High-resolution habitat suitability maps for all widespread Italian breeding bird species

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Abstract

Tackling the current global biodiversity crisis requires spatially accurate biodiversity data to rapidly assess knowledge gaps and set conservation priorities. Obtaining accurate data across large spatial scales is often challenging, due to the massive logistical and economic requirements of large-scale surveys. Here, we provide high-resolution (0.81 to 81 km^2, depending on species ecology) habitat suitability raster maps for all the 225 widespread breeding bird species in Italy. Maps were generated by means of species distribution models based on 2.5 million spatially accurate (≤ 1 km-scale) and expert-validated occurrence records. These distribution data were collected during the breeding seasons 2010-2016 by over 3000 skilled observers, mostly through the www.ornitho.it citizen science platform, with the aim of completing the second Atlas of Breeding Birds in Italy, released in 2022. These raster maps will be useful to ecologists, conservation scientists and practitioners for investigating broad spatial patterns in avian diversity and identifying conservation priorities. We illustrate a potential application of this dataset by analysing geographic, socio-economic and landscape drivers of the suitability of urban environments for avian taxa across 91 Italian urban areas.

Background & Summary

The ongoing biodiversity crisis is leading to alarming rates of population decline and species extinction[1,2]. Actions and policies are needed to address biodiversity losses through mitigating impacts, and where possible reversing population declines by restoring degraded natural habitats or improving habitat quality. However, data deficiency and knowledge gaps regarding basic aspects of the ecology of declining species (e.g. demography and distribution) often hamper the effectiveness of conservation policies and actions[3]. Indeed, obtaining accurate spatial data on biodiversity is challenging because of the often limited economic resources allocated to conservation science[4] and the high costs and massive logistical effort that biodiversity data collection across large spatial scales requires[5].

The development of Species Distribution Models (SDMs) in the last few decades has promoted the transition from a qualitative estimation of species range, based on a purely descriptive approach, to a quantitative estimation based on presence probabilities or environmental suitability. SDMs (also called Environmental Niche Models, Environmental or Habitat Suitability Models) link the presence (geographical locations) of a species to environmental variables within a study area for which such variables are spatially explicit and provide an effective measure of the environmental suitability of the reference area for the investigated species[6]. The ability to correlate species presence with specific values of key ecological parameters enables not only improved estimation of current distributions, but also predictions concerning temporal variations in distributions in response to observed or expected climate change[7,8], changes in land use, disturbance[9,10] or other anthropogenic pressures.

The use of SDMs has increasingly become standard practice in many conservation applications. Examples include defining areas of major importance for the conservation for one or more species[11], developing ecological networks[12] and future variations in connectivity[13], and improving the interpretation of demographic trends[14]. In some cases, a strong correlation has been observed between relevant demographic parameters, such as the abundance or reproductive success of a species, and environmental suitability calculated from SDMs [15,16,17].

The assessment of environmental suitability computed through the use of SDMs offers the opportunity to infer species distributions over large study areas, starting from stratified surveys[18] or even opportunistic datasets[19], drastically reducing the costs and effort required to obtain comparable information over a large scale through intensive surveys. In this context, the use of distribution models for biodiversity mapping is being increasingly adopted as a means to provide maps of the species' potential distribution[20,21,22]. SDMs can thus at least partly 'fill' knowledge gaps by estimating environmental suitability (or the probability of presence) for a given species in unsurveyed/poorly surveyed areas, where the absence of occurrence data may be due to a lack of sampling. SDMs are highly flexible and can be based both on presence-absence data[23] or presence-only data[24].

Here, we provide habitat suitability maps for 225 breeding species in Italy, i.e. all widespread species breeding in the country, corresponding to ~83% of the total number of breeding species. These suitability maps have a species-specific spatial resolution, with three different scales: 0.81 km^2 (0.9 x 0.9 km; 176 species showing small-size breeding home-ranges), 9 km^2 (3 x 3 km; 45 species with larger home ranges), and 81 km^2 (9 x 9 km; four species regularly exploiting very large areas during the breeding period).

We encourage researchers and policymakers to use these high-resolution raster files for e.g. improving biodiversity monitoring schemes, evaluating the effectiveness of the protected area network, identifying priority areas for conservation, landscape planning, and characterising threats to Italian biodiversity, including the assessment of current and future interactions with human infrastructures (e.g. roads, powerlines, wind turbines[25,26,27,28]). In Usage Notes, we provide an example of the use of the dataset for investigating the macroecological drivers of avian species richness in Italian urban areas.

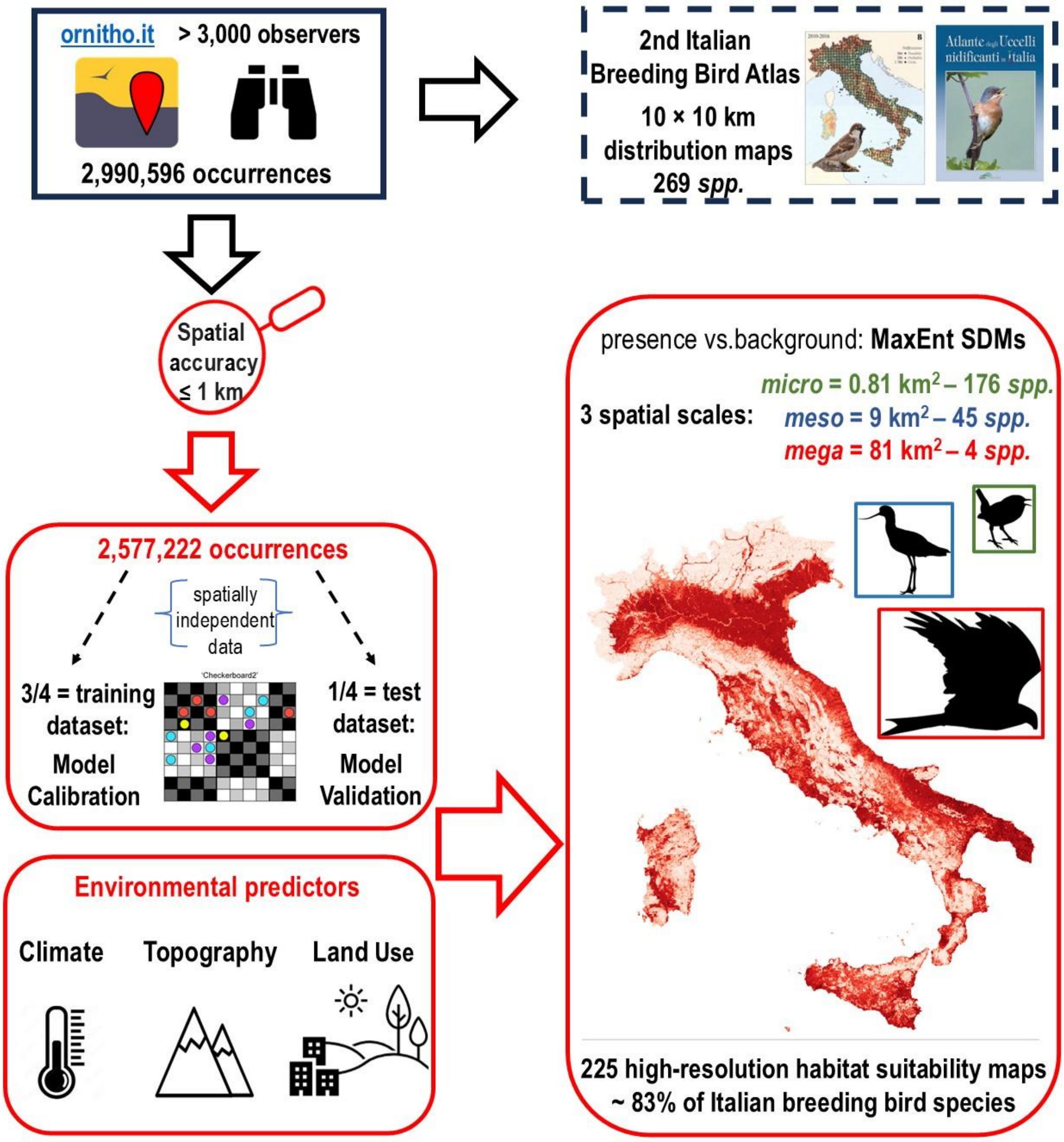

Fig.1 *Synthetic workflow for generating habitat suitability maps for 225 widespread breeding bird species in Italy.*

Methods

Italian breeding bird atlas and occurrence data

The habitat suitability maps were generated using occurrence data collected for the second Italian breeding bird atlas by over 3,000 skilled observers, mainly through the www.ornitho.it citizen science portal (see Lardelli et al.[21] for further details). The initial database contained 2,990,596 records of avian species with reproductive evidence (possible, probable or confirmed breeding; behavioural or physiological, including territorial behaviour, nest building, observations of fledged nestlings, etc.; reproductive evidence was assigned by observers in the field according to the standard European Bird Census Council methodology, see https://ebba2.info/about/methodology/) during the breeding seasons spanning from 2010 to 2016. All records were subjected to quality control (expert-based validation) to generate both distribution maps and SDMs. We excluded incomplete or incorrect data[29], including those supported by weak breeding evidence for colonial and rare species. The resulting dataset, containing 2,989,426 records and concerning 269 bird species, was used to generate distribution maps at a 10 km scale (UTM grid with 10 × 10 km cells, except for cells in the transition between adjacent UTM zones), illustrating the breeding distribution range of all Italian species as well as for building SDMs and producing habitat suitability maps for all widespread species (see Lardelli et al.[21]).

Modelling habitat suitability

Due to the nature of the collected data, to model habitat suitability we relied on presence-only data[21]. Models were built using MaxEnt[30], which was proven to be the most effective method when presence-only data are available[31]. MaxEnt relies on background data to define available environmental conditions for the target species within the study area. We parametrized MaxEnt models accounting for non-uniform sampling and optimised model complexity by carefully selecting environmental variables, in order to obtain robust and generalizable results[15,32,33,34,35]. The following paragraphs summarise the approach adopted for model development, from the preparation of input data to model validation (Figure 1).

Data selection, spatial scales and background points

The dataset used to build the models consisted of a subset of data employed in generating distribution maps. Specifically, only data related to observations with high spatial accuracy (< 1 km; i.e. we excluded records associated with broader areas, such as municipalities or protected areas, depending on how data were uploaded on www.ornitho.it) were considered and assigned to 1 × 1 km UTM grid cells. Eventually, the final database consisted of 2,577,222 occurrence records (considering only a single breeding record per species per cell).

Considering the substantial differences in species' ecology, spatial scales for SDM development were appropriately differentiated in order to assess the relationships between species and the environment at the scale at which they are ecologically most meaningful[36]. For instance, small passerines are influenced by environmental variables at a very local scale (i.e. thousands of square metres or a few hectares[37]). By contrast, large raptors are influenced by environmental characteristics of much larger territories[38]. Given the resolution of both ornithological data (1 × 1 km UTM grid) and environmental data (see 'Environmental variables'), we set the lowest spatial scale at 0.81 km^2. Additionally, two broader spatial scales were identified, taking into account the average home range sizes of the analysed species. The exact scale at which models were implemented depended on the exact number of cells that, under a focal feature approach (see 'Environmental variables'), provided the closest match to the desired scale. Therefore, the three spatial scales considered for environmental variables were: 'micro' (variables computed at 0.81 km^2 resolution), 'meso' (variables computed at 9 km^2 resolution), and 'mega' (variables computed at 81 km^2 resolution). Additional details on generated maps are provided in Supplementary Table 1.

The generation of background is a fundamental aspect for developing distribution models[39]. For instance, setting background points in unsurveyed areas could result in the environmental conditions observed at those points being considered as unsuitable for a species due to the lack of observations, rather than representing actual counter-selection for those conditions. To avoid including unsurveyed areas, we used the centroids of effectively sampled 1 × 1 km UTM cells as background points. For diurnal species, given the significantly larger number of observations (2,542,772 occurrence records) compared to nocturnal species (34,450 occurrence records), we chose as background points the centroids of the most intensively sampled cells (those with at least 20 occurrence records), whereas for nocturnal species we selected all sampled cells. This resulted in 30,180 background points for diurnal species and 14,672 for nocturnal ones.

Environmental variables

The environmental variables used in the models belonged to three distinct groups: climatic, topographic, and land use. Climatic variables (1981–2010) were retrieved from the CHELSA (www.chelsa-climate.org) database[40]. Several bioclimatic variables, summarising monthly values to obtain biologically meaningful predictors commonly used in SDMs[41], were calculated. As the CHELSA database's bioclimatic variables did not include open water bodies (coastal lagoons), the values of bioclimatic variables for these cells were recalculated from the original climate data used for the bioclimatic variables' calculation, using the same algorithms used for building the CHELSA database[42]. Topographic variables were calculated through GRASS[43] from a digital elevation model (DEM; eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-eu-dem) with a resolution of 25 m. From this, slope (in degrees) and solar radiation (total daily value, in kWh/m^2) for summer solstice, considering the shading effect of relief, were derived. Land use/land cover variables were derived from the CORINE Land Cover database[44]. The 2012 edition was chosen as it best overlapped with the occurrence data collection period (i.e. 2010-2016).

