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Original Research Article

Expert-based and correlative models to map habitat quality: Which gives better support to conservation planning?

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ABSTRACT

Biodiversity loss and habitat degradation are big challenges to be tackled by conservation planning since their effects on both ecological and social-economic systems are remarkably detrimental. Efforts to limit anthropogenic impacts on species and habitats need to be assisted by tools for biodiversity monitoring. Effective monitoring tools could help bridge the gap between science and policy, better assess trade-offs between biodiversity and other services, and potentially reduce the associated social costs of conservation. Here, we assessed the feasibility of monitoring habitat quality for bird communities in Central Italy using the InVEST Habitat Quality model. InVEST was parameterized using outputs from species distribution models (SDMs) and expert-based models to explore their viability to support conservation planning. Our results highlight that InVEST parameterized by SDMs produced habitat quality maps that correlated highly with spatial patterns of observed species richness, while the expert-derived InVEST outcomes showed lower correlation. However, the latter approach proved useful as a first-line analysis to identify large-scale areas of conservation concern, where field data and modeling approaches such as SDMs are needed to assess fine-scale conservation value. We show SDM-informed habitat quality maps can accurately identify conservation priority areas, though their applicability is overall limited by data availability. On the other hand, expert-based habitat quality maps can be used as a surrogate approach for preliminary and/or exploratory studies, especially in contexts characterized by poor data availability/quality and budgetary constraints.

1. Introduction

The conservation of habitats and species is at the basis of ecosystems' functionality and resilience (Mace et al., 2012), and in turn contributes to people wellbeing via the ecosystem services (ES) provision (Cardinale et al., 2012). However, global

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transformations such as climate and land use change increasingly alter biological systems worldwide (e.g., Ellis, 2013), in terms of e.g. species losses (Hooper et al., 2012) and subsequent greater environmental changes (Cardinale et al., 2012). Recently, several strategies to halt biodiversity loss and reduce ecosystems' degradation have been developed, from global (CBD Strategic Plan for Biodiversity, 2011–2020 and the Aichi Biodiversity targets) to European scale (the EU Biodiversity Strategy to 2020). Nevertheless, conservation targets are still far to be met, both globally (e.g., Tittensor et al., 2014) and in Europe (European Commission, 2015). This means that further efforts are necessary to improve the currently available tools for the assessment and monitoring of biodiversity conservation at various scales, even incorporating external barriers and drivers (e.g. integrated modeling; Mokany et al., 2016.

Indeed, during the last decades, several initiatives have been undertaken to slow down species extinction rates, shifting of species ranges, and habitats degradation, such as enlarging Protected Areas' Network (Watson et al., 2014), or reducing the gap between costs and social benefits of conservation (e.g., the case of Natura, 2000 network in Europe; Gantioler et al., 2014). In the same way, systematic conservation planning has been proposed as a framework to improve conservation efforts within and outside protected areas, in particular through monitoring biodiversity threats, and incorporating modeling and mapping tools (Margules and Pressey, 2000). Such aspects are demonstrated to improve the effectiveness of prioritizing conservation goals, and implementing actions on ground (e.g., for Mediterranean landscapes; Levin et al., 2013). Nevertheless, much more efforts are needed to halt biodiversity loss and habitat degradation at both global (i.e., entering the sixth mass extinction; Ceballos et al., 2015) and EU scale (Maiorano et al., 2015).

On the research side, biodiversity modeling – consisting of process- and expert-based approaches – has been demonstrated to support conservation planning in several ways (e.g., Clevenger et al., 2002; Guisan et al., 2013). Species distribution models (SDMs) are the most widely used correlative models (see Elith and Leathwick, 2009 for an exhaustive review) and are able to support conservation planning (McShea, 2014) by: (*i*) identifying short-term consequences of policy decisions that can be then evaluated; (*ii*) constructing future scenarios to be discussed with stakeholders; and (*iii*) bridging the gap between research and policy making, typically in an iterative process involving revisions to the modeling approach, parameters, and scenarios. However, SDMs are prone to some weaknesses and pitfalls, which mainly concern the representation of niches, sampling biases, failure in accounting for species associations, scale mismatches, and predictive accuracy evaluation (Araújo and Guisan, 2006; Fourcade et al., 2018; Morelli and Tryjanowski, 2015, 2014; Sinclair et al., 2010). In particular, while supporting conservation planning, an important limitation of (mostly static) SDMs stems from uncertainty in future projections, i.e. the difficulty to incorporate changing environmental parameters, climate, and other variables (e.g., McShea, 2014). Furthermore, conservation planners should implement SDMs according to contextualized needs, ecology of species, and data availability (e.g., Johnson and Gillingham, 2005). Improving effectiveness of both modeling and decision-making processes, while reducing uncertainty linked to the adopted approaches and environmental variables taken into consideration, is extremely important in conservation planning. For example, expert-based approaches have been successfully adopted to model distribution and abundance of sambar deer in Australia (Yamada et al., 2003), as well as map distribution of "focal species" in Northern Italy (Gobbi et al., 2012). Even though experts often play a key role in supporting model development and interpretation of results at relatively low costs, their knowledge and rationale behind may be less transparent and robust than other approaches, i.e. correlative ones (e.g., Johnson et al., 2004).

Species distribution and richness are strongly interconnected with the suitability of a site (i.e., habitat). Habitat suitability assesses the likelihood a certain location can host a given species over a spectrum of environmental conditions. In turn, habitat loss and degradation are useful for indicating to conservation planners a reduced probability to find a species within its distribution range, as well as for highlighting threatened areas critical for biodiversity conservation (Johnson, 2007; Terrado et al., 2016). Several studies have focused so far on calibrating SDMs for common birds in Europe (e.g. Vallecillo et al., 2016). On the same line, recent efforts have been made to strengthen the utility of models combining habitat suitability and potential threats to assess habitat quality (HQ) as a support to conservation planning. For example, the models implemented in the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) software have been used to analyze changes in HQ in freshwater ecosystems in Spain (Terrado et al., 2016), map HQ in relation with biodiversity protection levels in Italy (Sallustio et al., 2017), and spatially correlate HQ and multiple ES according to alternative scenarios in a Taiwanese watershed (Lin et al., 2017). Nevertheless, further research is needed to explore the potential contribution of SDMs and expert-based models in providing information to aid spatially-explicit assessment of HQ, especially in conservation planning (Store and Kangas, 2001). Indeed, the possibility to obtain cost-effective and reliable spatially –explicit information on HQ, and more generally on ES, is particularly relevant to identify optimal scenarios of habitat protection and restoration (e.g., Crossman and Bryan, 2009; Lehtomäki and Moilanen, 2013). This need is crucial in data-poor and multiple stakeholders' demands contexts (e.g., coastal areas; Rova et al., 2018), where approaches like systematic conservation planning (Lehtomäki and Moilanen, 2013) can offer a viable support in the decision-making arena, even facilitating stakeholders' engagement and active participation as well as trade-offs analysis among multiple ES (Lin et al., 2017; Pandeya et al., 2016). InVEST represents a comprehensive and flexible decision support tool not limited to conservation planning, but, broadly, to landscape policy and planning (Sallustio et al., 2017). For instance, this tool allows to i) enlarge the bundle of ES taken into account, thus allowing to explore the impact of certain choices on ES other than biodiversity, ii) actively engage stakeholders in the ES assessment and scenario building, iii) have a free and open-source interface easily adaptable to specific users' needs. These features clearly represent an advantage if expanding nature conservation purposes out of the strictly designed protected areas as e.g. in the perspective of a working lands conservation approach (Kremen and Merenlender, 2018).

Considering the above-mentioned issues, the present work aims to compare two approaches to modeling HQ within the InVEST tool — one based on SDMs, the other based on expert opinion — and assess the implications for conservation planning. HQ of bird communities in central Italy is mapped by using two alternative parameterizations of InVEST. In particular, we alternatively input InVEST with a SDMs-derived and an expert-judgment derived species richness index, obtaining two bird-specific HQ predictions for the study area. Predictive accuracy of the two HQ predictions was then evaluated by using independent data on bird species richness. The specific objectives of the study were to: (*i*) predict bird species distribution and richness using SDMs and expert-opinion approaches; (*ii*) calculate HQ from SDMs-derived and expert-based derived species richness indexes; (*iii*) evaluate predictive accuracy of HQ predictions; (*iv*) identify spatial aggregates in HQ predictions. Finally, recommendations on how SDMs and expert-based models can be used for conservation planning are drawn, along with related potentialities and limitations of both approaches.

2. Materials and methods

2.1. Study area

The study area encompasses the Molise region (Central Italy), covering ca. 450,000 ha with altitude ranging from sea level to 2050 m a.s.l. Climate heterogeneity, ranging from a Mediterranean type along the coastline to continental characteristics in the interior (Pesaresi et al., 2017), coupled with the litho-morphological variability (Smiraglia et al., 2013) strongly influence habitat diversity through the region. This is demonstrated by the coexistence of different ecosystems and potential natural vegetation types (Blasi et al., 2017).

The land cover comprises more than 157,000 ha of Mediterranean and temperate forests (approximately 35% of the study area), with also ca. 49% of croplands and grasslands (Sallustio et al., 2016; Vizzarri et al., 2015a). Forests are dominated by Turkey oak (*Quercus cerris* L.) (40% of the total forest area), downy oak (*Q. pubescens* Willd.) (22% of the total forest area), and European beech (*Fagus sylvatica* L.) (9.5% of the total forest area) (Vizzarri et al., 2015a). Forests are primarily managed as coppices (76% of the total forest area) rather than high forests (Bottalico et al., 2016) thus further contributing to habitat diversification.

