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Potential distribution of Ural Owl *Strix uralensis macroura* in Central and South-East Europe

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Abstract

The Ural Owl *Strix uralensis* PALLAS 1771 populates large areas of northern Europe, Siberia and Japan. A relict population, the subspecies *S. u. macroura* WOLF 1810, can be found in Central and Southeast Europe. It occupies open woodland mainly in mountainous regions, although critical studies on habitat requirements do not suggest that altitude itself is of special importance to the species. The quality of the woodland seems to be far more relevant. Only few studies concerning the Ural Owl in its natural habitat have been published so far, and accordingly information about factors that govern its distribution are rare. This study aims at (i) delineating the current potential distribution of the species on a large scale and (ii) identifying the environmental factors that can best explain the current distribution pattern by means of ecological niche modeling and geographic information systems (GIS). A set of climatic variables, land-cover data, elevation and a recently published layer compiling data of the human footprint was used to compute a species distribution model with the help of MAXENT, a machine-learning algorithm developed for modeling with species presence-only data. The model was projected to the study area to produce a map of the current potential distribution, or habitat suitability. Areas with medium and high suitability mainly concentrate on mountainous regions. The results further show that habitat elevation had a similar effect on the prediction as compared to human footprint. Consequently, the concentration of the Ural Owls distribution in mountainous regions rather appears to be an artifact of the lower extent of human activities in such areas.

keywords: environmental niche model (ENM), MAXENT, habitat suitability, GIS, human footprint, WorldClim

1 Introduction

The Ural Owl *Strix uralensis* is a medium-sized bird of prey and the largest species of the genus *Strix*. Its main distribution area ranges from Northern Europe to Siberia and Japan, occupying boreal and temperate lowland forests, as well as wetlands. 10-11 subspecies are distinguished, of which *S. u. macroura* represents a relict population in Central and South-East Europe. It prefers richly structured deciduous open woodland for nesting, mainly in mountainous regions. (Glutz von Blotzheim and Bauer, 2001)

According to BirdLife International the species' status on the IUCN Red List is 'least concern', justified by an estimated population size of 53,000 to 140,000 breeding pairs in Europe and its extremely large range. The populations are stable or even increasing in most regions (BirdLife International, 2011). However, these facts apply to the overall European population, without distinction between the subspecies. Distribution data concerning *S. u. macroura* is generally insufficient or lacking for some countries (Bashta, 2009; Perušek, 1998). A search in the ISI Web of Knowledge and the Zoological Record resulted in 3 respectively 8 publications for *S. u. macroura*, and 56 respectively 135 publications for *Strix uralensis* (search performed: 6.4.2011). These publications in large part relate to local populations and are mostly published in national languages. Information about the ecology of the subspecies on a larger, pan-European scale clearly remains under-represented in scientific literature.

One way to overcome the lack of information about the distribution of a species is to apply ecological modeling methods. Ecological niche models (ENM) or species distribution models (SDM) have been widely discussed in recent studies and were applied for a wide range of species (Segurado and Araújo, 2004). For example, SDM are used to evaluate the spreading potential of invasive species (Peterson, 2003; Peterson and Robins, 2003; Thuiller et al, 2005), identify and manage threatened species (Engler et al, 2004; Norris, 2004), prioritize places for biodiversity conservation (Araújo et al, 2004; Chen and Peterson, 2002), evaluate the potential impact of climate change on species distributions (Araújo et al, 2005; Coetzee et al, 2009) and to obtain insights into the biology and biogeography of species (Anderson et al, 2002).

Generally, SDM compute probabilities of occurrence, which could be interpreted as estimates of the probability that species might find suitable habitats in a given area (Araújo and Williams, 2000). Therefore, SDM produce estimates of a species' fundamental niche - the intersection of necessary conditions for multiple environmental variables (Hutchinson, 1957). Several biological and historical realities typically prevent a species from occupying suitable areas to a full geographic extent, and the interaction of these constraints with the multi-dimensional space delimiting the potential habitat constitute the realized niche - a fraction of the fundamental niche actually being exploited (Hutchinson, 1957). Although the discrepancy between potential and realized distributions and the "overprediction" resulting from the niche-based nature of the models at first appear to be an unacceptable defect, this actually allows for synthetic evolutionary and ecological applications comparing potential and realized distributions (Anderson et al, 2002; Peterson et al, 1999).

Numerous approaches and algorithms have been developed to accomplish these tasks, like GARP, BIOCLIM, MAXENT, or GLM (Johnson and Gillingham, 2005; Manel et al, 1999; Meynard and Quinn, 2007). Out of the many of modeling algorithms, MAXENT was here chosen for modeling purposes. MAXENT has been developed within the machine learning community and estimates species distributions by finding the distribution of maximum entropy (i.e. closest to uniform) subject to the constraint that the expected value of each environmental variable under this estimated distribution matches its empirical average (Phillips et al, 2006). MAXENT's advantages lie in the ability to estimate species distributions with presence-only data, computing a continuous output that allows fine distinctions between modeled habitat suitability of different areas and great flexibility in the choice of threshold if binary models are desired (Phillips et al, 2006). Several studies showed that MAXENT outperforms well-established modeling methods, such as GARP, BIOCLIM or general additive models and performs well even with sparse occurrence data (Elith et al, 2006; Phillips et al, 2004; Mingyang et al, 2008).

