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Can LiDAR data improve bird habitat suitability models?

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ABSTRACT

Habitat suitability models are based on digital maps that very often describe the environment at a human scale and, hence miss ecological structures and features that are important for wildlife. LiDAR (Light Detection And Ranging) data, laser scanning acquired by remote sensing, can fill this gap by providing useful information not only on the spatial extent of habitat types but also information on the vertical height. The advantage of LiDAR derived variables lays also in the availability at a large scale, instead of just in the survey sites. In this work we evaluated the effect of three LiDAR derived variables (tree height, percentage of trees in open areas and length of ecotone) on the performance of habitat models, developed for four farmland bird species. For each species multiple runs of stepwise Logistic Regression (LR) and Maximum Entropy Models (Maxent) were performed. For each run we included and excluded the LiDAR variables and recorded the improvement in model performance using the AUC, AIC, Sensitivity, Specificity. Model results were applied in a GIS in order to create habitat suitability maps. Results for the RL models showed that for most of the species at least one LiDAR variable was selected and significant ($p < 0.05$). Additionally the inclusion LIDAR data gave a positive percentage of contribution to the AUC of the Maxent models. The models calculated using LiDAR derived variables identified a smaller area on the map, with a better overlap with open areas, thus showing a more realistic spatial pattern. The interpretation of these variable is also more straightforward, both from the ecological point of view and when defining management guidelines.

1. Introduction

Habitat suitability models are a widely used tool in conservation because they can identify species distributions and abundances in a spatially explicit way and can support planning and decision making (Pearson, 2007; Guisan and Zimmermann, 2000), especially over large areas. Regardless of the modelling techniques involved, a reliable prediction of habitat suitability depends on the quality of the data used to build the model. Species surveys can affect the output of a model in various ways, as can the descriptors of the environment in which the species of interest lives (Manly et al., 1993; Keating and Cherry, 2004). A classical source of data on environmental variables at large scales is digital cartography, such as land use, geological or climate maps, which very often describe the environment at a “human scale”, that is, they highlight the features most useful for agriculture and urban planning. These maps tend to miss ecological structures and features that are less important for humans but have a strong impact on wildlife. In some cases, explanatory variables that have known impacts on the species of interest are measured at the site level but are not available over the large areas at which the models need to be applied. Remotely sensed data appear to be almost indispensable for assessing habitat features over large areas (Graf et al., 2009) and the advent of LiDAR data seems very promising for ecological modelling (Bradbury et al., 2005; Lefsky, 2002). LiDAR (Light Detection and Ranging) data are acquired by active remote sensing utilising a laser scanning technique. The LiDAR sensor, usually mounted on an aeroplane, is a device that sends an infrared signal and registers the type and number of echoes of that signal received from the ground and from objects located above the ground such as trees, shrubs and buildings (Lefsky, 2002). Processed LiDAR data can measure earth elevations with a very high resolution compared to other remote sensing techniques, with a density of one point every 0.5–3 m. Standard processing of LiDAR data provides high resolution Digital Surface Models (DSMs) and Digital Terrain Models (DTMs) from which it is possible to derive useful information not only on the spatial extent of habitat types but also on the vertical height and structure of vegetation such as canopy structure, wood biomass and the number and height of trees (Goetz et al., 2007; Kaartinen and Hyyppa, 2008; Lefsky, 2002). LiDAR data are beginning to be used in wildlife modelling and ecological studies with interesting results, especially for woodland species, where vegetation structure plays an important role (Vierling et al., 2008; Martinuzzi et al., 2010; Müller and Brandl, 2009; Flaspohler et al., 2010). Concerning bird studies, LiDAR data describing vegetation features have mostly been used in forest environments (Goetz et al., 2007; Graf

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et al., 2009; Hinsley et al., 2006, 2008; Seavy et al., 2009), although a few examples of their application to farmland species are reported by Bradbury et al. (2005).

However, using LiDAR data has some drawbacks in terms of processing time because such high resolution data creates very large files. Further, covering a large area with laser scanning can be very expensive. In addition, due to the lack of standard techniques for extracting meaningful ecological information apart from the standard of vegetation height, various trials and ground validation are needed (Kaartinen and Hyyppa, 2008).

The final aim of the study was to find the best model for management and conservation purposes for all of the birds in the study area regarded as priorities for conservation. Before modelling the species, we wanted to evaluate the possibility of using LiDAR data to build a new set of variables based on habitat features that can be derived from this type of remotely sensed data. Four species of farmland birds were selected to test the effect of three LiDAR-derived variables (tree height, percentage of trees in open areas and length of ecotone) on the performance of habitat models. The focus of this paper is on the effect of LiDAR-derived variables on habitat suitability models calculated with and without LiDAR data. In particular, we wanted to evaluate the following:

- the level of significance of LiDAR data in models;
- the effect of the introduction of LiDAR data on the performance of habitat models (ROC analysis);
- the effect of LiDAR data on spatial patterns.

