol* 20:115–121
- Hassall M, Lane SJ (2005) Partial feeding preferences and the profitability of winter-feeding sites for Brent geese. *Basic Appl Ecol* 6:559–570
- Heinonen JPM, Palmer SCF, Redpath SM, Travis MJM (2014) Modelling hen harrier dynamics to inform human-wildlife conflict resolution: a spatially-realistic, individual-based approach. *PLoS ONE* 9:e112492
- Hötter H, Thomsen K-M, Jeromin H (2006) Impacts on biodiversity of exploitation of renewable energy sources: the example of birds and bats—facts, gaps in knowledge, demands for further research, and ornithological guidelines for the development of renewable energy exploitation. Michael-Otto-Institut im NABU, Bergenhusen

- Inger R, Ruxton GD, Newton J, Colhoun K, Mackie K, Robinson JA, Bearhop S (2006) Using daily ration models and stable isotope analysis to predict biomass depletion by herbivores. *J Appl Ecol* 43:1022–1030
- Irvin E, Duren KR, Buler JJ, Jones W, Gonzon AT, Williams CK (2013) A multi-scale occupancy model for the grasshopper sparrow in the mid-Atlantic. *J Wildl Manag* 77:1564–1571
- Jefferies RL, Jano AP, Abraham KF (2006) A biotic agent promotes large-scale catastrophic change in the coastal marshes of Hudson Bay. *J Ecol* 94:234–242
- Jensen RA, Wisz MS, Madsen J (2008) Prioritizing refuge sites for migratory geese to alleviate conflicts with agriculture. *Biol Conserv* 141:1806–1818
- Johnson WP, Schmidt PM, Taylor DP (2014) Foraging flight distances of wintering ducks and geese: a review. *Avian Conserv Ecol* 9:1–19
- Kannen A (2014) Challenges for marine spatial planning in the context of multiple sea uses, policy arenas and actors based on experiences from the German North Sea. *Reg Environ Chang* 14:2139–2150
- Kear J (2005) Ducks, geese and swans volume 1: general chapters; species accounts (*Anhima* to *Salvadorina*). Oxford University Press, Oxford
- Keller V (1991) The effects of disturbance from roads on the winter distribution of feeding sites of geese wintering in north-east Scotland. *Ardea* 79:229–231
- Kenchington R, Day J (2011) Zoning, a fundamental cornerstone of effective Marine Spatial Planning: lessons learnt from the Great Barrier Reef, Australia. *J Coast Conserv* 15:271–278
- Klaassen M, Bauer S, Madsen J, Possingham H (2008) Optimal management of a goose flyway: migrant management at minimum cost. *J Appl Ecol* 45:1446–1452
- Kostadinova I, Dereliev S (2001) Results from the mid-winter counts of waterbirds in Bulgaria for the period 1997–2001. BSPB, Sofia
- Kowallik C, Borbach-Jaene J (2001) Windrädler als Vogelscheuchen?—Über den Einfluss der Windkraftnutzung in Gänserastgebieten an der nordwest-deutschen Küste. *Vogelkundliche Berichte aus Niedersachsen* 33:97–102
- Kristan WB (2006) Sources and expectations for hierarchical structure in bird-habitat associations. *Condor* 108:5–12
- Kruckenberg H, Jaene J (1999) The effect of a group of wind turbines on a staging area of white-fronted geese (*Anser albifrons*). *Nat Landsch* 74:420–427
- Larsen JK, Madsen J (2000) Effects of wind turbines and other physical elements on field utilization by pink-footed geese (*Anser brachyrhynchus*): a landscape perspective. *Landscape Ecol* 15:755–764
- Leopold CR, Hess SC (2013) Multi-scale habitat selection of the endangered Hawaiian goose. *Condor* 115:17–27
- Madsen J (1985) Impact of disturbance on field utilization of pink-footed geese in West Jutland, Denmark. *Biol Conserv* 33:53–63
- Madsen J (1998) Experimental refuges for migratory waterfowl in Danish wetlands. II. Tests of hunting disturbance effects. *J Appl Ecol* 35:398–417
- Madsen J, Boertmann D (2008) Animal behavioral adaptation to changing landscapes: spring-staging geese habituate to wind farms. *Landscape Ecol* 23:1007–1011
- Madsen J, Bjerrum M, Tombre IM (2014) Regional management of farmland feeding geese using an ecological prioritization tool. *Ambio* 43:801–809
- Masden EA, Haydon DT, Fox AD, Furness RW (2010) Barriers to movement: modelling energetic costs of avoiding marine wind farms amongst breeding seabirds. *Mar Pollut Bull* 60:1085–1091
- Mayor SJ, Schaefer JA, Schneider DC, Mahoney SP (2007) Spectrum of selection: new approaches to detecting the scale-dependent response to habitat. *Ecology* 88:1634–1640
- Mayor SJ, Schneider DC, Schaefer JA, Mahoney SP (2009) Habitat selection at multiple scales. *Ecoscience* 16:238–247
- McKinnon L, Berteaux D, Gauthier G, Bety J (2013) Predator-mediated interactions between preferred, alternative and incidental prey in the arctic tundra. *Oikos* 122:1042–1048
- McWhinnie L, Briers RA, Fernandes TF (2015) The development and testing of a multiple-use zoning scheme for Scottish waters. *Ocean Coast Manag* 103:34–41
- Ministry of Agriculture and Foods (2015) Ordinance No 7/24.02.2015 on the implementation Measure 10 “Agriculture and ecology” of the Rural Development Programme 2014–2020, published in State Gazette 16/27.02.2015. [http://prsr.government.bg/Admin/upload/Media\\_file\\_bg\\_1429490811.rar](http://prsr.government.bg/Admin/upload/Media_file_bg_1429490811.rar)
- Moilanen A (2007) Landscape zonation, benefit functions and target-based planning: unifying reserve selection strategies. *Biol Conserv* 134:571–579
- Nabe-Nielsen J, Sibly RM, Forchhammer MC, Forbes VE, Topping CJ (2010) The effects of landscape modifications on the long-term persistence of animal populations. *PLoS ONE* 5:e8932
- Orians GH, Wittenberger JF (1991) Spatial and temporal scales in habitat selection. *Am Nat* 137:S29–S49