The aim of this study was to delimit the current potential distribution of Ural Owl *Strix uralensis macroura* by applying novel methods of ecological modeling. The results will give information about environmental needs of the species and their impact on habitat suitability. Further, a probabilistic distribution map was produced to help to identify suitable habitats for further observations, conservation planning or reintroduction experiments.

2 Materials and Methods

2.1 Study area and occurrence data

In regard to the current extent of the species distribution (Glutz von Blotzheim and Bauer, 2001) the study area was limited to Central and Eastern European countries with known or supposed occurrences of *Strix uralensis macroura* (Austria, Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Germany, Hungary, Italy, Kosovo, Macedonia, Montenegro, Poland, Romania, Serbia, Slovakia, Slovenia, Ukraine) and some neighboring countries (Greece, Liechtenstein, Moldova, Switzerland). Several sources were consulted to gather presence points of *Strix uralensis* in the study area (see Tab. 1). Since only few data were available, both breeding sites and observation localities were used, resulting in 179 presence points in total. Most of the occurrences were provided as GPS-data, some were obtained from published distribution maps and manually converted to GPS-localities. Historical records from museums were neglected since data representing the actual land cover were used for modeling. Thus the earliest occurrence used in the study was recorded in the year 1985, most of the other occurrences were recorded in the last decade.

In general, it was difficult to obtain data from the study area. Species databases providing detailed information are not available and only few observations have been formally published. Most of the information are in possession of individual scientists, birdwatchers or NGOs such as BirdLife.

Table 1: Number and sources of *Strix uralensis* occurrence data for the different countries of the study area

Country	No. of points	Source
Slovakia	36	Samuel Pacenovsky (SOS/Birdlife Slovakia)
Czech Republic	20	Zdenek Vermouzek (Czech Society for Ornithology), Dan Křenek
Poland	17	Stachyra et al (2005)
Ukraine	8	Bashta (2009)
Romania	67	Szilárd Daróczi (Milvus Group Bird and Nature Protection Association)
Bulgaria	2	Petar Shurulinkov (National Museum of Natural History, Sofia), published in Nikolov et al (2001)
Slovenia	29	Perušek (1998), Prešern and Kohek (2001)
<i>Total:</i>	<i>179</i>	

Unfortunately not all of them were able or willing to contribute data to the study. Apart from the countries shown in Tab. 1, assured populations of the species can further be found in Germany, Hungary and Italy. Data from Germany were neglected, since these populations have been reintroduced since the 1970ies. In the region of Hungarian Zemplén Hills some breeding pairs can be observed, but detailed information was not provided due to species conservation policies. Detailed information about small populations in Italy were also not available.

2.2 Environmental data

Climatic variables were downloaded from WorldClim (www.worldclim.org). WorldClim provides data sets for monthly precipitation, mean, minimum and maximum temperature, as well as a set of 18 variables derived from the monthly values called BioClim (Hijmans et al, 2005). For this study, temperature and precipitation layers for the breeding season and all of the BioClim layers were used, with a spatial resolution of 30 arc-seconds (approx. 1km). Elevation data was obtained from an altitude map, also available from WorldClim.

Information about land cover and vegetation is provided by a freely available map of the Global Land Cover Project (www.esa.int/dua/ionia/globcover). This satellite image based map reflects the global land-cover in 22 categories (version 2.2, 2005-2006), for example different forest types, water bodies or urban areas, with a spatial resolution of 300m (Bicheron et al, 2008).

Additionally, with the Human Footprint map version 2 (Last of the Wild Data, 2005) the potential influence of human activities on breeding sites and occurrences of the Ural Owl was analyzed. Four types of data (population density, land transformation, accessibility, and electrical power infrastructure) represented by nine datasets were used to compute per pixel values for the human footprint, ranging

from 0 to 100 (percentage of human influence)(Sanderson et al, 2002).

All GIS operations were performed with ArcMap (ESRI, version 9.2, 2006). The environmental layers were clipped to the study area, spatially projected (WGS1984) and formatted for further use in MAXENT. The globcover map was resampled from 300m to 30 arc-seconds resolution with ArcMaps Spatial Analyst Resample Tool using the majority resampling technique. The final maps represent the environmental envelope of the study area with 29 variables and a spatial resolution of approx. 1km.

2.3 MAXENT

Since few modeling software packages yet include the MAXENT algorithm, SJ Phillips, M Dudík and R Schapire developed a java-based (and therefore platform independent) program, which was used in this study (MAXENT 3.3.3e, www.cs.princeton.edu/~schapire/MAXENT).

