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Is there an optimum scale for predicting bird species' distribution in agricultural landscapes?

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ABSTRACT

Changes in forest cover in agricultural landscapes affect biodiversity. Its management needs some indications about scale to predict occurrence of populations and communities. In this study we considered a forest cover index to predict bird species and community patterns in agricultural landscapes in south-western France. We used generalized linear models for that purpose with prediction driven by wooded areas' spatial distribution at nine different radii.

Using 1064 point counts, we modelled the distribution of 10 bird species whose habitat preferences are spread along a landscape opening gradient. We also modelled the distribution of species richness for farmland species and for forest species. We used satellite images to construct a 'wood/non-wood' map and calculated a forest index, considering the surface area of wooded areas at nine radii from 110 m to 910 m. The models' predictive quality was determined by the AUC (for predicted presences) and ρ (for predicted species richness) criteria.

We found that the forest cover was a good predictor of the distribution of seven bird species in agricultural landscapes (mean AUC for the seven species = 0.74 for the radius 110 m). Species richness of farmland and forest birds was satisfactorily predicted by the models ($\rho = 0.55$ and 0.49, respectively, for the radius 110 m). The presence of the studied species and species richness metrics were better predicted at smaller scales (i.e. radii between 110 m and 310 m) within the range tested.

These results have implications for bird population management in agricultural landscapes since better pinpointing the scale to predict species distributions will enhance targeting efforts to be made in terms of landscape management.

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1. Introduction

In an agricultural environment, patches of woody vegetation play a key role owing both to their presence for forest-habitat specialist species, and to their absence for open-habitat specialist species (Balent and Courtiade, 1992; Bennett, 1999; Bonthoux et al., 2012). Any change in patchy or linear forest elements is therefore likely to affect biodiversity in agricultural landscapes (Baz and Garcia-Boyero, 1996; Geertsema et al., 2002; Holzkämper and Seppelt, 2007; Jokimäki and Huhta, 1996; Renfrew and Ribic, 2008). Changes in forest cover in an agricultural landscape occur on different scales. Mobile animals, such as birds, can react quickly to

such multi-scale modifications since they are likely to appraise habitat features at a variety of scales (nest sites, territory, wider landscape) (Skórka et al., 2006).

In order to conserve biodiversity in agricultural landscapes, it is important to know on what scales the occurrence of targeted species are best explained and predicted by forest cover (Coreau and Martin, 2007) and whether the predictions vary according to the scale at which habitat variables are measured (Grand and Cushman, 2003; Pickett and Siriwardena, 2011). Is the optimum scale for predicting species distribution different from one species to another or does it exist a unique scale of prediction for the whole community?

To evaluate the impact of the modification in forest cover on biodiversity, we have to be able to measure the influence of this discontinuous forest patches at any point in a territory in a continuous way. To assess the effects of forest fragments on species'

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Table 1
(a) Latin and common names of bird species, habitat type (open, forest or intermediate), occurrences, and mean AUC values for the best radius and (b) species richness for the farmland and forest birds and mean Rho values for the best radius.

(a)

Latin species name	Common species name	Occurrence number	Type of habitat	Mean AUC value
Alauda arvensis	Skylark	356	Open	0.71
Emberiza calandara	Corn bunting	314	Open	0.68
Erithacus rubecula	European robin	651	Forest	0.81
Fringilla coelebs	Common chaffinch	535	Forest	0.73
Lullula arborea	Woodlark	66	Intermediate	0.65
Phylloscopus collybita	Common chiffchaff	663	Forest	0.71
Sylvia communis	Common whitethroat	347	Intermediate	0.71
Saxicola torquata	European stonechat	212	Open	0.70
Turdus philomelus	Song thrush	205	Forest	0.81
Troglodytes troglodytes	Eurasian wren	693	Intermediate	0.73

(b)

Community species richness	Mean (min; max)	Mean Rho value
Farmland birds	2.72 (0; 10)	0.55
Forest birds	3.05 (0; 8)	0.50

distribution the authors generally use landscape indicators that involve several forest cover components, e.g. patch area and morphology, between patches connectivity and isolation. These indicators often produce redundant information owing to the crossed correlations between these environmental variables (Lescourret and Genard, 1994). In this study, we used the Neighbouring Forest Cover (NFC index) proposed by Lauga and Joachim (1992) and Lauga et al. (1996). The NFC includes the main characteristics of the wooded islets: the extent of the forest patches' and the distance between the patch and the calculation point.

