"CONSERVATION OF THE WINTERING POPULATION OF THE
GLOBALLY THREATENED RED-BREASTED GOOSE
(*BRANTA RUFICOLLIS*) IN BULGARIA" LIFE 09/NAT/BG/000230

Fine-scale distribution of geese in relation to key landscape elements in coastal Dobrudzha, Bulgaria

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Table of Contents

Summary

Wind farm development in the Coastal Dobrudzha region of Bulgaria has boomed over the last decade, due to the requirements to meet EU renewable energy targets. Recently, a number of wind farm developments in the region have met strong opposition, which has resulted in an EU court case that asserts, among other things, that projects were approved without due consideration of potential impacts on Annex I bird species and their habitats.

The globally Endangered Red-breasted Goose *Branta ruficollis* may be particularly sensitive to wind farm development in Coastal Dobrudzha, due to the overlap of foraging habitats with prime locations for turbines. Over 90% of the world population can spend the winter in this small area, feeding primarily on winter wheat. Availability of sufficient good quality feeding habitat is essential, allowing individuals to meet their daily energy requirements and maintain good body condition for migration and successful breeding.

Various reviews have summarised the effects of wind farms on geese and other wildfowl, and consider collision, barrier effects and displacement (reduced use of prime feeding habitat) as the most likely potential impacts. This is the first study to investigate the displacement effect of wind turbines on wintering geese in Dobrudzha, by examining their fine-scale feeding distribution.

Goose-use was assessed in relation to both number and proximity of wind turbines and other landscape elements that may also influence fine-scale distribution. We used systematic goose dropping counts as a proxy for cumulative goose-use over a preceding period of several weeks. Droppings were counted in 891 sampling points spread across 39 fields of winter wheat. A modelling approach identified the key features influencing goose-use, and model parameters were used to predict relative habitat suitability across the wider landscape.

Highly localised, fine-scale avoidance of tall landscape elements by geese was detected, with power lines, tree lines and wind turbines found to have the strongest influence on within-field distribution. Highest goose-use was predicted in areas with low power line, tree line and turbine scores, and, to a lesser extent, negatively associated with roads and settlements and positively associated with landscape openness.

By investigating how these associations translate into landscape-scale impacts, we infer that the suitability of the current landscape is on average 52% lower than the maximum habitat suitability expected in the absence of key landscape elements. By excluding the influence of existing turbines (simulating a turbine-free landscape) we predict overall suitability of the landscape to be 6% higher. While at the landscape scale this influence appears relatively small, areas with high turbine densities e.g. the southern part of Coastal Dobrudzha, show higher local reduction in habitat suitability.

In a scenario where all consented and currently proposed turbines in Coastal Dobrudzha become operational, we predict habitat suitability to be 18% lower than that predicted for the present landscape. Wind turbines would cause a 24% reduction in overall habitat suitability in this scenario.

We conclude that, when other landscape elements that deter feeding geese – such as power lines, treelines and roads - are taken into account, the planned expansion of wind turbines represents a very large reduction in the availability of preferred habitat in the area. Although the ultimate impacts of this on the goose populations are difficult to predict without further study, there is clearly potential for a substantial negative effect.

Introduction

Wind farm development in the region of Coastal Dobrudzha, north east Bulgaria has boomed over the last decade, following the country's accession to the EU and the requirements to meet the EU renewable energy targets. However, the construction of and planning of further wind farms in the region has been controversial. In October 2013 the EC referred the Bulgarian government to the European Court of Justice over its failure to protect internationally important nature areas and species (http://europa.eu/rapid/press-release_IP-13-966_en.htm?locale=en). The case (Case C - 141/14) asserts that a large number of turbines and other developments have been authorised in the Kaliakra region in Coastal Dobrudzha without adequate environmental impact assessments, and that the Government has failed to comply with Article 4(4) of the Birds Directive (2009/147/EC), requiring member states to take appropriate measures to avoid deterioration of habitats of and significant disturbance of Annex I (2008/147/EC) species occurring in Natura 2000 sites, or in parts of the Important Bird Area (IBA) that have not been designated as Special Protected Areas (SPA).

While the Bulgarian Government has now put measures in place, if properly implemented, to stop all new wind energy development in the Dobrudzha region, there still remain large numbers of potentially damaging projects at various stages of consent.

Bulgarian Dobrudzha is a key wintering site for the Endangered Red-breasted Goose *Branta ruficollis*, supporting up to 90% of the global population (40,000 - 50,000 birds, see http://www.birdlife.org/datazone/speciesfactsheet.php?id=387) in some winters. The region has four notified SPAs – Durankulak Lake; Shabla Lake Complex; Kaliakra SPA; and the recently designated Bilo SPA (Figure 1) – which include wintering Red-breasted Goose in their designations. Durankulak Lake and Shabla Lake Complex are the most important known wintering sites for the species, in terms of the numbers they support (Cranswick et al. 2012).

Geese are believed to be one of the most sensitive taxa to wind turbines (Gove et al. 2013). This is compounded by their congregating in large numbers over large, open agricultural areas over several months, and the tendency to situate onshore wind farms in such landscapes, where high average wind speeds prevail (Larsen & Madsen, 2010).

The impacts of wind farms on birds are varied, and depend on a wide range of factors, such as the specification of the development, the topography, the habitat and the numbers and species of birds present (Drewitt & Langston 2006; Gove et al. 2013). Three main impact types have been identified: 1. Displacement/habitat loss (reduced use of feeding areas following turbine construction due to avoidance or actual destruction of habitat due to turbine infrastructure); 2. Barrier effects (changes in migration routes or local flight routes to avoid wind farms, leading to potential increased energy expenditure and disruption of links between sites; and 3. Collision mortality (Rees 2013).

This study examines the impacts of wind turbines on fine-scale habitat use by wintering geese (specifically White-fronted Geese *Anser albifrons* and Red-breasted Geese) in Bulgarian Dobrudzha. We describe this effect as fine-scale displacement, defined as the distribution response of feeding geese to wind turbine proximity, in fields that geese have been feeding. Because of the lack of opportunity to measure displacement before and after turbine construction, a modelling approach is used to assess goose-use as a function of turbine proximity, as well as other potentially relevant landscape elements such as tree lines, power lines and roads. Inferred goose-use is here used as a

proxy for perceived habitat suitability, thus allowing us to predict the distribution of a fixed number of feeding geese within the landscape of Coastal Dobrudzha.

Previous studies of the effects of wind turbines and other landscape elements on goose distribution have tended to model goose-use as a function of the distance to the nearest turbine (or other features) (e.g. Kruckenberg & Jaene, 1999; Madsen & Boertmann, 2008). However, it is reasonable to suspect that geese respond not just to the closest feature, but to the set of features within view – they may, for example, exhibit greater avoidance of a location that has two wind turbines at 100 m distance than a location with a single turbine 75 m distant. However, the manner in which they respond to the combination of a number of features and distance is unclear. Here we examine this response by considering goose-use of sites as a combined function of the number of landscape elements and their proximity.

Aims

The aims of this study are to:

- Quantify the degree of fine-scale displacement response due to existing wind turbines and other key anthropogenic landscape elements in Dobrudzha, Bulgaria;
- Quantify the added loss of goose feeding habitat due to fine-scale displacement response to wind turbines, after accounting for effects of other landscape elements;
- Summarise the likely impacts of existing wind turbines on local ('within-field') habitat use;
- Review the likely cumulative impacts of existing and planned wind farm developments on overall habitat availability for wintering geese.

Study area

The study was carried out in two consecutive winters, in February 2012 and between mid-January and early March 2013, in the region of coastal Dobrudzha, north east Bulgaria (Figure 1).

Geese in Dobrudzha mostly comprise White-fronted Geese and Red-breasted Geese, which often form mixed flocks. Goose numbers in the region usually start building from early December, with peak numbers generally occurring in mid to late January. Numbers are highly variable within and between winters in response to weather conditions across the wintering range. Geese roost primarily at two coastal lakes– Durankulak and Shabla – and occasionally on the open sea. They leave the roosts at dawn, moving to agricultural feeding areas around the roosts and inland, primarily using the area within c. 10 km of the coast (LIFE09/NAT/BG/000230 'Safe Grounds for Redbreasts' project, unpublished data). Around 750 km^2 of cereal fields cover the landscape of Coastal Dobrudzha, of which around 23% (c. 170 km^2) is included within protected areas, adjacent to Shabla and Durankulak lakes, along the coast at Kaliakra and in the recently designated Bilo SPA.

At certain times, when conditions dictate, large numbers of geese roost along the Black Sea coast, a few kilometres offshore. Data retrieved from tagged Red-breasted Geese and systematic counts at lakes and along the coast have shown this to be a regular occurrence (LIFE09/NAT/BG/000230 'Safe Grounds for Redbreasts' project, unpublished data). This coastal roosting is believed to occur in periods of intense hunting disturbance around the lakes, and when the lakes freeze over.

The region is primarily agricultural, with cereal crops, mostly wheat, dominating the landscape in winter. Fields are usually farmed on two-year cycles, alternating winter cereals and oilseed rape with

summer crops of sunflower and maize, such that between successive winters, fields alternate between seeded and fallow.

Geese in Dobrudzha feed predominantly on winter wheat and to a lesser extent on barley, oilseed rape, pasture grasses and spilt grain from stubbles, particularly early in the season (Sutherland & Crockford 1993, Cranswick et al. 2012).

The landscape is intersected by roads with low traffic intensity, dirt tracks for agricultural access, windbreaks mainly of deciduous trees, often in double lines, and power lines (Figure 2). Settlements are mostly villages and small towns, with little urban sprawl outside these main centres.