MAXENT builds a model on given input data, i.e. species presence points and environmental layers. Building the model considering all pixels of the study area is very time-consuming, so MAXENT uses only a subset of 10000 randomly picked "background points", when the total number of pixels exceeds 10000. This leads to a dramatic decrease of computing time with no loss in model performance (Phillips and Dudík, 2008). Once built, the model is projected to the whole area.

Some basic parameters of the program were changed in accordance with former studies (Phillips and Dudík, 2008) to adjust the procedure to the input data. The number of background points was set to 20000 due to the extent and resolution of the study area. 'Clamping' identified the degree of uncertainty in model predictions caused by areas with environmental conditions outside of the training range. 'Fade by clamping' then decreased the prediction by the degree of 'clamping'. Duplicate records (more than one presence point per pixel) were removed, leaving 178 presence points for modeling out of the available 179.

MAXENT divides the presence points into training points used for building the model, and testing points to calculate the predictive performance of the model. Since the points are picked randomly (unless an independent data set is provided for testing), every single run yields slightly different results. To obtain more reliable results n-fold replicate runs were performed and the mean of these results was further analyzed. Two different modes for replicate runs were used. 'Cross-validation' splits the presence points into equal sized 'folds', leaving out one fold every run. The left-out fold is then used for validation. At the end all of the presence points had been used for validation. 'Subsampling' repeatedly splits presence points into random training and testing subsets.

Summarized statistical information is then computed for the replicate runs. Average AUC (area under the receiver-operating characteristic curve), one of the most widely used accuracy measures for modeling (Liu et al, 2009), determines model quality. For estimating the importance of the environmental variables jackknife tests were performed for each variable. In doing so two models were calculated for every variable, one excluding the variable, and one using the variable in isolation. These were then be compared to a third model using all variables, showing the dependence of AUC value on

Table 2: Final set of predictors used for further modeling. % contribution and permutation importance give the range of values from the last predictor test for the 4 different testing sets.

Predictor	% contrib.	Perm. import.	Description
altitude	13.1 - 13.4	5.1 - 7.1	Elevation
hfp_2	3.2 - 3.4	2.8 - 4.5	Human footprint version 2
glc_global	16.9 - 19.8	7.1 - 9.7	Global Land Cover
precwarmqu	26.6 - 32.2	3.9 - 12.9	Precipitation of warmest quater
precseason	13.5 - 15.2	8.1 - 14.9	Precipitation seasonality (coefficient of variation)
tempseason	15.3 - 19	16.4 - 21	Temperature seasonality (standard deviation *100)
mintmpcoldm	11.2 - 13.7	42.4 - 52.2	Minimum temperature of coldest month

each variable. In addition, for each variable the percentage of contribution to the model and a score for permutation importance (i.e. change in performance when randomly permuting the variables) is calculated.

2.4 Predictor selection

Prior to modeling, the available variables had to be reduced to a subset of predictors describing the environmental needs of the species. A common way is to manually select the variables assumed to be relevant for the species. Nevertheless, this may result in incorrect or incomplete predictor subsets, since the distribution of species on a large scale may depend on more abstract variables (Phillips et al, 2006). A more objective approach, which also was adopted here, is to eliminate irrelevant variables with statistical methods.

First, all variables were tested for multicollinearity by examining cross-correlations (Pearson correlation coefficient, r) among them with R version 2.10.0 (R Development Core Team, 2009). From a set of highly correlated variables ($r > 0.9$) only the variable that is more generally describing the environmental circumstances was kept. For example, annual rainfall was considered to be more relevant for modeling than monthly values, because on large scale precipitation at a certain time may be of less importance than the overall availability of rainwater (Phillips et al, 2006). Using this strategy the set of predictor variables was reduced from 29 to 14.

These were then used to run 10-fold cross-validation models in MAXENT for testing the importance of each variable. The variable with least contribution to the model and at the same time most improvement of AUC when omitted was left out in the next run. Step by step the variables were reduced until a further reduction would lead to a decrease of model accuracy. By that means a final set of 7 predictors was computed (Table 2).

To analyze the influence of the human footprint and elevation on habitat suitability, four different predic-

tor sets were tested: (i) all predictors, (ii) without altitude, (iii) without footprint, and (iv) without both. The testing resulted in the same subset of predictors apart from human footprint and altitude for all four cases, which can be seen as an indication of the high explanatory strength of the selected variables.

2.5 Modeling

With the resulting sets of predictors four different models were generated. Recent studies stressed the use of ensemble forecasting methods for ecological modeling to eliminate variations between single models or modeling methods (Araújo and New, 2007; Thuiller, 2003). Hence a set of 100 models was generated for each of the 4 predictor sets. In each case the 10 best models in terms of highest test AUC and lowest omission were chosen for further work. Since a hundred-fold cross-validation would leave just 1 or 2 presence points per run for testing, 'subsampling' was chosen for the replicate runs, i.e. for every run 25% of the presence data were randomly set aside for validation.