2.2. Analytical framework

The analytical framework proposed in this study included three main components: SDMs, expert-based (EXBAS) and InVEST models (Fig. 1). We alternatively used SDMs and EXBAS to predict bird species distribution in the study area. Single-species distributions derived by each method were then stacked (D'Amen et al., 2015; Distler et al., 2015; Scherrer et al., 2017) obtaining two species richness predictions. We used these richness predictions as input data for InVEST, along with a species-specific threats matrix derived from expert knowledge. Using these inputs, InVEST generated two predictions of HQ for bird species in the study area, whose spatial accuracy was evaluated using independent occurrence data. Finally, we assessed the

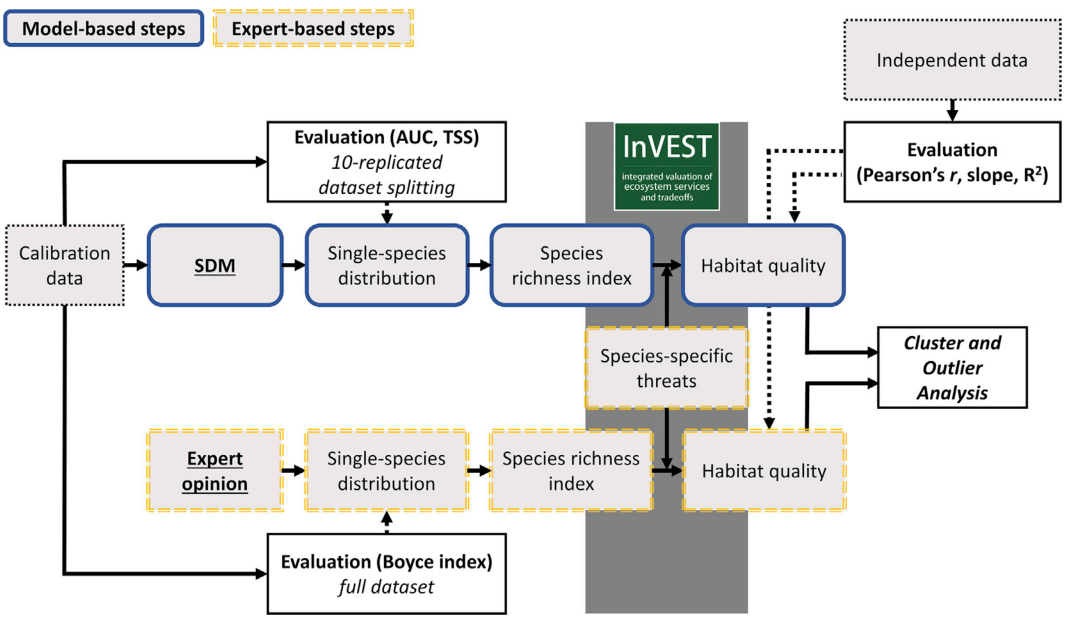

Fig. 1. Analytical framework.

coherence between the two InVEST predictions in identifying areas of high/low conservation concern by calculating HQ hotspots/coldspots (Sallustio et al., 2017) and cross-tabulation matrices (Pontius et al., 2004).

2.3. Predicting species distributions

2.3.1. Correlative models

As most of the analyzed species are widely distributed across the Palearctic (BirdLife International, 2015), with the study area representing just a small portion, SDMs were produced using a hierarchical structure, from global to regional scale (Di Febbraro et al., 2015; Gallien et al., 2012; Lomba et al., 2010), in order to avoid truncated niche estimations that could bias the predictions (Barbet-Massin et al., 2010; Guisan et al., 2014; Raes, 2012). Accordingly, models were at first implemented to estimate species niches at their global range scale using bioclimatic variables (Global SDMs; Appendix S1). Then, local predictors (see below) were used to refine the predictions at a regional scale (Regional SDMs, 'SDMs' hereafter; Di Febbraro et al., 2015; Gallien et al., 2012; Lomba et al., 2010).

Presence/absence data used for SDMs calibration were derived from the "Italian Breeding Bird Monitoring" (MITO2000 Project; Fornasari et al., 2010, but see also Chiatante, 2017; Stephens et al., 2016; Valerio et al., 2016) spanning from 2009 to 2013. The MITO2000 sampling scheme is based on the UTM 10 km $\times$ 10 km grid over the Italian peninsula. Within each UTM square, bird surveys are conducted yearly by the point counts method in 15 sites randomly placed at a minimum distance of 1 km (Fornasari et al., 2010). Occurrence data derived by point counts surveys have been successfully used to predict bird species distribution in several studies (Brotons et al., 2007; Howard et al., 2014; Moudrý et al., 2017; Sheehan et al., 2017; Vallecillo et al., 2009). Data were filtered by removing duplicated records, thus obtaining a final dataset of 263 sampling points randomly located within the study area. We considered only species occurring in at least 25 sites, retaining 29 species in total (Table S1). Data were temporally split in two blocks (Roberts et al., 2017; Smith et al., 2013), a first set including 185 records (2011–2013) adopted to train SDMs and a second set of 78 points (2009–2010) used as independent data to evaluate the final InVEST outputs (i.e., the two HQ maps). This data splitting setup allowed calibrating SDMs on approximately two-thirds of the available occurrence records, while keeping the remaining one-third for evaluation purposes. To check for spatial independence of calibration data (Dormann et al., 2007; Zuur et al., 2010), we tested SDMs residuals for spatial autocorrelation using Moran's correlograms (Bellamy et al., 2013; Di Febbraro et al., 2015; Pottier et al., 2013; Sheehan et al., 2017). In addition, we tested if values of environmental variables sampled at calibration sites were statistically different from those sampled at an equal number of points randomly placed in the study area (see Appendix S2 for further details).

The initial set of environmental predictors included 19 bioclimatic and six topographic variables, in combination with 13 habitat heterogeneity predictors derived from remotely sensed products (see Table S2). The bioclimatic variables were derived from the WORLDCLIM database (Hijmans et al., 2005; http://www.worldclim.com/current) at a native resolution of 1 km. To equalize the spatial resolution of predictors, bioclimatic variables were statistically downscaled following Dullinger et al. (2012; Appendix S3) to 250 m, thus according to the spatial resolution of remotely sensed products (see below). The digital elevation model (DEM) was derived from Jarvis et al. (2008) at a spatial resolution of 100 m, aggregated at 250 m through a bilinear interpolation, and used to derive the slope map and the topographic roughness index (Wilson et al., 2007). To calculate habitat heterogeneity predictors, we used the MODIS Enhanced Vegetation Index (EVI) product (MOD13Q1 version 5; 250 m resolution), an index correlated to net primary productivity (Ramesh et al., 2017). We extracted the 90th percentile of EVI from 16-day composites between 2011 and 2013 to capture the greenness of the land surface at the peak of a growing season, while avoiding the inclusion of spuriously high EVI values (Tuanmu and Jetz, 2015). Starting from these layers, we used a moving-window approach testing multiple window radius lengths (Ducci et al., 2015; see also Appendix S4), to calculate 13 textural metrics of habitat heterogeneity (Tuanmu and Jetz, 2015; Table S2). We applied the same approach also to topographic predictors, calculating their mean and standard deviation values within the moving-windows. The final set of 10 predictors was subselected considering a variance inflation factor $\leq$3 (Zuur et al., 2010, Table 1).

Table 1
Final set of predictors used for SDMs calibration. For topographic and habitat heterogeneity predictors, the selected radius for the moving window approach is indicated (see also Appendix S4).

Variable	Type	Acronym	Moving window radius
Temperature seasonality	Bioclimatic	BIO4	none
Temperature annual range	Bioclimatic	BIO7	none
Mean temperature of wettest quarter	Bioclimatic	BIO8	none
Precipitation seasonality	Bioclimatic	BIO15	none
Mean slope	Topographic	SLOPE_MN	5000 m
Mean EVI	Habitat heterogeneity	EVI_MN	500 m
EVI uniformity	Habitat heterogeneity	EVI_ASM	1000 m
EVI correlation	Habitat heterogeneity	EVI_CORR	2000 m
EVI contrast	Habitat heterogeneity	EVI_CONTR	5000 m
EVI difference variance	Habitat heterogeneity	EVI_DV	5000 m

To avoid models overfitting, a problem that is common when only few occurrences are available relative to the number of predictors (Guisan and Zimmermann, 2000), we opted for the “ensemble of small models” approach (Breiner et al., 2015; Di Febbraro et al., 2017). In particular, we calibrated for each species a set of models considering all possible combinations of the 10 variables taken two at a time (for a total of 45 combinations; Breiner et al., 2015). The final ensemble model was calculated as the average of the 45 models weighted on their respective AUC values (see below). SDMs were calibrated using an ensemble forecasting approach, as implemented in the R package “biomod2” (Thuiller et al., 2009). We considered the following four modeling algorithms (Niittynen and Luoto, 2017): generalized linear models (GLM), generalized additive models (GAM), generalized boosted models (GBM), and random forests (RF). Each occurrence dataset was randomly split into an 80% sample, used for the calibration of the model, and a remaining 20%, used to evaluate model predictive performance, repeating the procedure 10 times. The predictive performance of each model was assessed by measuring the area under the receiver operating characteristic curve (AUC; Hanley and McNeil, 1982) and the true skill statistic (TSS; Allouche et al., 2006). Values of AUC (TSS) range from 0 (-1) for models with no predictive ability, to 1 for models giving perfect predictions (Landis and Koch, 1977; Swets, 1988). To avoid using poorly calibrated models, only projections from models with AUC $\geq$0.7 were retained in the subsequent analyses. The model averaging was performed by weighting the individual model projections by their AUC (Marmion et al., 2009). Finally, we calculated species richness by stacking continuous suitability maps (Calabrese et al., 2014; D'Amen et al., 2015; Distler et al., 2015; Niittynen and Luoto, 2017; Scherrer et al., 2017; Fig. S1).