Over the last 10 years, 276 wind turbines have been constructed in Coastal Dobrudzha, mostly in the southern part close to the coast, between Shabla and Kavarna towns and Kaliakra Cape. Turbines are usually erected around the edges of fields, close to tree lines, and are accessed by gravel tracks.

Materials and methods

Dropping density as response variable

Within-field distribution of feeding geese was assessed by undertaking dropping counts in fields known to have been used by geese in February 2012 and January-February 2013. Geese produce droppings at short intervals (every few minutes while actively feeding), which may remain visible for at least 2-3 weeks, depending on the amount of precipitation. Hence, dropping densities provide a good indicator of cumulative goose-use over a period of several weeks (Madsen & Boertmann 2008).

In 2012 the study area was limited to a 5x5 km area in the region of the AES St Nikola wind farm. Dropping counts were made at sampling points (a circle of 1m radius) across a systematic grid with 150 m separation between points. All fields of wheat known to have been occupied by goose flocks in the previous 2-3 weeks of the study were visited. Beyond this timescale, droppings were believed to be too disintegrated to be reliably detected, though this is highly dependent on recent weather conditions. Information on the condition of the crop, availability of standing water, and percentage snow cover was also recorded for each sampling point.

In 2013 following some preliminary analyses of the 2012 data, the study was expanded to cover a wider area, stretching from the north, near the Romanian border, south to Kaliakra Cape, and over a longer period of the winter. The methodology was refined in order to maximise the sample size. Sampling fields were chosen in areas with a range of wind turbine proximities. Fields were assigned to four strata on the basis of their turbine influence – high, medium, low and no turbine influence – based on the density of turbines within 2 km of a field. Geese tended to use a particular field for feeding for a short period (generally 2–5 days). Fields known to have been occupied by geese were then randomly selected from the different strata and sampled 3–5 days after the geese had stopped using that field. Sampling points were pre-defined in ESRI ArcGIS using a systematic grid with a random origin, placed across the field. The separation distance between sampling points varied depending on field size, but was chosen to roughly allow 20-30 plots to be sampled across the whole field with a separation between points of ≥50m. Fields that were too small to fit 20 plots at 50 m separation were eliminated from the study. Each field was visited 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 0.64 km^2 (n=39, SD=0.46, min=0.04, max=1.97).

Landscape elements as explanatory variables

Maps of landscape elements: field boundaries; surfaced roads; unsurfaced tracks; tree lines; and settlements (towns and villages) were generated from 1:5,000 Cadaster maps (Bulgarian Ministry of Agriculture, 2008) by digitising and storing in a geodatabase in ESRI ArcGIS. Power lines were digitised from a combination of 1:25,000 topographic maps (1985-1995), and Google Earth images (pre 2010). Wind turbine locations were obtained from the Bulgarian Society for the Protection of Birds (BSPB) database (last updated January 2014).

At each sampling location, values to describe the influence of turbines, tree lines, roads, tracks, power lines and settlements were generated in Arc GIS 10.2. For turbines, the distance from each sampling point to all turbines within a 2-km radius was obtained. The values of inverse distances for each sampling point were used to calculate the explanatory variable, as:

$$Turbine\ influence_y = \sum_{i=1}^{n_{(y)}} \left(1/d\right)^x$$

where n = number of turbines within 2 km of point y, d = distance of each turbine from y and x = the selected decay exponent.

This provides a measure of the influence of turbines on the sampling point. We assume that more distant turbines have less influence than nearby turbines, but the 'decay rate' of influence is unknown. In order to examine which decay rate fits the goose-use data best, the inverse distances were calculated using five different power functions (0.25, 0.5, 0.75, 1 and 2), where an exponent of 0.25 describes a very shallow decline with distance, and an exponent of 2 gives a steep decline with distance (Figure 3). Thus the 'turbine' variable was calculated in five different forms. The first step of our modelling was to evaluate which form had the best fit to the goose-use data (see below).

The linear landscape elements – tree lines, roads, tracks and power lines – were first split into 250 m sections, and the same inverse distance weighting approach applied, using distances to each line segment within 2 km of the sampling point, and using the same weightings applied to turbines; hence each of these variables existed as five different versions. Distance to the edge of the nearest settlement was chosen as the most important variable for describing the influence of settlement distance on dropping density and was determined for each sampling point.

Viewshed analyses were undertaken for each sampling point in order to describe the perceived 'openness' of the landscape from each point. Viewsheds were developed using a 26x26 m resolution ASTER Global Digital Elevation Model (DEM; 17/10/2011). The DEM was combined with height values from a tree lines raster, using an assumed average tree height of 15 m. Viewsheds used an offset of 0.5 m from the DEM to represent the approximate eye-level of an alert 'virtual' White-fronted Goose, and were calculated separately for radii of 100 m, 200 m, 500 m and 1,500 m around the sampling points. The proportions of pixels within each radius that were visible to our 'virtual goose' were used as parameters in the model. The four separate calculations for the four radii are analogous to the different exponents used to model turbines, tree lines and power lines. We selected the version with the best fit to the data as the first step in modelling.

Analysis

We aimed to model goose-use as a function of six landscape elements: turbines, power lines, tree lines, roads, distance to settlement and openness.

A negative binomial GLMM was developed using each sampling point (n=891) as an observation, and the number of goose droppings as the response variable. The six explanatory fixed effects were *turbine*, *power line*, *tree line*, *road*, *openness*, *and distance from settlement* (see above for how these were calculated).

Sampling points were clustered within fields, so we declared 'field' as a random intercept in all models. This effectively captures the between-field variation in the total amount of goose-use, which is due to field-level nuisance variables such as crop type, distance from roost, number of geese in the study area at the time of sampling and rate of dropping deterioration.

There remained the possibility of spatial autocorrelation among points within fields. We examined this using spatial correlograms (package NCF) on the standardised model residuals. Initial correlograms on the models indicated significant autocorrelation among points that were less than ca.90 m apart. To remove this problem, we 'thinned' the data by removing points such that no points within the same field were within 75 m of one another. One field was deleted at this stage, because thinning the points left it with <10 sampling points. This procedure left n=775 sampling points and n=38 fields. Subsequent correlograms indicated no spatial autocorrelation.

All explanatory variables were standardised and centred prior to analysis. These allow direct comparison of effect sizes among different explanatory variables, but the values of the explanatory variables are specific to the data-set, because they are relative to other values in the set. To create generalisable predictions (i.e. across the real landscape of Dobrudzha), the final model sets were re-run using the raw values for explanatory variables. All models were fit using R v.3.03 library LME4 (v.1.1-5), using Maximum Likelihood.

Model selection

There was just one version of the distance to settlement variable. For the remaining five explanatory variables, there were multiple versions, calculated using different spatial scales/decay rates around the sampling point (see above). We aimed to develop models containing only one 'best version' of each of these five variables.

In order to avoid undue data dredging, model selection was conducted in two steps. First, we used AIC to select the single best version for each of the five variables for which we had calculated multiple versions. Second, we used AIC to select the best model set from among a full candidate model set that comprised the best version for each variable.

Selection of best exponents for each explanatory variable

We initially ran univariate models for each version of each of the five variables that existed in more than one version, and made an initial selection of which version produced the best model (lowest AIC). Then, for each of these variables, we ran a set of full models containing all six explanatory variables. The models within this model set differed only in having a different version (exponent) for the variable of interest. The selected versions of the remaining five variables were those that had previously been selected. If the variable selection procedure indicated that the initial selection of best version based on univariate models had been incorrect, we iterated the models again, using the best version of the variable.

Selection of best models

A full model of the form:

Dropping count ~ distance to settlement + turbines + power lines + roads + trees + openness

was run (field as random intercept, see above), using the best versions of the explanatory variables.

All possible combinations (including the null) of these explanatory variables were modelled (n=64). No interaction terms were included; although it is reasonable to hypothesise that there may be positive interactions between explanatory variables in this system, the complexity of the models would lead to problems of convergence and interpretation.

A profile plot of ranked AIC values was examined to identify obvious discontinuities. There was a sharp discontinuity between models rank #8 and rank #9 (AIC difference of 11.8). Model rank 8 had a ΔAIC of 5.26, whereas ΔAIC of between 5 and 6 is widely considered an appropriate cut-off for a top model set. Hence, we selected the top eight models as the top model set (Table 2).

Model averaging (library AICmodavg) was used on the top model set to generate parameter estimates and their confidence intervals.

Model validation

Pearson residuals were strongly positive-skewed and heteroscedastic. It is unclear whether and to what extent this is a problem (see e.g. http://www.petrkeil.com/?p=393). Possibly the inclusion of two-way interactions would resolve the problem, but see above. Alternatively, relationships between explanatory variables may be non-linear. However, plots of Pearson residuals vs. explanatory variables indicated no obvious patterns.

Spatial autocorrelation was not present (see above) and variance-inflation factors indicated no multicollinearity among variables (using mer-utils.R). However, we manually removed outlying values for the explanatory variables and these had minimal impact on the model outcomes. Further, we examined Cook's Distance of the binomial models (see below). No values exceeded the 10th percentile of an F distribution with p and n-p df, where n=number of observations and p=number of estimated parameters (http://www.stat.berkeley.edu/classes/s133/Lr1.html).

Because of the skewed and heteroscedastic residuals from the negative binomial model, we also developed binomial models of the data, a simpler (though less sensitive) and more established method, in order to validate our results. The glmer from the lme4 package was used, with the same model selection and validation procedures, but with dropping count converted to a binomial 1/0 variable. The binomial model generated far more normally distributed residuals, and there was little difference in the model outcome (see below).

Prediction of habitat use at the landscape level

The resulting model averaged parameter estimates were used to predict habitat suitability for geese in cropped fields across the wider landscape of Coastal Dobrudzha. Rasters were created from derived values for each of the variables included in the model, using the same techniques described for the sampling points. A pixel size of 75x75 m was chosen for rasters of tree lines, power lines, turbines, roads and distance to settlements; while a lower resolution (300x300 m) was used for openness due to processing limitations.

