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Presence-only modelling for indicator species distribution: Biodiversity monitoring in the French Alps

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ABSTRACT

The problem in biodiversity monitoring and conservation is that usually exist vast gaps in available information on the spatial distribution of biodiversity that poses a major challenge for the development of biodiversity indicators and regional conservation planning.

Within this context, models that establish relationships between environmental variables and species occurrence have been developed to predict species distribution over large areas. We present an example using two indicator bird species, Tengmalm owl (*Aegolius funereus*) and Pygmy owl (*Glaucidium passerinum*). Maximum entropy (Maxent), a presence-only modelling approach, is used to model the distribution of these two species within a large study area in the French Alps. Despite biased sampling design, this method performs very well in predicting spatial distribution of the two owl species and brings useful information to help decision-making concerning the protection of valuable habitats.

RESUME

*Le problème actuel dans les domaines de la gestion et de la conservation de la biodiversité est que les informations disponibles sur la distribution spatiale de la biodiversité sont souvent incomplètes. Dans ce contexte, des modèles qui établissent des relations entre des variables environnementales et des observations d'espèces ont été développés pour prédire la distribution des espèces à grande échelle. Nous présentons un exemple basé sur deux espèces emblématiques : la chouette de Tengmalm (*Aegolius funereus*) et la chevêchette d'Europe (*Glaucidium passerinum*). Le Maximum d'entropie (Maxent), une méthode de modélisation basée uniquement sur des données de présence, a été utilisée pour modéliser la distribution de ces deux espèces de chouettes sur une grande zone d'étude dans les Alpes françaises. Malgré un échantillonnage biaisé, cette méthode donne un très bon résultat pour la répartition potentielle des deux espèces et apporte des informations très utiles pour aider à la prise de décision concernant la protection des habitats à forte valeur écologique.*

KEY WORDS

Maxent, distribution modelling, conservation planning, biodiversity indicators, cavity-nesting owls, French Alps

MOTS CLES

Maxent, modélisation de la répartition d'espèces, planification de la conservation, indicateurs de biodiversité, chouettes cavernicoles, Alpes françaises

Introduction

Improving knowledge on the distribution of indicator and emblematic but locally poorly known species is of great importance for managers as well as for naturalists (Baldwin, 2009). These species can be used as a surrogate for biodiversity monitoring and conservation (Lindenmayer *et al.*, 2000). Still vast gaps in available information on the spatial distribution of biodiversity exist, that poses a major challenge for the development of relevant biodiversity indicators for regional conservation and forest management planning.

In addition, the development of spatial knowledge on the habitat requirements and ecology of these species would facilitate conservation of a great number of related species.

Models that establish relationships between environmental variables and species occurrence have been developed and are widely used with many applications in conservation and management-related fields (Cowley *et al.*, 2000; Elith *et al.*, 2006; Gibson *et al.*, 2004; Pearce and Ferrier, 2000; Stockwell and Peterson, 2002). They can help to guide additional field work, by identifying unknown population locations. It also supports management decisions with regard to biodiversity, to determine suitable sites for reintroductions or to assist selection of protected areas (Baldwin, 2009). First, these models were mainly developed for presence-absence data modelling. However, absence data are often lacking or biased and a new generation of models adapted to presence-only data modelling have been proposed (Baldwin, 2009; Hirzel *et al.*, 2002; Phillips *et al.*, 2006). An important number of such methods exist and differ from their data requirements, statistical models used, output formats, performance in diverse situations (Elith *et al.*, 2006; Guisan and Zimmermann, 2000).

Much of them are based on the ecological niche theory (Hirzel and Le Lay, 2008; Phillips *et al.*, 2006). Ecological-niche based models generally define a function that links the fitness of individuals to their environment (Hirzel and Le Lay, 2008). Thus, theoretically, if we know precisely the habitat characteristics of a species, it is possible to rebuild its ecological niche from the environmental variables describing its habitat.

In this study, we have chosen to use the Maximum Entropy modelling approach, which is a relatively recent method developed by Phillips (2006). Maxent is a presence-only modelling approach with a proved good potential to predict wildlife distribution. Despite biased sampling design, this method performs very well in predicting spatial distribution of species data (Elith *et al.*, 2006; Pearson *et al.*, 2007).