Environmental variables were calculated using raster grids of 100 x 100 m and 1 x 1 km. Environmental variables were attributed to cells using a 'focal features' (or 'moving window') approach. For each focal cell (i.e. the raster cell where the centroid of the UTM cell associated with observations or the background point fell), we calculated a summary value of each environmental variable within a neighbourhood of surrounding cells. At each spatial scale, environmental variables were measured in a neighbourhood of focal cells established to approximate as much as possible the spatial scale of bird data. At the finest scale (micro), 9 x 9 cells of 100 m each were considered, covering a total area of 0.81 km^2 within which to calculate the values of environmental variables associated with the focal cell. At the intermediate scale (meso), 3 x 3 cells of 1 km each were considered (total 9 km^2), while at the broadest scale (mega), predictor values were calculated using 9 x 9 cells of 1 km each (total 81 km^2). This approach allowed us to best handle calculations of environmental variables for those UTM grid cells that spanned across different UTM zones, which had slightly irregular and deformed shapes. Furthermore, it improved the ecological realism of bird-habitat associations, especially at the broader spatial scales

Data splitting into training and test datasets

To develop robust and generalizable SDMs, it is crucial to assess their predictive capacity on independent datasets. To this end, a fraction of the data was not used in model building and kept as a test dataset to evaluate model performance. To select spatially independent data for the test dataset, we relied on the 'checkerboard 2' function of the ENMeval R package[33]. Only presence data, not background data, were split between training and test datasets. At each scale, the procedure produced a 'double checkerboard', with 10 and 2 as grouping factors at the two levels, at each scale. This resulted in four different subsets of data. Three subsets constituted the training dataset, while the remaining subset was used as the test dataset. This process yielded two spatially independent sets of data, corresponding roughly to ¾ and ¼ of the original data (training and test datasets, respectively).

Model building

To reduce the number of variables included in the models and to avoid collinearity, sets of environmental variables were defined for different species groups based on their ecology. Hence, different environmental variables were considered for forest species, farmland species, wetland species, mountain areas, and generalist species, as listed in Supplementary Table 2.

Although machine learning methods (such as MaxEnt) are much less sensitive to the effects of correlated predictors compared to classical statistical methods, including strongly collinear predictors may lead to unpredictable effects in the extrapolation phase[35]. Therefore, at each spatial scale and for each subgroup of variables identified according to species' ecology, the strongest correlations between predictors ($r \geq 0.8$) were highlighted. The correlation between environmental variables was calculated for all cells with at least one occurrence record (107,649 cells), in order to consider a large and representative dataset of environmental conditions. We then included in SDMs the most ecologically relevant predictors among correlated ones and removed the other(s).

Model calibration was performed on the training dataset and aimed at identifying the best combination of model parameters for each species. Accurately parameterizing models yields significant improvements in model predictions[45;] adequate parameterization prevents overfitting and increases the ecological relevance of species-habitat relationships, resulting in robust and effective predictions of species distributions.

MaxEnt models were tuned according to the following parameters:

1) functions for species-habitat relationships: to avoid overfitting in species-habitat relationships, we included only linear or quadratic terms of environmental predictors. This prudential approach may slightly reduce the model's accuracy on training data, but it reduces the risk of considering unlikely species-habitat relationships, inconsistent with real ecological effects.

2) number of iterations: the number of iterations was set to 1,000; if the model converges earlier, the actual number will be smaller, otherwise it will continue to seek convergence until that value. In fact, for all species, the number of iterations in the final model was smaller.

3) value of regularization multiplier: the regularization multiplier is a crucial parameter in SDMs, as it determines whether distributions are more fragmented or more homogeneous, relaxing or tightening the effect of environmental parameters on suitability. The selection of the most suitable value was performed by testing values from 0.5 to 4, in 0.5 steps (i.e. 8 values)[46]. The AICc value (Akaike's Information Criterion, corrected for small samples[47,48]) was then calculated for the model based on each of these eight values, and the most parsimonious one was chosen.

4) selection of environmental variables: after selecting the initial value for the regularization multiplier, variables that were correlated with each other were tested one by one, determining for each pair of collinear parameters the variable whose inclusion led to the most supported model (lower AICc). From the model thus selected, any variables with a lambda coefficient (i.e. index for variables' contribution in predicting distribution) equal to zero, and hence irrelevant, were excluded. At this point, a variable selection procedure based on AICc was performed: for each environmental variable, the permutation importance, i.e., the importance of the specific factor in explaining the species' distribution according to MaxEnt, was calculated. The variable with the lowest permutation importance value was removed from the model, and the AICc was calculated; if the model improved (i.e., the AICc decreased), we continued with removing the least important variable until the model showed no further improvements.

The most parsimonious model was considered as the final model. For the calculation of AICc, a recently developed *ad hoc* method was used[49].

Data Records

Of the 269 breeding bird species in Italy during 2010-2016, we could implement robust SDMs, and therefore generate reliable habitat suitability maps, for 225 of them (~83%; see 'Model evaluation and validation').

Suitability maps are made available as rasters (.tif) files on https://doi.org/10.13130/RD_UNIMI/LUC3K6. The raster names correspond to the EURING species codes (see https://euring.org/data-and-codes/euring-codes) and the first three letters of genus and species (e.g. "E00070_Tac.ruf.tif" for the little grebe *Tachybaptus ruficollis*).

The statistical outputs corresponding to each species' habitat suitability model are available as folders, named with the scientific name of the species. Folders contain: 1) model evaluation (.csv file); 2) model results (.csv file); 3) permutation importance of used environmental predictors (.csv file); 4) barplot of the five most important predictors (.jpg); and 5) all the response plots to environmental predictors (.jpg). For ease of visualisation, we provide a single PDF file with the response plots for the five most important predictors for each species, as well as the barplot with their permutation importance (Supplementary Information 1).

Two threshold values, namely Maximum Training Sensitivity plus Specificity (MTSS) and 10th percentile, useful for deriving binary predictions of species occurrence[50], are reported in Supplementary Table 4.

Technical Validation

Model evaluation and validation

We tested the robustness of models for each species using the test dataset. Statistics used for the evaluation and validation were calculated based on the final models based on both the training and the test datasets. The most important aspect of validation was the consistency of predictive ability on both the training and test datasets. Comparable values indicate a generalizable model unconstrained from overfitting issues and able to predict environmental suitability in sites not used for its construction, as well as in those used for its development.

To evaluate model performance, four reference statistics were considered:

- AUC (Area Under the Curve of the Receiver Operating Characteristic plot), which assesses the discriminatory ability of a model[51]. Values equal to 0.5 represent a chance-level performance, while 1 indicates a perfect ability to distinguish between presences and background points. In absolute terms, AUC is not a good measure of model accuracy, as rare species tend to have higher AUC values than common species[52]; therefore, we mainly used AUC to compare values calculated on training and test datasets. The model can be regarded as valid and generalizable when similar AUC values are obtained (difference < 0.05);

- TSS (True Skill Statistic), which compares the number of correct predictions, minus those attributable to chance, to those of a hypothetical set of perfect predictions (defined as sensitivity + specificity - 1). TSS ranges from -1 to +1, with the maximum value indicating a perfect match and zero indicating performance equal to chance[53]. Differences in the values of TSS between test and training dataset models > 0.05 suggest possible overfitting issues;

- Minimum training presence omission rate on test dataset, which evaluates the proportion of occurrences included in the test dataset falling below the lower suitability value at which the species occurs, based on the locations used to develop the model (training dataset). Ideally, it should be zero or close to zero (no or a very few test locations occurring at suitability values lower than the minimum values recorded at training locations);

- 10th percentile omission rate on the test dataset, which evaluates the proportion of occurrences included in the test dataset falling below the threshold value of the 10th percentile from occurrences of the training dataset. Ideally, it should be close to 10% of records. Values higher than 0.1 (e.g. > 0.2-0.3) indicate likely overfitting issues.

Validation statistics for all SDMs are provided in Supplementary Table 5. The minimum sample size used for implementing SDMs was set at 50 occurrence records for non-colonial species and 20 for colonial ones. In the case of a few species for which models were based on a very low sample size (i.e. Mediterranean gull (*Larus melanocephalus*), n = 20; Eurasian spoonbill (*Platalea leucorodia*), n = 30; Savi's warbler (*Locustella luscinioides*), n = 67; great spotted cuckoo (*Clamator glandarius*), n = 78), the evaluation statistics were unreliable and model validity was only visually assessed on the basis of the concordance between predicted and observed distributions. Overall, the average difference between training and testing dataset was 0.00 ± 0.03 for TSS (mean ± SD; only 10 species showed a difference > 0.05 but always < 0.09) and 0.00 ± 0.01 for AUC (only one species showed a difference > 0.05, being 0.06), indicating in general very good performances in that sense. Also, omission rates at minimum training presence and 10th percentile generally showed optimal values, with a few exceptions mostly related to species with a low sample of occurrence records. Furthermore, the reliability of each final model was verified by means of visual check of the resulting habitat suitability map, conducted by species' experts (see Lardelli et al.[21]).

Restriction of environmental suitability predictions to presence-only areas

Due to biogeographical reasons, not all species may actually occur in all areas classified as suitable by distribution models. Given the main purpose of these models (i.e. assisting in defining species distribution, even in poorly investigated areas), we excluded these regions from environmental suitability maps, setting environmental suitability to zero in areas where a given species has never been recorded. To this end, environmental suitability maps were intersected with actual distribution maps in order to exclude regions located outside a given species' distribution range from potentially suitable sites. For instance, the Eurasian nuthatch (*Sitta europaea*) does not breed in Sardinia due to biogeographical/historical reasons, hence we set suitability to zero there despite suitable woodland habitats were identified by SDMs. The types of correction applied to environmental suitability maps based on species distribution were as follows (see Supplementary Table 1 for details and species concerned):

1. Exclusion of mainland Italy from suitable areas for species limited to the islands;

2. Exclusion of Sardinia and/or Sicily and/or adjacent smaller islands from suitable areas for species breeding only on the Italian mainland;

3. Restriction to a buffer surrounding actual occurrence sites: for species with a concentrated distribution but not falling into any of the previous cases, an informative layer representing the actual range was created. For most species, a distance of 200 km around the presence sites was used; for some with a particularly restricted or concentrated distribution, the adopted distance was 50 km. For species distributed throughout the national territory, even if scattered, no range restriction was applied.

Interpretation of environmental suitability maps

The raster maps indicated the environmental suitability for each species based on the environmental suitability model. The reported values in each raster's cell (obtained through the cloglog transformation of raw MaxEnt output) range from zero (i.e. no suitability) to one (i.e. maximum suitability). For a correct interpretation of the habitat suitability maps, it should be kept in mind that 1) they represent habitat suitability, not species' probability of presence. Although these two variables are highly correlated, an environmental suitability of 0.5 does not correspond to a 50% probability of species presence; 2) they do not represent abundance, even though there is published evidence of positive correlations between environmental suitability and local density[15,16].

Usage Notes

Inferring species richness and assessing its drivers in Italian urban areas

In this section, we provide an example for the usage of environmental suitability. Given the importance of understanding urban ecology for addressing the current sustainability goals for cities and dense human agglomerates[54], we focused on identifying the ecological and socio-economic drivers of avian species richness among the main Italian urban areas. Since actual occurrence data are missing for several urban 1 × 1 UTM cells and sampling was uneven, habitat suitability maps implemented through SDMs allowed us to fill geographical data gaps by inferring the composition of local urban avian communities. We aimed at showing the potential use of these tools in predicting and assessing species and community variation in areas where comprehensive bird occurrence data are unavailable (or are available at coarse spatial resolution) due to uneven spatial sampling[55].

Identification of Functional Urban Areas (FUAs)

We identified 91 Italian municipalities as spatial units, adopting the European Union's definition of Functional Urban Areas (FUAs; for further information see https://www.oecd.org/regional/regional-statistics/functional-urban-areas.htm). Since the core of each FUA comprises the whole municipal area, we have considered only those 1 × 1 km UTM cells characterized by at least 50% urbanized land cover based on the CORINE database[44]. Thus, the analysis focused on a homogeneous urban matrix, excluding FUA cells dominated by other land uses (see Figure 2; Supplementary Table 3).