2. Materials and methods

2.1. Study area

This study was conducted for all of Trentino Autonomous Province, a region of north-eastern Italy located in the Southern Alps encompassing approximately 6200 km^2 (46 04′ N, 11 07′ E, see Fig. 1). The total population of approximately 500,000 inhabitants (2006) lives primarily in the cities of Trento and Rovereto, along the Adige Valley and in other valleys.

Since 1950, three general trends in land cover change have been observed in the Alps, including Trento Province: the growth of urban areas, taking over large extents of agricultural and natural lands; the abandonment of marginal agricultural areas due to the distance from the cities and lower productivity; and the intensification of agricultural practices in the most favourable areas (Sitzia, 2009; Tattoni et al., 2010).

The present land use of the province reflects those changes: more than 52% of Trentino is covered by forests, in which Norway Spruce (*Picea abies*) is the most representative species, covering approximately 72.25% of the forested areas (Sitzia, 2009). The rest of the province consists of approximately 16% unproductive areas (rocks, glaciers, etc.), 5% urban areas, 13% pastures and less than 5% agriculture (data from the Provincial Environmental Protection Agency). Even if the agricultural land is marginal in terms of extent, it is intensively exploited for the cultivation of high-value crops such as grapes for local wineries, apples and small fruits. In this context, grasslands and open areas are disappearing and or modified due to the changes in traditional farming practices (Sitzia, 2009; Zanella et al., 2010). As a result, the wildlife and plant species typical of open areas or extensively managed agriculture are declining in the study area as well as in many parts of Europe (MacDonald et al., 2000; Söderström and Pärt, 2000).

Fig. 1. Location of the Autonomous Province of Trento (black) in Italy.

2.2. Species data

This study focuses on four conservation-priority bird species that are typical of open areas and extensive agricultural ecosystems: the red-backed shrike (*Lanius collurio*), the corncrake (*Crex crex*), the scops owl (*Otus scops*) and the green woodpecker (*Picus viridis*). These species were selected by considering their habitat, conservation priority and the number of available records.

All of the bird presence data in this study were obtained from the Museo delle Scienze of Trento's database. Part of the data was collected during the Italian Breeding Birds Monitoring Programme, a survey that has been under way since the year 2000 at a national level (MITO project Fornasari et al., 2001) In the MITO project, bird data are collected with a simplified 10 min point count, wherein birds that are heard or seen are recorded as either within or beyond 100 m from the point count location: the protocol is described in detail by Blondel et al. (1981) and Fornasari et al. (1998). Other data came from specific monitoring programmes carried out by the Museum of Trento at the Province level: scops owl and corncrake records have been collected since the year 1996 (Sergio et al., 2009; Pedrini et al., 2002), and additional data for the red-backed shrike and green woodpecker were collected as part of two Master's theses in 2009 and 2010 (unpublished data). For three out of the four species, absence records were also available, as reported in Table 1.

Additional information about bird densities or home ranges was collected from the literature and is summarised in Table 2. Densities and home ranges were used to estimate the potential range of population for each species, based on the extent of suitable habitat identified by the models. The populations estimated by the model were then compared with the estimated numbers of individuals

Table 1
Available presence and absence records for the species considered in this work.

Species	Presence	Absence
Red-backed shrike	318	1162
Green woodpecker	306	1162
Corncrake	1223	1200
Scops owl	498	0

reported in the Atlas of nesting birds in Trento Province (Pedrini et al., 2003), which are reported in Table 2.

2.3. LiDAR data and explanatory variables

LiDAR scanning of the entire study area was commissioned by the Province of Trento and performed by the company CGR s.p.a.: the surveys took place between 2006 and 2008. The available LiDAR products delivered by the company are: the Digital Surface Model (DSM) and the Digital Elevation Model, both with a resolution of 0.5 m.

To detect vegetation using the DSM and DTM, LiDAR data were processed together with the Normalised Difference Vegetation Index (NDVI), adopting the procedure explained in detail by Demir et al. (2008) and Brovelli et al. (2002). The NDVI was computed in GRASS GIS from 4-band ortho-photos from a national project also carried out in 2008.

The Province of Trento has a very detailed digital cartography regarding many features of forested areas, but for agricultural land, it lacks descriptions of some ecological aspects that are deemed relevant for the species of interest of this study, such as the presence of shrubs and hedgerows in open areas (Brambilla et al., 2009).