2.6 Final distribution map and analysis

The final best models were converted to presence-absence maps by applying thresholds to the probability values per pixel. Liu et al (2005) showed that one has to take care when choosing the right thresholds. In accordance with their study, 'minimum training presence', i.e. the least predicted probability greater than 0 on pixels with known presence, and '10 percentile training presence', i.e. the probability value below which 10 percent of the known presence points were predicted present, were chosen. A third threshold applied is 0.5, representing the 'prevalence', MAXENT's default definition of the probability of presence for input presence points (Phillips and Dudík, 2008).

These thresholds were applied to the 10 selected best models, resulting in 120 presence-absence maps in total (4 predictor sets, 10 best models for each set, 3 thresholds applied to each model). By blending subsets of those maps the influence of human footprint or elevation data can be shown. The final map was generated by blending all 120 maps. Low probability of presence was assigned to pixels where all of the minimum training presence thresholded models overlap, medium probability where all of the 10 percentile training presence thresholded models overlap, and high probability where all of the 120 maps (including prevalence thresholded models) predicted presence. Thus the variation between the different models was eliminated to achieve a maximum of reliability.

Table 3: Comparison of impacts of human footprint and elevation data on habitat suitability. For each model areas of *high*, *medium* or *low* suitability are shown, as well as the total area predicted suitable. *Area* is specified as pixels respectively km².

Model		Area	% of area	Model		Area	% of area
footprint	high	13,064	3.41	altitude	high	13,771	3.53
	medium	36,575	9.53		medium	40,290	10.32
	low	334,110	87.06		low	336,138	86.15
total		383,749		total		390,199	
nofootprint	high	12,632	2.57	noaltitude	high	15,719	2.95
	medium	37,892	7.70		medium	39,099	7.33
	low	441,617	89.73		low	478,608	89.72
total		492141		total		533426	
finalmodel	high	9,699	2.60				
	medium	29,975	8.03				
	low	333,609	89.37				
total		373,283					

3 Results

Overall accuracy of the four different model sets was very high, with mean AUC values (from 100 single models for each set) ranging from 0.983 to 0.986, indicating excellent model accuracy (Araújo et al, 2005). Omission values are threshold-dependent and therefore calculated for 11 different thresholds. Mean omission ranged from 0.522 to 0.633.

The final map is shown in Fig. 1 and illustrates the habitat suitability per pixel. Examining the documented occurrences on this map shows that 98 points were predicted as highly suitable, 52 as medium suitable, 28 at low suitability and only one was predicted as absent. Averaging the maps without applying thresholds would predict all points suitable, even though some of them with very low probability. However, 99.46% of the occurrences were predicted positive and thereof 83.8% with medium or high suitability. This observation further corroborates high model accuracy. The total area of predicted habitats of the final map is 373,283 pixels respectively km², thereof 2.6% presenting high, 8.03% medium and 89% low suitability habitats. Table 3 shows the impact of human footprint and elevation data on the size of predicted areas.

Three different forest types, as classified by the Global Land Cover Project, are seen as suitable concerning the occurrence points: 'closed broad-leaved deciduous forest', 'closed needle-leaved evergreen forest' and 'closed to open mixed broad-leaved and needle-leaved forest'. 93.2% of the predicted pixels represent these forest types, 0.6% other possibly suitable vegetation classes, and 6.2%

represent areas which are in fact unsuitable for the species (e.g. 'croplands' or 'artificial surfaces' such as urban areas). Most of these areas of low habitat suitability, but predicted to belong to the potential range, are situated in Central Romania.

Although some lowland areas like the inner Carpathian basin regions with very scattered forests or some areas in the Ukrainian Roztocze region were predicted as suitable, most of the other suitable areas concentrate in mountainous regions, but below the timber line (approx. 1700m above sea-level, shown as white areas in Fig. 1), such as the Eastern Alpine regions or the Carpathians.

Comparing the four subset maps with the final map showed that the differences were quite small (see Tab. 3 and Fig. 2). Most strikingly the extent of the predicted area varied. The final map predicted the smallest area (373,282 km²), whereas the largest area (533,426 km²) was predicted when leaving out elevation data. However, apart from the extent the general distribution pattern of suitable habitats did not change much, as well as the percentage of areas of high, medium and low suitability (relative to the models total predicted area). When modeling without altitude, more lowland areas were predicted with low suitability, whereas areas of medium and high suitability were mainly bound to mountainous regions throughout all 4 models. Models computed with human footprint compared to those computed with altitude showed very similar distribution patterns and predicted areas of suitability were nearly of same size and extent.