Rasters of predicted habitat suitability were created by back-transforming the parameter estimates, to allow visualisation of the real data. Predicted values were converted to percentages of the maximum predicted habitat suitability (i.e. in the absence of landscape elements which deter them),

to aid interpretation of the maps. The maximum predicted habitat suitability for the entire area is less than that predicted from the model using the lowest values for the explanatory variables that occur in the real dataset (lowest turbine, tree line, power line and road scores; highest distance to settlement and highest visibility scores), thus the variables in the predicted dataset correspond well with those in the real dataset.

Predictive maps were generated to illustrate the influence of each variable individually (where parameters of other variables are set to zero), as well as describing the additive influence of all variables, using the parameter estimates from the top model set.

Results

The locations of sampling points within Coastal Dobrudzha are presented in Figure 4. The mean dropping count at points was 17 (range 0-243; SD=26.2; median=8; Figure 5). Zero dropping counts made up 32% (n=282) of samples. A summary of the distances from sampling points to landscape elements is presented in Table 1.

Negative binomial GLMMs

Best variable selection

For turbine, power line and tree line, the best fitting version of the variable, as measured by AIC of full models (containing all other explanatory variables) was with decay exponent =2. This is the highest rate of decline of weighting with distance that we tested. Thus our models suggest that goose response is primarily to features that are very close to them. For road, the best version was with a decay exponent of 0.75, implying that the influence of roads reduces less with distance than for the other landscape elements. For openness, the proportion of visible pixels within a 500 m radius of the point was the selected as the best version of the variable, suggesting that perceived openness at this scale is the most influential.

Model selection

Using centred and standardised explanatory variables, all eight of the top models contained the turbine, power line and tree line variables (Table 2). Openness also had a high relative importance, whereas settlement and road were less important (Table 3). High goose-use was associated with low turbine influence, low power line influence and low tree line influence, and the confidence limits of the parameter estimates for these variables did not approach zero. In our data-set, power lines had the greatest influence (most negative parameter estimate), followed by tree lines and then turbines. High goose-use was also associated with high openness scores. Although the 95% confidence limits do not overlap zero, the effect was relatively small. Goose-use was associated with low road influence and higher distance to settlement, but in both cases the 95% confidence limits heavily overlapped zero.

Binomial GLMMs

The binomial GLMMs generated very similar models to the negative binomial GLMM (Table 4).

In selection of best variables, the decay exponent of 2 was again chosen for turbine, power line and tree line, whereas for road, exponent =1 was chosen as the best version. Openness at the 500 m radius was again chosen as the best version of this variable.

The main model selection process produced the same set of eight top models with ΔAIC <6, although in a slightly different order, with the top binomial model being the full model with all six explanatory variables. The relative importance of variables was also very similar in the binomial models, although openness was markedly less important in the binomial models, and road and settlement somewhat more important (Table 5).

In the binomial models there were strong, significant negative effects of power line, tree line and turbine on the probability of goose occurrence. There was a positive association of probability of occurrence with large distance from settlement, low road influence and high openness, but the 95% confidence limits for all three variables marginally overlapped zero.

Prediction at landscape scale

Maps of predicted habitat suitability for all cropped fields across the study region, were generated using the parameter values included in the top model set from the negative binomial GLMMs, for each of the individual landscape elements in the current landscape (Figure 6a-f), and, in addition, using the GIS layer of all planned and consented wind turbines to simulate the potential future extent of wind farms in the area (Figure 6g). Prediction maps incorporating the additive influence of multiple landscape elements were then generated; firstly, for the current landscape, in the presence and absence (parameter estimate for turbine set to zero) of operational turbines (Figure 6a and 6b respectively); and then with inclusion of the potential future turbines (Figure 6c).The maps are presented side-by-side to allow comparison of the influence on habitat suitability of different scenarios of turbine distribution in the landscape.

The relative habitat suitability of the landscape as a consequence of individual and combined landscape elements is summarised in Table 6. Figures are expressed as percentages of the maximum habitat suitability predicted in the absence of any influence from each of the studied landscape elements in turn, and are averaged from raster values of the prediction maps (Figures 5 & 6; see above). In the current landscape, individually, i.e. when parameters of all other elements are set to zero influence, tree lines and power lines result in the biggest average percent reduction in habitat suitability (>20% each), while operational turbines result in a 13% reduction in habitat suitability, which is consistent with the influences of these variables predicted by the model. The potential future turbine scenario would result in a 46% reduction in suitability.

When parameter estimates for all elements in the current landscape are included, the average predicted habitat suitability within the study area is 48% of the maximum (n=133,554 pixels; SD=27; Table 6). Excluding the influence of operational turbines i.e. with parameter estimates for operational turbines set to zero), the average predicted habitat suitability is 54% (n=133,554 pixels; SD=25.9) of the expected maximum. In the hypothetical future turbine situation (whereby all planned and approved turbines are constructed) an average habitat suitability of 29.7% (n=133,554 pixels; SD=26.9) of the expected maximum would result. Figure 8 shows the distribution of predicted habitat suitability values, for the current landscape - in the presence and absence of operational turbines - and in the potential future scenario, among pixels of the derived raster layers (Figure 7).

Discussion

We have shown that the fine-scale (within-field) distribution of geese in the study area, which encompasses a core part of the Dobrudzha goose wintering area, is very strongly and negatively associated with tall landscape elements, specifically power lines, tree lines and wind turbines. The

effect of these features is very localised: our best fit models suggest that their influence on goose-use at 100 m distance is only 25% of their influence at 50 m.

The negative association of goose distribution with power lines is substantially stronger than that with tree lines, which is in turn stronger than with turbines.

There is some evidence that goose-use is also negatively associated with the presence of roads, and proximity to settlements, and is positively associated with high openness. However, these effects are relatively small and have low confidence.

As a result of these associations we have been able to investigate how this translates into the landscape-scale impact of these features (i.e. combining the statistical estimates of the associations with the 'real-world' distribution of the features). Relative habitat suitability across the current landscape is on average 48% of the maximum expected in the absence of these key landscape elements (Table 6). By excluding the influence of existing wind turbines i.e. simulating the current landscape in the absence of turbines, habitat suitability is predicted to be 6% higher than in the present situation (54% of the predicted maximum). In the hypothetical future scenario in which all planned and consented turbines in the region are constructed, the average habitat suitability across the region is predicted to be 18% lower than the figure predicted for the current landscape (30% of the maximum expected in the absence of key landscape elements that deter them). In this scenario wind turbines alone would cumulatively reduce the overall suitability of the landscape by 24%.

In effect, operational turbines are predicted to account for an effective loss of 45 km^2 of the total area of cropped landscape (748 km^2) mapped here. An additional 134 km^2 (179 km^2 in total) could effectively be lost (i.e. of reduced suitability for geese) in the future if all planned and approved turbines were constructed. Predictions of effective habitat suitability/habitat loss are based on the preconception that all of the cropped landscape is seeded with winter wheat or a crop of equivalent suitability for geese. However, due to the crop rotation system in Dobrudzha, only around 50% of agricultural land is seeded, and thus available to feeding geese, in any one winter. More accurate predictions for a given winter are therefore dependent on the seasonal distribution of available feeding areas.

The prediction maps (Figure 7) show the distribution of influences from turbines on habitat suitability across the landscape, with patches of relatively low habitat suitability occurring around clusters of turbines, e.g. in the region of the AES Sveti Nikola wind park in the southern central part of the region. This cumulative influence of large numbers of turbines is further highlighted in the mapped scenario in which all planned and approved turbines are operational: in this scenario, few areas of high goose-use would remain in the southern half of the region, particularly to the south west of the town of Shabla and to the west of Durankulak, around the villages of Smin, Chernomortsi and Zahari Stoyanovo (Figure 1).

Availability of sufficient good quality foraging habitat is vital to ensuring individuals meet their daily energy requirements and maintain good body condition for their spring migration to the Russian Arctic. Poor body condition driven by reduced access to resources in winter may have knock-on impacts on individual fitness and reproductive success, and potential population level impacts (Marr, Hobson & Holmes 1998, Norris 2005, Robb et al. 2008). For the already threatened Red-breasted Goose, additive or synergistic effects from multiple sources of resource limitation e.g. habitat

displacement and hunting disturbance, could potentially cause further impacts on the species or limit its recovery.

Although we predict the magnitude of effective habitat loss in the region due to tall landscape elements, there are important limits to the inference that can be made. We do not know how much habitat is needed by the current, or in the case of Red-breasted Geese, recovering or future goose population. Hence we do not know whether habitat availability is currently limiting, or whether there is substantial 'spare capacity', such that further effective habitat loss would not actually translate into population-level impacts. Further, geese presumably distribute themselves in an 'ideal free distribution'; that is, they occupy the most favourable sites first, and then occupy progressively less profitable sites. Hence their apparent avoidance of areas close to tree lines, power lines and turbines may not necessarily reflect an absolute limitation on their use of these areas, but rather a relative preference for other areas. If less of the preferred habitat were available, it is unclear whether the geese would be able successfully to occupy areas that are currently avoided close to tall landscape elements, and whether behavioural adaptations such as increased vigilance, disturbance or predation would occur, potentially with consequent fitness costs.

This study is by far the most comprehensive yet conducted of goose displacement by landscape elements; it comprises many hundreds of sampling points in almost 40 fields, spread over 23 km^2, and influenced by multiple different landscape elements - power lines, tree lines and wind turbines - in various configurations and under varying influence of other factors such as topography. The analysis simultaneously assesses the influence of multiple types of landscape element: in Dobrudzha, wind turbines are invariably built around the edges of fields, close to tree lines and tracks, so it is impossible to infer influences of one feature without consideration of others.