2.3.2. Expert-based models

We developed EXBAS models by evaluating the habitat suitability of each bird species according to the land cover categories (*sensu* Terrado et al., 2016). Specifically, we asked four experts with a strong ornithological background and a solid knowledge on the study area to assign suitability scores to the 29 bird species according to the 27 III level land cover categories derived by the Corine Land Cover 2012 (https://www.eea.europa.eu/data-and-maps/data/clc-2012-raster; Table S3). We considered three levels of habitat suitability (Rondinini et al., 2011): high (the primary habitat of a species), medium (the secondary habitat where a species can occur), and unsuitable (where species cannot occur). The land cover map was then reclassified according to suitability scores and rasterized at 250 m spatial resolution. SDMs calibration data (see above) were used to assess EXBAS models predictive performance by calculating the Boyce index (Hirzel et al., 2006). Values of the Boyce index range between -1 (no predictive ability) and $+1$ (perfect predictions), where values close to 0 mean that the model is not different from a random model. Finally, we binarized EXBAS predictions by assigning “1” (i.e., presence) to the cells with high and/or medium suitability values and “0” (i.e., absence) to unsuitable cells, as suggested by Rondinini et al. (2011), then stacking the resulting maps to produce the EXBAS species richness map (Fig. S1).

2.3.3. Habitat quality assessment

The InVEST HQ model (Sharp et al., 2016) has been widely used to calculate this metric with several conservation planning purposes as already seen in the introduction section. Modeling HQ with InVEST requires setting four input parameters: *i*) the habitat suitability *(H)*, i.e. the suitability of a land cover class to provide habitat for a given species (Leh et al., 2013); *ii*) the sensitivity of each land cover class to a given threat (*S*); *iii*) the relative impact of each threat (*W*); *iv*) the maximum distance between the land cover and the threat beyond which the threat does not affect habitat quality (*Max.D*). For further details on the InVEST Habitat Quality model and its parameterization, please see Sallustio et al. (2017) and Sharp et al. (2016).

We implemented two alternative InVEST parametrizations, i.e. by translating *H* input values from the species richness maps obtained through SDMs and EXBAS, respectively. In particular, richness values were rescaled between 0 and 1 on their maximum and then used as *H* values. In addition, we ran InVEST models on a pixel base, i.e. without aggregating cells in land cover classes, in order to account for the variability in the species richness values predicted by SDMs within the same land cover class. We used the same approach for both InVEST parametrizations, even though, for EXBAS, pixels belonging to the same land cover categories had the same *H* value. The four experts were asked to evaluate the impact of 16 threats on each bird species in terms of *S, W* and *Max.D*. Threats values for each species were then averaged obtaining a unique value for each parameter (see Table S4 for the list of threats). The same threats values were used in both the InVEST parametrizations (i.e., SDMs- and EXBAS-driven). Five maps of HQ were obtained, four through EXBAS (one per expert) and one through SDMs. The four EXBAS HQ maps were then averaged. Average HQ values and their variability (i.e., coefficient of variation), at regional or land cover class level, were calculated through the “Zonal Statistic” tool in the ESRI ArcGIS® software package.

To evaluate the spatial accuracy of HQ predictions derived by the two alternative InVEST parametrizations, we regressed predicted HQ values against observed species richness from independent (2009–2010) data, calculated as the count of bird species occurring at each sampling site (D'Amen et al., 2015). Specifically, we considered the slope and the coefficient of determination (R^2) of each regression, also calculating the Pearson's correlation coefficient *r* between observed species richness and the predicted values of HQ.

2.4. Habitat quality hotspots/coldspots

We calculated the Anselin Local Moran's *I* statistic (as implemented in the “Cluster and Outlier Analysis” tool in the ESRI ArcGIS® software package) on EXBAS and SDM habitat quality maps to highlight the spatial similarity/dissimilarity of HQ values (clusters and outliers, respectively). Cluster and outliers analysis is widely recognized for its valuable contribution in supporting, e.g., strategic and systematic conservation planning, GAP analysis to check for the effectiveness of existing protected areas, or the prioritization of conservation efforts (Lin et al., 2017; Sallustio et al., 2017). Indeed, this analysis allows for comparing not only the single values obtained through the two approaches but also their spatial aggregation in the study area. The output of the clustering algorithm can be summarized as: *i*) outliers in which a high value is primarily surrounded by low values (*HL*), *ii*) outliers in which a low value is primarily surrounded by high values (*LH*), *iii*) statistically significant (0.05 level) clusters of high values (namely hotspot; *HH*), and *iv*) statistically significant (0.05 level) clusters of low values (namely coldspot; *LL*), (see ESRI 2014 for more details). Hotspots/coldspots outcomes deriving by the two InVEST parametrizations were compared by means of a cross-tabulation matrix, an approach formerly proposed by Pontius et al. (2004) in land use science to analyze land use changes and persistence.

3. Results

SDMs achieved a good predictive performance (*sensu* Landis and Koch, 1977 and Swets, 1988) reporting a mean AUC = 0.814 (±0.051) and a mean TSS = 0.592 (±0.094). EXBAS models also reached good predictive performances, showing a mean Boyce index = 0.743 (±0.314), with none of the experts scoring average Boyce index values < 0.60. For the large majority of the species, no spatial autocorrelation was observed in models residuals, also remaining very low even when significant (Moran's $I = -0.004$; see Appendix S2).

InVEST predictions showed higher mean HQ values under the SDM parameterization than under EXBAS (0.70 and 0.44, respectively), even though both parametrizations show the same range of variation (i.e., 0.79). HQ map obtained through EXBAS showed a higher coefficient of variation than SDMs (40.9% and 11.4%, respectively), also highlighting more clumped and aggregated HQ values (Fig. 2). In addition, the four HQ maps derived by the four experts' judgments reported a coefficient of variation of 16.2%, ranging from 38.5% in urban areas to 11.8% in other wooded lands. Overall, both maps showed a clear polarization of high and low HQ values. Specifically, high HQ values are clustered mostly in the north-west and south parts of the region, whereas low HQ values occur in south-west and east sides of the region (Fig. 2).

Marked differences emerged in the spatial accuracy of habitat quality predictions driven by SDMs and EXBAS outputs. Specifically, InVEST predictions using EXBAS outcomes showed significant albeit low Pearson's *r* (0.36; $p < 0.01$) and regression slope values (4.14; $p < 0.01$), with a $R^2 = 0.10$. On the other hand, InVEST predictions based on SDMs outcomes showed high, significant Pearson's *r* (0.61; $p < 0.01$) and regression slope values (19.21; $p < 0.01$), with a $R^2 = 0.38$ (Fig. 3).

Cluster and Outlier Analysis highlighted that most of the HQ hotspots for both EXBAS and SDM occur in south-western parts of the study area, while coldspots are mainly located in the east side (Fig. 4). HQ hotspots and coldspots have approximately the same extension, covering 35% and 34% of the study area, respectively (Table 2). Despite this, the map obtained through EXBAS has a higher relative coverage of outlier pixels (i.e., pixels with high HQ values surrounded by pixels with low HQ values and vice-versa) than SDM (13% and 6%, respectively). Conversely, the latter shows a higher coverage of pixels classified as "not significant" (19% and 25%, respectively).

According to the cross-tabulation matrix, the overall agreement between the two HQ maps is 51.7%. Particularly, the relative agreements with respect to SDM map (total values in rows), range from 61 to 64% for hotspots and coldspots, to 10% for LH (pixels with low HQ values surrounded by pixels with high HQ values). Furthermore, the degree of agreement between HQ hotspots for EXBAS and SDM is particularly high within natural and semi-natural land uses (i.e., other wooded lands and

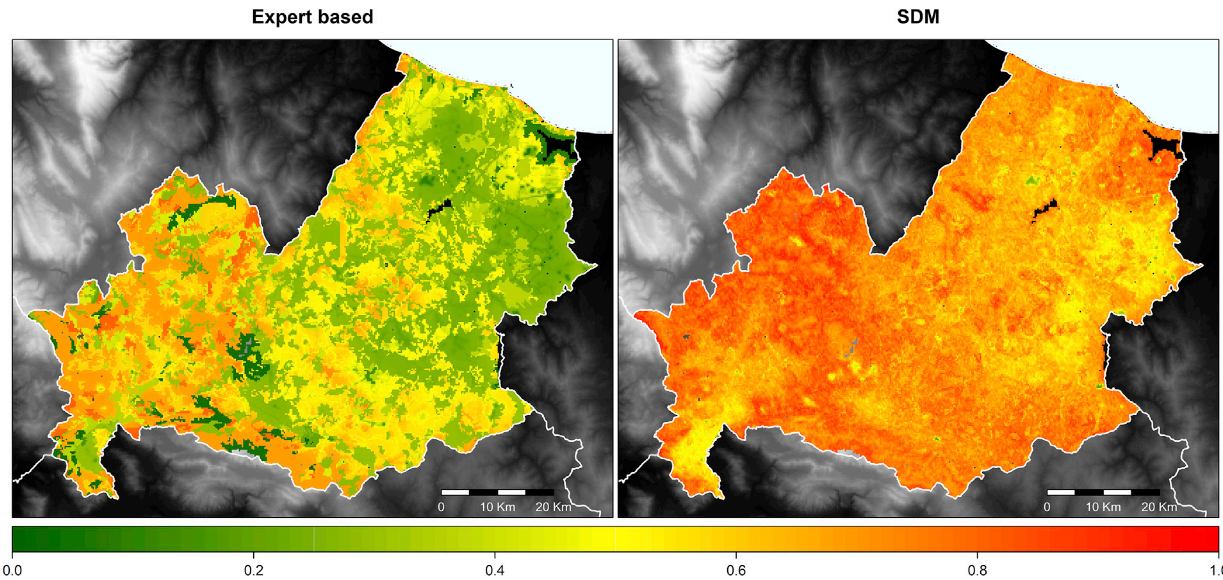

Fig. 2. Habitat quality predicted by InVEST. The left (right) panel depicts the InVEST predictions driven by EXBAS (SDMs) outcomes.

