Combining satellite data and resource selection functions for large scale habitat mapping of wildlife species - preliminary results for capercaillie and black grouse

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Abstract - The main aim of this study is to investigate the suitability of 1) combining map data derived from the Landsat satellite and other sources with statistical methods for analyzing habitat selection and making probability maps for large areas, and 2) testing a sampling design where volunteers arbitrarily select a walking route within specific areas for conducting transects surveys of wildlife.

We selected capercaillie and black grouse as example species in this case study. The analysis uses resource selection functions (RSF) to identify the relationship between locations of birds and habitat variables derived as percent coverage within buffer areas. We also include one distance variable.

Most of the variables are based upon classified products from analysis of multi-temporal (May, July, October) satellite images (Landsat7). In addition some variables are derived from a national topographic map and a land inventory map.

Keywords: satellite data, wildlife habitat analysis, resource selection functions, large scale analysis, black grouse, capercaillie.

1. INTRODUCTION

There is an increasing demand for better and more precise knowledge of wildlife populations, also regarding factors explaining the spatial distribution of individuals. Habitat modeling with the use of resource selection functions (RSFs) is one way of both identifying attractive and repellent factors affecting the distribution of individuals and making probability maps of the distribution (Manly et al., 2002). RSFs are efficient tools for species management when they are combined with observational data of animals and habitat information from satellite data or other sources in a GIS (Boyce and McDonald, 1999).

Capercaillie (*Tetrao urogallus*) and black grouse (*Tetrao tetrix*) are managed as game species in Scandinavia, but are vulnerable and threatened in western and central Europe. The populations have declined due to large changes in forestry practice, but also as a result of human disturbance, predation, pollution, collisions and exploitation (Storch, 2000). The management authorities and hunters in Norway seek more precise data about these species. Habitat selection at a local scale is well studied and documented for these species (Storch, 2000), while habitat selection on a broader scale (landscape and regional) is not and needs a stronger focus (Storch, 1997a, b).

Tetraonids depend on large, continuous habitat. Capercaillie males and females rely on 30 – 90 km^2 large areas (Rolstad and Anderson, 2003). A medium sized lek and the habitat used by individuals in connection with the lek corresponds to an area of 300 km^2. In Finland Kurki et al. (2000) experienced lowered breeding success due to landscape fragmentation.

Due to management interests of capercaillie and black grouse and the need for updated information on population status, distribution and threat factors we have investigated the possibility of identifying important habitat factors and making maps of potential distribution by linking the species to habitat variables identifiable in satellite images or available on maps from other sources.

When habitat data is available in a GIS covering large areas it is possible to adjust for a non-random sampling design by recording the search pattern of the observer. We have looked at this possibility by equipping volunteers with handheld GPS receivers.

2. STUDY AREA

The study area, Østfold county, is situated in the southeastern part of Norway. Østfold county is 4 100 km^2 in total with a relative flat topography ranging from sea level to 336 m.a.s.l. Western parts are below the marine limit, and those areas are characterized by farm land and urban areas. Above the marine limit the landscape is dominated by forests of Norway spruce (*Picea abies*) at lower elevation and Scots pine (*Pinus sylvestris*) on ridges.

3. METHODS

To get observational data (units of habitat occupied) of bird's locations we divided Østfold county into smaller sampling units. Within these units volunteers, mostly hunters and others with good knowledge of these species, picked out an area to search for birds. In the search area one or two persons walked along a transect and used pointing dogs to search for birds. Both the search track and the bird's position where recorded on the GPS. The location of transects and the walking routes where selected arbitrarily by the observers

(Fig. 1). To get information of units of habitat available we selected random points along the recorded footpaths. We measured the distance to the coast line and calculated percent coverage of different habitat variables within buffers of 50, 500 and 5000 meters around each point. The buffer distances were chosen with the aim of covering bird habitat selections at different spatial scales. The 5000 meter buffer should represent grouse habitat selection on a coarse landscape scale (Rolstad and Andersen, 2003).

The variables we used were taken from a satellite-based land cover dataset and from either a national topographic map (scale 1:50 000) or a national land inventory map (DMK) interpreted from aerial photographs by the Norwegian Institute of Land Inventory. We scaled the distance variable to a value between 0-100 to make the coefficient comparable to the other variables.

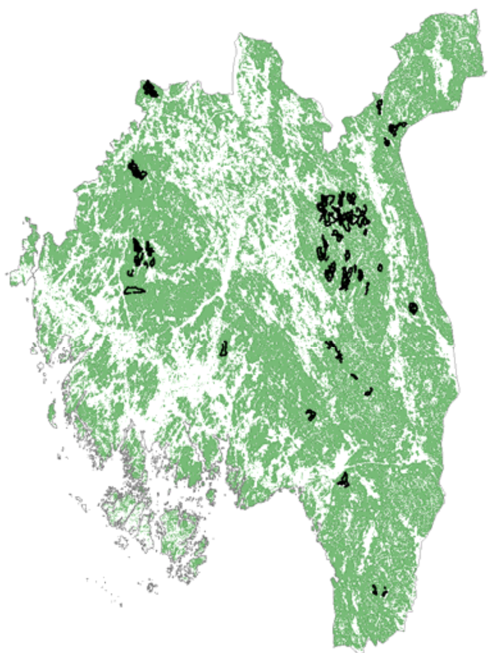

Figure 1. The distribution of bird transects (black) in relation to the forest areas (green) in Østfold county.