The degree to which geese may have habituated to tall landscape features in Bulgarian Dobrudzha, since their installation, is unknown. While some evidence of behavioural adaptation to changing landscapes created by wind farms exists for Pink-footed Geese around two wind farms in Denmark over a 10 year period (Madsen & Boertmann 2008), few other studies of long enough duration and for other species and situations are available to suggest this is likely. The large numbers of wind turbines consented and proposed in Dobrudzha, in combination with a wide range of other influences on goose distribution, suggest that a precautionary approach to further construction and planning consents should be exercised.

For the first time we are able to assess the influence on goose-use of multiple turbines in varying degrees of proximity, rather than simply estimating distance to the nearest turbine, and to evaluate the rate at which the influence of turbines (and other elements) decreases with distance. Finally, we are able to extrapolate our results across the landscape of Dobrudzha to make predictions about the landscape-scale effective habitat loss caused by tall landscape elements.

This study is correlative in nature rather than experimental (such as a before-and-after study). We cannot therefore rule out that the apparent negative association of geese with tall landscape elements is not causal, but rather a by-product of other factors that are correlated with the presence of turbines, power lines or tree lines. However, this seems unlikely as these landscape elements do not share many features apart from their height.

It is also important to note that this study is an examination of within-field goose distribution. It is predicated on the fact that geese have chosen to forage in the study fields, and it examines how

they distribute themselves within those fields, and the degree of micro avoidance/displacement from landscape elements. A separate question relates to the factors determining field choice (or even larger-scale site selection or avoidance), and whether and how the proximity of features such as turbines, power lines etc affects these decisions. These questions are addressed for Bulgarian Dobrudzha in a separate study; though note that this work too is correlative rather than before-and-after-control-impact.

Further refinements to the modelling method may be revealing. In particular it would be useful to examine interactions between landscape elements, because there may be synergistic effects. It may also be useful to model non-linear patterns of goose response (e.g. threshold and asymptotic responses) using Generalised Additive Mixed Models. However, these approaches are not readily applied to the data at present. Alternative data distributions such as zero-inflated negative binomial and Poisson-lognormal might potentially be appropriate and could improve goodness-of-fit, but these were not implemented here.

Conclusion

We have detected and quantified localised fine-scale avoidance of tall landscape elements by geese in Coastal Dobrudzha, Bulgaria. Power lines, tree lines and wind turbines are the most influential in determining within-field goose distribution, with geese showing preference for areas away from multiple features in close proximity. Wind turbines exhibit additional influence on habitat suitability in a landscape where the habitat is already of varying suitability for geese. While at the landscape scale their influence appears relatively small, areas with high turbine densities show greater reduction in habitat suitability at a local level. Further study to investigate the factors influencing field choice across the landscape may indicate whether such clustering of turbines also causes avoidance or reduced use of otherwise suitable feeding habitat at a larger scale e.g. at the field level.

We predict considerable further reduction in habitat suitability in Coastal Dobrudzha in a scenario where all planned and approved turbines become operational. The derived model also allows predictions for different, potentially more realistic, future turbine configurations, and will form part of an important development planning tool to be developed under the 'Safe Ground for Red-breasts' project (LIFE09/NAT/BG/000230) funded by the Life financial instrument of the European Community.

Acknowledgements

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Tables

Table 1. Summary distances from sampling points to nearest landscape elements included in top model set (n= 891). Note that for tree lines, roads, power lines and turbines, distance weightings were applied (see text), so values used in the modelling do not reflect the actual distances from the table.

Landscape feature	Mean	Max	Min	SD
Tree lines (m)	586.57	2550.62	2.82	671.33
Roads (m)	1100.45	2854.93	0.85	661.67
Settlements (m)	1461.1	3181.34	16.51	697.33
Power lines (m)	1084.1	2376.39	9.09	671.33
Visibility (% visible pixels in 500m radius)	11.74	54.36	1.02	6.63
Turbines (m)	4864.7	16712.4	65.42	4720.38

Table 2. Top model set explaining variation in goose-use in sampling points (negative binomial models).

| Model number	Distance from settlement	Turbines	Openness	Power lines	Tree lines	Roads	*df*	ΔAIC	weight
m1		+	+	+	+		7	0.00	0.32
m2		+	+	+	+	+	8	0.89	0.21
m3	+	+	+	+	+		8	1.18	0.18
m4	+	+	+	+	+	+	9	2.52	0.09
m5		+		+	+		6	2.86	0.08
m6		+		+	+	+	7	3.80	0.05
m7	+	+		+	+		7	3.84	0.05
m8	+	+		+	+	+	8	5.26	0.02

+ = included in the model

Table 3. Average model coefficients, 95% confidence intervals and relative importance for fixed effects in top model set (negative binomial models).

Fixed effects	Parameter estimate (with shrinkage)	5% CI	95% CI	Relative importance
(Intercept)	1.57	1.20	1.95	-
Power line	-4.00	-5.08	-2.93	1.00
Tree line	-2.12	-2.90	-1.34	1.00
Turbine	-0.57	-0.82	-0.32	1.00
Openness	0.12 (0.093)	0.01	0.22	0.80
Road	-0.16 (-0.059)	-0.47	0.16	0.37
Distance from settlement	0.11 (0.039)	-0.15	0.38	0.34

Table 4. Top model set explaining variation in goose-use in sampling points (binomial models).

	Distance from settlement	Turbine	Openness	Power lines	Tree lines	Roads	*df*	ΔAIC	weight
m1	+	+	+	+	+	+	8	0.00	0.23
m2		+	+	+	+	+	7	0.46	0.18
m3	+	+		+	+	+	7	0.53	0.17
m4	+	+	+	+	+		7	1.03	0.14
m5		+		+	+	+	6	1.20	0.12
m6	+	+		+	+		6	1.68	0.10
m7		+	+	+	+		6	3.47	0.04
m8		+		+	+		5	4.44	0.02

+ = included in the model

Table 5. Average model coefficients, 95% confidence intervals and relative importance for fixed effects in top model set (binomial models).

Fixed effects	Parameter estimate (with shrinkage)	5% CI	95% CI	Relative importance
(Intercept)	0.69	0.17	1.21	-
Power line	-5.0	-7.35	-2.75	1.00
Tree line	-2.39	-3.39	-1.38	1.00
Turbine	-1.30	-1.80	-0.80	1.00
Road	-0.90 (-0.63)	-1.83	0.03	0.70
Distance from settlement	0.43 (0.27)	-0.04	0.81	0.63
Openness	0.18 (0.10)	-0.00	0.35	0.58

Table 6. Predicted habitat suitability across the agricultural landscape of coastal Dobrudzha, expressed as a percentage of the maximum expected suitability, and including the percent reduction in habitat suitability; as a consequence of individual and combined landscape elements. Predictions are based on the parameter estimates from model averaging, and are averaged from raster values mapped across all crop fields of the study area.

| Explanatory variable	Mean habitat suitability (% of max.)	SD	n pixels	% reduction in habitat suitability
Tree lines	79.6	23.1	133,554	20.4
Roads	93.9	5.8	133,554	6.1
Settlements	84.6	3.7	133,554	15.4
Power lines	79.7	27.9	133,554	20.3
Openness	99.94	0.009	9,862	0.06
Turbines_current	87	23.7	133,554	13
Turbines_future	54.1	37.2	133,554	45.9
All variables (excl. turbines)	53.7	25.9	132,121	46.3
All variables (incl. turbines)	47.7	27.4	132,121	52.3
All variables(incl. future turbines)	29.7	26.9	132,121	70.3

Figures
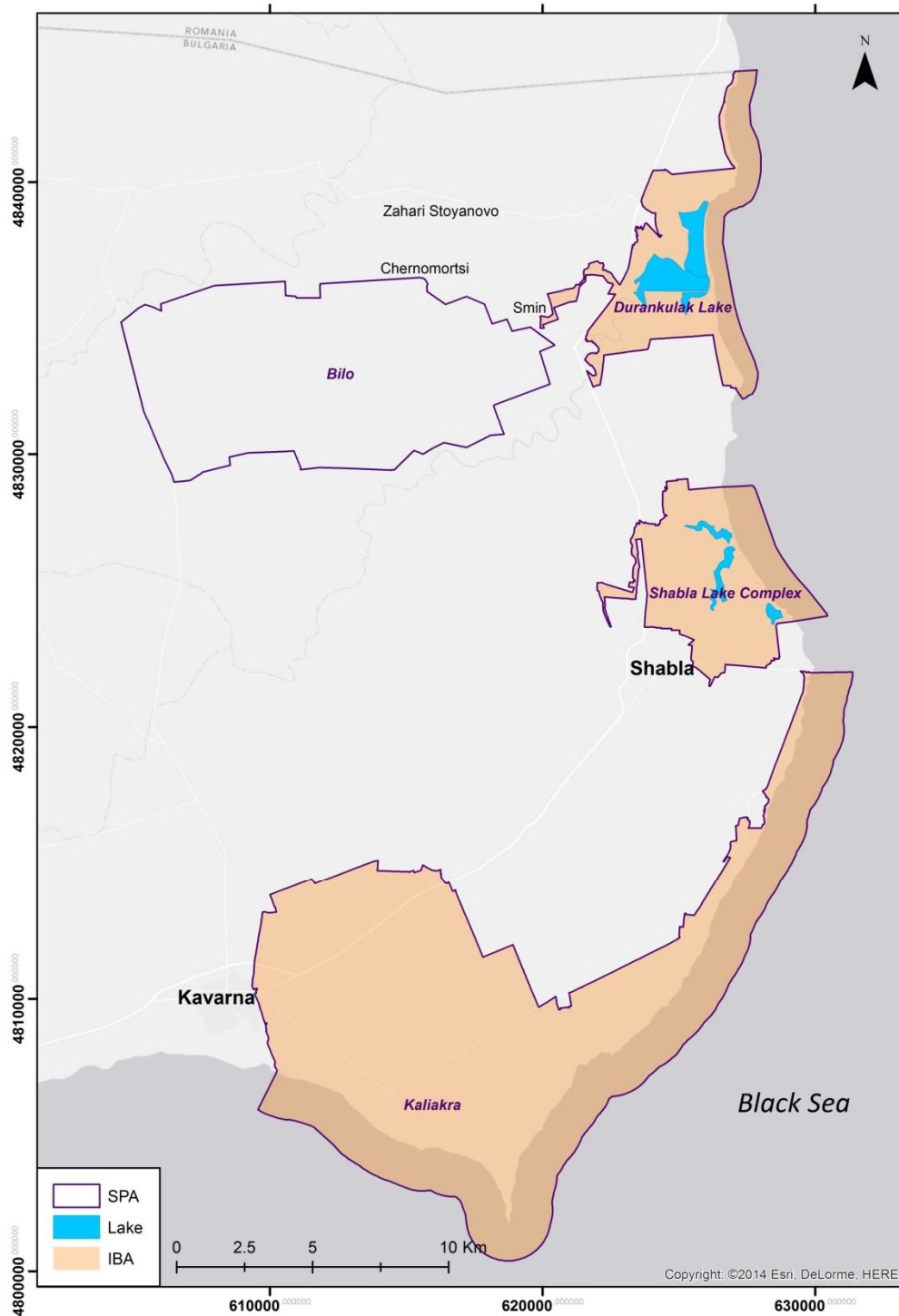
Figure 1. Location of study area in Coastal Dobrudzha, Bulgaria, including boundaries of IBAs and SPAs important for Red-breasted Geese[1], major roosting lakes for geese, and places referred to in the text.