LiDAR data can fill that type of gap in the available environmental data, allowing the computation of some of the missing information.

Once the vegetation cover was extracted from the LiDAR DSM, it was possible to derive three new environmental variables: tree height, the percentage of tree cover in open areas and the length of ecotones in open areas. Tree height accounts for the three-dimensional structure of the vegetation: this variable was directly derived from the LiDAR DSM. GIS analyses were performed to compute the relative coverage of trees and shrubs for each open area. The length of the ecotone was evaluated by considering the interface between the trees and the rest of the open area.

The presence or absence, quality and amount of tree coverage in an open area are thus believed to affect the four species in various ways (Latus et al., 2004; Titeuxa et al., 2007; Sergio et al., 2009; Brambilla et al., 2009).

The computation of these three variables for the extent of the study area was a time-consuming task because of the high resolution of the LiDAR data, and it was necessary to divide the study area into 10 smaller subregions to store the data in memory. The results were mosaicked at a second stage with the aid of scripts to automate the entire procedure.

Table 2
Additional information about bird densities or home ranges for the four species. Densities are taken from Cramp (2000) and Brambilla et al. (2009). Numbers of nesting pairs or estimated numbers of pairs for each species in Trento Province are reported in Pedrini et al. (2003). * For the scops owl, only the number of territories was available in the cited publication.

	Red-backed shrike	Green woodpecker	Corncrake	Scops owl
Min. density	1/ha	3/	0.11/ha	
Max density	4.7/ha	5/	0.13/ha	0.5/
Home range		120–250 ha		3.6/
Nesting pairs	100–1000	1000–10,000	60–140	100*

Table 3
List of the maps and orthophotos used in this work as environmental variables or to create new ones. PAT "Provincia Autonoma di Trento" indicates original data from the Province geodatabase and CGR stands for "Compagnia Generale delle Riprese", the company that carried out the aerial surveys; the other maps were created from the cited originals.

Data	Spatial resolution	Source
Elevation (DEM)	10 m	PAT
Slope	10 m	Derived from DEM
Aspect	10 m	Derived from DEM
Average hours of sun per season	10 m	Derived from DEM
Land use map (Pguap 2006) reclassified	10 m	PAT
Diversity index	10 m	Derived from Land use map
Percentage of open, shrub and forest in 3 ha buffer	10 m	Derived from Land use map
Distance from isolated houses, roads	10 m	Derived from Land use map
Distance from roads	10 m	Derived from Land use map
Open areas	10 m	Derived from Land use map
Idrography	10 m	PAT
Distance from rivers and lakes	10 m	Derived from Idrography
Digital ortho Photo 4 bands 2008	1 m	CGR s.p.a.
DSM LiDAR 2008	0.5 m	CGR s.p.a.
Tree height	2 m	Derived from LiDAR
Percentage of trees in open areas	2 m	Derived from LiDAR
Length of ecotones in open areas	2 m	Derived from LiDAR

The other environmental variables and the base maps from which they were derived are summarised in Table 3. GIS analyses were performed with GRASS GIS 6.4 (GRASS Development Team, 2008), figures and map layouts were produced using Quantum GIS 1.6 (Quantum GIS development team, 2011). The whole geographic data set is projected according to the Italian Gauss-Boaga reference system, West Fuse, datum Rome 1940; the spatial resolution for the final models is 25 m.

2.4. Habitat models and statistical analyses

Presence and, when available, absence data were used as response variables, and the LiDAR-derived data together with the other geographical data were used as explanatory variables to build different models of habitat suitability. We first performed an exploratory data analysis following the steps suggested by Zuur et al. (2010) to make an initial reduction in the number of variables to avoid collinearity.

We chose to model the species distributions using forward stepwise logistic regression (GLM with a logit link function) and maximum entropy (Maxent) models. For each species, we ran both models including LiDAR and excluding LiDAR variables 30 times; for each run, a random 25% sub-sample of unique observations was selected for model testing. Further variable selection was then performed in the GLM approach but not in the Maxent approach because the Maxent software lacks a tool for variable selection.

Therefore, for each species a total of 120 models were computed: 30 iterations of each method with two sets of environmental variables (including and excluding LiDAR) for a grand total of 420 models. ROC analysis was then performed on all results: the AUC, specificity and sensitivity were evaluated for the training and test datasets (Fawcett, 2006). Those parameters were used to select the best model amongst the thirty versions computed for each combination of method, dataset and species (Anderson et al., 2003; Lobo et al., 2008). The aim was to select foe each species the best LR model with LiDAR data, the best LR model without LiDAR data and the best Maxent models with and without LiDAR data to make comparisons within and amongst different methods.