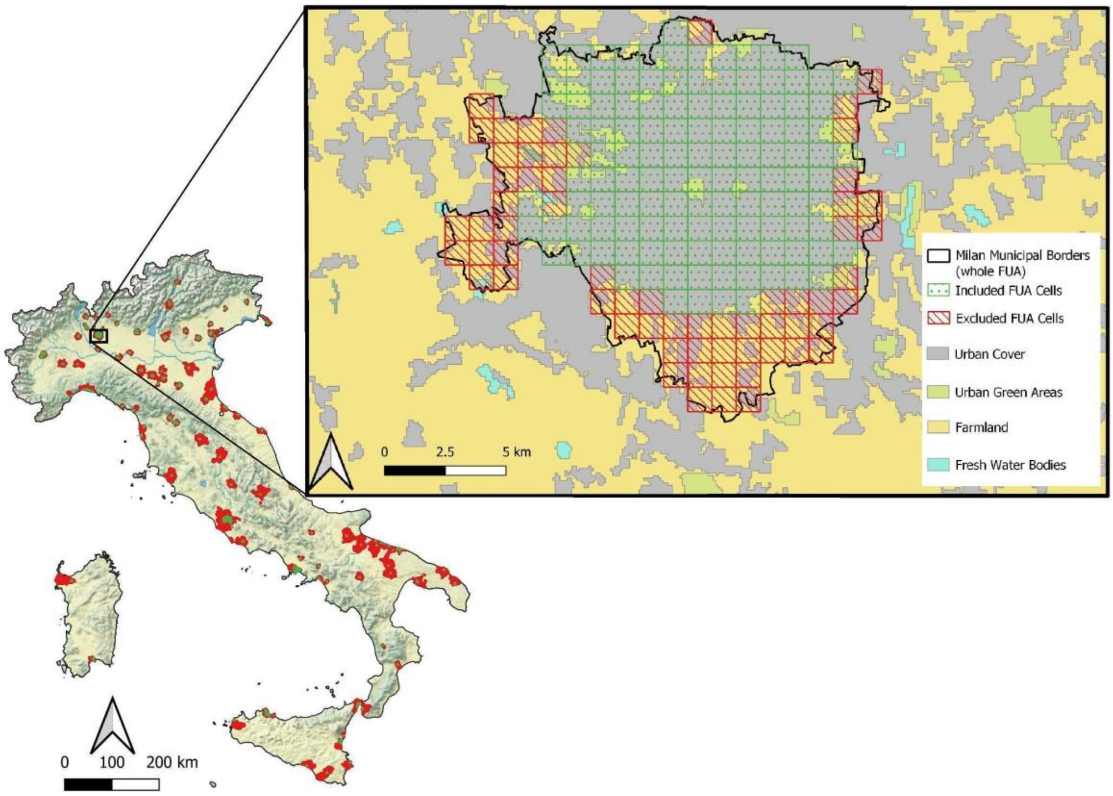

Fig.2 *A visual example of 1 × 1 UTM grid cells for one of the 91 FUAs (city of Milan), showing the original limits of the considered FUA (i.e. the municipal borders), and the set of grid cells featuring ≥ 50% urban land cover and considered for this FUA (in green). Cells over Italy (on the left) represent the geographic location of all 91 FUAs.*

Retrieving inferred species richness

Given the assumption that habitat suitability inferred by SDMs is strongly correlated with the occurrence probability of a species[56], we converted environmental suitability into a binary variable (0 = absence, 1 = presence) using the species-specific values of the two thresholds provided in Supplementary Table 4. After an expert-based evaluation of the two communities inferred communities with these thresholds, we opted for using the MTSS threshold, as it generally provided more conservative and realistic estimates of species potential presence. We then obtained a list of possible species occurring within each FUA, representing a potential species community and species richness. Finally, to address the issue of species overprediction in SDMs[57], we included in the analysis only the 128 species (~56.9% out of 225 SDMs) occurring in at least two different FUAs, according to the dataset used for model building. This approach reduced the potential for overprediction bias by filtering out 97 species—those that never occurred in any FUA (n = 74; ~32.9%) and those that were very rare in Italian urban areas (n = 23, ~10.2%; i.e. not occurring in more than a single FUA).

Predictors of potential species richness

We assessed the relationship between the inferred species richness and three groups of potential predictors characterizing the urban investigation units that according to previous evidence[58,59] may shape urban bird communities, i.e. geographic, socio-economic and landscape variables. Geographic variables were latitude, longitude and elevation of the FUA (mean values of cells in each FUA). Socio-economic variables considered the FUA's economic welfare (using average annual per capita income as a proxy; source: https://www.finanze.gov.it/) and the human population density (the average number of inhabitants in the included FUA cells; source: ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat). Landscape variables comprised the percentage land cover for seven categories obtained by merging original CORINE categories[44] (1 = urban cover; 2 = urban parks; 3 = farmlands; 4 = natural vegetation/land cover; 5 = wetlands; 6 = freshwater bodies; 7 = saltwater bodies; figure 2). Moreover, in order to evaluate possible cumulative effects of the land cover categories, we retrieved as additional variables the Shannon diversity index of the FUA land cover and the overall percentage of 'urban green' areas (i.e. by merging urban parks with residual farmland/natural vegetation). The effect of these potential drivers on species richness was tested using linear models fitted using R v. 4.4.2[60]. We tested also for quadratic effects of predictors, and included them in models only when they were statistically significant. FUA area (log_{10}-transformed) was included as a predictor in all models to account for species-area relationships[61]. To address multicollinearity among predictors, we assessed the variance inflation factors (VIFs), discarding predictors with the highest multicollinearity[62] (VIF > 3), and selecting those with higher statistical performance (i.e. lower AICc). Model performance checks revealed no deviations from assumptions. We then fitted a final model including only statistically significant ($p < 0.05$) predictors highlighted in previous steps.

Results and discussion

The inferred avian species richness within the 91 Italian FUAs ranged from 35 to 76 species (mean = 53.16; s.d. = 10.29). Testing the effectiveness of habitat suitability models in predicting urban species richness is challenging. In fact, although urban breeding bird atlases are available for many Italian cities[59], comparing inferred and actual species richness is complicated by inconsistent spatial criteria used to define urban environments in different atlases[63]. To check the accuracy of SDMs in predicting urban species communities, we thus compared inferred species richness with actual bird occurrence data used for model building (these original bird occurrence data could not be made publicly available due to restrictions on their public release by data owners, i.e. individual observers or entities contributing data for realizing the atlas). We overlapped 1 × 1 km raster cells of species presence with the 1 × 1 km FUA cells used in the analysis in order to retrieve an observed species richness value within the considered urban areas (including all possible spatial gaps in the observation data). The correlation between observed and inferred species richness was positive and significant ($r = 0.50$, $n = 83$ FUAs, $p < 0.001$; Figure 3; FUAs with less than 5 reported species from occurrence data were discarded as they were clearly undersampled; see Supplementary Table 3), empirically supporting the ability of SDMs in effectively predicting species richness. Although inferred species richness was greater than the observed one (Figure 3), this was due to survey gaps in occurrence data. For instance, for two FUAs the observed species richness was 0, which could only denote a survey gap, and the difference between observed and inferred species richness tends to decrease with increasing observed species richness, suggesting that in highly surveyed areas the two measures may converge (Figure 3).

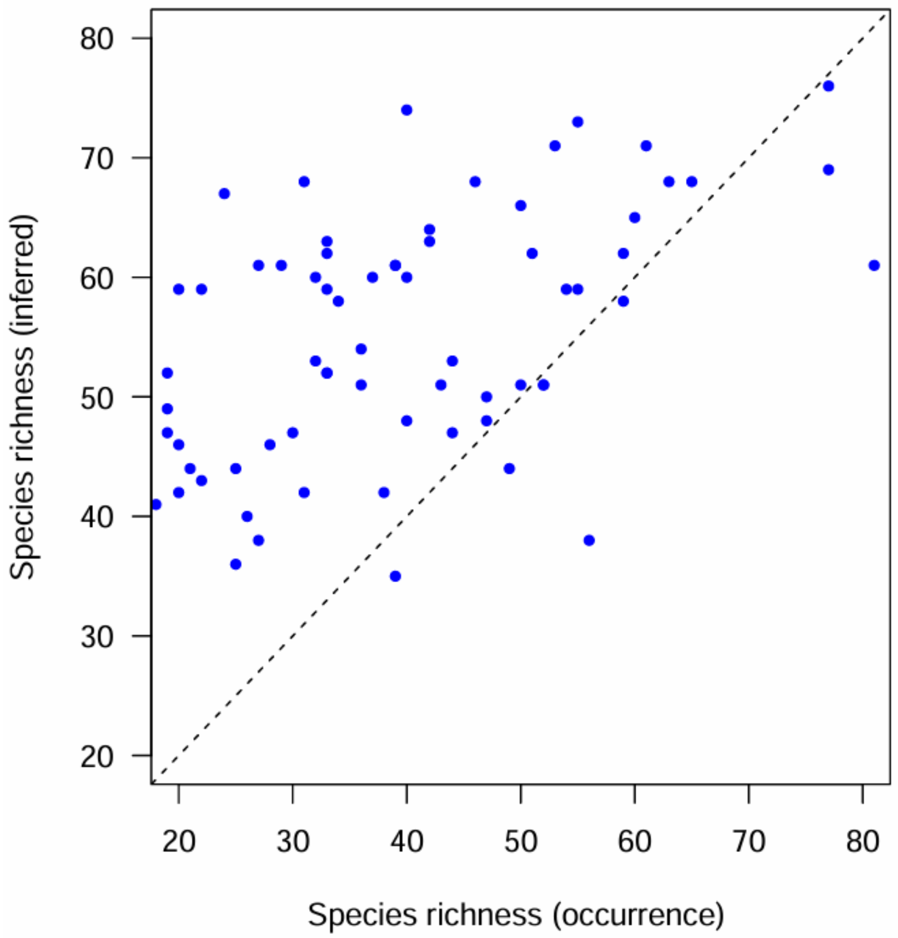

Fig.3 *Relationship between inferred and observed species richness in 83 Italian FUAs where at least 5 bird species were reported in original bird occurrence data. Dashed line shows the 1:1 line, i.e. inferred species richness equals occurrence.*

The results of linear models fitted for each of the three groups of variables (geographic, socio-economic, landscape) are reported in Table 1. The final model, fitted including significant predictors of the previous groups, is reported in Table 2.

Table 1. *Linear models assessing the effect of predictors belonging to three distinct groups of variables on species richness in urban areas, while controlling for FUA area.*

Predictor	***Estimate* ± SE**	***t***	***P***
Geographic variables (AIC = 625.12)			
FUA area	5.59 ± 0.86	6.46	< 0.001
Latitude	3.37 ± 1.32	2.56	< 0.05
Latitude^2	2.09 ± 0.85	2.45	< 0.05
Longitude	-0.47 ± 1.15	-0.41	0.68
Elevation	-0.73± 0.82	-0.89	0.38
Socio-economic variables (AIC = 631.92)			
FUA area	6.17 ± 0.97	6.35	< 0.001
Human population density	-1.27 ± 0.90	-1.41	0.16
Average per capita income	1.26 ± 1.06	1.19	0.24
Landscape variables (AIC = 629.81)			
FUA area	6.46 ± 0.80	8.08	< 0.001
Urban green	2.22 ± 0.80	2.78	< 0.01
Freshwater	1.00 ± 0.80	1.24	0.22

Table 2. *Final linear model assessing the effects of statistically significant predictors for each group of variables (geographic, socio-economic and landscape) reported in Table 1, while controlling for FUA area.*

Predictor	***Estimate* ± SE**	***t***	***P***
All variables (AIC = 616.00)			
FUA area	5.71 ± 0.76	7.47	< 0.001
Latitude	3.67 ± 0.89	4.15	< 0.001
Latitude^2	2.31 ± 0.77	2.99	< 0.01
Urban green	2.07 ± 0.73	2.83	< 0.01

The model including geographic variables was the most supported one (lowest AIC value, Table 1). Latitude was the only significant predictor, displaying a moderate quadratic effect, suggesting a moderate decrease in species richness in the urban areas of central Italy compared to northern and southern cities, likely due to biogeographic patterns of species distribution[59,64]. The socio-economic model showed no significant effects, whose sign was however in accordance with previous evidence (i.e. negative of human population density[65] and positive of average per capita income[58]). Concerning the landscape model, several predictors showed moderate collinearity, and the combination of urban green and freshwater percentage provided the best explanatory performance. Urban green cover fostered species richness, highlighting a tendency for a decline in biodiversity with increasing levels of urbanization[65]. These results are in line with the general ecological paradigm of environmental heterogeneity–biodiversity relationships applied to urban landscapes[66], suggesting that increasing biodiversity in urban areas is achieved primarily by increasing urban green spaces [58,65,67].

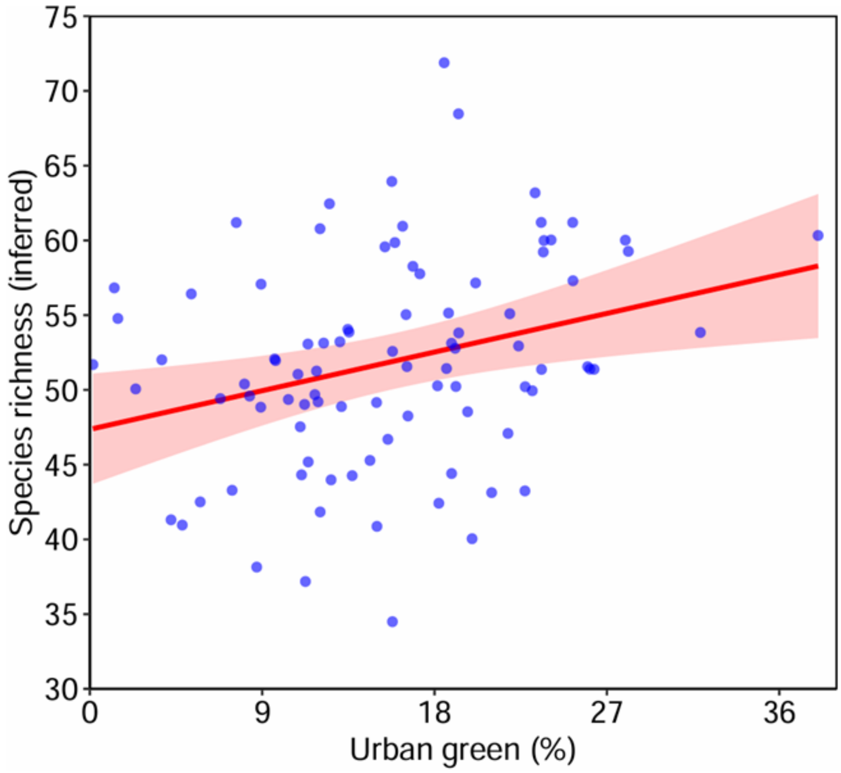

Fig. 4 *Partial plot showing the relationship between inferred species richness within FUAs and the percentage of urban green (from the model reported in Table 2).*

Code Availability

The R script used to develop the species distribution models is the same adopted by[49] and is publicly available in[68].