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[1] In December 2013 Kaliakra SPA was expanded to cover the entire area of the IBA. Bilo was also designated an SPA in late 2013, over the course of this study.
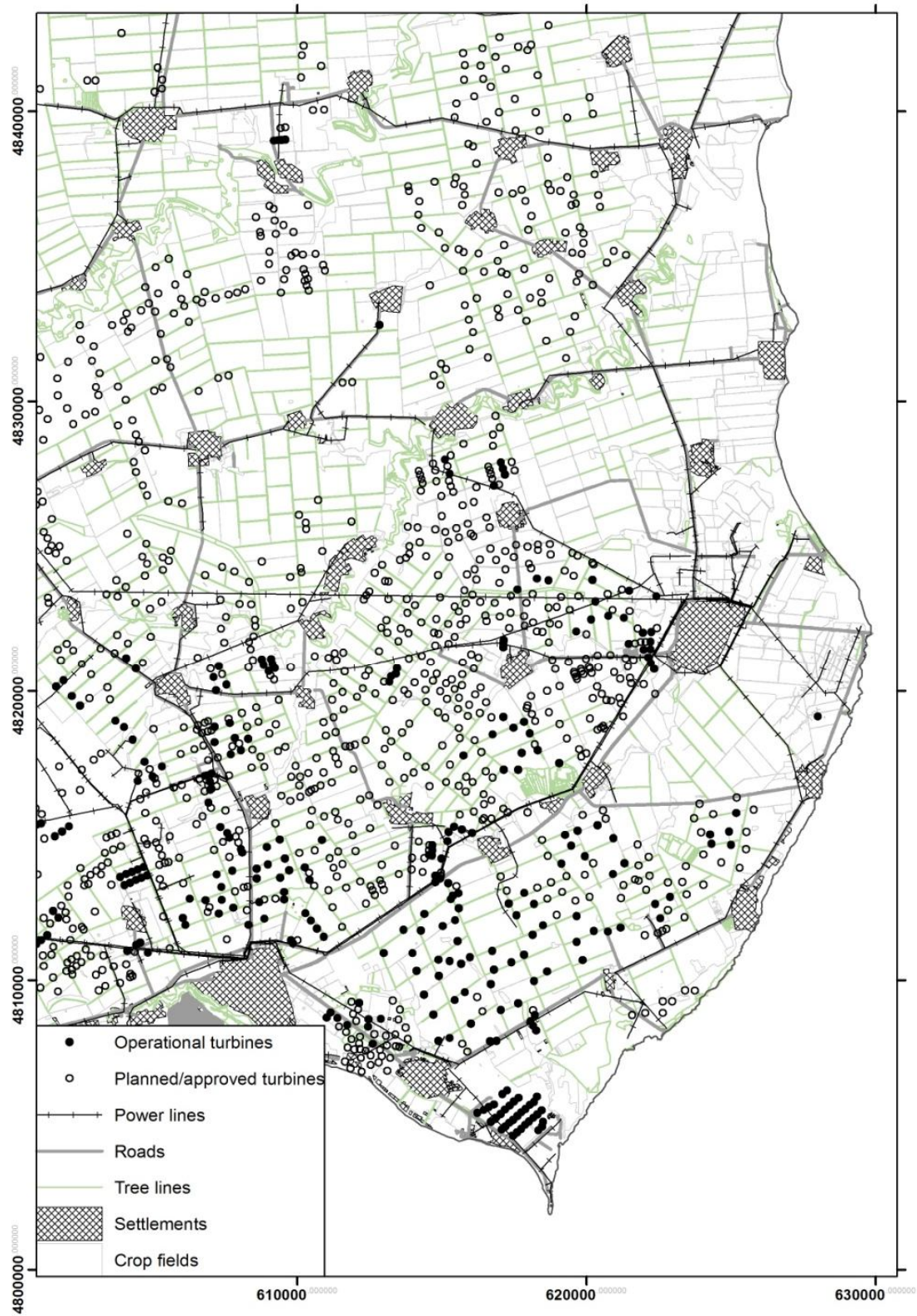
Figure 2. Distribution of existing landscape elements, including locations of operational, planned and approved wind turbines, within the area of Bulgarian Dobrudzha included in this study.
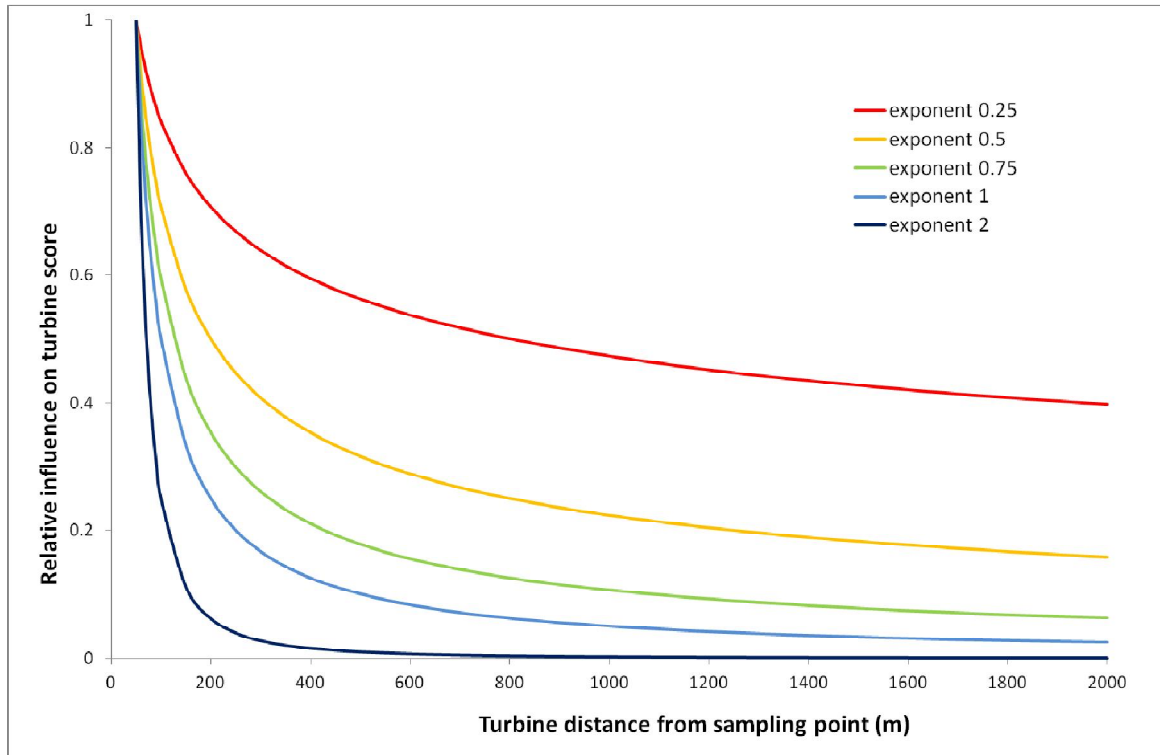
Figure 3. Illustrative graph showing how the weighting of individual features (such as turbines) decreases with distance from a sampling point, for the different exponents tested in the models.[2]