For each species and modelling method, we made an initial selection of the best model with the training and test datasets to identify the model with the best ROC parameters for both fitting (training) and prediction (test).

Despite the fact that AUC is a widely reported parameter in works about species distribution modelling, its use as a single index of model performance has been criticised (Jiménez-Valverde, 2011; Jiménez-Valverde et al., 2011; Lobo et al., 2008).

In this work, with the availability of absence data, AUC can be considered a valuable index of model performance *sensu* (Jiménez-Valverde et al., 2011; Lobo et al., 2008). However, model comparison was performed using all of the information about commission and omission errors issued by the ROC analysis, as recently recommended by (Jiménez-Valverde et al., 2011; Lobo et al., 2008).

The importance of the contribution of LiDAR data was then assessed using the best model for each approach for each species. The best LR models were compared using ANOVA, whereas the importance of LiDAR in Maxent modelling was evaluated by considering the contributions of LiDAR-derived variables in improving the AUC.

Logistic regression and ROC analyses were computed using R 2.13.1 and the additional ROCR package (R Core Team, 2005; Sing et al., 2005). Maxent modelling was computed with version 3.3.3e of the Maxent software by Phillips et al. (2006).

3. Results and discussion

3.1. Level of significance in models

To understand the role played by LiDAR variables, we recorded the number of iterations in which LiDAR variables were significant. The level of significance was selected differently in the two modelling approaches. For Stepwise LR, we used the standard output given by the GLM in R: for each variable we considered the coefficients, their standard errors and their z-statistic (Wald z-statistic). If a LiDAR-derived variable was selected during the stepwise procedure and its Wald statistic had a $p < 0.05$, we counted it as significant. LR models were not computed for the scops owl because no absence data were available for this species; we preferred not to create pseudo absence data in this case so that the results would be comparable with the species for which we had real absence data. As assessed by Keating and Cherry (2004), the logistic outputs of models computed using real versus generated absence data can have different interpretations in terms of habitat suitability. To avoid the introduction of too many hypotheses, the LR model for the scops owl was not computed.

The Maxent approach does not provide a variable selection tool, so the level of significance was based on the percent contribution of the variable to the explanatory power of the model, one of the metrics reported in the model output for Maxent. We chose a threshold of a 5% contribution and counted how many times the contribution of each LiDAR variable was greater than that level.

Table 4 summarises the number of times that any LiDAR-derived variable was selected as significant in the 30 iterations of LR and Maxent for each data set. The results presented in Table 5 show that, as expected, the impact of LiDAR variables varies according to the species being modelled, but quite surprisingly, also varies within the modelling techniques for the same species.

For the red-backed shrike and the corncrake, there is a difference between the two modelling approaches. The red-backed shrike appears to be more affected by the length of the ecotone and the height of the trees, which were identified as significant 60% of the time (18 out of 30 iterations, see Table 4), whereas the percent coverage of open areas was not significant most of the time in LR. In the Maxent models, the contribution of the length of the ecotone was significant in approximately 30% of the iterations, but contributions were negligible or null for the other two variables. For the corncrake, according to the LR results, the impacts of all three LiDAR variables were significant, and all three of them were selected in almost all iterations (see Table 4), whereas for Maxent, only the percentage of tree coverage contributed significantly to the model.

For the green woodpecker, both the Maxent and LR modelling techniques identified ecotone length as a significant variable in most iterations, whereas the other LiDAR-derived metrics had a smaller or null impact.

Concerning the first aim of the study, the level of significance of the LiDAR variables in the models varies according to the species and the modelling technique. The interpretation of this result lies in the biology of the different study species. In general, the most important feature for the four species is the presence and amount of ecotone. In an intensive agricultural environment, the presence of an interface between cultivated land and small forested areas or hedgerows is recognised to play an important role for birds. The vertical structure in terms of the height of the trees appears to be less significant in this kind of environment, perhaps because for these birds, it is more important to have something to perch on (ecotone) independent of its height. A different interpretation is necessary for the corncrake, which instead needs an open area with high grasses at intermediate elevations. The presence of trees and

Table 4
(a) Number of times that any LiDAR-derived variable was selected as significant during the forward stepwise selection in LR models. The results are reported for the three species where LR was applicable. Number of iterations per species: 30, significance level: $p < 0.05$. (b) Number of times that any LiDAR-derived variable made a contribution to the AUC of a Maxent model that was greater than 5%, 30 iterations per species.