Bird species represent good model organisms sensitive to changes in forest cover (Cushman and McGarigal, 2003) and are likely to respond differently to the NFC calculated at different radii, representing different spatial scales of potential species' responses to forest spatial distribution. Balent and Courtiade (1992), Berg (2002) or Moreira et al. (2005) have shown that wooded elements are major factors for explaining the assembly of bird species in agricultural habitats. Lauga and Joachim (1992) showed that NFC was a good predictor of three species of forest birds: the song thrush (*Turdus philomelos*), the common chaffinch (*Phylloscopus collybita*) and the European robin (*Erithacus rubecula*).

Here we tested the validity of the NFC as a good predictor of (i) the distribution of 10 agricultural landscape species positioned along a forest to open landscape gradient and (ii) the species richness of farmland and forest birds. Using this index measured at nine different radii we estimated the predictive performance of the individual species and species richness distribution models to determine whether there was an optimum radius for predicting the distribution of ten bird species found in the study area and two species richness metrics using the NFC.

2. Methods

2.1. Study area, sampling design and bird species

The study area is located on the "Vallées et Coteaux de Gascogne" Long Term Ecological Research (LTER) site in South West France centred on the point with geographic coordinates N43°15′53″, E0°51′50″. It is a hilly region where agriculture is devoted to mixed crop-livestock systems and landscapes are a mosaic of diversified land uses including forest patches and hedgerows. We carried out three bird survey campaigns, in 1990, 1995 and 1998, in a zone made up of wooded and unwooded areas (Appendix 1). Bird sampling consisted of 1064 point counts (676 point counts in 1990, 280 in 1995 and 108 in 1998), using 125 m point count radius which corresponds to the extent of the home range for most species of passerine birds (East and Hofer, 1985; Naefdaenzer, 1994). This large sample is well adapted to the building of predictive models (Wisz et al., 2008).

Point counts were stratified according to the agricultural landscapes' forest cover gradient (from 0 to 100% of forest cover, mean = 23%). The dominance of open spaces was linked to the fact that this is an agricultural area with a dispersion of small wooded fragments. Furthermore, because of the spatial resolution of the Spot 4 satellite image used (20 m), the smallest wooded elements and some hedgerows were under-represented. We continued to use this map dating from 1998 with this resolution because we wanted to be as synchronous as possible with the bird data dating from the 90s. We checked that the forest cover in the study area had remained stable between 1990 and 2000, corresponding to the sampling period (Guyon et al., 1999; European forest map available for these two 2 dates and Pekkarinen et al., 2009; <http://forest.jrc.ec.europa.eu/forest-mapping/forest-cover-map>).

The bird presence–absence data were taken from 20-min point counts carried out each sampling year in the month of May between 6 and 11 a.m., during the peak of vocal activity, in the absence of heavy wind and rain. Counting only began 3 min after arrival at the point in order to limit the disturbances caused by the observer to the detection of individuals.

We selected 10 species (Table 1) on the basis of their preference along the forest to open landscape gradient (see Balent and Courtiade, 1992), which made it possible to choose species associated with open, forest, and intermediate habitats. All the selected species have an occurrence of more than 20 (Table 2) which is sufficient to avoid problems of modelling rare species (Stockwell and Peterson, 2002). We also calculated species richness for the 1064 point counts as the sum of all present species, excepted large species (e.g. raptors, corvids) with home range larger than the point count area, and human-related species (e.g. sparrows, swallows) because they are gregarious and closely related to human settlements. Because all bird species were not expected to respond uniformly to the wooded gradient, we calculated separately richness for forest bird species (as identified in Balent and Courtiade, 1992) and for farmland bird species (as identified in Filippi-Codaccioni et al., 2010). All scientific bird names are available in Appendix 2.