Herein we aim to predict the distribution of two owls' species, Tengmalm owl (*Aegolius funereus*) and Pygmy owl (*Glaucidium passerinum*), in the French Alps. These species have specific habitat needs and their presence reflects those of numerous other forest-dwelling species. They are considered as relicts from Ice Age and need quite cold areas (LPO, 2008), which make them good candidates to develop further studies in relation to global climate changes.

In addition, their distributions are poorly known and their protection statuses are not well defined (Loose *et al.*, 2003). It is also important to denote that Pygmy owl populations in the Vercors Mountains area (Alps range) represent the occidental limit of the European range of the species (Anonyme, 2007). It represents also an additional stake to learn more about distribution and habitat structure of this species at the limit of its range.

Requirements and distribution of Tengmalm owl are less well known because this species is nocturnal and discreet (Hakkarainen *et al.*, 2008); therefore census data are difficult to gather. Modelling its potential distribution will allow to improve knowledge on its habitat and ecological needs. Several local surveys efforts took place in order to develop a census of the populations within the “Vercors” region. But these works are limited to very small areas, and a distribution model which covers the entire mountain region would be very useful to help to define adequate surveys efforts for the future while at the same time will provide an overview of the likely distribution of the two species.

1. Material and methods

1.1 Case study area and species occurrence data

This work was conducted within the Vercors’ Natural Regional Park (VNRP), located at the frontier between northern and southern French Alps (Figure 1; <http://parc-du-vercors.fr>). It covers 206 000 hectares with 139 000 hectares of forests. Approximately a half of these forests are Public (State and municipalities forests) and the rest is in the hands of private stakeholders. The main tree species are Silver Fir (*Abies alba*), Norway Spruce (*Picea abies*) and European Beech (*Fagus sylvatica*).

We used Tengmalm owl (*Aegolius funereus*) and Pygmy owl (*Glaucidium passerinum*) point counts data from several surveys conducted in the ‘Hauts Plateaux du Vercors’ Natural Reserve (HPVNR), which is located within the VNRP. The Reserve is mainly composed of three main forest types: i) mixed uneven-aged beech/spruce/fir forests, ii) pure quite sparse even-aged or uneven-aged spruce forests and at high elevation, iii) pure sparse naturally even-aged Mountain Pine forests. The bigger State forest in the Reserve has recently been classified as an Integral Biological Reserve (IBR).

All local surveys have take place in this State forest and mainly in the IBR. The two owls’ species are from the North European boreal forests and the cold sparse spruce Reserve forests look-like their original habitat. Therefore, local people generally thought that the range of the two species is limited to these particular forests in the Vercors.

In this part of the Alps, Pygmy owl depends on cavities carved by the Great spotted woodpecker (*Dendrocopus major*) and Tengmalm owl by the Black Woodpecker (*Dryocopus martius*) for breeding.

These cavity providers favour respectively spruce and beech trees to breed. It implies that the presence of the woodpeckers and their host trees are likely to be important habitat variables for the two owls.

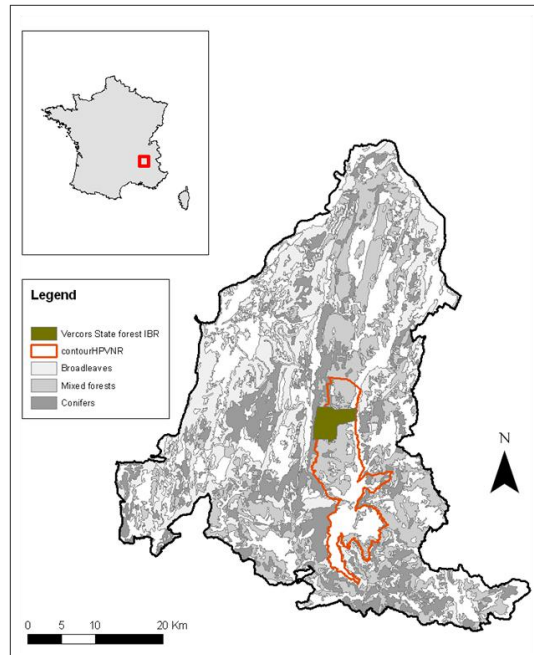


Figure 1. Study area localisation

The point counts data come from the observation network of the National Forest Office and the “Ligue de Protection des Oiseaux” (Bird protection organisation), an NGO which aims to improve knowledge on the local fauna species. These data are a combination of visual and eared bird contacts in addition to nests locations. Each contact point is located with a Global Positioning System (GPS). The reliability of these data is very heterogeneous because each data source has its own sampling design and its own database system. We therefore harmonize data before integration into a common database.