The variables we picked out for analysis were selected a priori based on earlier studies (Rolstad and Wegge, 1987, Rolstad and Wegge, 1989) and personal field experience. The variables tree volume, forest age class, tree species composition and human impervious were based on multi-temporal satellite images (Landsat7) and classified after decision TREE rules (Vikhamar and Fjone, 2004). We divided tree volume per pixel into the three classes; 1-10 m^3 (low), 10-25 m^3(medium) and >25 m^3(high) and forest age into the classes; young: representing clear cuttings, plantations: representing younger forest and older: representing forest of cutting class IV and V. The forest was classified as spruce-, pine- or deciduous-dominated forest if a tree species covered more than 75% of a Landsat pixel (30 m x 30 m). Mixed forest represented a situation where all tree species covered less than 75%. Human impervious represented densely populated areas (buildings and other infrastructure). Bogs, forested bogs, coniferous forest with productivity classes low, medium and high and coniferous forest within a 30 meter buffer of streams (moist coniferous forest) were derived from either the topographic or the DMK map. Distance to coast was derived from the topographic map and transformed into a distance grid.

The analysis was based on the use of Resource Selection Functions (RSFs) where the units are counts (Manly et al., 2002). Variables were implemented in logistic regressions (equation 1) and analyzed in R by generalized linear models, GLM.

$$W(x)= \frac{e^{(\alpha + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \beta_3 \cdot X_3 + ... + \beta_n \cdot X_n)}}{1 + e^{(\alpha + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \beta_3 \cdot X_3 + ... + \beta_n \cdot X_n)}} \qquad (1)$$

Models of relative probability of use were calculated and ranked according to the Akaike Information Criterium (AIC; Akaike, 1973). We further used a weighted mean of the five best models to estimate the relative probabilities and to analyse the importance of the variables. The weight for each model was calculated as $\Delta_i = AIC_i - \min(AIC)$ where AIC_i is the AIC for the *i*th model and min(AIC) is the minimum AIC value for the five models (Burnham and Anderson, 1998). The AIC weights were then calculated as,

$$W_i = \frac{\exp(-\frac{1}{2}\Delta_i)}{\sum_{i=1}^{5} \exp(-\frac{1}{2}\Delta_i)} \qquad (2)$$

For mapping, the predicted relative probabilities of use were calculated for every point in a 1 km grid over Østfold county, and visualized on a map as circles (Fig. 2 and Fig. 3). The grid points, based on percentiles, were divided into the four categories: very low, low, medium and high probability of use. Validation of the model result has not done yet, but will be carried out following the method described by Howlin et al. (2003).

The variables in the two tables represent all used variables in the five best models of each species. To measure the importance of each variable, we summed the Akaike weights over the models that included a given variable (Burnham and Anderson, 1998). The strength of influence of each variable on the results was the estimated mean of the coefficients, and the direction (attractive or repellent) of its influence was expressed by the sign of the coefficient.

4. PRELIMINARY RESULTS AND DISCUSSION

The variables at 5000 meter scale were all highly correlated (Pearson's r > 0.8), and therefore are not considered in any further analysis. We will look for variables that better distinguish the habitat differences at this scale later. 483 km of transects are surveyed resulting in 104 observations of capercaillie and 123 observations of black grouse.

Table 1. Scale, importance values, strength of the variables and their direction based on the estimated Resource Selection Functions for capercaillie a) and black grouse b).

a)

Variable	Buff. dist.	Imp.value	Power	Direction
Pine forest	500	1	3.97	+
Old forest	500	1	2.74	-
Low tree volume	500	1	1.79	-
High tree volume	500	1	0.88	-
Clear-cuts	500	1	0.79	-
High prod. moist coniferous forest	500	1	0.58	+
High prod. Coniferous forest	500	1	0.53	+
Bogs	500	1	0.49	-
Low tree volume	50	1	0.44	-
High tree volume	50	1	0.36	-
Old forest	50	1	0.32	-
Mixed forest	50	1	0.24	-
Clear-cuts	50	0.66	0.47	-
Bogs w/ forest	500	0.4	0.37	+
Med. Tree volume	50	0.2	0.14	+
Med. Tree volume	500	0.08	0.5	-

b)