2.2. Calculation of the forest influence index at different smoothing radii

For each point count, we calculated the NFC, varying between 0 and 1, from the area of all the forest patches present in a given radius, weighting it in inverse proportion to the distance of each forest patch to the calculation point by means of a decreasing exponential function (Lauga and Joachim, 1992). This is a continuous variable that can be calculated at every point of the territory (Lauga et al., 1996). The NFC is calculated using a binary classification of a Spot 4 image taken from a satellite in 1998. Each pixel (20 × 20 m) takes the value 1 or 0 depending on whether or not the pixel is wooded. A layer with the 1064 georeferenced point counts is superimposed to the classified image. We obtained these maps using the Idrisi software after a supervised image classification. The radius referred to the shortest distance (i.e. in an orthogonal direction) between the focal cell and the side of the square window. We calculated the NFC for nine different concentric radii (Table 2).

Table 2
Correspondence in number of pixels and surface area (ha) of the nine smoothing radii used for square moving window to calculate the Neighbouring Forest Cover: 1 pixel = 20m.

Radius abbreviation	Radius size (m)	Number of pixels	Area (ha)
R1	110	11 × 11	4.84
R2	210	21 × 21	17.64
R3	310	31 × 31	38.44
R4	410	41 × 41	67.24
R5	510	51 × 51	104.04
R6	610	61 × 61	148.84
R7	710	71 × 71	201.64
R8	810	81 × 81	262.44
R9	910	91 × 91	331.24

2.3. Modelling and estimate of the predictive quality of the models

The different steps of the analysis are illustrated Fig. 1. We constructed generalized linear models (GLMs) with binomial distribution to link the presence–absence data of each species to the NFC measured at nine different radii. We used GLMs with Poisson distribution to model species richness metrics (nine models per species and per species richness metric). We compared models with and without quadratic term of NFC on the basis of the Akaike Information Criterion (AIC) (Burnham and Anderson, 2002). AIC is a parsimonious approach that covers both model fit and parameter number. We tested the predictive performance of models with the smallest AIC values.

To account for spatial autocorrelation, we added auto-covariate terms (i.e. autologistic and autopoisson models, Augustin et al., 1996; Lichstein et al., 2002). These terms estimated how much the response variable at one site reflects the response values at neighbouring sites. To check whether each level term properly

Fig. 1. Summary of statistical analysis for the $n = 10$ species (- - -) and the $k = 2$ communities (= = =). NFC: neighbouring forest cover index, P/A: presence/absence of birds, SR: species richness, SBB: spatial block bootstrap, rs: resampling, AUC: area under roc curve, and ρ: Spearman rank correlation value.

accounted for autocorrelation, we used difference of coding test (Guyon, 1995, p. 195), it is an efficient test and the reference distribution is a χ^2.

To assess the predictive performance of the models for the selected 10 species, we compared the predictions and the observations using the AUC "Area Under the ROC Curve" criterion (Egan, 1975). This criterion is often used to assess the capability of the models to distinguish between occupied sites and unoccupied sites (Pearce and Ferrier, 2000). The reliability of the predictions is considered to be null for AUC values lower than 0.5, poor when the AUC values are comprised between 0.5 and 0.7, satisfactory for values between 0.7 and 0.8 and good when they are higher than 0.8 (Metz, 1986; Swets, 1988; Manel et al., 1999). We compared predictions and observations of species richness metrics using the Spearman Rank Correlation (ρ coefficient). This method provides an indication of similarity between the ranks of the observed and predicted values. It varies from -1 to $+1$. The correlation is considered to be weak for ρ values between 0 and 0.25 (or 0 and $-$0.25), fair for ρ values between 0.25 and 0.5 (or -0.25 and -0.5), moderately strong for ρ values between 0.50 and 0.75 (or -0.5 and -0.75) and very strong for ρ values higher than 0.75 (or -0.75) (Colton, 1974).