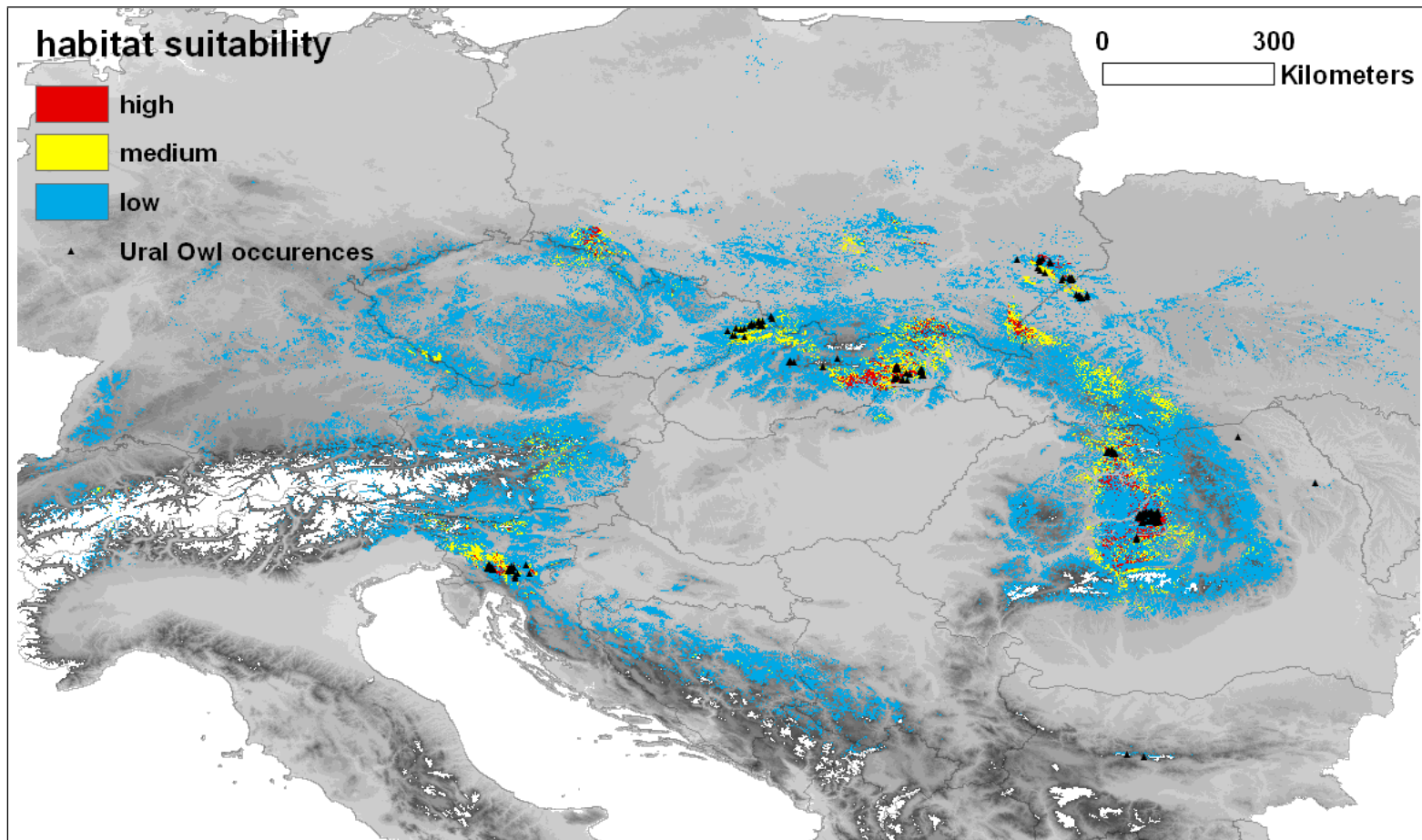


Figure 1: Final map showing the habitat suitability per pixel for the Ural Owl in the study area. The model was computed with a basic predictor set consisting of 4 climate variables (precipitation of warmest quarter, precipitation seasonality, temperature seasonality, minimum temperature of coldest month), a vegetation layer (global land cover) and elevation data (altitude). White areas mark regions above the approximated timberline (1700m above sea-level) to show if areas were predicted outside of the training range. Occurrence points used for modeling are illustrated by black triangles.

4 Discussion

Environmental Niche Models (ENM) clearly have some limitations which have been discussed widely in recent studies. ENM focus on modeling the environmental conditions where a species could persist (i.e., the ecological or fundamental niche), but do not include historical and ecological constraints that prevent species from fully occupying the spatial extent of their ecological niches (e.g., biogeographic barriers and biotic interactions) (Soberón and Peterson, 2005; Peterson et al, 1999). There is an ongoing debate especially concerning the inclusion of interspecific interactions into ENM (Pearson and Dawson, 2003), although it is unclear whether the use of the occurrence of a species in the model of another species truly reflects a biotic interaction, or simply reflects the absence of an important environmental predictor in the model (Guisan and Thuiller, 2005). Nevertheless, it is important to acknowledge that natural systems are not closed. Hence it is not possible to account for all potential driving forces of species distributions (Araújo et al, 2005).