	Perc. of trees	Height of trees	Length of ecotone
(a) LR			
Red-backed shrike	12	18	18
Green woodpecker	7	11	25
Corncrake	23	30	30
(b) Maxent			
Red-backed shrike	2	0	11
Green woodpecker	0	10	30
Corncrake	30	0	0
Scops owl	0	0	30

Table 5
Summary of the results for the best models for each species: Model type indicates the modelling approach for the best model that resulted from the analysis; the parameters of the ROC analysis consisted of AUC, Sensitivity and Specificity; LiDAR indicates whether LiDAR variables were present in the model. Suit. area stands for suitable area, and it is measured in. Estimates of the minimum and maximum number of pairs (Pairs min and max rows) were derived from the literature (see Section 2 for more details).

	Red-backed shrike	Green woodpecker	Corncrake	Scops owl
Model type	Maxent	LR	LR	Maxent
AUC train	0.95	0.89	0.96	0.98
AUC test	0.88	0.83	0.93	0.98
Specificity	0.53	0.81	0.90	–
Sensitivity	0.81	0.67	0.86	–
LiDAR	Yes	Yes	Yes	No
Suit. area	133	1241	240	57
Pairs min.	133	3722	205	16
Pairs max.	624	6204	2255	114

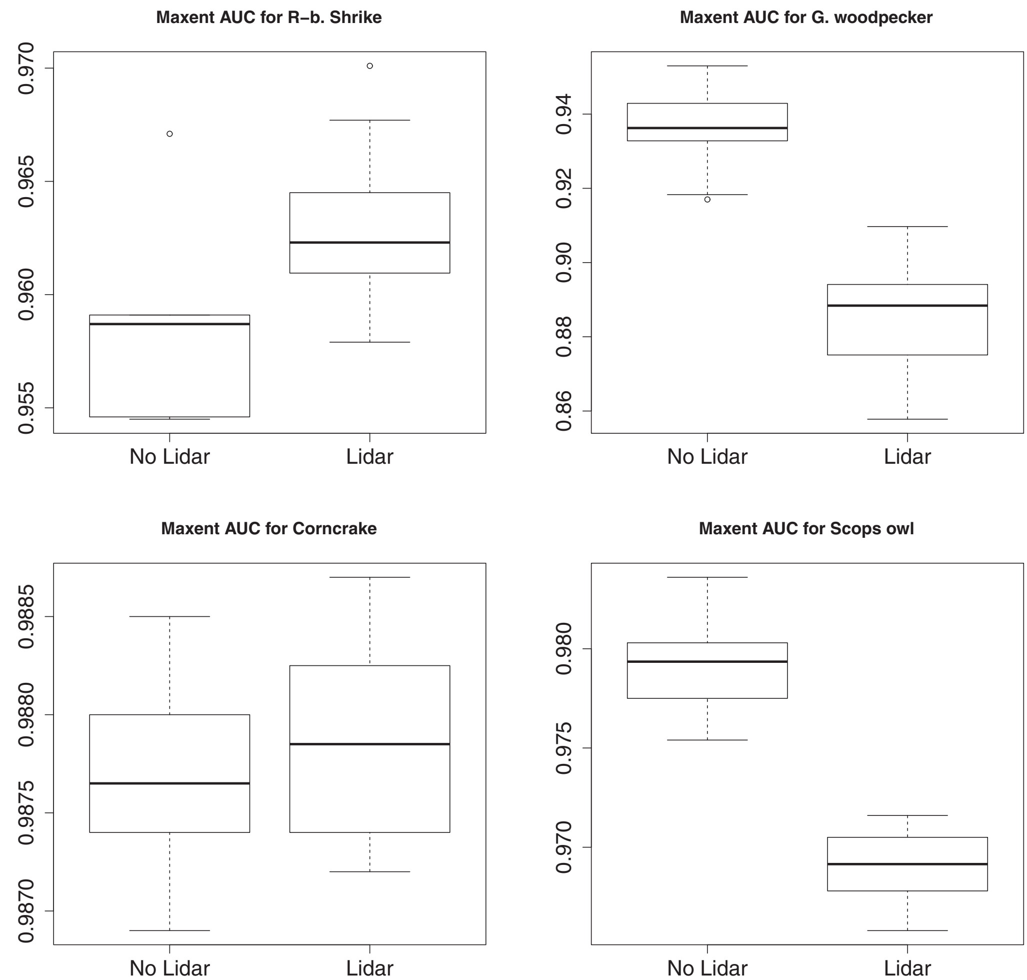

Fig. 2. Box-plots of the parameters from the ROC analysis; the inclusion of LIDAR-derived variables improves the performance of the models.

shrubs can negatively affect the suitability of an open area for this species.