We used a bootstrap procedure to get the variation of the AUC and ρ coefficients. Because there were spatial dependence and the locations of point counts were irregularly spaced, we used the procedure of boostrap with spatial block described in Lahiri and Zhu (2006). With respect to the correlation study based on autoregressive models, we chose a grid for the bootstrap block that corresponded to a square of 5 lines and 5 rows of the grid part of the sample.

3. Results

3.1. Responses to NFC index

The direction of the response curves differed depending on the species (Fig. 2). Five species had a probability of occurrence which decreased with the NFC and five species had a probability of occurrence which increased with the NFC. For some species, the shape of the response changed among radii. For example, for common chaffinch the response was linear for smaller radii and became quadratic with the increase in the radius size.

3.2. NFC index as predictor of bird distribution

In this part, we present AUC value for each species for the best radius. The European robin and the song thrush had AUC values higher than or equal to 0.8 (Table 1a). In 6 cases out of 10 (for skylark, common chaffinch, common chiffchaff, common whitethroat, European stonechat and Eurasian wren) the AUC values were satisfactory and comprised between 0.7 and 0.8. The species corn bunting and woodlark had a poor AUC value (0.68 and 0.65, respectively) (Table 1a). Mean ρ values calculated from the species richness of farmland and forest birds were moderately strong (Table 1b).