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Competing interests

The authors declare no competing interests.

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Supplementary Table 1*: Details of the 225 habitat suitability maps for all widespread Italian breeding birds. Species are listed by their EURING code, and columns provide the following information: the abbreviation of the scientific name (Sp. abbr); number of presence records (Occurrences); the spatial scale of the raster (Scale); the environmental variable group used (Habitat); and the applied range restriction (Crop) — 'b50' = exclusion outside a 50 km buffer from presence sites, 'con' = exclusion from the Italian peninsula, 'isl' = exclusion from main and small islands, 'no' = no range restriction, 'sar' = exclusion from Sardinia, 'std' = exclusion outside a 200 km buffer from presence sites.*

Order	EURING	Species	Sp. abbr	Occurrences	Scale	Habitat	Crop
1	E00070	*Tachybaptus ruficollis*	Tac.ruf	12012	micro	Wetland	no
2	E00090	*Podiceps cristatus*	Pod.cri	13635	meso	Wetland	no
3	E00720	*Phalacrocorax carbo*	Pha.car	2049	meso	Wetland	no
4	E00800	*Phalacrocorax aristotelis*	Pha.ari	585	meso	Wetland	std
5	E00820	*Phalacrocorax pygmeus*	Pha.pyg	663	meso	Wetland	std
6	E00950	*Botaurus stellaris*	Bot.ste	1052	micro	Wetland	std
7	E00980	*Ixobrychus minutus*	Ixo.min	3213	micro	Wetland	no
8	E01040	*Nycticorax nycticorax*	Nyc.nyc	3510	meso	Wetland	no
9	E01080	*Ardeola ralloides*	Ard.ral	1447	meso	Wetland	no
10	E01110	*Bubulcus ibis*	Bub.ibi	2840	meso	Wetland	no
11	E01190	*Egretta garzetta*	Egr.gar	4634	meso	Wetland	no
12	E01210	*Casmerodius albus*	Cas.alb	814	meso	Wetland	std
13	E01220	*Ardea cinerea*	Ard.cin	10721	meso	Wetland	no
14	E01240	*Ardea purpurea*	Ard.pur	2759	meso	Wetland	no
15	E01310	*Ciconia nigra*	Cic.nig	263	meso	Forest	isl
16	E01340	*Ciconia ciconia*	Cic.cic	2838	meso	Farmland	no
17	E01440	*Platalea leucorodia*	Pla.leu	494	meso	Wetland	no
18	E01520	*Cygnus olor*	Cyg.olo	8049	meso	Wetland	isl
19	E01610	*Anser anser*	Ans.ans	1534	meso	Wetland	isl
20	E01730	*Tadorna tadorna*	Tad.tad	2009	micro	Wetland	no
21	E01820	*Anas strepera*	Ana.str	695	micro	Wetland	std
22	E01860	*Anas platyrhynchos*	Ana.pla	37203	micro	Wetland	no
23	E01910	*Anas querquedula*	Ana.que	438	micro	Wetland	std

24	E01940	*Anas clypeata*	Ana.cly	420	micro	Wetland	std
25	E01960	*Netta rufina*	Net.ruf	767	micro	Wetland	no
26	E01980	*Aythya ferina*	Ayt.fer	866	micro	Wetland	no
27	E02020	*Aythya nyroca*	Ayt.nyr	515	micro	Wetland	no
28	E02030	*Aythya fuligula*	Ayt.ful	998	micro	Wetland	std
29	E02230	*Mergus merganser*	Mer.mer	1793	micro	Wetland	std
30	E02310	*Pernis apivorus*	Per.api	6890	meso	Generalist	sar
31	E02380	*Milvus migrans*	Mil.mig	10073	meso	Generalist	std
32	E02390	*Milvus milvus*	Mil.mil	1345	mega	Generalist	std
33	E02460	*Gypaetus barbatus*	Gyp.bar	334	mega	Mountain	std
34	E02510	*Gyps fulvus*	Gyp.ful	339	mega	Generalist	std
35	E02560	*Circaetus gallicus*	Cir.gal	3430	meso	Generalist	std
36	E02600	*Circus aeruginosus*	Cir.aer	2585	meso	Wetland	std
37	E02630	*Circus pygargus*	Cir.pyg	1522	meso	Farmland	std
38	E02670	*Accipiter gentilis*	Acc.gen	1143	meso	Forest	no
39	E02690	*Accipiter nisus*	Acc.nis	4880	micro	Generalist	no
40	E02870	*Buteo buteo*	But.but	35268	meso	Generalist	no
41	E02960	*Aquila chrysaetos*	Aqu.chr	3913	mega	Generalist	no
42	E02990	*Aquila fasciata*	Aqu.fas	62	meso	Generalist	con
43	E03030	*Falco naumanni*	Fal.nau	1750	meso	Farmland	std
44	E03040	*Falco tinnunculus*	Fal.tin	33337	micro	Farmland	no
45	E03070	*Falco vespertinus*	Fal.ves	510	meso	Farmland	std
46	E03100	*Falco subbuteo*	Fal.sub	6311	meso	Generalist	no
47	E03110	*Falco eleonorae*	Fal.ele	99	meso	Generalist	std

48	E03140	*Falco biarmicus*	Fal.bia	321	meso	Generalist	std
49	E03200	*Falco peregrinus*	Fal.per	5640	meso	Generalist	no
50	E03260	*Bonasa bonasia*	Bon.bon	363	micro	Forest	b50
51	E03300	*Lagopus muta*	Lag.mut	494	micro	Mountain	std
52	E03320	*Tetrao tetrix*	Tet.tetrix	1996	micro	Forest	b50
53	E03350	*Tetrao urogallus*	Tet.uro	253	micro	Forest	b50
54	E03450	*Colinus virginianus*	Col.vir	212	micro	Farmland	b50
55	E03570	*Alectoris graeca*	Ale.gra	824	micro	Farmland	std
56	E03580	*Alectoris rufa*	Ale.ruf	1257	micro	Farmland	b50
57	E03590	*Alectoris barbara*	Ale.bar	437	micro	Farmland	std
58	E03670	*Perdix perdix*	Per.per	198	micro	Farmland	std
59	E03700	*Coturnix coturnix*	Cot.cot	7873	micro	Farmland	no
60	E03940	*Phasianus colchicus*	Pha.col	19456	micro	Farmland	no
61	E04070	*Rallus aquaticus*	Ral.aqu	1964	micro	Wetland	no
62	E04210	*Crex crex*	Cre.cre	427	micro	Farmland	std
63	E04240	*Gallinula chloropus*	Gal.chl	19618	micro	Wetland	no
64	E04270	*Porphyrio porphyrio*	Por.porphy	294	micro	Wetland	con
65	E04290	*Fulica atra*	Ful.atr	22432	micro	Wetland	no
66	E04500	*Haematopus ostralegus*	Hae.ost	1110	meso	Wetland	std
67	E04550	*Himantopus himantopus*	Him.him	7603	meso	Wetland	no
68	E04560	*Recurvirostra avosetta*	Rec.avo	1026	meso	Wetland	no
69	E04590	*Burhinus oedicnemus*	Bur.oed	1968	micro	Wetland	no
70	E04690	*Charadrius dubius*	Cha.dub	4401	micro	Wetland	no
71	E04770	*Charadrius alexandrinus*	Cha.ale	3088	micro	Wetland	no
72	E04930	*Vanellus vanellus*	Van.van	9682	micro	Farmland	std
73	E05460	*Tringa totanus*	Tri.tot	628	micro	Wetland	no
74	E05560	*Actitis hypoleucos*	Act.hyp	1000	micro	Wetland	no
75	E05750	*Larus melanocephalus*	Lar.mel	140	meso	Wetland	std
76	E05820	*Chroicocephalus ridibundus*	Chr.rid	680	meso	Wetland	std

77	E05850	*Chroicocephalus genei*	Chr.gen	337	meso	Wetland	std
78	E05880	*Larus audouinii*	Lar.aud	167	meso	Wetland	std
79	E05926	*Larus michahellis*	Lar.mic	8688	meso	Wetland	no
80	E06150	*Sterna hirundo*	Ste.hir	2753	meso	Wetland	std
81	E06240	*Sternula albifrons*	Ste.alb	1209	meso	Wetland	no
82	E06680	*Columba oenas*	Col.oen	440	micro	Forest	std
83	E06700	*Columba palumbus*	Col.pal	60428	micro	Generalist	no
84	E06840	*Streptopelia decaocto*	Str.dec	85725	micro	Farmland	no
85	E06870	*Streptopelia turtur*	Str.tur	28960	micro	Farmland	no
86	E07120	*Psittacula krameri*	Psi.kra	1675	micro	Generalist	no
87	E07160	*Clamator glandarius*	Cla.gla	150	micro	Farmland	no
88	E07240	*Cuculus canorus*	Cuc.can	42900	micro	Generalist	no
89	E07350	*Tyto alba*	Tyt.alb	1219	micro	Farmland	no
90	E07390	*Otus scops*	Otu.sco	8997	micro	Generalist	no
91	E07440	*Bubo bubo*	Bub.bub	1100	meso	Generalist	isl
92	E07510	*Glaucidium passerinum*	Gla.pas	273	micro	Forest	b50
93	E07570	*Athene noctua*	Ath.noc	14949	micro	Farmland	no
94	E07610	*Strix aluco*	Str.alu	7370	micro	Forest	std
95	E07670	*Asio otus*	Asi.otu	2452	micro	Forest	no
96	E07700	*Aegolius funereus*	Aeg.fun	341	micro	Forest	b50
97	E07780	*Caprimulgus europaeus*	Cap.eur	3638	micro	Generalist	no
98	E07950	*Apus apus*	Apu.apu	44904	micro	Generalist	no
99	E07960	*Apus pallidus*	Apu.pal	3385	micro	Generalist	no
100	E07980	*Apus melba*	Apu.mel	3857	micro	Generalist	no
101	E08310	*Alcedo atthis*	Alc.att	5072	micro	Wetland	no

102	E08400	*Merops apiaster*	Mer.api	15560	micro	Farmland	no
103	E08410	*Coracias garrulus*	Cor.gar	3573	micro	Farmland	no
104	E08460	*Upupa epops*	Upu.epo	19041	micro	Farmland	no
105	E08480	*Jynx torquilla*	Jyn.tor	9787	micro	Farmland	no
106	E08550	*Picus canus*	Pic.can	743	micro	Forest	b50
107	E08560	*Picus viridis*	Pic.vir	37465	micro	Forest	isl
108	E08630	*Dryocopus martius*	Dry.mar	3553	meso	Forest	isl
109	E08760	*Dendrocopos major*	Den.maj	36588	micro	Forest	no
110	E08830	*Dendrocopos medius*	Den.med	422	micro	Forest	std
111	E08870	*Dendrocopos minor*	Den.min	3460	micro	Forest	isl
112	E08980	*Picoides tridactylus*	Pic.tri	226	micro	Forest	b50
113	E09610	*Melanocorypha calandra*	Mel.cal	1474	micro	Farmland	std
114	E09680	*Calandrella brachydactyla*	Cal.bra	1476	micro	Farmland	no
115	E09720	*Galerida cristata*	Gal.cri	14277	micro	Farmland	sar
116	E09740	*Lullula arborea*	Lul.arb	11148	micro	Farmland	no
117	E09760	*Alauda arvensis*	Ala.arv	21297	micro	Farmland	no
118	E09810	*Riparia riparia*	Rip.rip	736	micro	Wetland	sar
119	E09910	*Ptyonoprogne rupestris*	Pty.rup	11641	micro	Generalist	no
120	E09920	*Hirundo rustica*	Hir.rus	73179	micro	Farmland	no
121	E09950	*Cecropis daurica*	Cec.dau	427	micro	Farmland	no
122	E10010	*Delichon urbicum*	Del.urb	41415	micro	Generalist	no
123	E10050	*Anthus campestris*	Ant.cam	3149	micro	Farmland	no
124	E10090	*Anthus trivialis*	Ant.tri	9684	micro	Farmland	isl
125	E10140	*Anthus spinoletta*	Ant.spi	5629	micro	Mountain	std
126	E10170	*Motacilla flava*	Mot.fla	8145	micro	Farmland	no
127	E10190	*Motacilla cinerea*	Mot.cin	10356	micro	Wetland	no
128	E10200	*Motacilla alba*	Mot.alb	30456	micro	Farmland	sar
129	E10500	*Cinclus cinclus*	Cin.cin	4719	micro	Wetland	sar
130	E10660	*Troglodytes troglodytes*	Tro.tro	46255	micro	Forest	no