The presented model has to face the same limitations, biotic interactions could not be included. It has been shown that interspecific interactions did not affect the Ural Owls choice of habitat, since it is considered to be the dominant and largest species of forest owl guilds (Vrezec and Tome, 2004a,b). Therefore, it can be concluded that at least interspecific interactions with other owl species are, if at all, of minor importance for habitat selection.

Overall, the presented habitat suitability map of the Ural Owl shows excellent modeling accuracy. Usually, models computed with MAXENT show higher AUC values compared to other modeling algorithms. This is partially caused by the continuous output which predicts more occurrences present than algorithms producing presence-absence maps by applying thresholds (Phillips et al, 2006). However, several sources of evidence suggest that the patterns observed reflect real distributions of the study species. First, the overall pattern of modeled suitable areas is similar to the assumed distribution of Ural Owl as published in various ornithological monographs (Vrezec, 2009; Svennson et al, 1999; Hagemeyer and Blair, 1997). Second, some detailed published maps for Italy (Benussi and Genero, 2008) and Slovakia (Štastný et al, 2006) show Ural Owl findings exactly in areas predicted here as suitable. Small populations in the Central Balkans National Park (Hagemeyer and Blair, 1997) in Bulgaria and around the Zemplén and Bükk hills in Hungary (Glutz von Blotzheim and Bauer, 2001; Petrovics, 1995) were also predicted as presences in the model. Third, in the Bavarian Forest in south-east Germany, at the border to the Czech Republic, a population of Ural Owls was reintroduced (Scherzinger, 2006) and therefore ignored for the present modeling exercise. However, the region turned out to be suitable in the final model. Predicted distribution areas in Slovenia could be confirmed as well (Mihelič et al, 2000).

Although the validation corroborated the predictive power of the model, it has to be admitted that regions in Croatia were predicted as less suitable than the actual extent of the occupied area (Tutis et al, 2009). This can be traced back to the fact that occurrence data from these regions were not available and were therefore not included in the models. In addition, the choice of thresholds of course

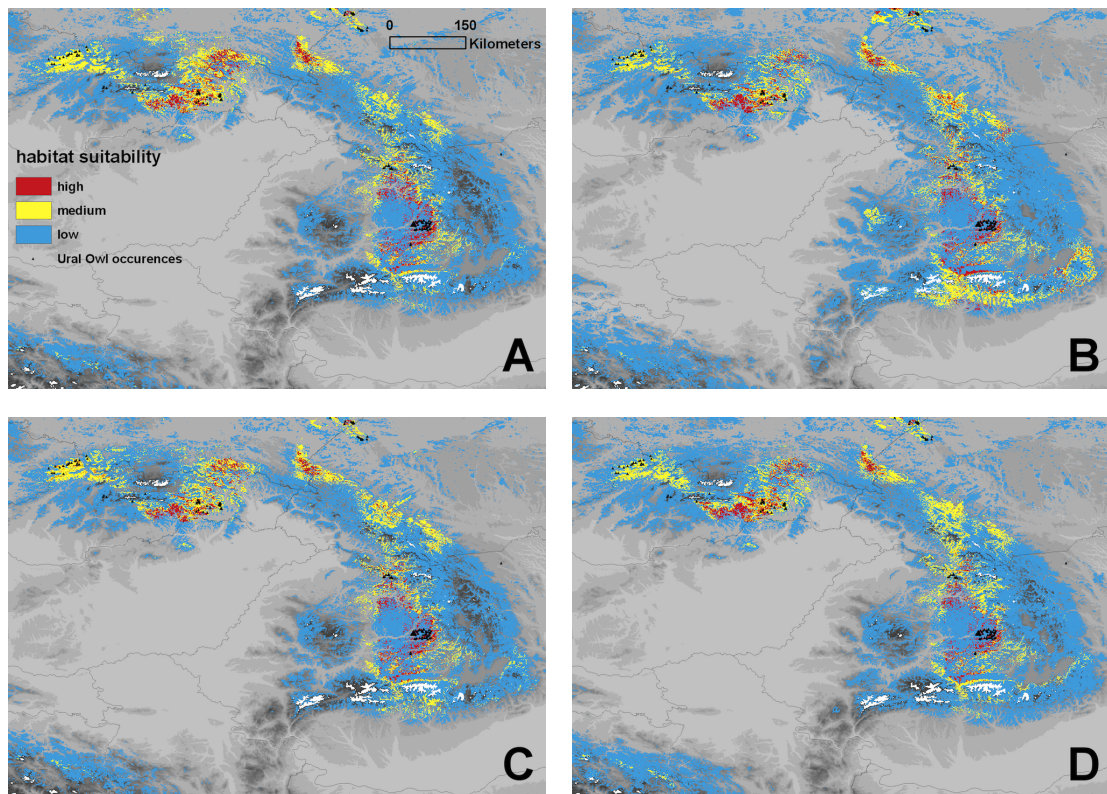


Figure 2: Detailed maps of the Carpathian region showing the differences of models created with altitude (A), without altitude (B), with human footprint (C) and without human footprint (D). White areas show regions above the timberline (approx. 1700m).

affects the portion of suitable areas according to model outputs as well.