It is important to denote that despite the low precision of visual and eared occurrence data we include them into our database since these are owl’s activity centres within their territory. Gathering of all available point counts gives 95 points for Pygmy owl and 76 for Tengmalm owl.

The resulted dataset is composed of presence points represented as latitude/longitude coordinates, and then no absence points are considered. This is a common issue when someone works with wildlife surveys data (Anderson *et al.*,

2003; Chefaoui and Lobo, 2008). Therefore the interest of models like Maxent, as aforementioned, is the use of presence data only for the computation of the habitat modelling.

1.2 Modelling algorithm

Maxent was first developed to make predictions or inferences from incomplete information in many different fields (Phillips *et al.*, 2006). Since recently it has been widely used as a general approach for presence-only modelling of species distribution. It estimates the less constrained distribution of training points compare to random background locations with environmental data layers defining constrains (Baldwin, 2009). The results show how well the model fits the location data as compared to a random distribution (Phillips *et al.*, 2006; Phillips *et al.*, 2004).

An increasing number of comparisons with others modelling methods show that Maxent performs better than much of them (Ortega-Huerta and Peterson, 2008; Ward, 2007; Yun-sheng *et al.*, 2007). This performance is due to the numerous advantages of the method. For example, it can be run with very few occurrence data (Hernandez *et al.*, 2006; Pearson *et al.*, 2007), it manages with different kind of environmental data, as continuous and discrete datasets, without any transformation (Ortega-Huerta and Peterson, 2008) and it includes a parameter to avoid over-fitting (Phillips *et al.*, 2006). The strategy to manage with lack of absence data, based on random pseudo-absence, performs better than other ways such as those of ENFA (Hirzel *et al.*, 2002) or BIOCLIM (Busby, 1991) (Wisn and Guisan, 2009). It also shows percentage variable contributions to the final model and response curves for each variable, which allows targeting those which can be deleted to improve model performance and to detect variable correlations (Baldwin, 2009). The output is continuous that allows a great flexibility in threshold choice and results representation. Resulting maps can be very easily exported in a GIS database (Phillips *et al.*, 2006). Outputs are also easy to interpret from an ecological point of view.

Maxent presents also some drawbacks, the main is linked to the exponential model for probability which can give very large predicted values for environmental conditions outside the range present in the study area. The method can have therefore some difficulties to extrapolate to other study area (Peterson *et al.*, 2007; Phillips *et al.*, 2006).

1.3 GIS environmental data and model implementation

We used a set of environmental data based on the knowledge of the species ecology and factors affecting distribution of the species within the entire study area (Array 1).

These data are represented as raster layers with a 50 m resolution, which is those of the most restrictive raster included in the analysis. We used ArcGIS 9.3 to prepare the different data layers.

Implementation of Maxent requires that rasters were perfectly overlapping and have exactly the same number of cells. A single raster mask delimiting the study area was therefore used to assure that all raster layers have the same dimensions.

For the two species, we used 25% randomly selected occurrence data for cross-validation, leaving the remaining 75 % for analysis, as done by (Ward, 2007).

We implemented the model with freeware Maxent developed by (Phillips *et al.*, 2005). It is friendly use, as species occurrence training and test files and environmental data layers are automatically recognize by the application.

We used simultaneously continuous and discrete data. We let almost all default parameters, but we set the regularization value to 1 for the two species. To evaluate the relative contribution of each variable to the model we first chose to see the jackknife test of variable importance. It shows how each variable contributes to the model by testing variation of model gain with and without including each variable separately. We also analyzed the response curves which show the response of each variable to presence probability.

We first include all the environmental variables in the model. We then delete those which did not show any significant contribution to the model.

Six variables were finally selected for Pygmy owl: elevation, topography, land cover, mean annual temperature, forest / non-forest map and presence of Norway Spruce; and five for Tengmalm owl: Land cover, elevation, slope, forest/non-forest map and European Beech presence. Fifty model replicates were run for each species and we select the best among the 50. The contribution of each variable can be visualized through jackknife tests of variable importance and calculation of variables percentage contributions.