131	E10840	*Prunella modularis*	Pru.mod	5357	micro	Farmland	isl
132	E10940	*Prunella collaris*	Pru.col	1541	micro	Mountain	isl
133	E10990	*Erithacus rubecula*	Eri.rub	43723	micro	Forest	no
134	E11040	*Luscinia megarhynchos*	Lus.meg	59869	micro	Generalist	no
135	E11210	*Phoenicurus ochruros*	Pho.och	31140	micro	Generalist	sar
136	E11220	*Phoenicurus phoenicurus*	Pho.pho	36883	micro	Generalist	sar
137	E11370	*Saxicola rubetra*	Sax.rubetr	2428	micro	Farmland	sar
138	E11390	*Saxicola torquatus*	Sax.rubico	15175	micro	Farmland	no
139	E11460	*Oenanthe oenanthe*	Oen.oen	7647	micro	Farmland	no
140	E11480	*Oenanthe hispanica*	Oen.his	477	micro	Generalist	sar
141	E11620	*Monticola saxatilis*	Mon.sax	1465	micro	Farmland	no
142	E11660	*Monticola solitarius*	Mon.sol	3642	micro	Farmland	no
143	E11860	*Turdus torquatus*	Tur.tor	2711	micro	Forest	std
144	E11870	*Turdus merula*	Tur.mer	167142	micro	Forest	no
145	E11980	*Turdus pilaris*	Tur.pil	2658	micro	Generalist	b50
146	E12000	*Turdus philomelos*	Tur.phi	18441	micro	Forest	isl
147	E12020	*Turdus viscivorus*	Tur.vis	13034	micro	Generalist	no
148	E12200	*Cettia cetti*	Cet.cet	23170	micro	Wetland	no
149	E12260	*Cisticola juncidis*	Cis.jun	21327	micro	Farmland	no
150	E12380	*Locustella luscinioides*	Loc.lus	363	micro	Wetland	std
151	E12500	*Acrocephalus palustris*	Acr.pal	5178	micro	Wetland	std
152	E12510	*Acrocephalus scirpaceus*	Acr.sci	10231	micro	Wetland	no
153	E12530	*Acrocephalus arundinaceus*	Acr.aru	10535	micro	Wetland	no
154	E12600	*Hippolais polyglotta*	Hip.pol	11899	micro	Farmland	isl
155	E12610	*Sylvia sarda*	Syl.sar	239	micro	Farmland	std
156	E12620	*Sylvia undata*	Syl.und	872	micro	Farmland	std
157	E12640	*Sylvia conspicillata*	Syl.con	787	micro	Farmland	std

158	E12650	*Sylvia cantillans*	Syl.can	6654	micro	Farmland	sar
159	E12652	*Sylvia subalpina*	Syl.sub	6546	micro	Farmland	b50
160	E12670	*Sylvia melanocephala*	Syl.mel	23349	micro	Farmland	no
161	E12730	*Sylvia nisoria*	Syl.nis	124	micro	Farmland	b50
162	E12740	*Sylvia curruca*	Syl.cur	2973	micro	Generalist	std
163	E12750	*Sylvia communis*	Syl.com	8325	micro	Farmland	no
164	E12760	*Sylvia borin*	Syl.bor	1742	micro	Farmland	b50
165	E12770	*Sylvia atricapilla*	Syl.atr	134500	micro	Farmland	no
166	E13070	*Phylloscopus bonelli*	Phy.bon	7461	micro	Forest	isl
167	E13080	*Phylloscopus sibilatrix*	Phy.sib	1208	micro	Forest	isl
168	E13110	*Phylloscopus collybita*	Phy.col	31859	micro	Forest	no
169	E13140	*Regulus regulus*	Reg.reg	5009	micro	Forest	isl
170	E13150	*Regulus ignicapilla*	Reg.ign	14621	micro	Forest	no
171	E13350	*Muscicapa striata*	Mus.str	13935	micro	Generalist	no
172	E13480	*Ficedula albicollis*	Fic.alb	459	micro	Forest	isl
173	E14070	*Leiothrix lutea*	Lei.lut	389	micro	Generalist	std
174	E14370	*Aegithalos caudatus*	Aeg.cau	19552	micro	Generalist	sar
175	E14400	*Poecile palustris*	Poe.pal	12372	micro	Forest	b50
176	E14420	*Poecile montanus*	Poe.mon	4928	micro	Forest	std
177	E14540	*Lophophanes cristatus*	Lop.cri	4562	micro	Forest	std
178	E14610	*Periparus ater*	Per.ate	27253	micro	Forest	no
179	E14620	*Cyanistes caeruleus*	Cya.cae	40884	micro	Generalist	no
180	E14640	*Parus major*	Par.maj	90575	micro	Generalist	no
181	E14790	*Sitta europaea*	Sit.eur	18227	micro	Forest	sar
182	E14820	*Tichodroma muraria*	Tic.mur	247	micro	Generalist	std
183	E14860	*Certhia familiaris*	Cer.fam	4043	micro	Forest	isl

184	E14870	*Certhia brachydactyla*	Cer.bra	16759	micro	Forest	sar
185	E14900	*Remiz pendulinus*	Rem.pen	1111	micro	Wetland	sar
186	E15080	*Oriolus oriolus*	Ori.ori	19531	micro	Generalist	no
187	E15150	*Lanius collurio*	Lan.col	15317	micro	Farmland	no
188	E15190	*Lanius minor*	Lan.min	778	micro	Farmland	isl
189	E15230	*Lanius senator*	Lan.sen	1826	micro	Farmland	no
190	E15390	*Garrulus glandarius*	Gar.gla	32110	micro	Forest	no
191	E15490	*Pica pica*	Pic.pic	77290	micro	Farmland	no
192	E15570	*Nucifraga caryocatactes*	Nuc.car	3454	micro	Forest	b50
193	E15580	*Pyrrhocorax graculus*	Pyr.gra	1945	meso	Mountain	std
194	E15590	*Pyrrhocorax pyrrhocorax*	Pyr.pyrrho	799	meso	Generalist	std
195	E15600	*Corvus monedula*	Cor.mon	13375	micro	Generalist	no
196	E15671	*Corvus corone*	Cor.corone	3773	micro	Farmland	std
197	E15673	*Corvus cornix*	Cor.cornic	107059	micro	Farmland	no
198	E15720	*Corvus corax*	Cor.corax	7447	meso	Generalist	no
199	E15820	*Sturnus vulgaris*	Stu.vul	87363	micro	Farmland	sar
200	E15830	*Sturnus unicolor*	Stu.uni	4579	micro	Farmland	con
201	E15910	*Passer domesticus*	Pas.dom	527	micro	Farmland	b50
202	E15912	*Passer italiae*	Pas.ita	85978	micro	Farmland	sar
203	E15980	*Passer montanus*	Pas.mon	24513	micro	Farmland	no
204	E16040	*Petronia petronia*	Pet.pet	1046	micro	Farmland	b50
205	E16110	*Montifringilla nivalis*	Mon.niv	1011	micro	Mountain	std
206	E16360	*Fringilla coelebs*	Fri.coe	93764	micro	Generalist	no
207	E16400	*Serinus serinus*	Ser.ser	65634	micro	Farmland	no
208	E16440	*Carduelis citrinella*	Car.cit	433	micro	Generalist	std
209	E16442	*Carduelis corsicana*	Car.cor	236	micro	Generalist	std

210	E16490	*Carduelis chloris*	Car.chl	40495	micro	Farmland	no
211	E16530	*Carduelis carduelis*	Car.car	50415	micro	Farmland	no
212	E16540	*Carduelis spinus*	Car.spi	1054	micro	Generalist	std
213	E16600	*Carduelis cannabina*	Car.can	10973	micro	Farmland	no
214	E16630	*Carduelis flammea*	Car.fla	2222	micro	Generalist	b50
215	E16660	*Loxia curvirostra*	Lox.cur	2823	micro	Forest	no
216	E17100	*Pyrrhula pyrrhula*	Pyr.pyrrhu	5765	micro	Forest	isl
217	E17170	*Coccothraustes coccothraustes*	Coc.coc	1246	micro	Forest	std
218	E18570	*Emberiza citrinella*	Emb.cit	4308	micro	Farmland	isl
219	E18580	*Emberiza cirlus*	Emb.cir	29456	micro	Farmland	no
220	E18600	*Emberiza cia*	Emb.cia	5036	micro	Farmland	sar
221	E18660	*Emberiza hortulana*	Emb.hor	2007	micro	Farmland	isl
222	E18770	*Emberiza schoeniclus*	Emb.sch	800	micro	Wetland	std
223	E18810	*Emberiza melanocephala*	Emb.mel	404	micro	Farmland	isl
224	E18820	*Emberiza calandra*	Emb.cal	30188	micro	Farmland	no
225	E20390	*Myiopsitta monachus*	Myi.mon	881	micro	Generalist	no

Supplementary Table 2: List of variables used in the implementation of habitat suitability models, including their codes, descriptions, abbreviations and units of measurement. The inclusion of a variable in the subsets related to species ecology (Farmland = FA; Forest = FO; Generalist = GE; Mountain = MO; Wetland = WE) is shown by "X".

Code	Description	Abbreviation	measure	FA	FO	GE	MO	WE
bio1f	mean annual temperature	mean_temp_°C	0.1°C	X	X	X	X	X
bio5f	maximum temperature of warmest month	max_temp_°C	0.1°C	X	X	X	X	X
bio12f	annual precipitation amount	precipitation_mm	mm	X	X	X	X	X
bio18f	precipitation of warmest quarter	prec_warm_quart_mm	mm	X	X	X	X	X
bio19f	precipitation of coldest quarter	prec_cold_quart_mm	mm	X	X	X	X	X
bio4f	temperature seasonality	seasonality_°C_(st.dev.*100)	0.1°C (standard dev.* 100)	X	X	X	X	X
solar_rad_glob_21J	solar radiation	solar_rad_ kWh/m^2	kWh/m^2	X	X	X	X	X
slope_3035_50mf	mean slope	mean_slope_%	%	X	X	X	X	X
slope_max_f	maximum slope	max_slope_%	%			X	X	
X131f	mining areas	mining_%	%			X		X
X132f	landfills	landfills_%	%			X		
X211f	non-irrigated arable land	not_irr_arable_%	%	X		X		X
X212f	irrigated arable land	irr_arable_%	%	X		X		X
X213f	rice fields	rice_fields_%	%	X		X		X
X221f	vineyards	vineyards_%	%	X		X		
X222f	orchards and berries	orchards_%	%	X		X		
X223f	olive groves	olivev_groves_%	%	X	X	X		

X231f	permanent grassland and pastures	perm_grass_%	%	X	X	X	X	X
X241f	mixed crops	mixed_crops_%	%	X	X	X		X
X242f	complex crops	complex_crops_%	%	X	X	X		X
X243f	agricultural mosaics	agro_mosaics_%	%	X	X	X		X
X244f	agroforestry areas	agroforestry_%	%	X	X	X		X
X311f	broadleaved forest	broadleaved_for_%	%		X	X		X
X312f	coniferous forest	coniferous_for_%	%		X	X		X
X313f	mixed forest	mixed_for_%	%		X	X		X
X321f	natural pastures and grassland	nat_grassland_%	%	X	X	X	X	X
X322f	shrubland and moorland	shrubland_%	%	X	X	X	X	
X323f	sclerophyllous vegetation	sclerophyllous_veg_%	%	X	X	X		
X324f	transitional woodland/shrubland	trans_vegetation_%	%	X	X	X	X	X
X331f	beaches, dunes and sands	sands_%	%	X		X		X
X332f	bare rocks	bare_rock_%	%	X	X	X	X	
X333f	sparsely vegetated areas	sparsely_veg_%	%	X	X	X	X	X
X334f	burnt areas	burnt_areas_%	%	X		X		
X335f	glaciers and perpetual snow	glaciers_%	%				X	
X411f	inland wetlands	inland_wetland_%	%	X	X	X	X	X
X412f	peatbogs	peatbogs_%	%				X	X
X421f	salt marshes	salt_marshes_%	%					X
X422f	salines	salines_%	%					X
X511f	water courses	water_courses_%	%		X	X		X

X512f	waterbodies	waterbodies_%	%		X	X		X
X521f	lagoons	lagoons_%	%					X
X522f	estuaries	estuaries_%	%					X
X523f	sea	sea_%	%			X		X
urban_focal	urban areas	urban_areas_%	%	X	X	X	X	X
urb_green_focal	green urban areas	green urban areas_%	%		X	X		
alberato_tot_focal	total tree cover	total tree cover_%	%	X				
coltivi_erbacei_tot_focal	total herbaceous crops	total herbaceous crops_%	%		X			
acque_tot_focal	total water bodies	total water bodies_%	%	X			X	

Supplementary Table 3: List of the 91 Italian Functional Urban Areas (FUAs), showing the number of considered 1 × 1 km UTM cells; the species richness inferred from habitat suitability models (S_inferred); and the species richness retrieved from available occurrence data (S_occurrence).