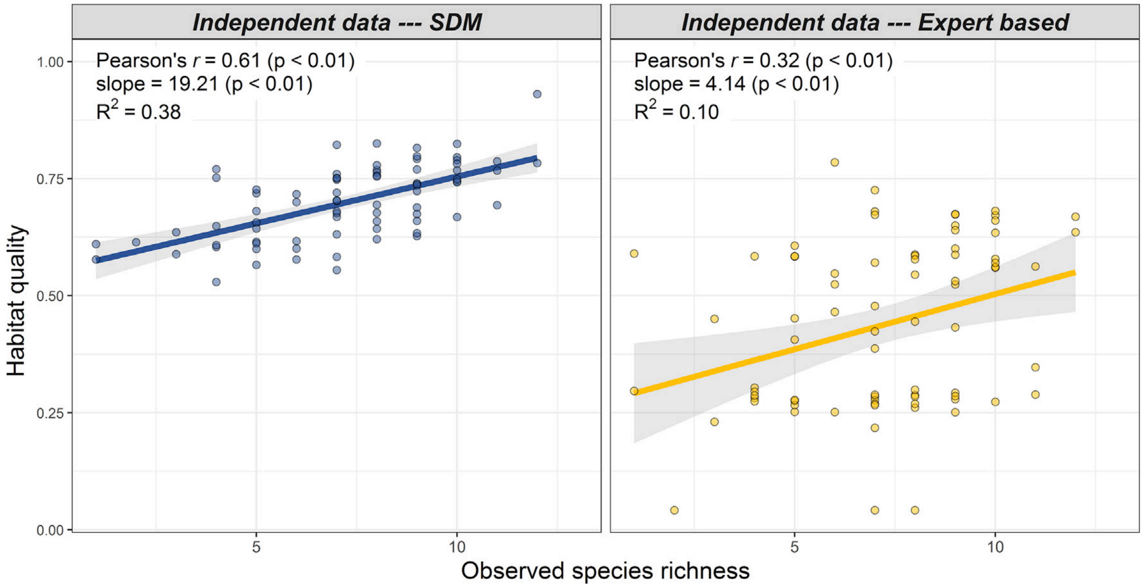

Fig. 3. Evaluation of InVEST HQ predictions with observed species richness (n = 78). Left (right) panel shows regression line between observed species richness and habitat quality prediction driven by SDMs (EXBAS).

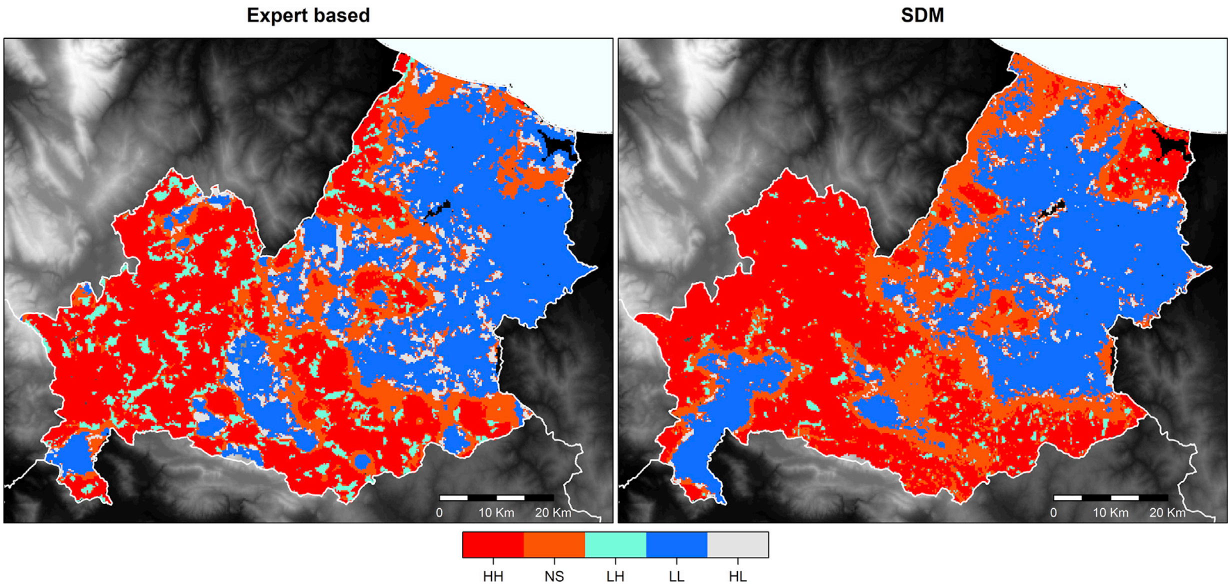

Fig. 4. Maps of the HQ clusters and outliers obtained through EXBAS (left side) and SDM (right side) approaches. The four clusters and outliers classes are: HL (outliers in which a high value is surrounded primarily by low values), LH (outliers in which a low value is surrounded primarily by high values), HH (clusters of high values-hotspots), LL (clusters of low values-coldspots), and NS (non-significant).

Forests, with 58 and 86%, respectively; Fig. 5). By contrast, HQ coldspots for EXBAS and SDM showed the highest degree of agreement within anthropized land uses (i.e., urban, pastures and grasslands, and agriculture, with 51, 68 and 75%, respectively).

4. Discussion and conclusions

4.1. Potentialities and limitations of habitat quality mapping

The present work is focused on independently testing the predictive accuracy of two alternative implementations of the InVEST model to map HQ for bird communities in central Italy. Specifically, we compared InVEST predictions derived by

Table 2
Cross tabulation matrix for HQ clusters and outliers' maps derived by Species Distribution Models (SDM; rows) and Expert-based Models (EXBAS; columns), respectively. Values refer to the relative pixel coverage (%) with respect to the entire study area extent. Entries along the diagonal (in bold) indicate the degree of agreement for the different clusters and outliers categories between the two maps (see also Pontius et al., 2004).

	EXBAS						
SDM		HH	HL	LH	LL	NS	Total
	HH	**22%**	1%	4%	3%	6%	35%
	HL	0%	**0%**	0%	1%	1%	3%
	LH	1%	0%	**0%**	1%	0%	3%
	LL	3%	3%	1%	**22%**	5%	34%
	NS	8%	2%	1%	7%	**7%**	25%
	Total	35%	6%	7%	34%	19%	100%

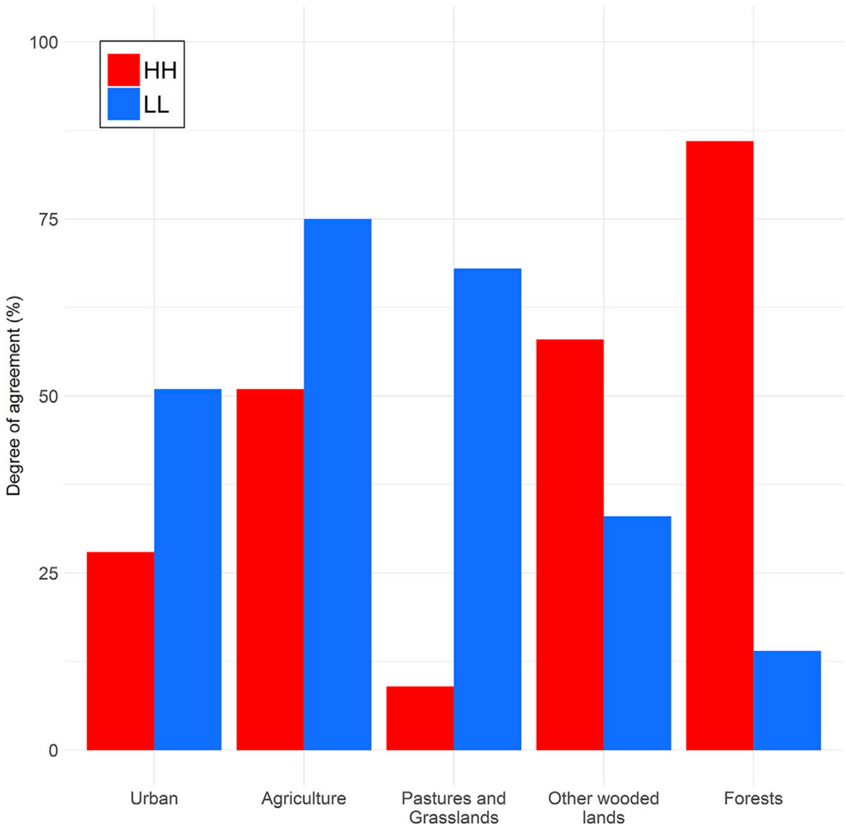

Fig. 5. Degree of agreement (in percentage) between hotspots (HH, blue bars) and coldspots (LL, red bars) maps derived by EXBAS and SDM approaches. Agreement was evaluated for each land use category, separately. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

correlative (i.e., SDMs) and expert-based (i.e., EXBAS) distribution models and evaluated their performance using independent data. Overall, InVEST parametrized through SDMs generated more accurate HQ predictions than EXBAS. However, further results from a cluster and outlier analysis reveal that spatial aggregates of HQ values are mostly concordant between the two modeling approaches.

The higher accuracy achieved by SDMs-derived InVEST prediction compared to EXBAS is primarily linked to the high predictive performance of single-species SDMs, which is very close to that obtained in other studies on bird species at European (e.g. Thuiller et al., 2004), national (e.g. Heikkinen et al., 2007), regional (e.g. Brotons et al., 2012; De Cáceres et al., 2013), and sub-regional (e.g. Arcos et al., 2012) scales. When considering the EXBAS approach, we found relatively good predictive accuracy and the Boyce index values from the present study are proximal to those obtained in similar works, focusing for example on mapping concentration areas for migratory birds (Pocewicz et al., 2013). The main differences in the predictive accuracy of the two approaches likely stems from stacking single-species predictions to obtain richness maps for InVEST parametrizations. Specifically, richness map obtained by stacking SDMs generated HQ values more accurately described the observed structure of bird communities. On the contrary, if EXBAS single-species predictions were fairly accurate, the richness map derived by their stacking and the subsequent HQ prediction failed to describe the structure of the whole communities as adequately as the SDM-derived products.