Examination of the results shows that especially areas of predicted low habitat suitability include some uncertainties, for various reasons: (1) MAXENT's continuous output resulted in rather low values, hence large areas were predicted with very low probability of presence. (2) Occurrence data were lacking for some regions, for example Croatia or Bosnia-Herzegovina, which of course contributes to the low predicted probability of presence in those regions. (3) The available occurrence points were not evenly distributed, but rather represent patches of clumped observations. Thus areas of medium or high suitability mainly concentrate on the same areas as the occurrences. This problem is also known as sampling bias (Phillips et al, 2006), which may complicate model interpretation because the resulting model might describe sampling effort rather than resource selection (Pearce and Boyce, 2006).

Nevertheless, applying methods of best subset selection of different models and aggregation of their output was an attempt to eliminate the uncertainties arising from the differences between the models

and to produce a resulting map of highest accordance with predicted areas. Some fundamental problems remain, especially concerning sampling bias and quantity of species data and their impact on ENM. Further studies will have to show if the availability of more widespread occurrence data can improve the predictive performance of the model.

The influence of elevation is expressed by an increase of size of the predicted area when elevation data is left out. It would be obvious to compute the species distribution without elevation data, for that in general the species is rather insensitive to elevation (Glutz von Blotzheim and Bauer, 2001; Mihelič et al, 2000; Vrezec, 2003). However mountainous regions proved to be more suitable, even in models that did not incorporate elevation as predictor. This prevalence of mountain areas suggests that conditions for nesting in these regions are superior to lowland regions. This can be explained by the lower human impact and less intense land use history in remote or more inaccessible areas, and therefore mature woodland is more likely to be still present in these regions. In support of this idea, inclusion of the human footprint data in the model analysis resulted in predictions that were largely equivalent to those where elevation was instead used as predictor. Compared to maps computed with elevation data the overall distribution pattern is very similar. The human footprint map itself shows least human influence in remote or mountainous areas. Thus the distribution of Ural Owl seems to be mainly restricted to mountainous areas with a higher probability of finding suitable conditions without being explicitly dependent on certain altitudinal ranges.

As it turns out by analyzing the distribution patterns and environmental layers the main driving force for the distribution of suitable habitats is land-cover, depicting the species' needs for vegetation classes containing trees (Glutz von Blotzheim and Bauer, 2001). Apart from the tree species of these classes alone, there are more characteristics of forests described to be of major influence for nesting and occurrence. Old-grown trees with a large diameter of the trunk are important, since the Ural Owl prefers tree holes or stumps for nesting (Mihelič et al, 2000; Saurola, 1989). The mean stand density of trees is supposed to be low, making it possible for the Ural Owl with its large wing-span to prey in the forests. It feeds on a wide variety of vertebrates, ranging from frogs and shrews to mammals and birds, and is highly dependent on voles, especially when breeding (Saurola, 1989; Vrezec and Kohek, 2002). Therefore environmental conditions have to be complied with for prey species as well.

In regard to the extent of the study area it is obvious that it is impossible to include these parameters in ecological modeling. On the one hand, detailed information about the quality of forests is sparsely available for some small regions and not at all for Europe as a whole. On the other hand, such variables would require a finer spatial resolution of input data, leading to a dramatic increase of computational time and resources. But the question remains whether it is actually essential to include these parameters in modeling, or whether they can be generalized somehow else. It can be assumed that intact, pristine forests meet the requirements of the Ural Owl and that the less influenced by human activities the more intact a forest will be. The human footprint map helps to identify regions of less or no human influence and, in combination with land-cover data, serves well to generalize the more detailed requirements of the Ural Owl.

Svetličič and Kladnik (2001) discussed the negative effect of wood exploitation and proposed a permanent protection of Ural Owl breeding areas in Slovenia. This proposal can be transferred to other regions as well. The produced map of habitat suitability can help to prioritize regions for conservation planning and reintroduction experiments. Further, selective examination of these regions may be necessary to prove the findings given in the habitat suitability map and to ascertain the suitability for the Ural Owl.

5 Conclusion

Several methodological aspects and decisions in modeling exercised, such as differences between statistical techniques and decisions on which model selection criteria and explanatory variables are used in modeling, can have a notable impact on species distribution models (Elith et al, 2002; Guisan and Thuiller, 2005). As far as studies stress the efforts of choosing the right modeling methods subject to the available data and the questions (Guisan and Zimmermann, 2000; Johnson and Gillingham, 2005), and the discussion about the quality and performance of model algorithms is ongoing (Peterson et al, 2007), more emphasis should be placed on methods that combine the outputs of different modeling algorithms or predictor sets, for example ensemble forecasting (Araújo and New, 2007; Thuiller et al, 2005) or hierarchical modeling (Pearson and Dawson, 2003) to reduce uncertainties arising from differences in modeling outputs.