3.2. Performance of habitat models

The introduction of additional variables in models does not always improve their performance in terms of predicting power (Zuur et al., 2010), so an ROC analysis was also computed for all of the models. AUC, sensitivity and specificity were used to select the best model within the models (LiDAR vs. No LiDAR) and then between Maxent and LR.

For LR, it was also possible to compare models using ANOVA. This analysis was performed before the ROC analysis, resulting in significant differences between the models including LiDAR-derived variables and those not including them for all of the species ($p < 0.05$). The results of the ROC analysis for the LR models are presented in Fig. 3. The ROC parameters of all of the Maxent iterations were tested with a *t*-test, which indicated a significantly better ($p < 0.05$) AUC for models including LiDAR in the case of the red-backed shrike, a better AUC for models without LiDAR variables for the scops owl and no difference in the case of the corncrake (Fig. 2).

Given that the final purpose of the assessment was to build habitat suitability models that would be useful for planning, the ability of the models to correctly predict a test data set was of particular importance. Therefore, the best model for each set was the one with the best ROC parameters on both training and testing data, using a cut-off of 0.5. Those parameters are useful for assessing model performance and making comparisons; occasionally a satisfying model accuracy can be obtained when absence points are better predicted than presences, but these kinds of results can lead to a misinterpretation of the model and misuse in planning. Table 5 summarises the final results for the selected best models.

The model chosen as best for the red-backed shrike was computed with Maxent using LiDAR variables: their contributions in improving the AUC of the model were 3.6% for percentage of tree cover, 3.3% for length of the ecotone and 1.4% for tree height.

For the green woodpecker, the best model came from the LR and included only two LiDAR variables as significant: percentage of tree cover, with a negative effect on presence, and length of the ecotone with a positive effect on the presence of the species.

The best LR model for the corncrake gave the best results compared to the best models of the other species in terms of classification power for presence and absence points, as shown in Table 5. The variable selection step for this model retained all three of the LiDAR variables as significant for defining the habitat of this species.

For the scops owl, the LiDAR variables added noise to the model but did not provide useful information; the model without LiDAR variables correctly classifies more presence points than the one with LiDAR. Thus, for this species, the best model (see Table 5) excluded the LiDAR variables. This model was computed using presence-only data, so the parameters of ROC analysis regarding absence points could not be computed and were not reported in Table 5.