Results from the two alternative InVEST parameterizations mainly reveal that SDMs produced higher HQ values than EXBAS, with lower variability (see Fig. 2). Particularly, the spatial pattern of HQ values was more clumped and aggregated for EXBAS when compared to the SDMs approach. The polarization between high and low HQ values is clearly visible, where high HQ values are mostly clustered in the north-west and south parts of the region, dominated by forests and natural ecosystems, while low values are clustered in south-west and east sides of the region, where agroecosystems are mainly located. This more emphasized proneness to polarization in EXBAS than SDMs-derived HQ values is mainly attributable to the effect of the land use polygons used as input in the former, which in turn facilitate the clusterization of high and low HQ values if compared to the more smoothed values obtained through SDMs (based on continuous remote sensing-derived data such as EVI). Moreover, comparing results obtained through SDMs and EXBAS approaches, the cluster and outlier analysis showed good levels of agreement between their relative HQ hotspots within natural and semi-natural land uses, as well as HQ coldspots within anthropized ones. Accordingly, our findings point out that even using the EXBAS map as an input to parametrize InVEST, the generalization obtained through using the cluster and outlier approach allows for identification of natural ecosystems with high HQ values as well as of anthropized ecosystems with low HQ values.

Differences between the outcomes of the two InVEST parametrizations can be explained by (*i*) availability and reliability of input data; (*ii*) scale of implementation; and (*iii*) purpose of application. SDMs may require detailed field information, which has to be collected through on-ground systematic surveys (see e.g., sampling costs; Guisan and Thuiller, 2005). Alternatively, the EXBAS approach requires less intensive data collection but relies on the subjectivity of the experts involved, a consistent background and an in-depth knowledge of the investigated species in a specific geographic context (Murray et al., 2009). Therefore, the latter approach seems more suitable than SDMs for large-scale analyses, where no specific focus on single species is required. Our outcomes also highlighted how using low-resolution spatial information (e.g. CLC maps), especially at a broad scale, likely affects the reliability of experts' evaluations and therefore the final accuracy of the outputs. Although this effect is largely coherent with the lower accuracy of EXBAS-derived HQ map if compared with SDMs (see Fig. 3), we cannot exclude that enhancing the EXBAS implementation might increase its overall accuracy and yield different outcomes in comparison with SDMs. Replicating such a comparison by further refining the EXBAS approach, e.g. through the inclusion of additional environmental predictors such as topography and hydrography, could represent an interesting future perspective.

4.2. Implications for conservation planning

The spatial distribution of HQ hotspots and coldspots, including their linkages with current land use pattern, demonstrates that both SDMs and EXBAS approaches coupled with InVEST model may effectively support decision-making processes in conservation planning. To our knowledge, no specific work evaluating the effectiveness of InVEST for conservation planning through adopting SDMs or EXBAS approaches is currently available. According to our results, the coverage of HQ hotspots and coldspots is consistent with that obtained in previous works adopting an expert-based approach, even though at national scale (Sallustio et al., 2017). Moreover, we found that the comparison of HQ alternatively derived by SDMs and EXBAS approaches allows for a deep understanding of what are the most important relationships between HQ values and associated natural, semi-natural, and artificial systems. For example, we highlighted a certain degree of agreement between HQ hotspots and natural and semi-natural areas, as well as HQ coldspots and anthropized lands such as urban areas. This pattern is consistent with previous studies that have successfully implemented InVEST to delineate, e.g., urban development boundaries in relation with ecological constraints (Liu et al., 2017), ecological security patterns (e.g., corridors and critical patches; Lin et al., 2016), and different impact of urban growth depending on the naturalness of the surrounding landscape (Sallustio et al., 2015). Therefore, HQ maps are extremely useful to set conservation priorities, and allocate them over a given territory, by also considering current land uses and associated threats (cf. Vallecillo et al., 2016). A further understanding (even spatially-explicit) of how species (birds, in our case) are associated with the investigated territory (i.e., HQ pattern) is crucial to set conservation planning priorities. For instance, Le Roux et al. (2017) argued that it is possible to reduce the anthropogenic impact (e.g. from roads) on bat species by identifying and mapping corridors for movements. In the context of systematic conservation planning, the analysis of the impacts of human activities (agriculture, forestry) on threatened species should represent a proper balance among land managers and conservationists' needs, e.g. when establishing new protected areas (see also Leblond et al., 2014). Consequently, maps of HQ hotspots and coldspots can represent valuable tools for decision-makers, local administrators, landscape planners and managers dealing with conservation issues (e.g., Marchese, 2015; Sallustio et al., 2017). Specifically, maps of HQ hotspots and coldspots allow to: (*i*) bridge the gap between planning, management, and information side; (*ii*) identify suitable or unsuitable areas for strengthening or limiting conservation actions; and (*iii*) disentangle the complexity of the interactions between anthropogenic activity and ecological functionality.

Our results also confirm that adopting the HQ model for aggregated species (i.e., InVEST) seems to be a cost- and time-effective approach to obtain spatially-explicit estimations about conservation status across a large area. The EXBAS-InVEST combination is particularly useful for conservation planning at larger scales, where species-specific and accurate data are often poor or absent (e.g., Terrado et al., 2016). Nevertheless, for example in the case of modeling species distribution, the input from experts may be not significant (e.g. Pearce et al., 2001). On the contrary, using SDMs predictions as input data for conservation planning tools such as InVEST, significantly improves the accuracy and reliability of HQ estimates, especially at a finer spatial scales (see also He et al., 2017). Finally, the combined use of different spatially-explicit methods for biodiversity assessment represents a powerful and promising tool for coupling biodiversity conservation priorities with opportunities for additional ecosystem services supply (e.g., Lin et al., 2017). In fact, understanding the complex relationships and balance between biodiversity and other goods and services is required to improve the effective implementation of conservation practices, not only in protected areas (cf. Kremen and Merenlender, 2018; Vizzarri et al., 2015b).

4.3. Final remarks

In regards to the possible use of these approaches within systematic conservation planning, our results demonstrate that the combination of SDMs and InVEST model represents a powerful tool to accurately predict spatial patterns of HQ and to assess areas for biodiversity conservation. However, SDMs implementation may require a certain effort to collect field data and implement modeling procedures. On the other hand, we highlighted how InVEST parametrized through EXBAS approach can be used as a surrogate solution in systematic conservation planning, especially in contexts with poor data availability, budgetary constraints or related to species difficult to deal with because of the lack of data (i.e., rare species, invasive alien species). Indeed, conservation planners often tend to use inaccurate or biased expert-based habitat maps to save money and time (e.g. Tulloch et al., 2016).

However, it is worth to highlight that the present results are limited to the comparison of the performances obtained through implementing two different approaches for HQ assessment, without taking into account the possible influence played by e.g., ecosystems and habitat heterogeneity or different taxa preferences (e.g., specialist *vs* generalist species). Accordingly, further research efforts and comparative studies are needed to better understand the role played by additional factors (e.g., environmental, ethological etc.) in determining the comparative performances of the two proposed methodological approaches.

As general remarks, we can conclude that based on our findings: *i)* the SDMs-driven approach achieved high levels of predictive accuracy when assessing spatial patterns of habitat quality, while the accuracy of the expert-based approach is limited; *ii)* spatial aggregates of habitat quality values are mostly concordant between SDMs and expert-based approaches; and *iii)* the expert-based approach represents a surrogate tool for preliminary and/or exploratory studies, especially in contexts characterized by poor data availability/quality and budgetary constraints.

Disclaimer

The views expressed are purely those of the writers and may not in any circumstances be regarded as stating an official position of the European Commission or any other Government Agency.

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Appendix A. Supplementary data

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References

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43, 1223–1232.

Araújo, M.B., Guisan, A., 2006. Five (or so) challenges for species distribution modelling. J. Biogeogr. 33, 1677–1688. https://doi.org/10.1111/j.1365-2699.2006.01584.x.

Arcos, J.M., Bécares, J., Villero, D., Brotons, L., Rodríguez, B., Ruiz, A., 2012. Assessing the location and stability of foraging hotspots for pelagic seabirds: an approach to identify marine Important Bird Areas (IBAs) in Spain. Biol. Conserv. 156, 30–42. https://doi.org/10.1016/j.biocon.2011.12.011.

Barbet-Massin, M., Thuiller, W., Jiguet, F., 2010. How much do we overestimate future local extinction rates when restricting the range of occurrence data in climate suitability models? Ecography (Cop.). 33, 878–886. https://doi.org/10.1111/j.1600-0587.2010.06181.x.

Bellamy, C., Scott, C., Altringham, J., 2013. Multiscale, presence-only habitat suitability models: fine-resolution maps for eight bat species. J. Appl. Ecol. 50, 892–901. https://doi.org/10.1111/1365-2664.12117.

BirdLife International, 2015. Species Distribution Data.

Blasi, C., Capotorti, G., Alós Ortí, M.M., Anzellotti, I., Attorre, F., Azzella, M.M., Carli, E., Copiz, R., Garfì, V., Manes, F., Marando, F., Marchetti, M., Mollo, B., Zavattero, L., 2017. Ecosystem mapping for the implementation of the European Biodiversity Strategy at the national level: the case of Italy. Environ. Sci. Pol. 78, 173–184. https://doi.org/10.1016/J.ENVSCI.2017.09.002.