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[2] Line represents the decay with distance modelled by each of the five exponents tested in our models. At an exponent of 0.25, distant features have a relatively large weighting, whereas at exponent of 2, distant features have very low weighting. Testing the fit of different exponents to the goose-use data allows us to explore the degree to which geese respond to features in a wide area around the point, or only to features that are very close.
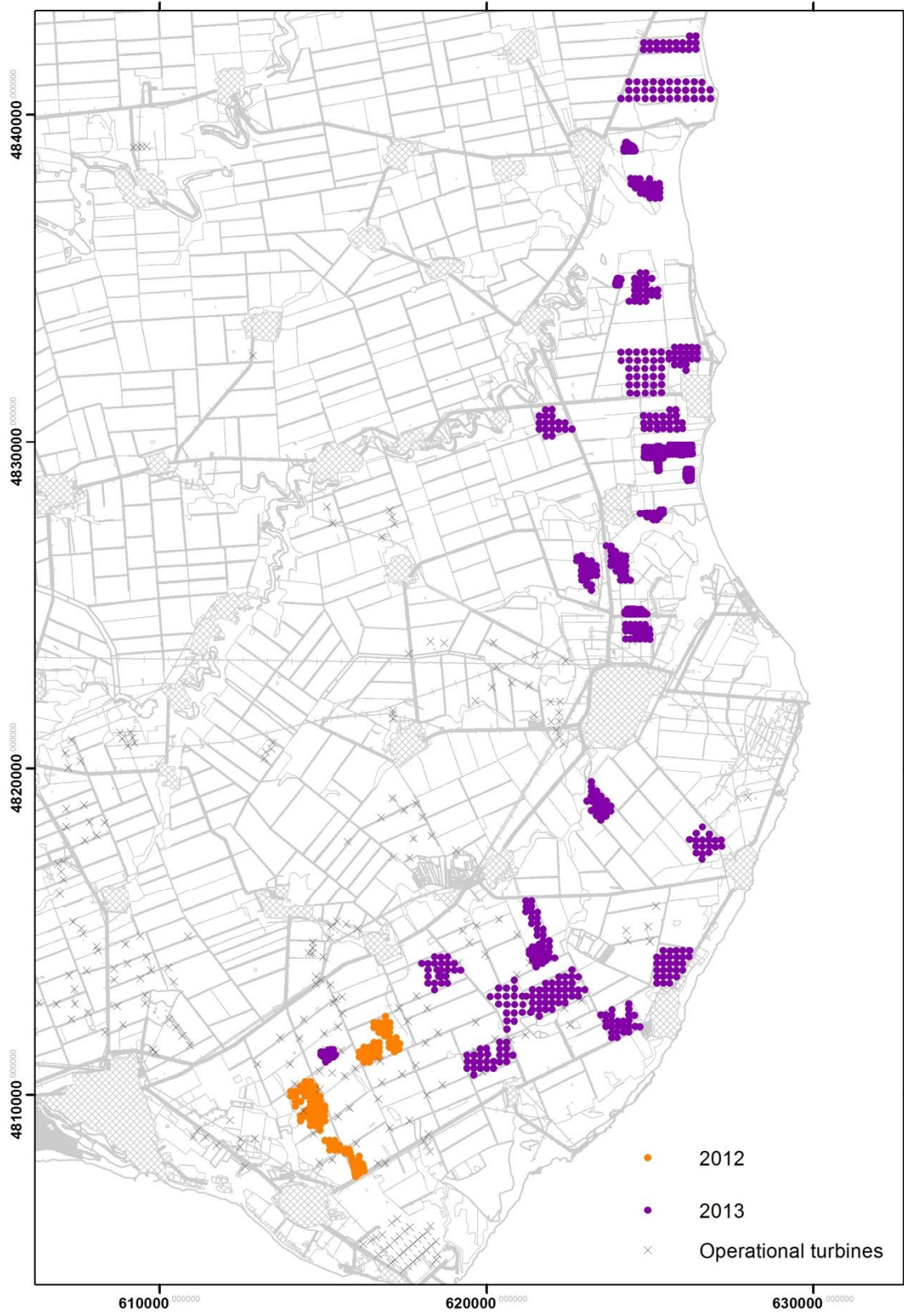
**Figure 4.** Sampling point locations visited in Bulgarian Dobrudzha, 2012 and 2013.
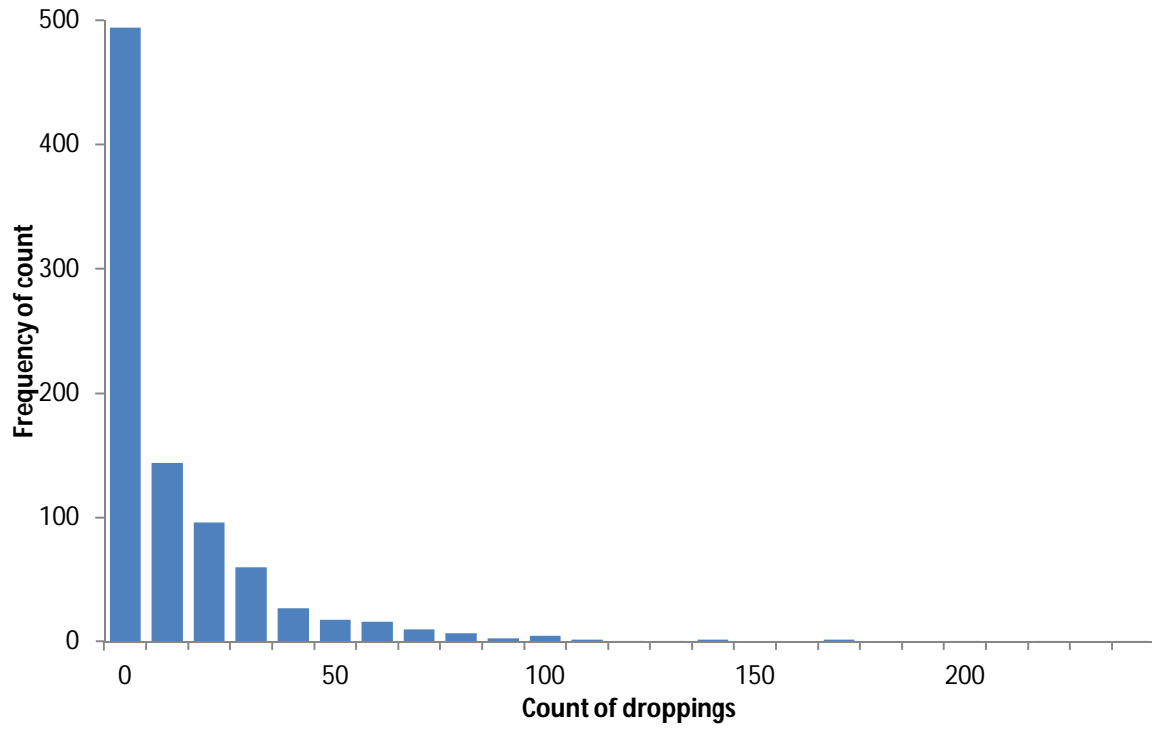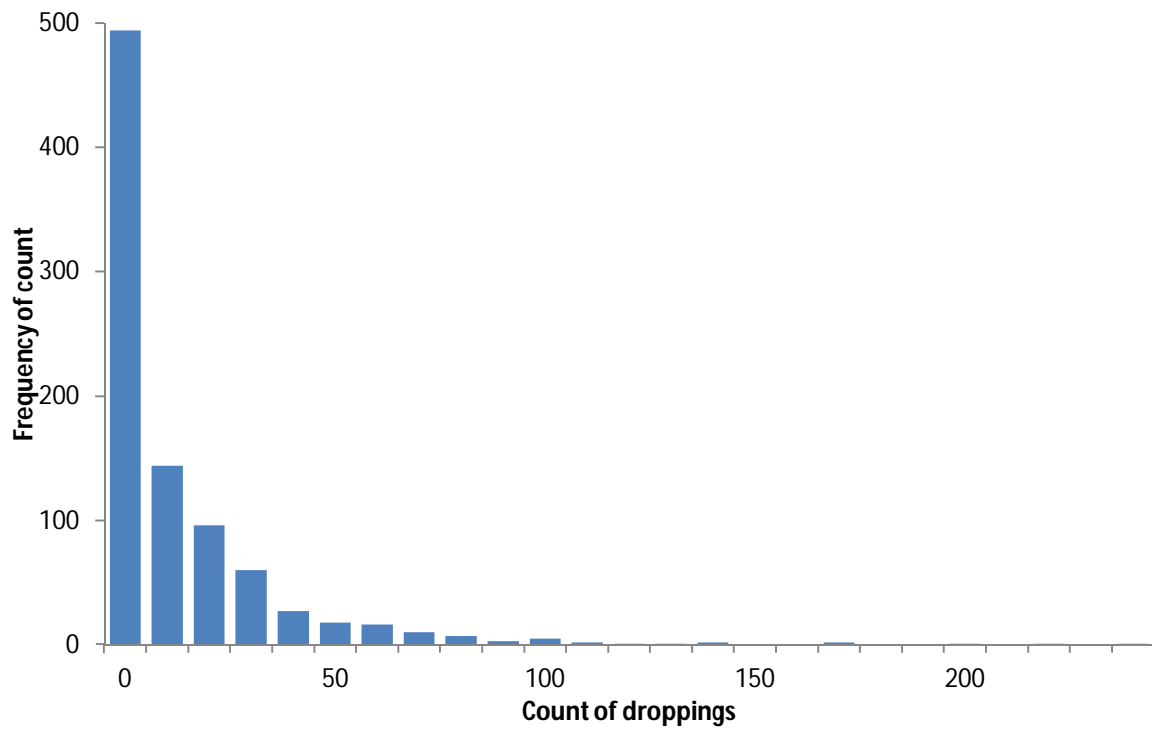
Figure 5. Frequency distribution of goose dropping counts among 891 sampling points (mean=16.8; SD=26.2; median=8)