- Owen M, Nugent M, Davies N (1977) Discrimination between grass species and nitrogen-fertilized vegetation by young barnacle geese. *Wildfowl* 28:21–26
- Patterson IJ (1991) Conflict between geese and agriculture—does goose grazing cause damage to crops? *Ardea* 79:178–186
- Petkov N, Harrison AL, Stamenov A, Hilton GM (2017) The impact of wintering geese on crop yields in Bulgarian Dobrudzha: implications for agri-environment schemes. *Eur J Wildl Res* 63:66
- Rees E (2012) Impacts of wind farms on swans and geese: a review. *Wildfowl* 62:37–72
- R Development Core Team (2008) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org>
- Stillman RA, Goss-Custard JD (2010) Individual-based ecology of coastal birds. *Biol Rev* 85:413–434
- Stillman RA, Moore JJ, Woolmer AP, Murphy MD, Walker P, Vanstaen KR, Palmer D, Sanderson WG (2010) Assessing waterbird conservation objectives: an example for the Burry Inlet, UK. *Biol Conserv* 143:2617–2630
- Stillman RA, Railsback SF, Giske J, Berger U, Grimm V (2015) Making predictions in a changing world: the benefits of individual-based ecology. *Bioscience* 65:140–150
- Sugimoto H, Matsuda H (2011) Collision risk of White-fronted Geese with wind turbines. *Ornithol Sci* 10:61–71
- Vickery JA, Gill JA (1999) Managing grassland for wild geese in Britain: a review. *Biol Conserv* 89:93–106
- Vickery JA, Sutherland WJ, Lane SJ (1994) The management of grass pastures for brent geese. *J Appl Ecol* 31:282–290
- Wetlands International (2016) Waterbird population estimates. Retrieved from [wpe.wetlands.org](http://wpe.wetlands.org) on Tuesday 23 Feb 2016. Accessed Retrieved from [wpe.wetlands.org](http://wpe.wetlands.org) on Tuesday 23 Feb 2016
- Wood KA, Stillman RA, Daunt F, O'Hare MT (2014) Can sacrificial feeding areas protect aquatic plants from herbivore grazing? Using behavioural ecology to inform wildlife management. *PLoS ONE* 9:e104034
- Yates KL, Schoeman DS, Klein CJ (2015) Ocean zoning for conservation, fisheries and marine renewable energy: assessing trade-offs and co-location opportunities. *J Env Manag* 152:201–209
- Zhang Y, Jia Q, Prins HH, Cao L, de Boer WF (2015) Individual-area relationship best explains goose species density in wetlands. *PLoS ONE* 10:e0124972
- Zhang Y, Prins HH, Cao L, Zhao M, de Boer WF (2016) Variation in elevation and sward height facilitate coexistence of goose species through allometric responses in wetlands. *Waterbirds* 39:34–44
- Zuur AF, Ieno EN, Walker NJ, Saveliev AA, Smith GM (2009) Mixed effects models and extensions in ecology with R. Statistics for biology and health. Springer, New York

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