Nevertheless, bioclimatic envelope models have certain advantages. They offer a tool for undertaking relatively rapid analyses for numerous individual species, and allow the identification of key relationships between species and the driving forces of their distributions (Gavin and Hu, 2005; Pearson and Dawson, 2003). The distribution model presented in this study could accomplish these tasks. The presented habitat suitability map proved to be robust compared to real occupied habitats. Furthermore, it could be shown that human activities can have a large influence on the distribution of species. The overall distribution model is based on climatic variables, coarse vegetation maps, and human footprint data, which helps to generalize detailed information about habitat quality.

However the model seems to be sensitive to the spatial dispersion of occurrence data used for modeling. Thus the quality of the model depends on the sampling effort and the willingness or ability of people to contribute their findings. As a conclusion of this study it is proposed to provide a database to share species findings for further scientific work.

The negative impact of human activities was shown in former studies, and could be shown here as well. Therefore it is proposed to establish conservation areas to ban disturbing influences in regions suitable for the Ural Owl.

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Zusammenfassung

Das Hauptverbreitungsgebiet des Habichtskauzes *Strix uralensis* erstreckt sich von Nordeuropa, über weite Teile Nordasiens, Sibirien bis hin nach Japan. Eine der zehn bis elf zu unterscheidenden Unterarten, *S. u. macroura*, besiedelt als Reliktart Zentral- und Südosteuropäische Waldgebiete, wobei offene, reich strukturierte Waldlandschaften bevorzugt werden. Obwohl die Art hauptsächlich in bergigen Regionen anzutreffen ist, belegen Studien, dass die Höhenlage kein entscheidender Faktor bei der Habitatwahl ist. Viel wichtiger scheint hierbei die Qualität der Waldgebiete zu sein. Die vorliegende Arbeit soll das potentielle Verbreitungsgebiet des Habichtskauzes in Zentral- und Südosteuropa, sowie die der Verbreitung zu Grunde liegenden Parameter beschreiben. Dazu wurden Klimavariablen, Landbedeckungsdaten, Angaben zur Höhe sowie Daten über den Grad anthropogener Aktivitäten (Human Footprint) mit Brutstandort- und Sichtungsdaten zu einem Habitatmodell verrechnet. Biotische Interaktionen des Kauzes können in einem Habitatmodell nicht berücksichtigt werden, zumindest zwischenartliche Beziehungen sind aber zu vernachlässigen, da der Habichtskauz den konkurrenzstärksten und größten Beutegreifer in diesen Wäldern darstellt und somit nur in geringem Maße von anderen Arten beeinflusst wird. In dieser Arbeit wurde der Modelltyp MAXENT verwendet, der, wie neuere Studien belegen, sehr gute Ergebnisse erzielen kann. Durch Extrapolation des Modells in Gebiete ohne (bekannte) Vorkommen konnte eine Karte erstellt werden, welche die potentielle Verbreitung des Habichtskauzes aufzeigt. Analysen der Prädiktoren zeigen, dass die Höhe über dem Meeresspiegel ähnliche Auswirkungen auf das Verbreitungsmuster hat, wie der Human Footprint. Die Vermutung liegt nahe, dass die Bevorzugung höherer Lagen vielmehr ein Artefakt des geringeren Ausmaßes anthropogener Aktivitäten ist. Gebiete in höheren Lagen weisen sich als schwieriger zugänglich oder ungeeignet für diverse Landnutzungsmaßnahmen aus, womit die Wahrscheinlichkeit steigt, unberührte und somit für die Art geeignete Wälder vorzufinden. Es hat sich gezeigt, dass auf diese Weise auch im Modell nicht berücksichtigte Variablen, wie Entwicklungsgrad des Waldes oder Baumdurchmesser, zusammengefasst werden können, da anzunehmen ist, dass die Qualität und Eignung eines Waldes für den Habichtskauz steigt, je geringer die menschliche Einflussnahme ausfällt. Somit können aus der erstellten Habitatauswahlkarte Gebiete ausfindig gemacht werden, die sich zum Schutz des Kauzes oder für Wiederansiedlungsprojekte eignen.

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Sprachkenntnisse

Deutsch	Muttersprache
Englisch	fließend in Wort und Schrift
Französisch, Spanisch	durchschnittliche Kenntnisse
Isländisch, Persisch	Grundkenntnisse

EDV-Kenntnisse

Ausbildungen	ESRI ArcMap, R
Office	Microsoft (Word, Excel, PowerPoint, Access), OpenOffice
zusätzliche Qualifikationen:	MaxEnt, OpenModeller, \LaTeX Programmiersprachen Java & VisualBasic