Bottalico, F., Pesola, L., Vizzarri, M., Antonello, L., Barbati, A., Chirici, G., Corona, P., Cullotta, S., Garfì, V., Giannico, V., Lafortezza, R., Lombardi, F., Marchetti, M. , Nocentini, S., Riccioli, F., Travaglini, D., Sallustio, L., 2016. Modeling the influence of alternative forest management scenarios on wood production and carbon storage: acase study in the mediterranean region. Environ. Res. 144, 72–87. https://doi.org/10.1016/j.envres.2015.10.025.

Breiner, F.T., Guisan, A., Bergamini, A., Nobis, M.P., 2015. Overcoming limitations of modelling rare species by using ensembles of small models. Methods Ecol. Evol. 6, 1210–1218. https://doi.org/10.1111/2041-210X.12403.
Brotons, L., De Cáceres, M., Fall, A., Fortin, M.J., 2012. Modeling bird species distribution change in fire prone Mediterranean landscapes: incorporating species dispersal and landscape dynamics. Ecography (Cop.). 35, 458–467. https://doi.org/10.1111/j.1600-0587.2011.06878.x.
Brotons, L., Herrando, S., Pla, M., 2007. Updating bird species distribution at large spatial scales: applications of habitat modelling to data from long-term monitoring programs. Divers. Distrib. 13, 276–288.
Calabrese, J.M., Certain, G., Kraan, C., Dormann, C.F., 2014. Stacking species distribution models and adjusting bias by linking them to macroecological models. Global Ecol. Biogeogr. 23, 99–112.
Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S., 2012. Biodiversity loss and its impact on humanity. Nature 486, 59–67.
Ceballos, G., Ehrlich, P.R., Barnosky, A.D., Garcia, A., Pringle, R.M., Palmer, T.M., 2015. Accelerated modern human-induced species losses: entering the sixth mass extinction. Sci. Adv. 1 https://doi.org/10.1126/sciadv.1400253 e1400253–e1400253.
Chiatante, G., 2017. Landscape structure influencing the spatial distribution of the Short-toed Treecreeper *Certhia brachydactyla* in a Mediterranean agroecosystem. Avian Biol. Res. 10, 49–57. https://doi.org/10.3184/175815617X14836196626584.
Clevenger, A.P., Wierzchowski, J., Chruszcz, B., Gunson, K., 2002. GIS-generated, expert-based models for identifying wildlife habitat linkages and planning mitigation passages. Conserv. Biol. 16, 503–514. https://doi.org/10.1046/j.1523-1739.2002.00328.x.
Crossman, N.D., Bryan, B.A., 2009. Identifying cost-effective hotspots for restoring natural capital and enhancing landscape multifunctionality. Ecol. Econ. 68, 654–668. https://doi.org/10.1016/j.ecolecon.2008.05.003.
D'Amen, M., Dubuis, A., Fernandes, R.F., Pottier, J., Pellissier, L., Guisan, A., 2015. Using species richness and functional traits predictions to constrain assemblage predictions from stacked species distribution models. J. Biogeogr. 42, 1255–1266. https://doi.org/10.1111/jbi.12485.
De Cáceres, M., Brotons, L., Aquilué, N., Fortin, M.J., 2013. The combined effects of land-use legacies and novel fire regimes on bird distributions in the Mediterranean. J. Biogeogr. 40, 1535–1547. https://doi.org/10.1111/jbi.12111.
Di Febbraro, M., Carotenuto, F., Castiglione, S., Russo, D., Loy, A., Maiorano, L., Raia, P., 2017. Does the jack of all trades fare best? Survival and niche width in Late Pleistocene megafauna. J. Biogeogr. 44, 2828–2838. https://doi.org/10.1111/jbi.13078.
Di Febbraro, M., Roscioni, F., Frate, L., Carranza, M.L., De Lisio, L., De Rosa, D., Marchetti, M., Loy, A., 2015. Long-term effects of traditional and conservation-oriented forest management on the distribution of vertebrates in Mediterranean forests: a hierarchical hybrid modelling approach. Divers. Distrib. 21, 1141–1154. https://doi.org/10.1111/ddi.12362.
Distler, T., Schuetz, J.G., Velásquez-Tibatá, J., Langham, G.M., 2015. Stacked species distribution models and macroecological models provide congruent projections of avian species richness under climate change. J. Biogeogr. 42, 976–988. https://doi.org/10.1111/jbi.12479.
Dormann, C.F., McPherson, J.M., Araújo, M.B., Bivand, R., Bolliger, J., Carl, G., G. Davies, R., Hirzel, A., Jetz, W., Daniel Kissling, W., Kühn, I., Ohlemüller, R., Peres-Neto, P.R., Reineking, B., Schröder, B., Schurr, F.M., Wilson, R., 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography (Cop.). 30, 609–628. https://doi.org/10.1111/j.2007.0906-7590.05171.x.
Ducci, L., Agnelli, P., Di Febbraro, M., Frate, L., Russo, D., Loy, A., Carranza, M.L., Santini, G., Roscioni, F., 2015. Different bat guilds perceive their habitat in different ways: a multiscale landscape approach for variable selection in species distribution modelling. Landsc. Ecol. 30, 2047–2159. https://doi.org/10.1007/s10980-015-0237-x.
Dullinger, S., Gattringer, A., Thuiller, W., Moser, D., Zimmermann, N.E., Guisan, A., Willner, W., Plutzar, C., Leitner, M., Mang, T., Caccianiga, M., Dirnbock, T., Ertl, S., Fischer, A., Lenoir, J., Svenning, J.-C., Psomas, A., Schmatz, D.R., Silc, U., Vittoz, P., Hulber, K., Dirnböck, T., Ertl, S., Fischer, A., Lenoir, J., Svenning, J.-C., Psomas, A., Schmatz, D.R., Silc, U., Vittoz, P., Hülber, K., 2012. Extinction debt of high-mountain plants under twenty-first-century climate change. Nat. Clim. Change 2, 619–622. https://doi.org/10.1038/nclimate1514.
Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40, 677.
Ellis, E.C., 2013. Sustaining biodiversity and people in the world's anthropogenic biomes. Curr. Opin. Environ. Sustain. https://doi.org/10.1016/j.cosust.2013.07.002.
ESRI, 2014. Cluster and Outlier Analysis (Anselin Local Moran's I) (Spatial Statistics).
European Commission, 2015. Report from the Commission to the European Parliament and the Council. The Mid-term Review of the Biodiversity Strategy to 2020. Brussels.
Fornasari, L., Londi, G., Buvoli, L., Florenzano, G.T., La Gioia, G., Pedrini, P., Brichetti, P., De Carli, E., 2010. Distribuzione geografca e ambientale degli uccelli comuni nidifcanti in Italia, 2000-2004 (dati del progetto MITO2000). Avocetta 34, 5–15.
Fourcade, Y., Besnard, A.G., Secondi, J., 2018. Paintings predict the distribution of species, or the challenge of selecting environmental predictors and evaluation statistics. Global Ecol. Biogeogr. 27, 245–256. https://doi.org/10.1111/geb.12684.
Gallien, L., Douzet, R., Pratte, S., Zimmermann, N.E., Thuiller, W., 2012. Invasive species distribution models - how violating the equilibrium assumption can create new insights. Global Ecol. Biogeogr. 21, 1126–1136. https://doi.org/10.1111/j.1466-8238.2012.00768.x.
Gantioler, S., Rayment, M., Brink, P. ten, McConville, A., Kettunen, M., Bassi, S., 2014. The costs and socio-economic benefits associated with the Natura 2000 network. Int. J. Sustain. Soc. 6, 135. https://doi.org/10.1504/IJSSOC.2014.057894.
Gobbi, M., Riservato, E., Bragalanti, N., Lencioni, V., 2012. An expert-based approach to invertebrate conservation: identification of priority areas in central-eastern Alps. J. Nat. Conserv. 20, 274–279. https://doi.org/10.1016/j.jnc.2012.05.003.
Guisan, A., Petitpierre, B., Broennimann, O., Daehler, C., Kueffer, C., 2014. Unifying niche shift studies: insights from biological invasions. Trends Ecol. Evol. 29, 1–10. https://doi.org/10.1016/j.tree.2014.02.009.
Guisan, A., Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecol. Lett. https://doi.org/10.1111/j.1461-0248.2005.00792.x.
Guisan, A., Tingley, R., Baumgartner, J.B., Naujokaitis-Lewis, I., Sutcliffe, P.R., Tulloch, A.I.T., Regan, T.J., Brotons, L., Mcdonald-Madden, E., Mantyka-Pringle, C., Martin, T.G., Rhodes, J.R., Maggini, R., Setterfield, S.A., Elith, J., Schwartz, M.W., Wintle, B.A., Broennimann, O., Austin, M., Ferrier, S., Kearney, M.R., Possingham, H.P., Buckley, Y.M., 2013. Predicting species distributions for conservation decisions. Ecol. Lett. 16, 1424–1435. https://doi.org/10.1111/ele.12189.
Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. Ecol. Model. 135, 147–186. https://doi.org/10.1016/S0304-3800(00)00354-9.
Hanley, J.A., McNeil, B.J., 1982. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology 143, 29–36. https://doi.org/10.1148/radiology.143.1.7063747.
He, J., Huang, J., Li, C., 2017. The evaluation for the impact of land use change on habitat quality: a joint contribution of cellular automata scenario simulation and habitat quality assessment model. Ecol. Model. 366, 58–67. https://doi.org/10.1016/j.ecolmodel.2017.10.001.
Heikkinen, R.K., Luoto, M., Virkkala, R., Pearson, R.G., Körber, J.H., 2007. Biotic interactions improve prediction of boreal bird distributions at macro-scales. Global Ecol. Biogeogr. 16, 754–763. https://doi.org/10.1111/j.1466-8238.2007.00345.x.
Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978. https://doi.org/10.1002/joc.1276.
Hirzel, A.H., Le Lay, G., Helfer, V., Randin, C., Guisan, A., 2006. Evaluating the ability of habitat suitability models to predict species presences. Ecol. Model. 199, 142–152. https://doi.org/10.1016/j.ecolmodel.2006.05.017.
Hooper, D.U., Adair, E.C., Cardinale, B.J., Byrnes, J.E.K., Hungate, B.A., Matulich, K.L., Gonzalez, A., Duffy, J.E., Gamfeldt, L., O'Connor, M.I., 2012. A global synthesis reveals biodiversity loss as a major driver of ecosystem change. Nature 486, 105. https://doi.org/10.1038/nature11118.
Howard, C., Stephens, P.A., Pearce-Higgins, J.W., Gregory, R.D., Willis, S.G., 2014. Improving species distribution models: the value of data on abundance. Methods Ecol. Evol. 5, 506–513. https://doi.org/10.1111/2041-210X.12184.