Variable	Buff. dist.	Imp.value	Power	Direction
Deciduous forest	500	1	1.41	+
High tree volume	500	1	1.18	+
Young forest	500	1	1.09	+
Distance to coast		1	1.05	+
Low tree volume	50	1	0.92	+
Clear-cuts	500	1	0.75	+
High prod. moist coniferous forest	500	1	0.74	-
Bogs	500	1	0.69	+
High tree volume	50	1	0.51	-
Bogs	50	1	0.22	-
Bogs w/ forest	500	0.72	0.40	-
Med prod. moist coniferous forest	50	0.47	0.32	+
Low prod. moist coniferous forest	50	0.28	0.19	-
Low tree volume	500	0.11	1.37	+

In all models where capercaillie and black grouse were considered together as tetraonids, the AIC value turned out higher than in models where the species are treated individually. Modeling at 50 meter, 500 meter and the two spatial scales combined resulted for both species in highest AIC values for combined models. Five of the most important variables in the capercaillie models are derived from satellite images and 4 out of 5 in the black grouse models (Tab. 1a and b). This gives an indication of the importance of using satellite image derived data in habitat analysis. Data derived from satellite images are more up to date and give us information about tree volume, forest age and forest composition.

4.1 Habitat selections

The models (Tab. 1) indicate that capercaillie select habitats mostly by the presence of pine forest, high productive coniferous forest close to streams and absence of old growth forest, low and high tree volume all at a 500 meter scale. They avoid areas with both high and low tree volume. The importance of coniferous forest in the model is as anticipated, while the negative effect of old growth forest is somewhat surprising. We believe this is caused by the fact that there is not much of old growth forest left in Østfold or due to larger areas of forest in cutting class IV is mapped as younger forest. However, this results fit relatively well with telemetry based studies, showing that capercaille prefer living in elderly pine or mixed forest on moderate productive soil with a good portion of humid forest types in the surroundings (Rolstad and Andersen, 2003).

Black grouse seems to be more dependent of dense and young deciduous forest, an earlier successional stage than capercaillie as suggested by Seiskari already in 1962. Variables reflecting more open areas have positive effect on the black grouse models (low tree volume, bogs and clear-cuts). The habitat models indicate that black grouse is more of a generalist, since both younger dense forest and fragmented areas have a positive affect on its habitat choice.

4.2 Probability maps

The map in Fig. 2 and Fig. 3 shows the probability of occurrence for capercaillie and black grouse at a combined 50 and 500 meter scale. Areas with less suitable habitat (light colors) are cultivated land and dense populated areas.

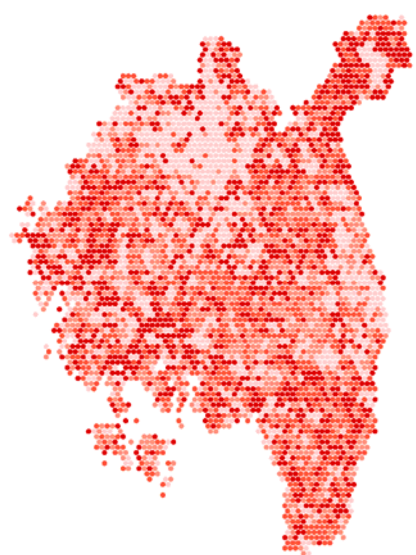

Figure 2. Map of predicted relative probability of capercaillie occurence Østfold county based on a weighted mean of the five best models.

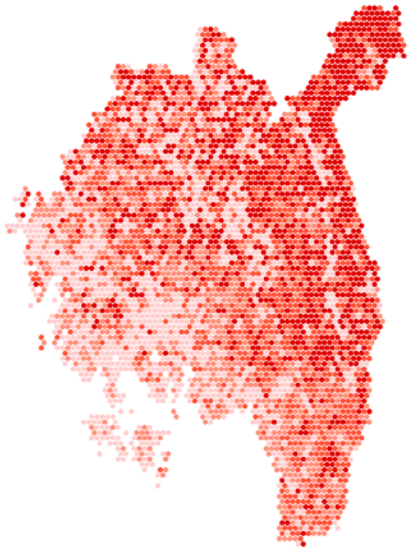

Figure 3. Map of predicted relative probability of black grouse occurence Østfold county based on a weighted mean of the five best models.

Capercaillie habitat is spread widely in Østfold, and seems not to have the same clear west-east gradient as black grouse. The farther away from the coast (eastwards) the more continuous suitable habitat is found. Black grouse shows more clear avoidance of human populated areas as well.

5. CONCLUSION

Analyzing habitat selection of capercaillie and black grouse in Østfold has resulted in the following conclusions. The best habitat model for both capercaillie and black grouse is models combining small (50 m) and larger (500 m) scale information. We experience that the scales used (buffer size) for habitat modeling strongly depend on the scales of the variables. On a regional and larger scale variables have to be selected with care, so they pick up the regional variances in the habitat.

The model selection procedure point out the importance of using quantitative variables that describe conditions and measurements, and not only classes. Quantitative variables are mapped efficiently with satellite data, and therefore make it easier to get habitat information updated and more in time with data from field surveys.

Further improvements of these models will be carried out followed by a validation of the models before a conclusion can be made about the usefulness of the approach and consequences for future management.

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