FUA	Cells	S_inferred	S_occurrence
Acireale	3	35	3
Alessandria	8	49	19
Altamura	5	42	10
Ancona	15	61	29
Andria	9	40	2
Arezzo	10	35	39
Asti	11	59	20
Avellino	6	42	38
Bagheria	2	41	2
Bari	31	53	32
Barletta	8	51	5
Battipaglia	8	53	13
Bergamo	21	68	46
Bisceglie	5	47	17
Bitonto	4	43	0
Bologna	41	62	59
Bolzano	11	48	47
Brescia	40	76	77
Brindisi	12	47	9
Busto Arsizio	17	68	31
Cagliari	21	51	52
Campobasso	4	38	27
Carpi	9	50	17
Caserta	9	46	20
Catania	37	61	39
Catanzaro	7	54	11

Cerignola	5	42	0
Como	10	59	33
Cosenza	7	40	26
Cremona	10	63	42
Ferrara	17	48	40
Firenze	42	71	61
Foggia	14	50	11
Forlì	22	65	60
Gallarate	11	58	34
Gela	9	54	1
Genova	42	59	54
Giugliano in Campania	8	37	3
Grosseto	8	67	24
La Spezia	13	61	27
L'Aquila	6	44	21
Latina	14	41	6
Lecce	14	42	20
Lecco	5	60	40
Livorno	22	38	56
Massa	21	46	28
Matera	7	42	31
Messina	24	63	33
Venezia (Mestre)	35	73	55
Milano	121	68	65
Modena	30	62	33
Molfetta	4	41	12
Monza	23	62	51
Napoli	91	58	59
Novara	14	54	36
Padova	40	61	39
Palermo	67	64	42

Parma	24	51	43
Pavia	9	59	55
Perugia	7	52	33
Pesaro	10	47	30
Pescara	22	57	11
Piacenza	19	70	16
Pisa	14	50	47
Pordenone	14	47	44
Potenza	7	43	22
Prato	24	66	50
Ragusa	11	52	12
Ravenna	13	60	32
Reggio Calabria	11	39	12
Reggio Emilia	24	51	50
Rimini	25	74	40
Roma	181	69	77
Salerno	13	51	52
Saronno	8	52	19
Sassari	12	41	18
Sassuolo	11	50	6
Savona	5	36	25
Siracusa	12	52	33
Taranto	10	47	19
Terni	7	44	25
Torino	87	68	63
Trani	6	45	4
Trapani	8	53	11
Trento	19	61	81
Treviso	16	60	37
Trieste	20	51	36
Udine	22	53	44

Varese	13	44	49
Verona	33	71	53
Vicenza	16	59	22

Supplementary Table 4: List of threshold values for each species (10th Percentile and Maximum Training Sensitivity plus Specificity (MTSS)) used to convert habitat suitability values of raster cells into species occurrences (i.e. values below the threshold = absence; values above the threshold = presence).

Species	**Sp. abbr**	**10th Percentile**	**MTSS**
Accipiter gentilis	Acc.gen	0.3267	0.3719
Accipiter nisus	Acc.nis	0.4481	0.5792
Acrocephalus arundinaceus	Acr.aru	0.2579	0.28
Acrocephalus palustris	Acr.pal	0.277	0.2562
Acrocephalus scirpaceus	Acr.sci	0.2865	0.3667
Actitis hypoleucos	Act.hyp	0.1761	0.2814
Aegithalos caudatus	Aeg.cau	0.4328	0.5254
Aegolius funereus	Aeg.fun	0.2919	0.0679
Alauda arvensis	Ala.arv	0.261	0.4521
Alcedo atthis	Alc.att	0.2755	0.3721
Alectoris barbara	Ale.bar	0.326	0.1589
Alectoris graeca	Ale.gra	0.2144	0.0994
Alectoris rufa	Ale.ruf	0.1749	0.2763
Anas clypeata	Ana.cly	0.1206	0.0606
Anas platyrhynchos	Ana.pla	0.3015	0.5286
Anas querquedula	Ana.que	0.2932	0.3654
Anas strepera	Ana.str	0.1335	0.1335
Anser anser	Ans.ans	0.1891	0.1312
Anthus campestris	Ant.cam	0.1598	0.2536
Anthus spinoletta	Ant.spi	0.2846	0.1238
Anthus trivialis	Ant.tri	0.3499	0.2136
Apus apus	Apu.apu	0.2827	0.4107
Apus melba	Apu.mel	0.1753	0.3409
Apus pallidus	Apu.pal	0.1514	0.1437
Aquila chrysaetos	Aqu.chr	0.2981	0.283
Aquila fasciata	Aqu.fas	0.1194	0.0302

Ardea cinerea	Ard.cin	0.2656	0.3752
Ardea purpurea	Ard.pur	0.2423	0.2359
Ardeola ralloides	Ard.ral	0.2353	0.2228
Asio otus	Asi.otu	0.3565	0.486
Athene noctua	Ath.noc	0.4541	0.5303
Aythya ferina	Ayt.fer	0.1067	0.1969
Aythya fuligula	Ayt.ful	0.2546	0.2416
Aythya nyroca	Ayt.nyr	0.1592	0.2537
Bonasa bonasia	Bon.bon	0.255	0.1249
Botaurus stellaris	Bot.ste	0.0592	0.0454
Bubo bubo	Bub.bub	0.1941	0.2688
Bubulcus ibis	Bub.ibi	0.2737	0.2577
Burhinus oedicnemus	Bur.oed	0.2246	0.3133
Buteo buteo	But.but	0.5135	0.6091
Calandrella brachydactyla	Cal.bra	0.1615	0.2615
Caprimulgus europaeus	Cap.eur	0.2819	0.4685
Carduelis cannabina	Car.can	0.2667	0.358
Carduelis carduelis	Car.car	0.4734	0.5903
Carduelis chloris	Car.chl	0.4836	0.5646
Carduelis citrinella	Car.cit	0.2551	0.1149
Carduelis corsicana	Car.cor	0.1321	0.0239
Carduelis flammea	Car.fla	0.2437	0.0799
Carduelis spinus	Car.spi	0.248	0.1381
Casmerodius albus	Cas.alb	0.2501	0.1169
Cecropis daurica	Cec.dau	0.144	0.2225
Certhia brachydactyla	Cer.bra	0.3493	0.4449
Certhia familiaris	Cer.fam	0.3031	0.2189
Cettia cetti	Cet.cet	0.3736	0.4376
Charadrius alexandrinus	Cha.ale	0.1795	0.0663
Charadrius dubius	Cha.dub	0.258	0.3724
Chroicocephalus genei	Chr.gen	0.2108	0.0317

Chroicocephalus ridibundus	Chr.rid	0.0901	0.0809
Ciconia ciconia	Cic.cic	0.2399	0.2399
Ciconia nigra	Cic.nig	0.153	0.3514
Cinclus cinclus	Cin.cin	0.267	0.3558
Circus aeruginosus	Cir.aer	0.1787	0.2215
Circaetus gallicus	Cir.gal	0.3421	0.4114
Circus pygargus	Cir.pyg	0.281	0.321
Cisticola juncidis	Cis.jun	0.322	0.3136
Clamator glandarius	Cla.gla	0.2197	0.4079
Coccothraustes coccothraustes	Coc.coc	0.2178	0.2833
Columba oenas	Col.oen	0.1557	0.3657
Columba palumbus	Col.pal	0.5469	0.5821
Colinus virginianus	Col.vir	0.2213	0.1006
Corvus corax	Cor.corax	0.2897	0.4077
Corvus cornix	Cor.cornic	0.5445	0.6155
Corvus corone	Cor.corone	0.1713	0.2298
Coracias garrulus	Cor.gar	0.2454	0.4079
Corvus monedula	Cor.mon	0.3653	0.4988
Coturnix coturnix	Cot.cot	0.2599	0.4208
Crex crex	Cre.cre	0.2418	0.1459
Cuculus canorus	Cuc.can	0.4646	0.5569
Cyanistes caeruleus	Cya.cae	0.4237	0.523
Cygnus olor	Cyg.olo	0.1894	0.2241
Delichon urbicum	Del.urb	0.4514	0.5564
Dendrocopos major	Den.maj	0.4624	0.5858
Dendrocopos medius	Den.med	0.2806	0.0637
Dendrocopos minor	Den.min	0.2725	0.4138
Dryocopus martius	Dry.mar	0.2286	0.2643
Egretta garzetta	Egr.gar	0.1934	0.2947
Emberiza calandra	Emb.cal	0.3364	0.4846

Emberiza cia	Emb.cia	0.2825	0.2942
Emberiza cirlus	Emb.cir	0.3612	0.4321
Emberiza citrinella	Emb.cit	0.2715	0.2696
Emberiza hortulana	Emb.hor	0.1637	0.3322
Emberiza melanocephala	Emb.mel	0.0928	0.1663
Emberiza schoeniclus	Emb.sch	0.2286	0.2286
Erithacus rubecula	Eri.rub	0.3469	0.5187
Falco biarmicus	Fal.bia	0.1056	0.154
Falco eleonorae	Fal.ele	0.1473	0.29
Falco naumanni	Fal.nau	0.2027	0.1681
Falco peregrinus	Fal.per	0.2753	0.4581
Falco subbuteo	Fal.sub	0.2998	0.4446
Falco tinnunculus	Fal.tin	0.4321	0.5965
Falco vespertinus	Fal.ves	0.3429	0.0986
Ficedula albicollis	Fic.alb	0.1289	0.1928
Fringilla coelebs	Fri.coe	0.4425	0.559
Fulica atra	Ful.atr	0.3105	0.411
Gallinula chloropus	Gal.chl	0.3355	0.4303
Galerida cristata	Gal.cri	0.3047	0.3002
Garrulus glandarius	Gar.gla	0.4714	0.5846
Glaucidium passerinum	Gla.pas	0.3398	0.0348
Gypaetus barbatus	Gyp.bar	0.2332	0.1012
Gyps fulvus	Gyp.ful	0.1536	0.0925
Haematopus ostralegus	Hae.ost	0.2138	0.0351
Himantopus himantopus	Him.him	0.2262	0.2231
Hippolais polyglotta	Hip.pol	0.4215	0.4668
Hirundo rustica	Hir.rus	0.4726	0.5833
Ixobrychus minutus	Ixo.min	0.2577	0.3374
Jynx torquilla	Jyn.tor	0.403	0.5847
Lagopus muta	Lag.mut	0.2029	0.0537
Lanius collurio	Lan.col	0.3283	0.5427

Lanius minor	Lan.min	0.2079	0.3128
Lanius senator	Lan.sen	0.2835	0.3948
Larus audouinii	Lar.aud	0.5251	0.2066
Larus melanocephalus	Lar.mel	0.3282	0.2702
Larus michahellis	Lar.mic	0.1365	0.1228
Leiothrix lutea	Lei.lut	0.108	0.2127
Locustella luscinioides	Loc.lus	0.1024	0.0897
Lophophanes cristatus	Lop.cri	0.2202	0.2502
Loxia curvirostra	Lox.cur	0.2517	0.1391
Lullula arborea	Lul.arb	0.3276	0.3829
Luscinia megarhynchos	Lus.meg	0.4678	0.5411
Melanocorypha calandra	Mel.cal	0.1719	0.0655
Merops apiaster	Mer.api	0.3697	0.4337
Mergus merganser	Mer.mer	0.1566	0.0934
Milvus migrans	Mil.mig	0.3197	0.4633
Milvus milvus	Mil.mil	0.2597	0.1583
Montifringilla nivalis	Mon.niv	0.2184	0.0473
Monticola saxatilis	Mon.sax	0.1945	0.1445
Monticola solitarius	Mon.sol	0.2018	0.2842
Motacilla alba	Mot.alb	0.4523	0.6024
Motacilla cinerea	Mot.cin	0.3327	0.5415
Motacilla flava	Mot.fla	0.2703	0.2828
Muscicapa striata	Mus.str	0.4297	0.5643
Myiopsitta monachus	Myi.mon	0.065	0.1581
Netta rufina	Net.ruf	0.1002	0.1162
Nucifraga caryocatactes	Nuc.car	0.3004	0.0877
Nycticorax nycticorax	Nyc.nyc	0.2114	0.3055
Oenanthe hispanica	Oen.his	0.1921	0.1474
Oenanthe oenanthe	Oen.oen	0.1723	0.1719
Oriolus oriolus	Ori.ori	0.4441	0.4842
Otus scops	Otu.sco	0.4719	0.5703