3.3. NFC radius and prediction of bird species distribution

The differences between the AUC values for the different radii were quite small but were nevertheless sufficient to determine optimum radii for the different species. Optimum radii for predicting the distribution of skylark were 110 m and 210 m, corresponding to a surface area between 5 and 18 ha (Fig. 3a). For predicting the distribution of corn bunting, woodlark and European robin, optimum radii were 110 m to 310 m which, on the moving
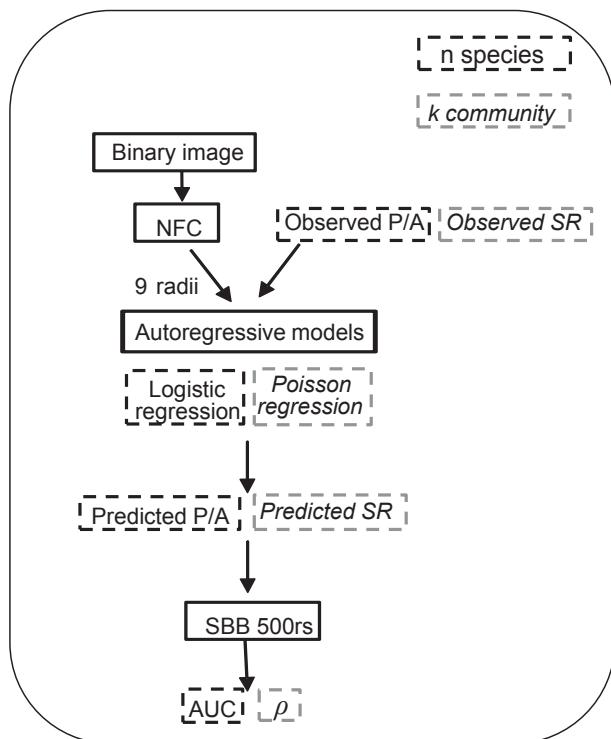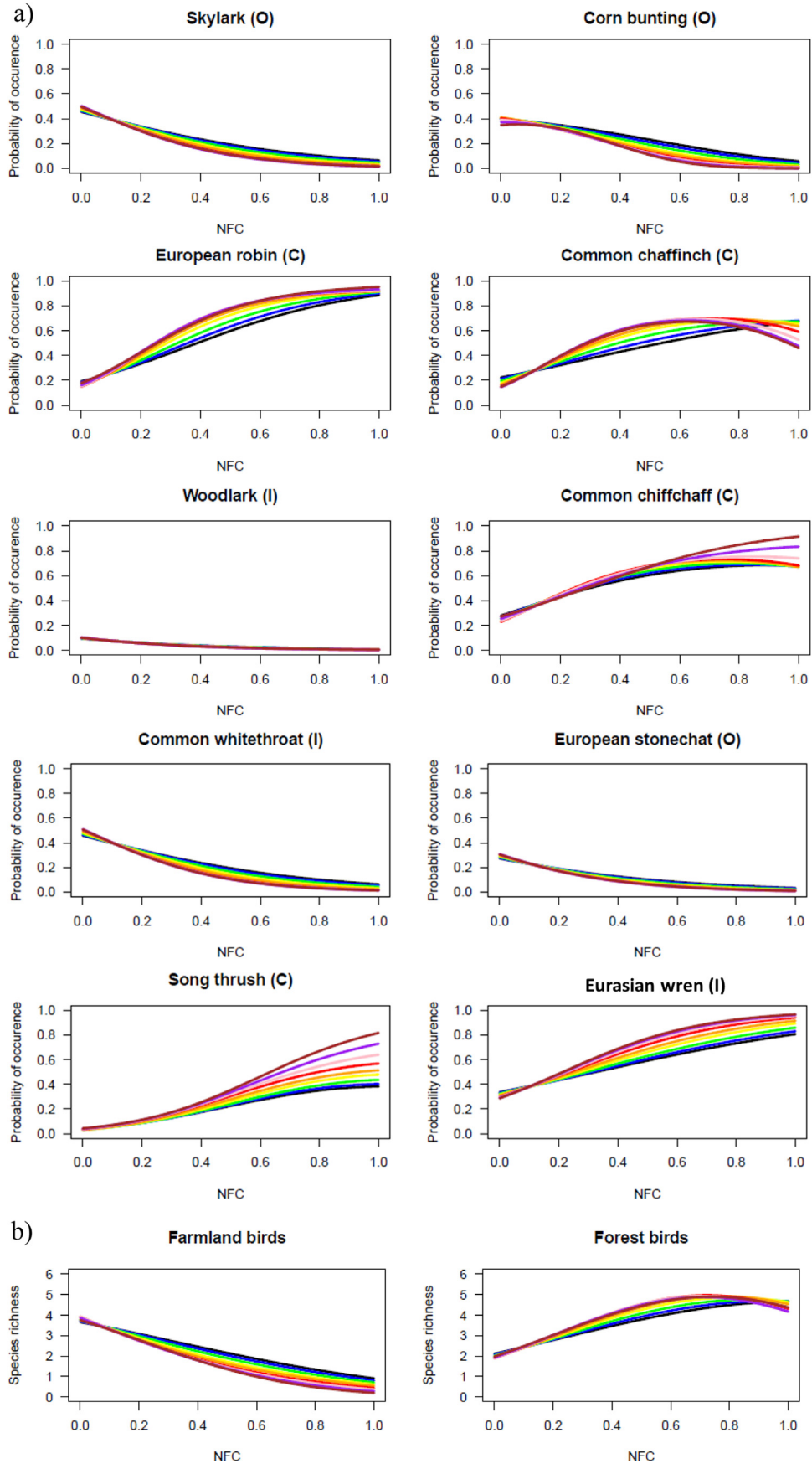
Fig. 2. (a) Probability of occurrence of the 10 bird species and (b) species richness of farmland and forest birds, in function of the