Jarvis, A., Reuter, H.I., Nelson, A., Guevara, E., 2008. Hole-filled SRTM for the Globe Version 4 [WWW Document]. available from: CGIAR-CSI SRTM 90m Database.

Johnson, C.J., Gillingham, M.P., 2005. An evaluation of mapped species distribution models used for conservation planning. Environ. Conserv. 32, 117. https://doi.org/10.1017/S0376892905002171.

Johnson, C.J., Seip, D.R., Boyce, M.S., 2004. A quantitative approach to conservation planning: using resource selection functions to map the distribution of mountain caribou at multiple spatial scales. J. Appl. Ecol. 41, 238–251. https://doi.org/10.1111/j.0021-8901.2004.00899.x.

Johnson, M.D., 2007. Measuring habitat quality: a review. Condor 109, 489. https://doi.org/10.1650/8347.1.

Kremen, C., Merenlender, A.M., 2018. Landscapes that work for biodiversity and people. Science 80, 362. https://doi.org/10.1126/science.aau6020 eaau6020.

Landis, J.R., Koch, G.G., 1977. The measurement of observer agreement for categorical data. Biometrics 33, 159–174.

Le Roux, M., Redon, M., Archaux, F., Long, J., Vincent, S., Luque, S., 2017. Conservation planning with spatially explicit models: a case for horseshoe bats in complex mountain landscapes. Landsc. Ecol. 32, 1005–1021. https://doi.org/10.1007/s10980-017-0505-z.

Leblond, M., Dussault, C., St-Laurent, M.-H., 2014. Development and validation of an expert-based habitat suitability model to support boreal caribou conservation. Biol. Conserv. 177, 100–108. https://doi.org/10.1016/j.biocon.2014.06.016.

Leh, M.D.K., Matlock, M.D., Cummings, E.C., Nalley, L.L., 2013. Quantifying and mapping multiple ecosystem services change in West Africa. Agric. Ecosyst. Environ. 165, 6–18. https://doi.org/10.1016/j.agee.2012.12.001.

Lehtomäki, J., Moilanen, A., 2013. Methods and workflow for spatial conservation prioritization using Zonation. Environ. Model. Software 47, 128–137. https://doi.org/10.1016/j.envsoft.2013.05.001.

Levin, N., Watson, J.E.M., Joseph, L.N., Grantham, H.S., Hadar, L., Apel, N., Perevolotsky, A., DeMalach, N., Possingham, H.P., Kark, S., 2013. A framework for systematic conservation planning and management of Mediterranean landscapes. Biol. Conserv. 158, 371–383. https://doi.org/10.1016/J.BIOCON.2012.08.032.

Lin, Q., Mao, J., Wu, J., Li, W., Yang, J., 2016. Ecological security pattern analysis based on InVEST and least-cost path model: a case study of dongguan water village. Sustain. https://doi.org/10.3390/su8020172.

Lin, Y.-P.P., Lin, W.-C.C., Wang, Y.-C.C., Lien, W.-Y.Y., Huang, T., Hsu, C.-C.C., Schmeller, D.S., Crossman, N.D., 2017. Systematically designating conservation areas for protecting habitat quality and multiple ecosystem services. Environ. Model. Software 90, 126–146. https://doi.org/10.1016/j.envsoft.2017.01.003.

Liu, J., Zhang, G., Zhuang, Z., Cheng, Q., Gao, Y., Chen, T., Huang, Q., Xu, L., Chen, D., 2017. A new perspective for urban development boundary delineation based on SLEUTH-InVEST model. Habitat Int. 70, 13–23. https://doi.org/10.1016/j.habitatint.2017.09.009.

Lomba, A., Pellissier, L., Randin, C., Vicente, J., Moreira, F., Honrado, J., Guisan, A., 2010. Overcoming the rare species modelling paradox: a novel hierarchical framework applied to an Iberian endemic plant. Biol. Conserv. 143, 2647–2657. https://doi.org/10.1016/j.biocon.2010.07.007.

Mace, G.M., Norris, K., Fitter, A.H., 2012. Biodiversity and ecosystem services: a multilayered relationship. Trends Ecol. Evol. 27, 19–26. https://doi.org/10.1016/j.tree.2011.08.006.

Maiorano, L., Amori, G., Montemaggiori, A., Rondinini, C., Santini, L., Saura, S., Boitani, L., 2015. On how much biodiversity is covered in Europe by national protected areas and by the Natura 2000 network: insights from terrestrial vertebrates. Conserv. Biol. 29, 986–995. https://doi.org/10.1111/cobi.12535.

Marchese, C., 2015. Biodiversity hotspots: a shortcut for a more complicated concept. Glob. Ecol. Conserv. 3, 297–309. https://doi.org/10.1016/j.gecco.2014.12.008.

Margules, C.R., Pressey, R.L., 2000. Systematic conservation planning. Nature 405, 243–253. https://doi.org/10.1038/35012251.

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. Divers. Distrib. 15, 59–69. https://doi.org/10.1111/j.1472-4642.2008.00491.x.

McShea, W.J., 2014. What are the roles of species distribution models in conservation planning? Environ. Conserv. 41, 93–96. https://doi.org/10.1017/S0376892913000581.

Mokany, K., Ferrier, S., Connolly, S.R., Dunstan, P.K., Fulton, E.A., Harfoot, M.B., Harwood, T.D., Richardson, A.J., Roxburgh, S.H., Scharlemann, J.P.W., Tittensor, D.P., Westcott, D.A., Wintle, B.A., 2016. Integrating modelling of biodiversity composition and ecosystem function. Oikos 125, 10–19. https://doi.org/10.1111/oik.02792.

Morelli, F., Tryjanowski, P., 2015. No species is an island: testing the effects of biotic interactions on models of avian niche occupation. Ecol. Evol. 5, 759–768. https://doi.org/10.1002/ece3.1387.

Morelli, F., Tryjanowski, P., 2014. Associations between species can influence the goodness of fit of species distribution models: the case of two passerine birds. Ecol. Complex. 20, 208–212. https://doi.org/10.1016/J.ECOCOM.2014.01.002.

Moudrý, V., Komárek, J., Šímová, P., 2017. Which breeding bird categories should we use in models of species distribution? Ecol. Indicat. 74, 526–529. https://doi.org/10.1016/j.ecolind.2016.11.006.

Murray, J., Goldizen, A., O'Leary, R., McAlpine, C., Possingham, H., Choy, S., 2009. How useful is expert opinion for predicting the distribution of a species within and beyond the region of expertise? A case study using brush-tailed rock-wallabies Petrogale penicillata. J. Appl. Ecol. 46, 842–851. https://doi.org/10.1111/j.1365-2664.2009.01671.x.

Niittynen, P., Luoto, M., 2017. The importance of snow in species distribution models of arctic vegetation. Ecography (Cop.). online ver 1–13. https://doi.org/10.1111/ecog.03348.

Pandeya, B., Buytaert, W., Zulkafli, Z., Karpouzoglou, T., Mao, F., Hannah, D.M., 2016. A comparative analysis of ecosystem services valuation approaches for application at the local scale and in data scarce regions. Ecosyst. Serv. 22, 250–259. https://doi.org/10.1016/j.ecoser.2016.10.015.

Pearce, J.L., Cherry, K., Drielsma, M., Ferrier, S., Whish, G., 2001. Incorporating expert opinion and fine-scale vegetation mapping into statistical models of faunal distribution. J. Appl. Ecol. 38, 412–424. https://doi.org/10.1046/j.1365-2664.2001.00608.x.

Pesaresi, S., Biondi, E., Casavecchia, S., 2017. Bioclimates of Italy. J. Maps 13, 955–960. https://doi.org/10.1080/17445647.2017.1413017.

Pocewicz, A., Estes-Zumpf, W.A., Andersen, M.D., Copeland, H.E., Keinath, D.A., Griscom, H.R., 2013. Modeling the distribution of migratory bird stopovers to inform landscape-scale siting of wind development. PLoS One 8, e75363.

Pontius, R.G., Shusas, E., McEachern, M., 2004. Detecting important categorical land changes while accounting for persistence, Agric. Ecosyst. Environ. 101, 251–268. https://doi.org/10.1016/j.agee.2003.09.008.

Pottier, J., Dubuis, A., Pellissier, L., Maiorano, L., Rossier, L., Randin, C.F., Vittoz, P., Guisan, A., 2013. The accuracy of plant assemblage prediction from species distribution models varies along environmental gradients. Global Ecol. Biogeogr. 22, 52–63. https://doi.org/10.1111/j.1466-8238.2012.00790.x.

Raes, N., 2012. Partial versus full species distribution models. Nat. Conserv. 10, 127–138.

Ramesh, V., Gopalakrishna, T., Barve, S., Melnick, D.J., 2017. Citizen science driven species distribution models estimate drastically smaller range sizes and higher threat levels for Western Ghats endemic birds. Biol. Conserv. 210, 205–221. https://doi.org/10.1016/j.biocon.2017.03.019.

Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J.J., Schröder, B., Thuiller, W., Warton, D.I., Wintle, B.A., Hartig, F., Dormann, C.F., 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. Ecography (Cop.). 40, 913–929. https://doi.org/10.1111/ecog.02881.

Rondinini, C., Di Marco, M., Chiozza, F., Santulli, G., Baisero, D., Visconti, P., Hoffmann, M., Schipper, J., Stuart, S.N., Tognelli, M.F., Amori, G., Falcucci, A., Maiorano, L., Boitani, L., 2011. Global habitat suitability models of terrestrial mammals. Philos. Trans. R. Soc. B Biol. Sci. 366, 2633–2641. https://doi.org/10.1098/rstb.2011.0113.

Rova, S., Pastres, R., Zucchetta, M., Pranovi, F., 2018. Ecosystem services' mapping in data-poor coastal areas: which are the monitoring priorities? Ocean Coast Manag. https://doi.org/10.1016/j.ocecoaman.2017.11.021.

Sallustio, L., De Toni, A., Strollo, A., Di, M., Gissi, E., Vizzarri, M., Casella, L., Geneletti, D., Munafò, M., Marchetti, M., 2017. Assessing habitat quality in relation to the spatial distribution of protected areas in Italy. J. Environ. Manag. 201, 129–137. https://doi.org/10.1016/j.jenvman.2017.06.031.

Sallustio, L., Munafò, M., Riitano, N., Lasserre, B., Fattorini, L., Marchetti, M., 2016. Integration of land use and land cover inventories for landscape management and planning in Italy. Environ. Monit. Assess. 188, 1–20. https://doi.org/10.1007/s10661-015-5056-7.

Sallustio, L., Quatrini, V., Geneletti, D., Corona, P., Marchetti, M., 2015. Assessing land take by urban development and its impact on carbon storage: findings from two case studies in Italy. Environ. Impact Assess. Rev. 54, 80–90.

Scherrer, D., Massy, S., Meier, S., Vittoz, P., Guisan, A., 2017. Assessing and predicting shifts in mountain forest composition across 25 years of climate change. Divers. Distrib. 23, 517–528. https://doi.org/10.1111/ddi.12548.

Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., Wood, S.A., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E., Kennedy, C., Verutes, G., Kim, C.K., Guannel, G., Papenfus, M., Toft, J., Marsik, M., Bernhardt, J., Griffin, R., Glowinski, K., Chaumont, N., Perelman, A., Lacayo, M., Mandle, L., Hamel, P., Vogl, A.L., Rogers, L., Bierbower, W., 2016. InVEST 3.3.1 User's Guide.

Sheehan, K.L., Esswein, S.T., Dorr, B.S., Yarrow, G.K., Johnson, R.J., 2017. Using species distribution models to define nesting habitat of the eastern metapopulation of double-crested cormorants. Ecol. Evol. 7, 409–418. https://doi.org/10.1002/ece3.2620.

Sinclair, S.J., White, M.D., Newell, G.R., 2010. How useful are species distribution models for managing biodiversity under future climates? Ecol. Soc. 15.

Smiraglia, D., Capotorti, G., Guida, D., Mollo, B., Siervo, V., Blasi, C., 2013. Land units map of Italy. J. Maps 9, 239–244. https://doi.org/10.1080/17445647.2013.771290.

Smith, A.B., Santos, M.J., Koo, M.S., Rowe, K.M.C., Rowe, K.C., Patton, J.L., Perrine, J.D., Beissinger, S.R., Moritz, C., 2013. Evaluation of species distribution models by resampling of sites surveyed a century ago by Joseph Grinnell. Ecography (Cop.). 36, 1017–1031. https://doi.org/10.1111/j.1600-0587.2013.00107.x.

Stephens, P.A., Mason, L.R., Green, R.E., Gregory, R.D., Sauer, J.R., Alison, J., Aunins, A., Brotons, L., Butchart, S.H.M., Campedelli, T., Chodkiewicz, T., Chylarecki, P., Crowe, O., Elts, J., Escandell, V., Foppen, R.P.B., Heldbjerg, H., Herrando, S., Husby, M., Jiguet, F., Lehikoinen, A., Lindström, Å., Noble, D.G., Paquet, J.-Y., Reif, J., Sattler, T., Szép, T., Teufelbauer, N., Trautmann, S., van Strien, A.J., van Turnhout, C.A.M., Vorisek, P., Willis, S.G., 2016. Consistent response of bird populations to climate change on two continents. Science 352, 84–87. https://doi.org/10.1126/science.aac4858 (80-.).

Store, R., Kangas, J., 2001. Integrating spatial multi-criteria evaluation and expert knowledge for GIS-based habitat suitability modelling. Landsc. Urban Plann. 55, 79–93. https://doi.org/10.1016/S0169-2046(01)00120-7.

Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240, 1285–1293 (80-.).

Terrado, M., Sabater, S., Chaplin-Kramer, B., Mandle, L., Ziv, G., Acuña, V., 2016. Model development for the assessment of terrestrial and aquatic habitat quality in conservation planning. Sci. Total Environ. 540, 63–70. https://doi.org/10.1016/j.scitotenv.2015.03.064.

Thuiller, W., Araújo, M.B., Lavorel, S., 2004. Do we need land-cover data to model species distributions in Europe? J. Biogeogr. 31, 353–361. https://doi.org/10.1046/j.0305-0270.2003.00991.x.

Thuiller, W., Lafourcade, B., Engler, R., Araújo, M.B., 2009. BIOMOD - a platform for ensamble forecasting of species distribution. Ecography (Cop.). 32, 369–373. https://doi.org/10.1111/j.1600-0587.2008.05742.x.

Tittensor, D.P., Walpole, M., Hill, S.L.L., Boyce, D.G., Britten, G.L., Burgess, N.D., Butchart, S.H.M., Leadley, P.W., Regan, E.C., Alkemade, R., Baumung, R., Bellard, C., Bouwman, L., Bowles-Newark, N.J., Chenery, A.M., Cheung, W.W.L., Christensen, V., Cooper, H.D., Crowther, A.R., Dixon, M.J.R., Galli, A., Gaveau, V., Gregory, R.D., Gutierrez, N.L., Hirsch, T.L., Hoft, R., Januchowski-Hartley, S.R., Karmann, M., Krug, C.B., Leverington, F.J., Loh, J., Lojenga, R.K., Malsch, K., Marques, A., Morgan, D.H.W., Mumby, P.J., Newbold, T., Noonan-Mooney, K., Pagad, S.N., Parks, B.C., Pereira, H.M., Robertson, T., Rondinini, C., Santini, L., Scharlemann, J.P.W., Schindler, S., Sumaila, U.R., Teh, L.S.L., van Kolck, J., Visconti, P., Ye, Y., 2014. A mid-term analysis of progress toward international biodiversity targets. Science 346, 241–244. https://doi.org/10.1126/science.1257484 (80-.).

Tuanmu, M.N., Jetz, W., 2015. A global, remote sensing-based characterization of terrestrial habitat heterogeneity for biodiversity and ecosystem modelling. Global Ecol. Biogeogr. 24, 1329–1339. https://doi.org/10.1111/geb.12365.

Tulloch, A.I.T., Sutcliffe, P., Naujokaitis-Lewis, I., Tingley, R., Brotons, L., Ferraz, K.M.P.M.B., Possingham, H., Guisan, A., Rhodes, J.R., 2016. Conservation planners tend to ignore improved accuracy of modelled species distributions to focus on multiple threats and ecological processes. Biol. Conserv. https://doi.org/10.1016/j.biocon.2016.04.023.

Valerio, F., Basile, M., Balestrieri, R., Posillico, M., Di Donato, S., Altea, T., Matteucci, G., 2016. The reliability of a composite biodiversity indicator in predicting bird species richness at different spatial scales. Ecol. Indicat. 71, 627–635. https://doi.org/10.1016/j.ecolind.2016.07.043.

Vallecillo, S., Brotons, L., Thuiller, W., 2009. Dangers of predicting bird species distributions in response to land-cover changes. Ecol. Appl. 19, 538–549.

Vallecillo, S., Maes, J., Polce, C., Lavalle, C., 2016. A habitat quality indicator for common birds in Europe based on species distribution models. Ecol. Indicat. 69, 488–499. https://doi.org/10.1016/j.ecolind.2016.05.008.

Vizzarri, M., Chiavetta, U., Chirici, G., Garfì, V., Bastrup-Birk, A., Marchetti, M., 2015a. Comparing multisource harmonized forest types mapping: a case study from central Italy. iForest - Biogeosciences For 8, 59–66. https://doi.org/10.3832/ifor1133-007.

Vizzarri, M., Tognetti, R., Marchetti, M., 2015b. Forest ecosystem services: issues and challenges for biodiversity, conservation, and management in Italy. Forests 6, 1810–1838. https://doi.org/10.3390/f6061810.

Watson, J.E.M., Dudley, N., Segan, D.B., Hockings, M., 2014. The performance and potential of protected areas. Nature 515, 67–73. https://doi.org/10.1038/nature13947.

Wilson, M.F.J., O'Connell, B., Brown, C., Guinan, J.C., Grehan, A.J., 2007. Multiscale terrain analysis of multibeam bathymetry data for habitat mapping on the continental slope. Mar. Geodes. 30, 3–35. https://doi.org/10.1080/01490410701295962.

Yamada, K., Elith, J., McCarthy, M., Zerger, A., 2003. Eliciting and integrating expert knowledge for wildlife habitat modelling. Ecol. Model. 165, 251–264. https://doi.org/10.1016/S0304-3800(03)00077-2.

Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. Methods Ecol. Evol. 1, 3–14. https://doi.org/10.1111/j.2041-210X.2009.00001.x.