Parus major	Par.maj	0.5582	0.6112
Passer domesticus	Pas.dom	0.1845	0.1807
Passer italiae	Pas.ita	0.4714	0.5833
Passer montanus	Pas.mon	0.3583	0.5483
Pernis apivorus	Per.api	0.3549	0.4284
Periparus ater	Per.ate	0.3054	0.3412
Perdix perdix	Per.per	0.2313	0.3957
Petronia petronia	Pet.pet	0.2668	0.2668
Phalacrocorax aristotelis	Pha.ari	0.2776	0.0216
Phalacrocorax carbo	Pha.car	0.1493	0.2111
Phasianus colchicus	Pha.col	0.355	0.4574
Phalacrocorax pygmeus	Pha.pyg	0.1727	0.1293
Phoenicurus ochruros	Pho.och	0.307	0.3717
Phoenicurus phoenicurus	Pho.pho	0.4006	0.5025
Phylloscopus bonelli	Phy.bon	0.3382	0.2656
Phylloscopus collybita	Phy.col	0.3151	0.458
Phylloscopus sibilatrix	Phy.sib	0.1639	0.2219
Picus canus	Pic.can	0.2824	0.1254
Pica pica	Pic.pic	0.4714	0.5486
Picoides tridactylus	Pic.tri	0.2424	0.0431
Picus viridis	Pic.vir	0.4668	0.5942
Platalea leucorodia	Pla.leu	0.3008	0.1803
Podiceps cristatus	Pod.cri	0.2054	0.2499
Poecile montanus	Poe.mon	0.3573	0.145
Poecile palustris	Poe.pal	0.2966	0.332
Porphyrio porphyrio	Por.porphy	0.3462	0.0372
Prunella collaris	Pru.col	0.2439	0.0943
Prunella modularis	Pru.mod	0.3432	0.194
Psittacula krameri	Psi.kra	0.1682	0.1658
Ptyonoprogne rupestris	Pty.rup	0.2742	0.3906
Pyrrhocorax graculus	Pyr.gra	0.2389	0.1161

Pyrrhocorax pyrrhocorax	Pyr.pyrrho	0.2001	0.0837
Pyrrhula pyrrhula	Pyr.pyrrhu	0.3166	0.1882
Rallus aquaticus	Ral.aqu	0.1855	0.3446
Recurvirostra avosetta	Rec.avo	0.1407	0.0564
Regulus ignicapilla	Reg.ign	0.3274	0.4227
Regulus regulus	Reg.reg	0.2711	0.2485
Remiz pendulinus	Rem.pen	0.2148	0.2918
Riparia riparia	Rip.rip	0.1664	0.2313
Saxicola rubetra	Sax.rubetr	0.2383	0.1761
Saxicola torquatus	Sax.rubico	0.3499	0.5011
Serinus serinus	Ser.ser	0.4879	0.5501
Sitta europaea	Sit.eur	0.3028	0.4402
Sternula albifrons	Ste.alb	0.166	0.0604
Sterna hirundo	Ste.hir	0.2025	0.2017
Strix aluco	Str.alu	0.2807	0.468
Streptopelia decaocto	Str.dec	0.4612	0.4981
Streptopelia turtur	Str.tur	0.4435	0.5015
Sturnus unicolor	Stu.uni	0.4173	0.2114
Sturnus vulgaris	Stu.vul	0.4449	0.517
Sylvia atricapilla	Syl.atr	0.565	0.609
Sylvia borin	Syl.bor	0.2385	0.2541
Sylvia cantillans	Syl.can	0.3141	0.3636
Sylvia communis	Syl.com	0.3047	0.4519
Sylvia conspicillata	Syl.con	0.2297	0.1831
Sylvia curruca	Syl.cur	0.316	0.1489
Sylvia melanocephala	Syl.mel	0.3298	0.3959
Sylvia nisoria	Syl.nis	0.1315	0.2194
Sylvia sarda	Syl.sar	0.1955	0.0415
Sylvia subalpina	Syl.sub	0.2801	0.3381
Sylvia undata	Syl.und	0.1146	0.0889
Tachybaptus ruficollis	Tac.ruf	0.3135	0.4601

Tadorna tadorna	Tad.tad	0.1333	0.1186
Tetrao tetrix	Tet.tetrix	0.3055	0.1279
Tetrao urogallus	Tet.uro	0.2854	0.1785
Tichodroma muraria	Tic.mur	0.107	0.0592
Tringa totanus	Tri.tot	0.1297	0.0475
Troglodytes troglodytes	Tro.tro	0.3783	0.5793
Turdus merula	Tur.mer	0.5731	0.5986
Turdus philomelos	Tur.phi	0.3463	0.3463
Turdus pilaris	Tur.pil	0.2723	0.1068
Turdus torquatus	Tur.tor	0.3412	0.1142
Turdus viscivorus	Tur.vis	0.2508	0.3702
Tyto alba	Tyt.alb	0.453	0.5788
Upupa epops	Upu.epo	0.4488	0.5659
Vanellus vanellus	Van.van	0.2961	0.1924

Supplementary Table 5: Statistics considered in evaluating habitat suitabilitry models implemented for 225 Italian breeding bird species. AUC on training dataset (auc_train); AUC on test dataset (auc_test); TSS on training dataset (tss_train); TSS on test dataset (tss_test); minimum training presence omission rate on test dataset (mtp_OR); 10th percentile omission rate on the test dataset (10_perc_OR).

Species	**auc_train**	**auc_test**	**tss_train**	**tss_test**	**mtp_OR**	**10_perc_OR**
Tachybaptus ruficollis	0.79587	0.80158	0.45161	0.47127	0.00000	0.08998
Podiceps cristatus	0.90704	0.90981	0.67513	0.67240	0.00000	0.10145
Phalacrocorax carbo	0.93000	0.94264	0.71175	0.77920	0.00000	0.00000
Phalacrocorax aristotelis	0.99712	0.99756	0.96047	0.99304	0.00000	0.17647
Phalacrocorax pygmeus	0.97494	0.97544	0.86366	0.89530	0.00000	0.20000
Botaurus stellaris	0.98261	0.99055	0.88782	0.92836	0.00000	0.06667
Ixobrychus minutus	0.88109	0.86169	0.60962	0.57721	0.00000	0.13587
Nycticorax nycticorax	0.89778	0.86137	0.66114	0.60331	0.00000	0.16000
Ardeola ralloides	0.94008	0.89967	0.76543	0.71323	0.04348	0.17391
Bubulcus ibis	0.90911	0.88386	0.69561	0.64829	0.01724	0.17241
Egretta garzetta	0.88777	0.87516	0.64733	0.65960	0.00000	0.08434
Casmerodius albus	0.96200	0.96842	0.80891	0.89338	0.00000	0.09091
Ardea cinerea	0.83069	0.83790	0.51793	0.55990	0.00000	0.09551
Ardea purpurea	0.94390	0.91676	0.76262	0.74950	0.02326	0.18605
Ciconia nigra	0.91903	0.92747	0.68980	0.72699	0.00000	0.12500
Ciconia ciconia	0.91142	0.89689	0.66715	0.65101	0.01087	0.11957
Platalea leucorodia	0.99043	0.95590	0.95719	0.89650	0.50000	0.50000
Cygnus olor	0.93728	0.93275	0.74362	0.73658	0.00000	0.10561
Anser anser	0.96339	0.97904	0.83995	0.87732	0.00000	0.04918
Tadorna tadorna	0.97723	0.97856	0.85867	0.89363	0.00000	0.07801
Anas strepera	0.94799	0.94338	0.74970	0.80847	0.02857	0.08571
Anas platyrhynchos	0.78325	0.77531	0.44113	0.43060	0.00000	0.10711
Anas querquedula	0.93694	0.91615	0.76441	0.76779	0.00000	0.16000
Anas clypeata	0.95198	0.96653	0.76187	0.87727	0.00000	0.00000
Netta rufina	0.94296	0.91074	0.72718	0.66717	0.00000	0.14894
Aythya ferina	0.91483	0.92891	0.70427	0.74215	0.00000	0.07143
Aythya nyroca	0.91139	0.88748	0.68932	0.72037	0.04545	0.18182
Aythya fuligula	0.90918	0.87369	0.66743	0.61061	0.04878	0.17073
Mergus merganser	0.98020	0.97801	0.85914	0.85752	0.00000	0.10577
Pernis apivorus	0.74511	0.74295	0.37811	0.38364	0.00000	0.10701
Milvus migrans	0.80394	0.80861	0.46601	0.48053	0.00000	0.09688
Milvus milvus	0.96462	0.95867	0.84015	0.83915	0.00617	0.11111
Gypaetus barbatus	0.99345	0.99199	0.95773	0.94740	0.00000	0.12195
Gyps fulvus	0.98520	0.98004	0.89773	0.86977	0.00000	0.17949
Circaetus gallicus	0.80170	0.81533	0.46738	0.48631	0.00000	0.08779
Circus aeruginosus	0.94612	0.93478	0.76068	0.76349	0.00000	0.09396
Circus pygargus	0.86097	0.85952	0.57640	0.59721	0.00000	0.08333
Accipiter gentilis	0.81617	0.78449	0.51877	0.48403	0.00000	0.12438
Accipiter nisus	0.63641	0.63799	0.20059	0.21414	0.00000	0.10246
Buteo buteo	0.62415	0.61725	0.18919	0.17396	0.00000	0.10026
Aquila chrysaetos	0.92883	0.92179	0.74180	0.72244	0.00000	0.13056

Aquila fasciata	0.99576	0.99519	0.97373	0.98826	0.00000	0.00000
Falco naumanni	0.95981	0.95593	0.80118	0.78326	0.00000	0.12088
Falco tinnunculus	0.65768	0.65587	0.23182	0.22933	0.00048	0.08910
Falco vespertinus	0.98268	0.98641	0.91950	0.95228	0.00000	0.08511
Falco subbuteo	0.75688	0.75885	0.39183	0.39944	0.00000	0.09628
Falco eleonorae	0.99884	0.99849	0.98935	0.98959	0.00000	0.15385
Falco biarmicus	0.93239	0.92514	0.70694	0.70289	0.00000	0.13043
Falco peregrinus	0.77704	0.77301	0.42357	0.43967	0.00000	0.11152
Bonasa bonasia	0.97468	0.97204	0.88334	0.87520	0.00000	0.08065
Lagopus muta	0.99547	0.99511	0.96331	0.96531	0.00000	0.13415
Tetrao tetrix	0.97227	0.97008	0.88738	0.87552	0.00403	0.12500
Tetrao urogallus	0.98033	0.97279	0.91580	0.88439	0.11111	0.16667
Colinus virginianus	0.97800	0.97212	0.87933	0.84375	0.00000	0.11765
Alectoris graeca	0.96815	0.97018	0.84378	0.85751	0.00000	0.14286
Alectoris rufa	0.87504	0.85968	0.58626	0.57207	0.00000	0.09836
Alectoris barbara	0.98997	0.98860	0.96044	0.94423	0.02857	0.14286
Perdix perdix	0.84449	0.84004	0.54847	0.56213	0.02326	0.09302
Coturnix coturnix	0.79150	0.79903	0.45431	0.48013	0.00000	0.08655
Phasianus colchicus	0.78573	0.78946	0.44485	0.46448	0.00000	0.08022
Rallus aquaticus	0.88529	0.87644	0.60711	0.60243	0.00000	0.11828
Crex crex	0.96652	0.96720	0.83999	0.84749	0.00000	0.10000
Gallinula chloropus	0.80295	0.79743	0.46959	0.47326	0.00076	0.10772
Porphyrio porphyrio	0.99372	0.99461	0.96239	0.98317	0.00000	0.12500
Fulica atra	0.81433	0.81607	0.47754	0.48468	0.00130	0.08808
Haematopus ostralegus	0.99682	0.99582	0.97777	0.96478	0.00000	0.13636
Himantopus himantopus	0.92823	0.93137	0.71378	0.74202	0.00000	0.07202
Recurvirostra avosetta	0.99174	0.98931	0.92558	0.92537	0.02174	0.15217
Burhinus oedicnemus	0.91645	0.91350	0.69426	0.69876	0.01429	0.10000
Charadrius dubius	0.86384	0.86764	0.56443	0.59011	0.00000	0.08529
Charadrius alexandrinus	0.98532	0.98373	0.90716	0.91029	0.00000	0.14189
Vanellus vanellus	0.94601	0.94403	0.79573	0.78698	0.00000	0.10927
Tringa totanus	0.99001	0.98454	0.93336	0.93824	0.00000	0.05000
Actitis hypoleucos	0.87056	0.83555	0.59664	0.53065	0.00862	0.16379
Larus melanocephalus	0.99845	0.99779	0.99572	0.99556	0.14286	0.14286
Chroicocephalus ridibundus	0.96844	0.97776	0.86731	0.91165	0.00000	0.04348
Chroicocephalus genei	0.99739	0.99854	0.97287	0.99675	0.00000	0.00000
Larus audouinii	0.99579	0.99582	0.98232	0.98627	0.00000	0.20000
Larus michahellis	0.95831	0.95187	0.81117	0.80547	0.00397	0.11111
Sterna hirundo	0.96166	0.95858	0.81671	0.80734	0.01000	0.13000
Sternula albifrons	0.98482	0.96282	0.91233	0.88671	0.03704	0.12963
Columba oenas	0.95866	0.94684	0.77537	0.81099	0.06061	0.12121
Columba palumbus	0.60714	0.59970	0.15341	0.14750	0.00018	0.10020