Neighbouring Forest Cover (NFC) (R1: black; R2: blue; R3: green; R4: yellow; R5: orange; R6: red; R7: pink; R8: purple; R9: brown). Letters in brackets refer to the habitat type of bird species (O for open, C for closed and I for intermediate). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a)
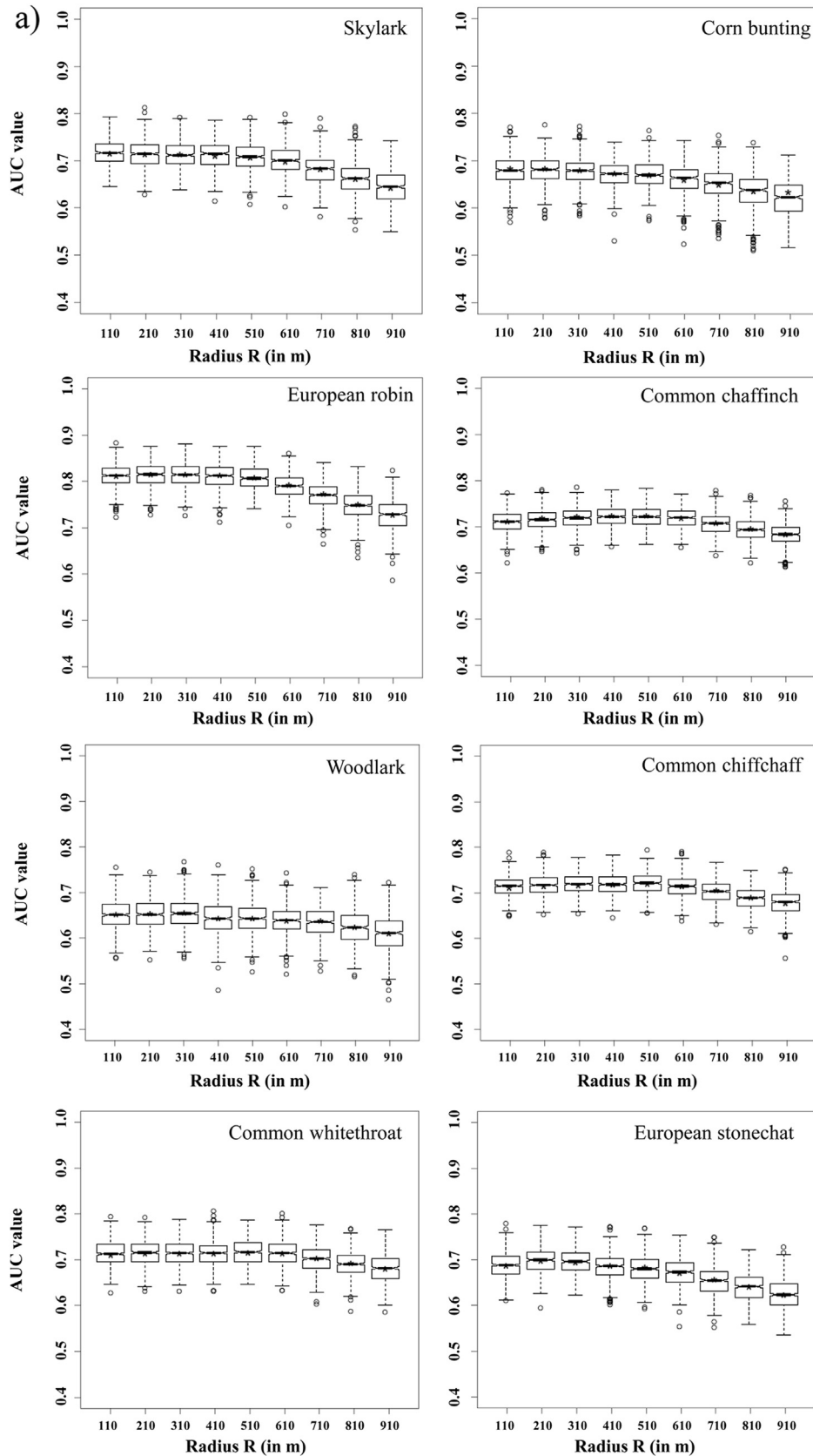
Fig. 3. Box plots of (a) the AUC values for the 10 bird species and (b) the Rho values for the farmland and forest birds, in function of the Neighbouring Forest Cover (NFC) calculated at different smoothing radii. The vertical lines represent the interquartile intervals and the circles represent the exterior values.
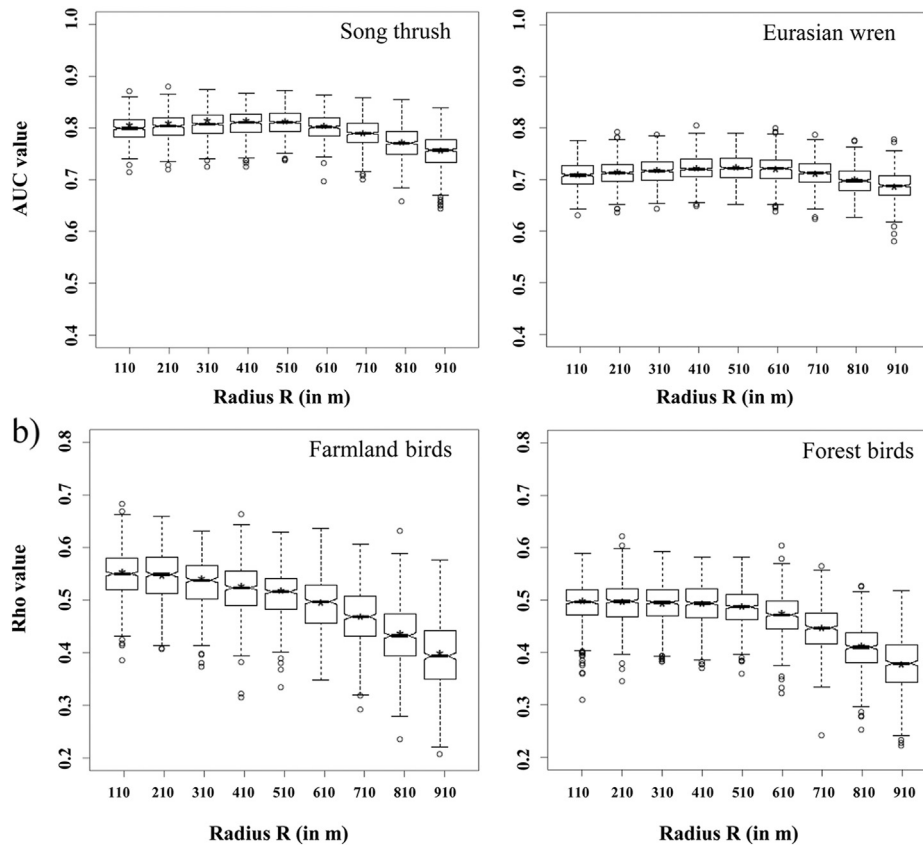
Fig. 3. (continued).