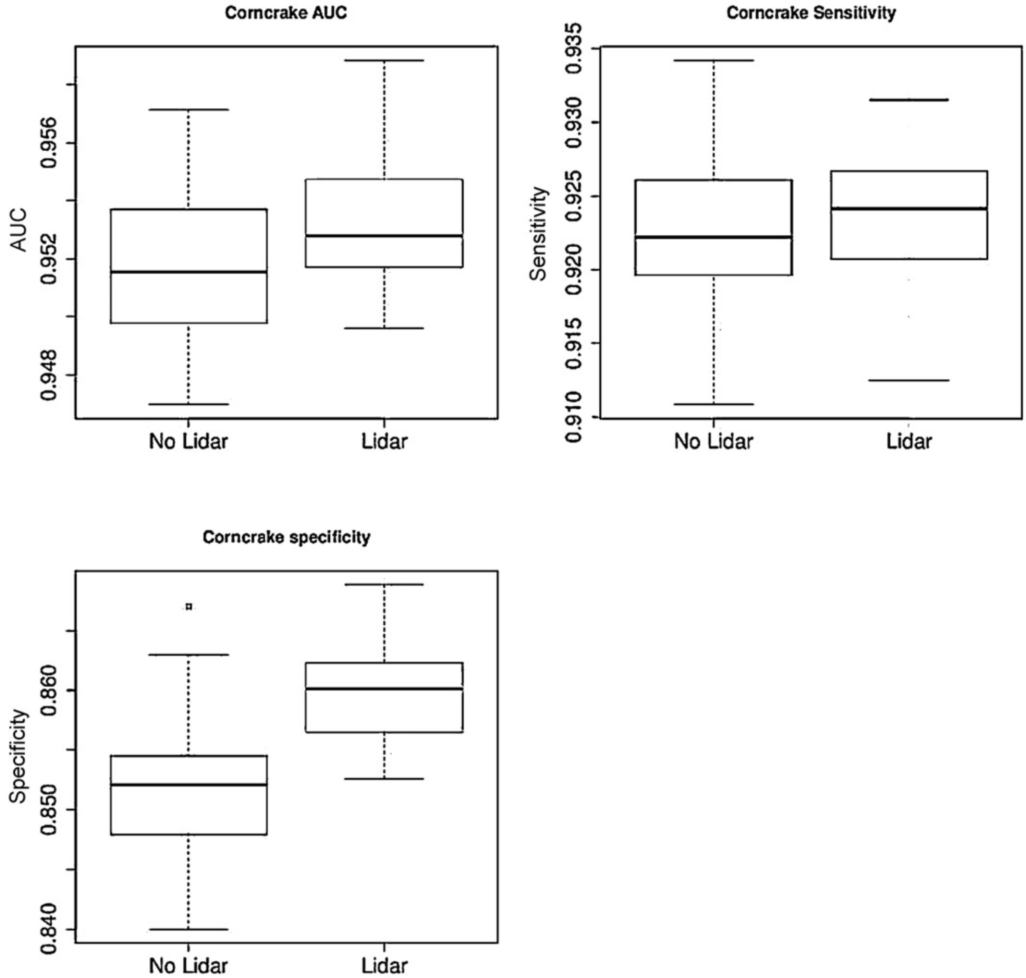

Fig. 3. Box-plots of the AUC for Maxent models with and without LiDAR data for the four species. Differences are significant for all species except the corncrake (*t*-test, $p < 0.05$).

3.3. Spatial pattern and number of pairs

The best models were applied in a GIS and the total areas covered by suitable habitat were computed for each species. Based on the bird minimum and maximum densities for the four species (reported in Table 5), we were able to estimate a minimum and maximum number of breeding pairs in the Province of Trento.

For the red-backed shrike, green woodpecker and corncrake (the three species whose best models included LiDAR), the maps obtained from the models without LiDAR followed the pattern of land use classes and tended to have larger suitable areas compared to the maps obtained from the models including the LiDAR variables. The inclusion of LiDAR variables resulted in a different suitability assigned to the same land use class because of the presence or absence of vegetation structures that were not included in the land use map.

The best models for these species selected only the patches or part of the patch of the suitable land use class according to the presence of features such as trees or edges represented by the LiDAR variables. For these three species, the models computed without LiDAR data have higher omission errors, that is, they made the mistake of classifying presence points as absences more often than the models with LiDAR data (Sensitivity for no LiDAR models: r.b. shrike 0.5; g.woodp 0.48; corncrake 0.68). Fig. 4 illustrates a spatial comparison of the best models without and with LiDAR for the corncrake as an example of the general results for all of the considered species.

The map of open areas, derived from the land use map, was taken as reference to quantify the overlap of the models using the Kappa index of agreement (Rosenfield and Fitzpatrick-Lins, 1986). A very high coincidence with this reference map indicates that the model selection is based on land use classes, whilst an intermediate degree of overlap is an index of selection amongst the same land use class. For instance, the red-backed shrike map obtained by LiDAR model selects approximately 45% of the open areas as suitable, whilst the one without LiDAR identifies as suitable almost all of them (86%). A similar proportion is observed also for the other two species. Distribution maps were also qualitatively evaluated by the Museum's experts in ornithology who identified a more realistic pattern in the maps obtained by LiDAR models; a visual check of the spatial outputs can complete the evaluation of model accuracy (Pontius et al., 2004).

The area predicted as suitable for the red-backed shrike in Trentino is approximately 132 km^2, which was computed based on a cut-off suitability value of 0.5 (Table 5). According to the species densities reported in the literature (see Table 2 for reference), 130–600 pairs of red-backed shrikes could potentially live in this area, a figure that is in agreement with the estimated number of nesting pairs for the region (100–1000).

The area predicted as suitable for the green woodpecker in the study area is of approximately 1240 km^2, as presented in Table 5; the potential number of pairs in this area ranges from 3700 to 6200, a figure that is in agreement with the estimated number of nesting pairs for the region, between 1000 and 10,000 pairs.