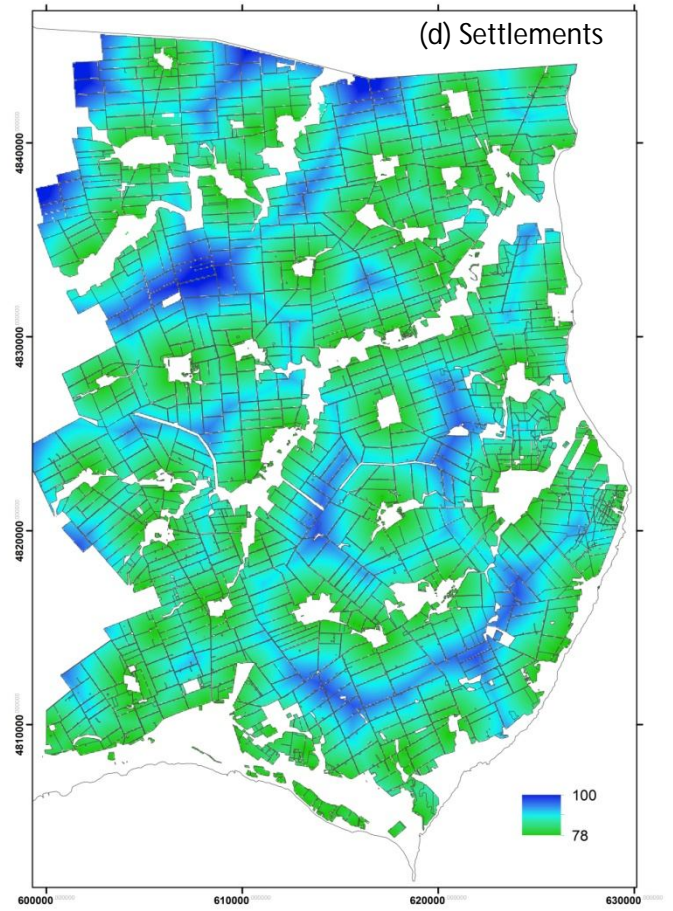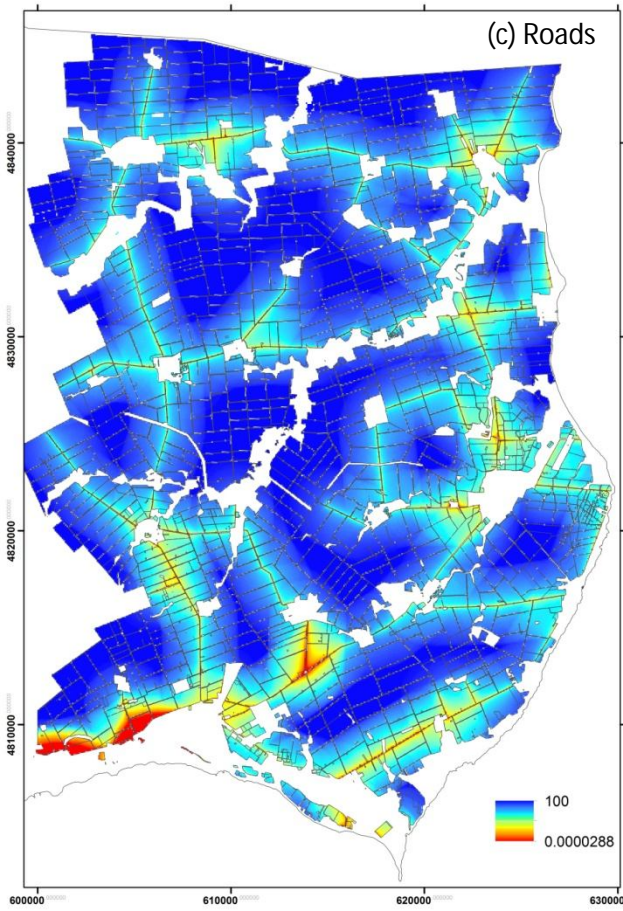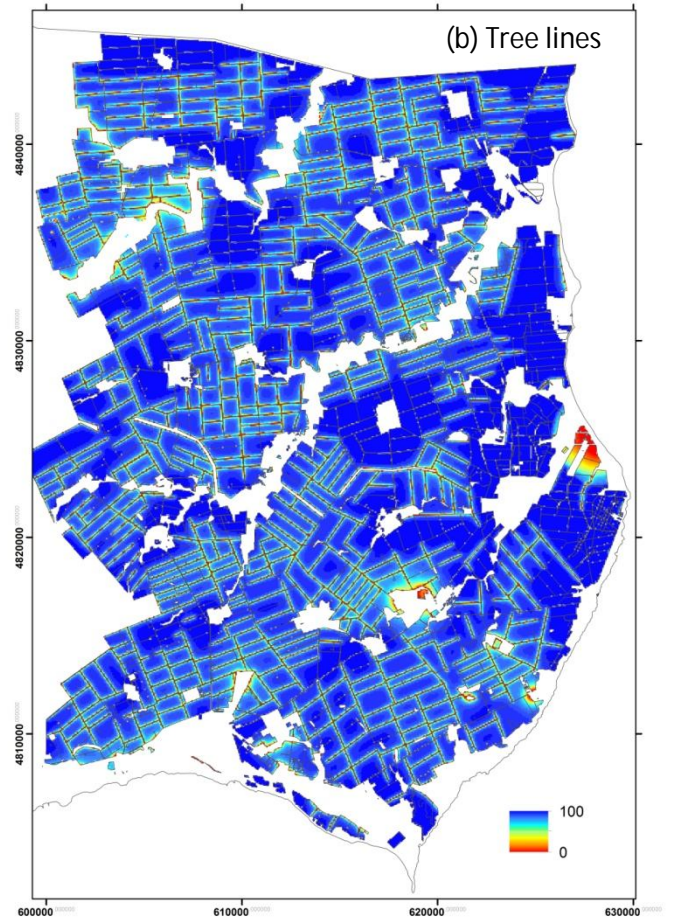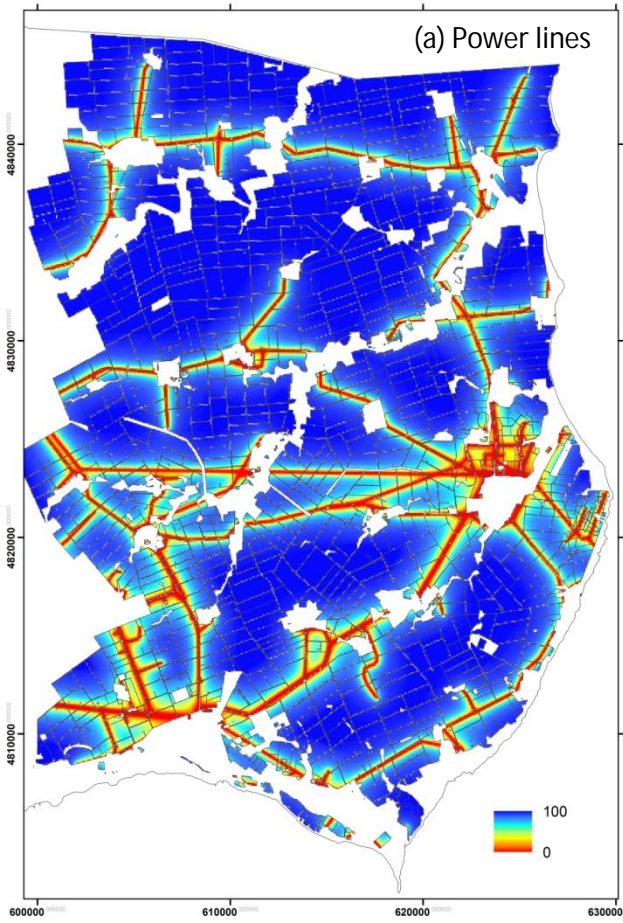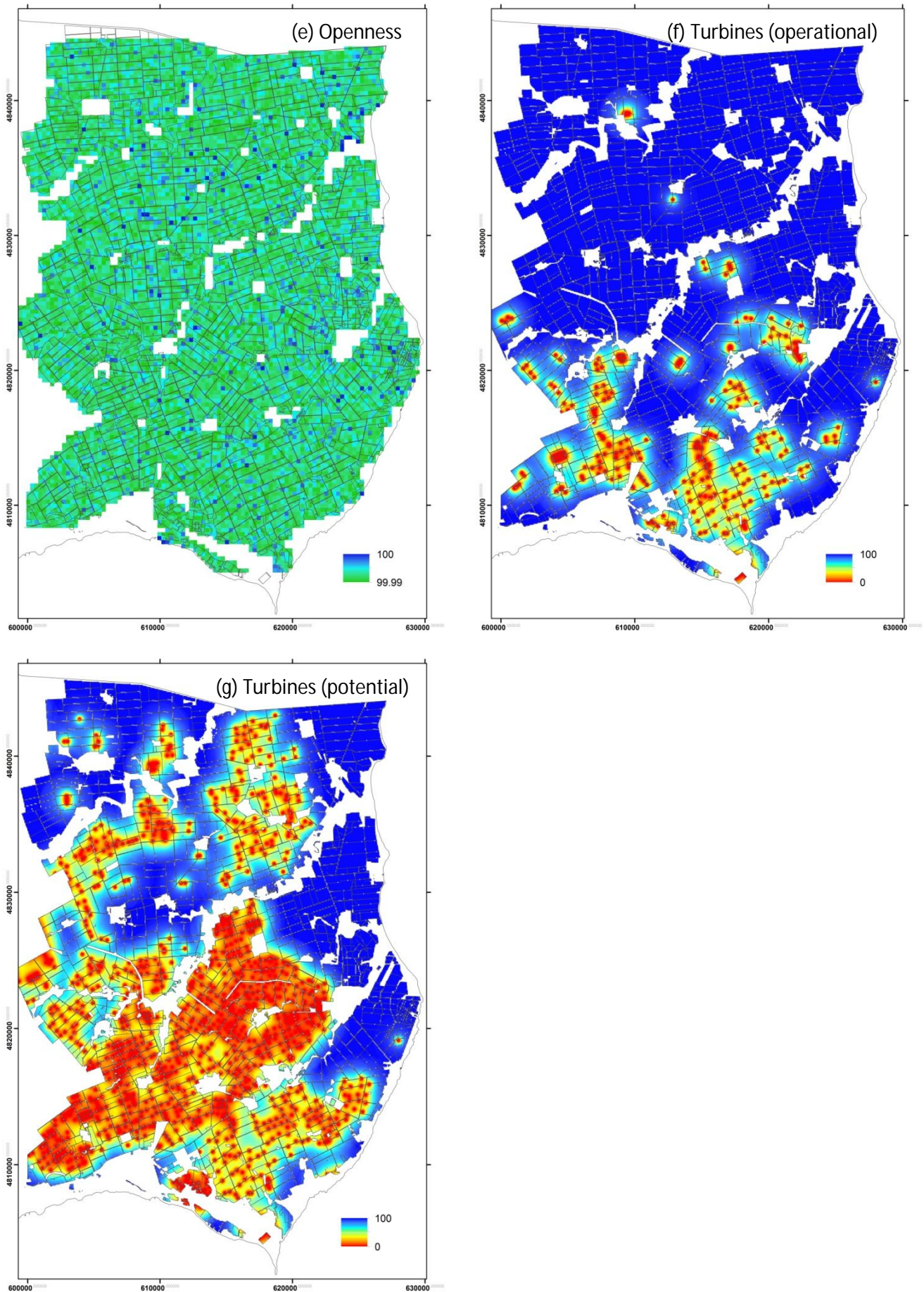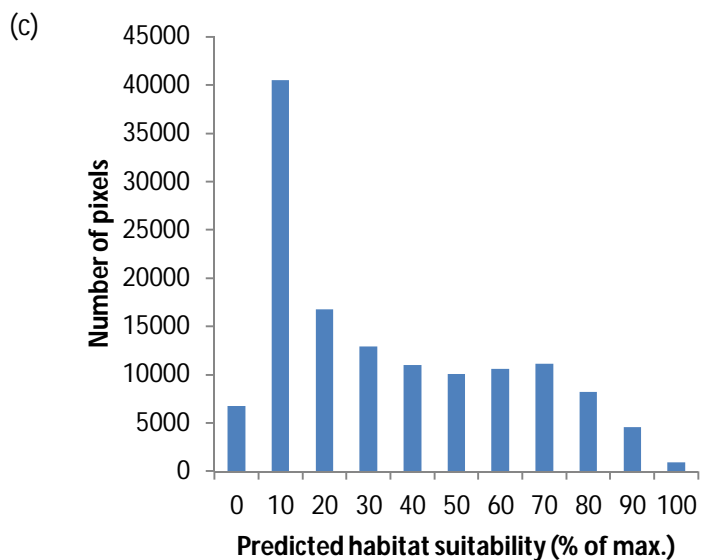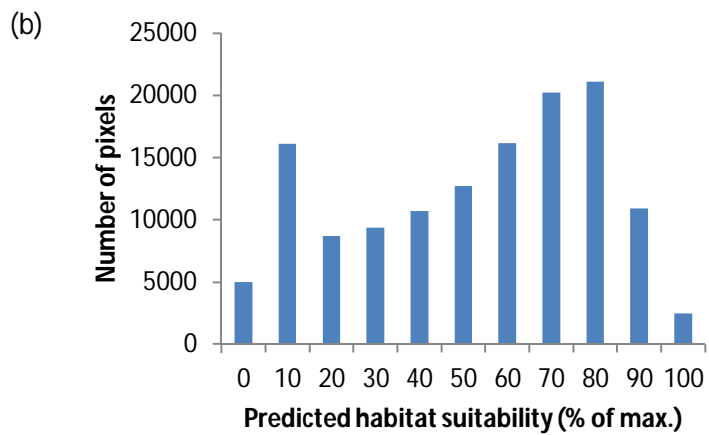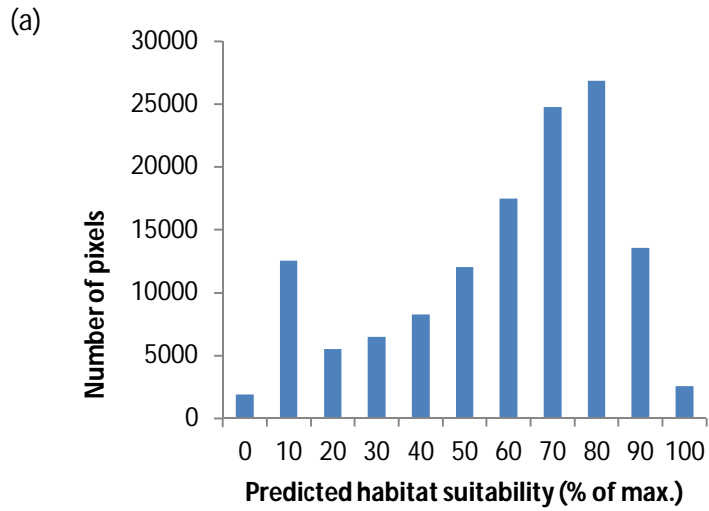
Figure 6. Predicted habitat suitability as a percentage of the maximum suitability predicted in the absence of any of the modelled landscape elements (bluest areas); derived from back transformed averaged model parameters applied to values of each variable across the cropped landscape (a-g).
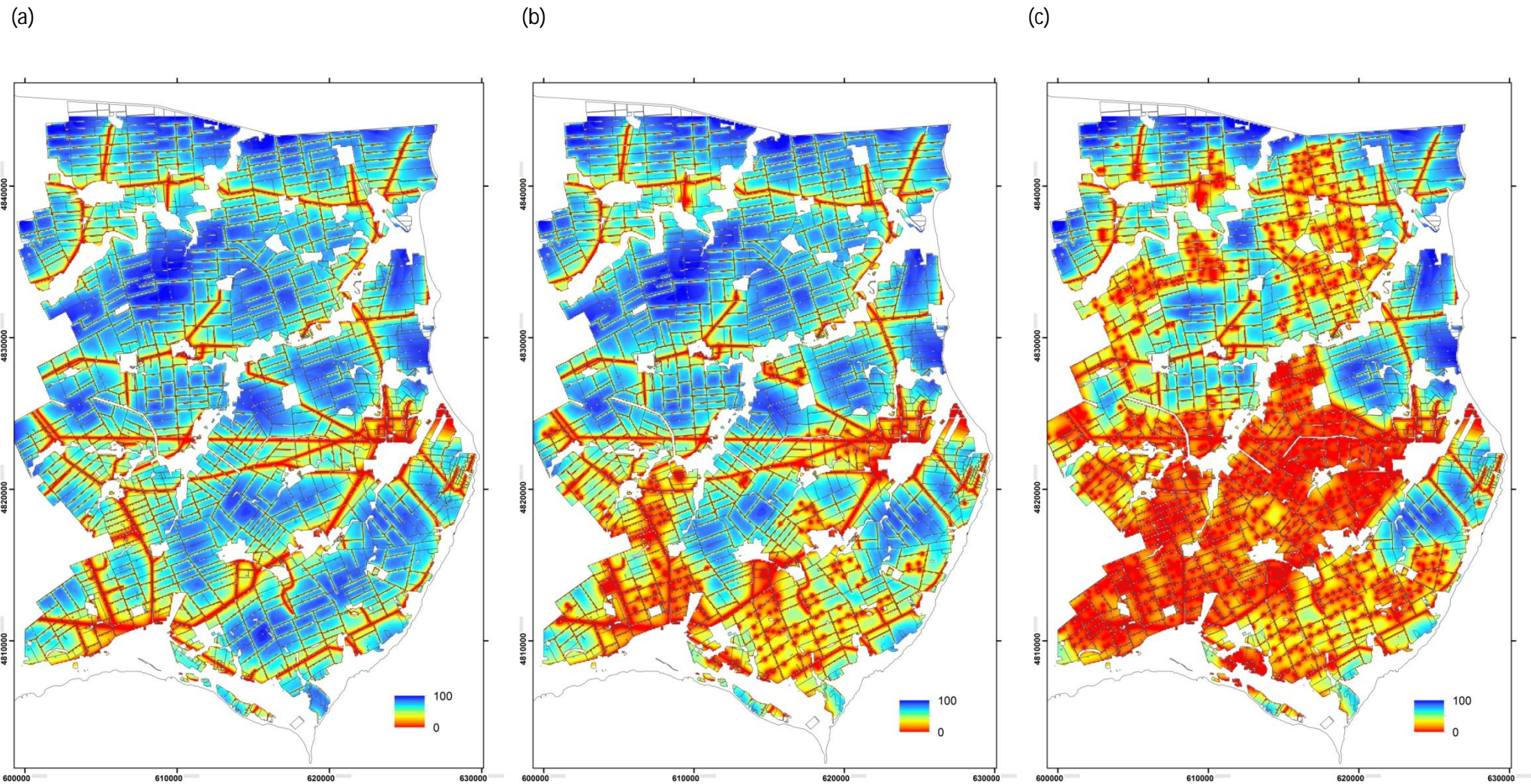
Figure 7. Predicted relative habitat suitability as a percentage of the maximum suitability predicted in the absence of any of the modelled landscape elements (bluest areas); derived from back transformed model parameters applied to (a) values of all variables in the present landscape, with zero influence of turbines; (b) values of all variables, including *currently operational* turbines, in the present landscape; and (c) values of all variables including all *operational*, *planned* and *approved* turbines i.e. the potential future scenario.

Figure 8. Frequency distributions of predicted habitat suitability as a percentage of the maximum, due to the influence of (a) variables in the current landscape, *excluding* wind turbines; (b) variables in the current landscape, *including* operational wind turbines; and (c) variables in the current landscape and all planned and approved turbines (the potential future scenario), across the agricultural landscape of Coastal Dobrudzha (n=132,121 raster pixels).