GIS layer	Data source	Pygmy owl	Tengmalm owl
Elevation*	French DEM (French National Geographic Institute)	×	×
Aspect		×	×
Slope ^o		×	×
Topography ⁺		×	×
Forest habitats (Alpine National Botanic Conservatory (ANBC))	Natural habitats map from ANBC	×	×
<i>Dendrocopus major</i> presence	Data from the Ligue de Protection des Oiseaux	×	
<i>Dryocopus martius</i> presence			×
Land cover*	CORINE LAND COVER 2006 (level 3)	×	×
Mean annual temperature ⁺	AURHELY model from Météo France	×	×
Norway Spruce presence ⁺	Database from ANBC	×	
European Beech presence ^o			
Forest / non forest*	Join Research Center JRC	×	×

Array 1. *Environmental variables used in Maxent modelling, by owl species.*
 (*significant contribution to the two species' models; +significant contribution to Pygmy owl model; °significant contribution to Tengmalm owl model).

Maxent provides three output formats. We select the logistic output as generally recommended. The result is a continuous value between 0 and 100. Each resulting raster pixel contains a value reflecting how well the predictive conditions for each pixel are.

We then export results into ArcGIS 9.3 in order to apply a threshold value to produce the occurrence map. Applying a threshold is the last step of many species modelling approaches. It is necessary to transform the probability map in presence/absence data. Many methods exist to determine the presence threshold. Objective thresholds seem to be more effective than subjective ones (Liu *et al.*, 2005). We used 10 percentile training presence (threshold 0.345 for Pygmy owl and 0.259 for Tengmalm owl) as suggested by (Phillips and Dudík, 2008). This threshold value provides a better ecologically significant result when compared with more restricted thresholds values. Therefore, the use of only one threshold value gives a very narrow overview of the species distribution. In addition, for conservation purpose it is more useful to have a presence gradient which is more realistic and easier to validate with expert knowledge. Hence, we produce output maps with four ranges of presence probability: 0-25% as unsuitable habitat, 25-50% as acceptable habitat, 50-75% as quite suitable and > 75% as suitable habitat.

2. Model evaluation

To evaluate model results, the best method would have been to use an independent data set. However, for the two owl's species, observation data are spatially aggregated and it would have had no sense to use data located in the same place than the training data to evaluate the performance of the model.

We test models performance with several other tools.

Maxent calculates the AUC (Area Under the receiver operating Curve) for each run. It is a standard, threshold-independent method for model evaluation. This method was initially developed for presence-absence data. In Maxent, absence data are replaced by random points (Phillips *et al.*, 2006). AUC tests if a prediction is better than random for any possible presence threshold. It varies between 0.5 when the result is not better than a random selection and 1 when the result is significantly better than random.

Another evaluation method lies in the analysis of the two types of prediction errors provided by all presence/absence models: false negatives (omission error) and false positives (commission error) (Ward, 2007). Maxent algorithm calculates an omission rate for training and test data. Omission rate indicates the percentage of test localities that falls into pixels not predicted as suitable for the species (Phillips *et al.*, 2006). It should be low for a good model performance. With presence-only

modelling, is it very difficult to calculate commission errors as no absence date is available and commission error often increases with omission decreasing (Hernandez *et al.*, 2006). We therefore use different evaluation tools to overcome this difficulty.

AUC and omission rate were nevertheless used to select the best model among fifty replicates for the two species. Models with the lowest training and test omission rates and with the highest AUC were chosen, as generally done by Maxent users. We also verify if all training points were predicted with a high probability.

In addition, expert knowledge was included in the validation process. We compare models results with a mental map drawn by an expert of the two owl species on the Vercors Mountains. We also gather a group of forest managers with good naturalist skills to validate the results.

3. Results and discussion

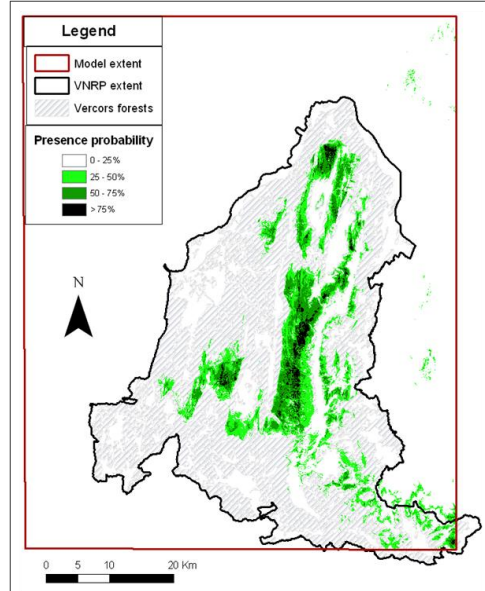
Despite the aggregation patterns of the training data, Maxent modelling method has successfully predicted owl's presence on a large range in the Vercors Mountains (Figure 2). Results show that the approach has a good capability to capture the intrinsic species-habitat relationships and to reconstruct the ecological niche even in sites where any data were available.