Streptopelia decaocto	0.71342	0.71782	0.33038	0.34530	0.00000	0.09227
Streptopelia turtur	0.71715	0.71829	0.33760	0.33410	0.00000	0.10213
Psittacula krameri	0.94748	0.93218	0.78582	0.75491	0.00000	0.12644
Clamator glandarius	0.89624	0.83211	0.68375	0.59792	0.17647	0.17647
Cuculus canorus	0.64704	0.64618	0.20911	0.21153	0.00000	0.09432
Tyto alba	0.66704	0.66992	0.23750	0.23605	0.00000	0.11261
Otus scops	0.66437	0.66938	0.25132	0.24998	0.00000	0.10533
Bubo bubo	0.93448	0.90342	0.74518	0.69893	0.00000	0.14103
Glaucidium passerinum	0.98682	0.98520	0.94397	0.92251	0.04444	0.17778
Athene noctua	0.66205	0.66505	0.24771	0.25618	0.00000	0.09496
Strix aluco	0.73849	0.73628	0.38120	0.37866	0.00000	0.10757
Asio otus	0.70528	0.68152	0.31272	0.28039	0.00000	0.11258
Aegolius funereus	0.98039	0.97915	0.92435	0.92464	0.01449	0.08696
Caprimulgus europaeus	0.75066	0.74863	0.38952	0.39884	0.00000	0.09553
Apus apus	0.76393	0.76060	0.40565	0.40132	0.00107	0.10493
Apus pallidus	0.95187	0.95030	0.78574	0.79776	0.01869	0.08411
Apus melba	0.87739	0.88342	0.61143	0.64848	0.00000	0.09009
Alcedo atthis	0.84294	0.82098	0.54197	0.50051	0.00000	0.14655
Merops apiaster	0.78619	0.78388	0.43955	0.43580	0.00000	0.10969
Coracias garrulus	0.90490	0.90379	0.67210	0.67950	0.00000	0.11204
Upupa epops	0.67973	0.68343	0.25890	0.27444	0.00000	0.10590
Jynx torquilla	0.67991	0.68533	0.26402	0.27442	0.00201	0.10060
Picus canus	0.95226	0.95357	0.81283	0.83276	0.00000	0.10924
Picus viridis	0.65640	0.65545	0.22987	0.22918	0.00000	0.10471
Dryocopus martius	0.88914	0.88394	0.63093	0.63038	0.00000	0.10526
Dendrocopos major	0.64558	0.64537	0.21319	0.21453	0.00027	0.10311
Dendrocopos medius	0.99303	0.98856	0.95190	0.93250	0.02857	0.08571
Dendrocopos minor	0.77442	0.77011	0.42697	0.42831	0.00505	0.10859
Picoides tridactylus	0.98402	0.98184	0.91703	0.93337	0.00000	0.15909
Melanocorypha calandra	0.97871	0.97662	0.86060	0.86377	0.00685	0.08219
Calandrella brachydactyla	0.92882	0.92220	0.72439	0.69697	0.00000	0.12821
Galerida cristata	0.88406	0.88115	0.61571	0.60490	0.00000	0.11247
Lullula arborea	0.82779	0.83014	0.52957	0.53570	0.00000	0.10120
Alauda arvensis	0.79578	0.79469	0.46268	0.46145	0.00053	0.10642
Riparia riparia	0.93347	0.93408	0.70400	0.71545	0.00000	0.08219
Ptyonoprogne rupestris	0.84483	0.84211	0.55024	0.54902	0.00087	0.09948
Hirundo rustica	0.64486	0.64324	0.20903	0.20946	0.00000	0.10382
Cecropis daurica	0.93005	0.93870	0.73439	0.78477	0.02564	0.05128
Delichon urbicum	0.66052	0.66389	0.23560	0.24431	0.00000	0.10570
Anthus campestris	0.89278	0.88338	0.64209	0.62416	0.00000	0.11175
Anthus trivialis	0.93142	0.92885	0.76762	0.76332	0.00000	0.11040
Anthus spinoletta	0.97864	0.97814	0.88927	0.88240	0.00000	0.11465
Motacilla flava	0.90437	0.89841	0.68127	0.67413	0.00000	0.10676
Motacilla cinerea	0.72621	0.73310	0.34336	0.35543	0.00074	0.09239
Motacilla alba	0.64289	0.64453	0.20470	0.21251	0.00000	0.09365

Cinclus cinclus	0.84959	0.86556	0.54882	0.57728	0.00000	0.09274
Troglodytes troglodytes	0.71108	0.70635	0.31743	0.31161	0.00000	0.10603
Prunella modularis	0.95714	0.95439	0.83399	0.82797	0.00000	0.12199
Prunella collaris	0.99115	0.98849	0.93486	0.91938	0.01418	0.13121
Erithacus rubecula	0.75325	0.75363	0.39414	0.39461	0.00000	0.09524
Luscinia megarhynchos	0.69914	0.69409	0.31478	0.30379	0.00020	0.11047
Phoenicurus ochruros	0.81427	0.81842	0.47483	0.48070	0.00000	0.10014
Phoenicurus phoenicurus	0.72781	0.72356	0.35303	0.34851	0.00000	0.09972
Saxicola rubetra	0.95372	0.95903	0.79898	0.83050	0.00366	0.06960
Saxicola torquatus	0.74572	0.73780	0.36001	0.34860	0.00111	0.10951
Oenanthe oenanthe	0.94480	0.93971	0.78456	0.77319	0.00000	0.11743
Oenanthe hispanica	0.96240	0.97984	0.83442	0.88984	0.00000	0.06061
Monticola saxatilis	0.96607	0.95918	0.84142	0.82996	0.00469	0.14554
Monticola solitarius	0.89035	0.88828	0.63238	0.63054	0.00000	0.09091
Turdus torquatus	0.97510	0.97560	0.89373	0.90236	0.00000	0.11507
Turdus merula	0.57611	0.57563	0.11096	0.11619	########	0.10612
Turdus pilaris	0.96501	0.96655	0.86263	0.86665	0.00000	0.08400
Turdus philomelos	0.85863	0.85934	0.60285	0.60031	0.00000	0.10317
Turdus viscivorus	0.84624	0.85195	0.57314	0.60061	0.00000	0.08671
Cettia cetti	0.79701	0.79904	0.45497	0.45312	0.00122	0.10860
Cisticola juncidis	0.88006	0.87866	0.64440	0.64036	0.00000	0.10327
Locustella luscinioides	0.97151	0.94991	0.81452	0.80944	0.07692	0.15385
Acrocephalus palustris	0.89570	0.89696	0.67885	0.68632	0.00000	0.09114
Acrocephalus scirpaceus	0.85580	0.85890	0.55738	0.56073	0.00000	0.09002
Acrocephalus arundinaceus	0.87158	0.87249	0.58106	0.60083	0.00000	0.09375
Hippolais polyglotta	0.76694	0.76395	0.41578	0.40770	0.00000	0.09967
Sylvia sarda	0.99187	0.98746	0.94224	0.94400	0.00000	0.25641
Sylvia undata	0.95850	0.95402	0.79947	0.78654	0.00917	0.11927
Sylvia conspicillata	0.95203	0.93274	0.78737	0.74919	0.03030	0.15152
Sylvia cantillans	0.83628	0.82975	0.54003	0.52762	0.00114	0.12000
Sylvia subalpina	0.87622	0.88350	0.61048	0.62573	0.00155	0.09288
Sylvia melanocephala	0.85610	0.85524	0.58492	0.58857	0.00087	0.10100
Sylvia nisoria	0.94173	0.98795	0.83862	0.93224	0.00000	0.00000
Sylvia curruca	0.96473	0.96574	0.86210	0.86749	0.00000	0.08353
Sylvia communis	0.81132	0.81164	0.47016	0.47317	0.00000	0.10477
Sylvia borin	0.92990	0.93596	0.73737	0.78179	0.00427	0.06410
Sylvia atricapilla	0.58458	0.58466	0.12062	0.12367	########	0.10130
Phylloscopus bonelli	0.87183	0.86758	0.62301	0.62201	0.00000	0.10957
Phylloscopus sibilatrix	0.93152	0.91692	0.71347	0.70218	0.00000	0.12994

Phylloscopus collybita	0.78939	0.78780	0.46699	0.46629	0.00000	0.10109
Regulus regulus	0.93335	0.93036	0.75079	0.75784	0.00000	0.10279
Regulus ignicapilla	0.77642	0.77048	0.41222	0.41043	0.00063	0.11027
Muscicapa striata	0.67168	0.67779	0.24838	0.26708	0.00061	0.09646
Ficedula albicollis	0.97187	0.97442	0.83469	0.85628	0.00000	0.08621
Leiothrix lutea	0.96216	0.97365	0.78427	0.86872	0.00000	0.01852
Aegithalos caudatus	0.66347	0.65466	0.24345	0.22792	0.00000	0.11795
Poecile palustris	0.84346	0.83850	0.55629	0.54844	0.00000	0.11307
Poecile montanus	0.95519	0.95655	0.84518	0.84784	0.00000	0.09718
Lophophanes cristatus	0.91110	0.91126	0.68518	0.68864	0.00419	0.10056
Periparus ater	0.86059	0.85639	0.58998	0.58827	0.00000	0.10440
Cyanistes caeruleus	0.68146	0.67925	0.27309	0.27021	0.00000	0.09844
Parus major	0.58761	0.58937	0.12496	0.13171	0.00000	0.09504
Sitta europaea	0.77102	0.76448	0.41963	0.40805	0.00000	0.10794
Tichodroma muraria	0.97121	0.97414	0.84093	0.86309	0.00000	0.08163
Certhia familiaris	0.94084	0.94016	0.79167	0.78218	0.00000	0.10980
Certhia brachydactyla	0.74692	0.74693	0.37417	0.37814	0.00000	0.10221
Remiz pendulinus	0.91026	0.89287	0.67922	0.66555	0.01190	0.09524
Oriolus oriolus	0.73686	0.73920	0.37451	0.37996	0.00000	0.10188
Lanius collurio	0.73350	0.73183	0.35692	0.35957	0.00000	0.10029
Lanius minor	0.90603	0.90437	0.66248	0.65999	0.00000	0.08772
Lanius senator	0.88660	0.88676	0.65755	0.67051	0.00000	0.08214
Garrulus glandarius	0.63887	0.63396	0.20829	0.20213	0.00000	0.10362
Pica pica	0.69604	0.69558	0.29151	0.29562	0.00000	0.09968
Nucifraga caryocatactes	0.96303	0.96460	0.85238	0.85594	0.00000	0.09184
Pyrrhocorax graculus	0.98238	0.98181	0.89333	0.89115	0.00651	0.11726
Pyrrhocorax pyrrhocorax	0.98885	0.98543	0.92042	0.89814	0.00826	0.16529
Corvus monedula	0.76762	0.75713	0.40506	0.39428	0.00000	0.11944
Corvus corone	0.89697	0.90344	0.65838	0.69065	0.00000	0.07338
Corvus cornix	0.61240	0.60790	0.16112	0.15651	0.00000	0.10043
Corvus corax	0.83034	0.82624	0.51837	0.53061	0.00000	0.09361
Sturnus vulgaris	0.72793	0.72613	0.35614	0.35125	0.00017	0.09878
Sturnus unicolor	0.97572	0.97479	0.92353	0.92593	0.00000	0.11881
Passer domesticus	0.94839	0.93220	0.77953	0.78216	0.00000	0.10909
Passer italiae	0.66834	0.66705	0.25018	0.25135	0.00000	0.10359
Passer montanus	0.73167	0.73360	0.34839	0.35294	0.00040	0.09996
Petronia petronia	0.94064	0.91846	0.77815	0.71318	0.00000	0.18750
Montifringilla nivalis	0.99367	0.99205	0.94199	0.93938	0.00893	0.14286
Fringilla coelebs	0.67071	0.67192	0.25788	0.25771	0.00000	0.09571
Serinus serinus	0.64802	0.65079	0.22399	0.22666	0.00000	0.09508
Carduelis citrinella	0.98597	0.97788	0.92389	0.90958	0.01961	0.23529
Carduelis corsicana	0.99507	0.99421	0.95958	0.96511	0.00000	0.09091
Carduelis chloris	0.64531	0.64765	0.20418	0.20638	0.00051	0.09667
Carduelis carduelis	0.64307	0.64429	0.21324	0.21211	0.00000	0.10011
Carduelis spinus	0.95080	0.94687	0.81975	0.81443	0.00000	0.08421

Carduelis cannabina	0.81814	0.81415	0.48760	0.47718	0.00070	0.10299
Carduelis flammea	0.97215	0.97122	0.86788	0.87768	0.00752	0.08271
Loxia curvirostra	0.94345	0.94297	0.78471	0.80029	0.00000	0.08178
Pyrrhula pyrrhula	0.92443	0.91827	0.74673	0.73657	0.00110	0.12623
Coccothraustes coccothraustes	0.85833	0.86463	0.55503	0.57223	0.00000	0.08523
Emberiza citrinella	0.91679	0.91019	0.71257	0.68676	0.00000	0.13542
Emberiza cirlus	0.78868	0.78956	0.47678	0.48041	0.00000	0.10172
Emberiza cia	0.88354	0.88713	0.62623	0.63785	0.00000	0.09807
Emberiza hortulana	0.90449	0.89237	0.65512	0.63884	0.00000	0.11009
Emberiza schoeniclus	0.96027	0.97242	0.79460	0.84832	0.00000	0.11111
Emberiza melanocephala	0.95838	0.92313	0.79425	0.70691	0.00000	0.19231
Emberiza calandra	0.81077	0.80791	0.47582	0.47006	0.00000	0.09926
Myiopsitta monachus	0.95135	0.92749	0.77411	0.71312	0.04082	0.12245