square window, corresponded to a surface area between 5 and 38 ha. For common chaffinch and European stonechat, the optimum radii were 210 m and 310 m (Fig. 3a; Table 2). For common chiffchaff the optimum was situated between 38 and 104 ha whereas it was between 67 and 104 ha for song thrush and at 104 ha for Eurasian wren (Fig. 3a). Lastly, the results did not make it possible to determine precisely an optimum radius for the species common whitethroat (between 110 m and 610 m) (Fig. 3a).

Moreover, the differences between the ρ values allowed determining optimum radii for the species richness metrics. Optimum radii for predicting the distribution of farmland birds were 110 m and 210 m, corresponding to a surface area between 5 and 18 ha (Fig. 3b). It was not possible to determine precisely an optimum radius for the species richness in forest birds (between 110 m and 410 m) (Fig. 3b).

4. Discussion

The NFC (Neighbouring Forest Cover) is a good predictor of distribution for most of the bird species examined in this study. The AUC values are at least satisfactory (AUC ≥0.7) in 70% of cases. They were lower than 0.7 for two open-habitat species (corn bunting and European stonechat) and one intermediate-habitat species (woodlark). In agreement with the results obtained by Lauga and Joachim (1992) for three forest-habitat species, the presence–absence of species favoured by forest cover is well predicted by the model developed in this study. This is the case for the European robin, a strictly forest species in South West France (AUC = 0.81). The three other forest-habitat species (common chaffinch, common chiffchaff and song trush) were also predicted well by the models. Among the most poorly predicted species were two open-habitat