Moreover, this method performed very well in predicting potential spatial distribution of the two owl species. Test omission rates are null at minimum training presence threshold for training and test datasets (rate = 0.000 for Pygmy owl and Tengmalm owl) and low at 10 percentile training presence threshold (Tengmalm owl: 0.093 for training data and 0.000 for test data and Pygmy owl: 0.095 for training data and 0.000 for test data).

For the two species, models show an AUC value very close to 1 for test data (0.992 for Tengmalm owl and 0.996 for Pygmy owl), which generally proves good model performance. However, when species have a narrow range (or training data are spatially aggregated), AUC is often overestimated (Phillips and Dudík, 2008), which is certainly the case here. The high AUC values are therefore not sufficient to evaluate model performance in this study.

Mean training data predictive rate is 0.65 (SD = 0.21) for Pygmy owl and 0.63 (SD = 0.20) for Tengmalm owl. The model predictive capacity seems to be good then based on the well predicted calibration points. In addition, for the two species, the resulting presence/absence maps overlap very well with the expert mental map and are in accordance with manager's knowledge.

a)



b)

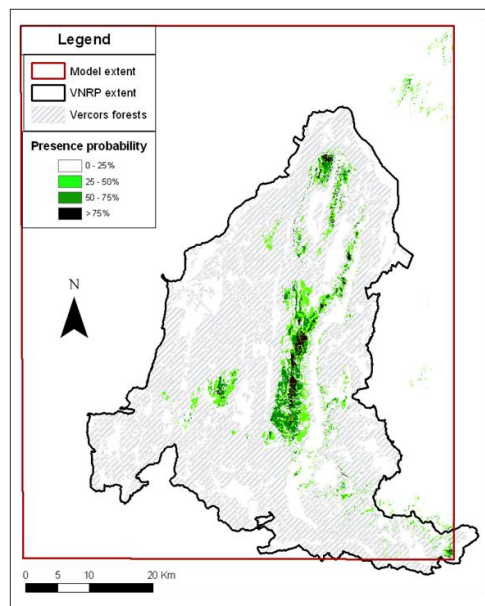


Figure 2 . Results of Maxent model on Vercors Mountains a) Tengmalm owl and b) Pygmy owl, with four ranges of presence probability.

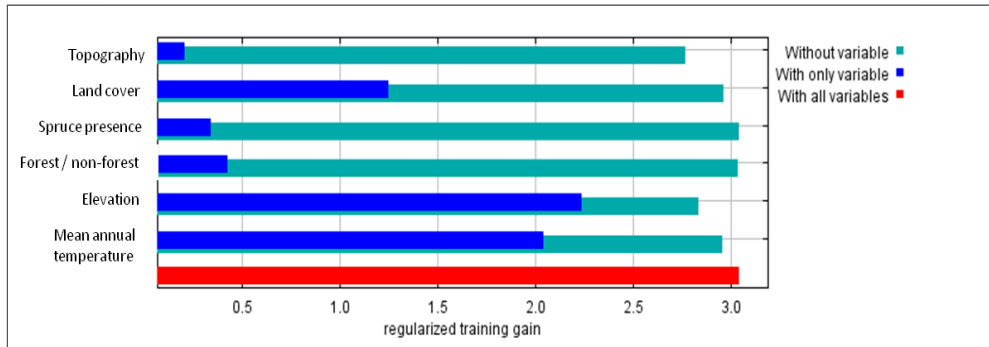
For Pygmy owl, the environmental variable with highest gain when used in isolation is elevation (Figure 3a), which therefore seems to contain the most useful information by itself. It is supported by local expert knowledge and literature where this species is linked with a quite narrow altitudinal range (between 1100 and 2200 meters). Mean annual temperature brings also high gain to the model. These two variables could be considered as very correlated, as temperature generally decreases with elevation, but omission of one of the two variables decreases model performance. This is not the case for Tengmalm owl, where removal of mean annual temperature increases elevation gain as it captures the gain deleted by removal of temperature.

The environmental variable that contains the most information that is not present in the other variable is topography (called “altitopo”), because it decreases the gain the most when is omitted (Figure 3a). As for mean annual temperature, this variable seems to be quite correlated with elevation, but removal of one of them decreases also model performance.