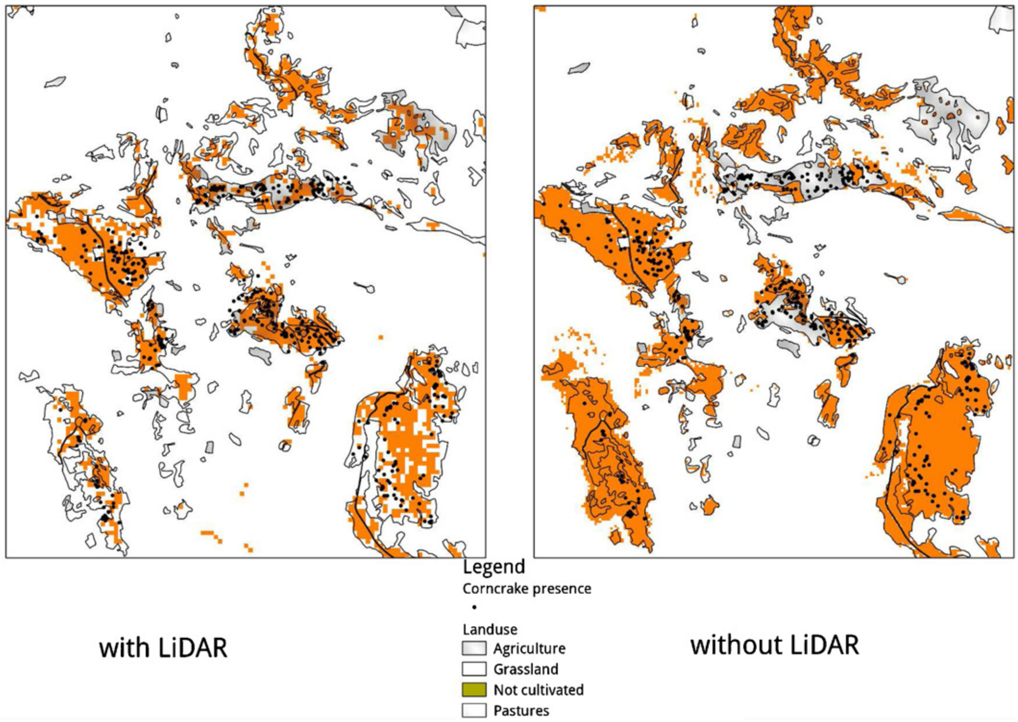

Fig. 4. Different spatial outputs of corncrake models within an enlarged area: (a) the map of LR results computed without LiDAR variables follows the pattern of land use classes; (b) the map of LR results including LiDAR data selects suitable habitat areas within the land use classes. Black dots are points of species presence.

The corncrake in Trentino is at the western margin of its range of occurrence and is considered rare. The suitable area identified by the model is 240 km^2, which could potentially host a population of up to 200 pairs, but the estimate from the atlas of nesting birds is quite a bit lower (maximum 140 pairs). Some of the suitable habitats in the western part of the Province were visited during the surveys of the study area, but the species was absent from those habitats. Other factors may influence the distribution of the corncrake in Trentino, such as migration routes or grassland management (Pedrini et al., 2002), but these were not included in the models at this stage.

The model for the scops owl predicted a suitable area of less than 60 km^2 over the entire study area. The number of pairs calculated using the home range size is approximately 114 pairs, which agrees well with the estimated number of nesting territories in the region.

4. Conclusions

Habitat models at large spatial scales can be useful for conservation (Graf et al., 2009) if the explanatory variables directly describe features that increase habitat suitability. Understanding which features improve habitat quality for conservation priority species can help managers to define effective guidelines. In the case of the agricultural environment of Trentino, the introduction of LiDAR-derived variables improved the model outputs for three out of four of the species considered in this work. These improvements concerned different aspects of the modelling process, from the ability to classify presence and absence to spatial pattern. Our estimates of the potential numbers of breeding pairs in the province based on the extent of suitable habitat agree well with those reported in the literature.

LiDAR-derived variables filled the gap in traditional land use cartography, which failed to describe some important vegetation features such as the presence of trees and shrubs and the presence of ecotones in agricultural landscapes. The interpretations of these variables are straightforward, both from the ecological point of view and when defining management guidelines. For example, the importance of the length of ecotones can enable managers to define effective actions for improving the habitat quality of agricultural land by promoting the plantation of hedgerows or favouring irregular shapes for the interface between cultivated areas and forests.

The effects of the three LiDAR-derived variables assessed in this work varied according to the species being modelled, which was expected because the four species of birds have different ecological requirements. It is possible that the ecological preferences of the scops owl could be better described by the three-dimensional structure of the vegetation and that further processing of LiDAR data could bear useful variables in the future.

An analysis of areas of the same agricultural type but with different habitat suitability levels can help managers to focus on the interventions needed in the Province. One of the next steps is to analyse the connectivity and spatial aggregation of potentially suitable agricultural patches for the species to set priorities for intervention. The species considered in this study are positively affected by the amount of ecotone in open areas and by the presence of trees and shrubs.

We encourage the introduction of LiDAR data into habitat modelling and the development of algorithms capable of deriving other structural information from this kind of remotely sensed data. LiDAR variables exhibit a great potential for conservation-oriented modelling that still needs to be explored.

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