specialist species (corn bunting and European stonechat), and one-intermediate species (woodlark), which had the lowest mean AUC value. However, mean AUC values for these three species were close to 0.7 that corresponds to a satisfactory value (see Section 2.3). The presence–absence of open-habitat species is thus well predicted by the model, but not as well as for forest-habitat species. This result can be explained by the fact that the model does not take into account the agricultural landscape elements likely to influence those open-habitat species, e.g. hedges or grasslands. This is particularly true for woodlark which is considered to be associated with shrub cover (Nikolov, 2010) that the NFC does not take into account. Instead, most of the biological needs (i.e. nesting, feeding) are taken into account with the NCF for forest-habitat species. Species richness of both farmland and forest bird species were moderately predicted by the models using the NFC, showing that the NFC is also a satisfactory predictor of species richness of open and forest-habitat specialist birds in agricultural landscapes.

To summarise, the used model reliably predicts the distribution of bird species that show an increasing or decreasing monotonic response to forest cover, using only a satellite image with a moderate spatial resolution (i.e. 20 m), which only captures the largest forest patches. Our results are in agreement with those of Segurado and Araujo (2004) and of Hernandez et al. (2006) who show that the end-of-gradient species (forest and open habitat) are better predicted than those in the middle of the gradient. These species can be seen as specialists for which it is easier to determine and predict habitat preferences than for generalists.

The comparison of the predictive performance of the model at different radii for each species shows moderate differences between species. Moreover, generally, one species well predicted well at 110 m remains well predicted at 710 m even if the general trend

tends towards degradation in the models' predictive performance when the smoothing radius increases from 110 m to 710 m. Optimum radii for predicting the distribution of the studied bird species range between 110 and 310 m or close to 510 m for some species. It is important to note that for 6 of the 10 species studied, the optimum radius for predicting the distribution is situated between about 110 and 310 m, which show that it is possible to find a common range of radii for the majority of the species. Indeed, these species seem to be influenced more by the local context than by the landscape context because our results show that on average the local distribution of species is predicted better with the local factors (small smoothing radii). Likewise, Cushman and McGarigal (2004) found that plot-level factors were better predictors of bird community structure than landscape-level factors in the Oregon Coast Range. In complex Mediterranean landscapes Coreau and Martin (2007) have shown that most bird species were correlated with at least two different scales of landscape description. DeMars et al. (2010) have shown the negligible impact of the landscape context, measured at different scales, on the frequentation of isolated trees by birds in agricultural landscapes, tree size and architecture being more important factors. Pickett and Siriwardena (2011) have demonstrated the influence of agricultural landscape heterogeneity on the abundance of most bird species on different scales, but they suggest that an increased heterogeneity does not always have a positive effect, in particular on the abundance of rare species that are under threat. The results are therefore variable from one study to another, and even contradictory according to the landscape context, the chosen species and the landscape description methods used. The variety of ways of explaining the structure and dynamics of landscapes using a multi-scale approach seems to us to constitute an obstacle to the comparability of the results provided by different studies. The NFC has the virtue of being simple and universal. It is possible everywhere today to obtain a binary wood/non-wood map based on a satellite image. It is therefore possible to compare the effect of a habitat on the presence–absence of birds on different scales. We are currently considering an approach which would combine, at every point of a territory, the influence of woods, hedges, grasslands, crops and dwelling places, etc.

5. Conclusions

This study presents results that may be helpful for predicting bird presence–absence and bird species richness in agricultural landscapes. Although it is acknowledged in the literature that species respond in different ways to their environment according to their living traits and that they select their habitat according to different factors, our study shows that the distribution of several species of birds can be predicted effectively by the presence/absence of wooded elements in their immediate environment (less than 500 m). It is therefore possible, in the biogeographical and landscape context of our study, to examine the surface area of the wooded elements in areas of between 5 and 38 ha, corresponding to the smoothing radii for which the models perform best, to predict the distribution of a bird population and for community conservation purposes. Further research will be required to confirm and refine these results.

Acknowledgements

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2014.01.022.

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