The environmental variable with highest gain for Tengmalm owl is elevation which is also the variable that decreases the most the gain when it is omitted (Figure 3b). Elevation brings therefore the most useful information by itself and contains the most information that is not represented by the other variables.

The linkage of the two owl’s species with elevation can be due to the fact that they are dependent of particular tree species to breed, these trees themselves growing in limited altitudinal ranges. They also need quite cold conditions, that are often linked with high elevation or soil depressions, which are frequent in limestone soils as present in the Vercors Mountains.

a)



b)

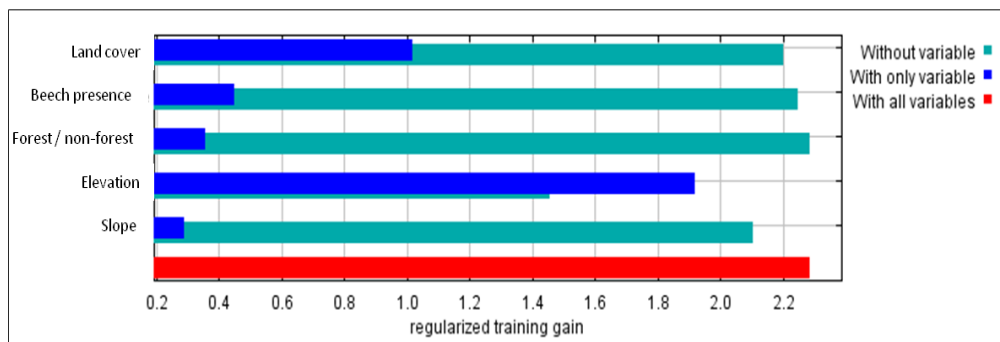


Figure 3. *Jakknife of regularized training gain a) Pygmy owl and b) Tengmalm owl.*

For the two species, the resulting distribution is wider than would be expected by local knowledge (see Figure 2). This result is not surprising because some observations have been done in Vercors forests outside of the HPVNR and in an adjacent mountain area with a different type of forest habitats (i.e. more humid, more productive and with closed canopy conditions).

The distribution maps bring new information on these poorly known species. For example, they are certainly present in some of the most productive Vercors forests, where their conservation will therefore become a new stake for forest management. In addition, the grain and extent of the resulting presence/absence maps allow their use at different scales. They can be used at management units scale (few hectares) to better integrate owl's conservation in forest planning as well at entire forests scale to avoid suitable sites when extension of road network is planned, for example.

However, it is important to note that species could not be present in a site even if they are predicted. Other factors, not taken into account in the analysis, can explain species absence. They can be for example: predator presence (notably Tawny owl

(*Strix aluco*) for the two owls and European pine marten (*Martes martes*) for Tengmalm owl), sites far from existing population and not yet colonized and a lack of prey resources (little mammals, passerine birds, etc.). The integration of a quantitative analysis of landscape heterogeneity, in terms of structure and composition, is underway to better take into account matrix characteristics.

4. Conclusion

Combination of GIS tools with species distribution modelling algorithm shows to have a good potential for species monitoring. In this study GIS was first used as a platform to gather, homogenise and prepare data layers before running the model. These steps are determinant to assure model quality and, in this study, the model algorithm Maxent performed very well in predicting potential spatial distribution of the two owls' species. GIS is then used to facilitate results interpretation and to create maps of presence probability useful for forest managers and naturalists.

This kind of modelling process would be useful to follow the evolution of their spatial distribution in years to come. Furthermore, the tools developed can be applied in assessing biodiversity value of both managed and protected forest areas to help decision-making concerning the protection of valuable habitats. As GIS tools are commonly used in management planning and Maxent algorithm is free and quite simple to implement, this kind of method can be easily adapted and implemented by local managers interested in species monitoring.

Sites of predicted presence would for example guide naturalists' future work in order to identify other suitable areas where the bird distribution is unknown while at the same time facilitate selection of areas with high ecological value. As numerous public forests are managed for wood production in the Vercors, these maps would allow to better integrating biodiversity conservation into management planning. In addition, as these species are linked to cold habitats, they could serve as good indicators of climate change with further work including temporal analysis.

Distribution modelling of these species is among the first attempts to model suitable habitat distribution of cavity-nesting owl species in France. We hope it will launch the use of such methods, which aim to improve species ecological knowledge and facilitate species censuses and conservation.

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