

1 **Conserving steppe-land birds under climate change: a gap analysis for the**  
2 **Eurasian Stone-curlew (*Burhinus oedicnemus*) in the Western Palearctic**

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43 19 **Short title:** Gap analysis under climate change for the Eurasian Stone-curlew

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27 **ABSTRACT**

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2 28 Climate change is having dramatic impacts on the distribution of animals. Birds, and especially  
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4 29 steppe-land birds, are particularly sensitive to climate change and identifying areas that are  
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6 30 critical for their conservation is pivotal, as well as estimating the expected impact on these  
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8 31 areas under different climate and land use change scenarios. In-situ climate refugia (areas  
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10 32 suitable under both current and future climates) are especially valuable for the conservation of  
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12 33 climate-sensitive species, and is therefore important to identify them and evaluate their  
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14 34 coverage by protected areas. Via species distribution modelling, we aimed to identify in-situ  
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16 35 climate refugia in the Western Palearctic for the Eurasian Stone-curlew *Burhinus oedicnemus*,  
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18 36 an umbrella steppic species of conservation concern. We used a comprehensive dataset of  
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20 37 occurrences in the breeding period to fine-tune a Maxent species distribution model and project  
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22 38 it under three carbon emission scenarios of increasing severity for the year 2050. We then  
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24 39 identified in-situ climate refugia and performed a gap analysis estimating the percentage of  
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26 40 refugia falling within the network of currently protected areas. In all modelled future scenarios  
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28 41 a northward expansion of suitable breeding habitats was predicted, and suitable areas had  
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30 42 similar extents, with a slight increase of the overall suitability under more severe scenarios.  
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32 43 According to our results, the Eurasian Stone-curlew has the potential to maintain viable  
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34 44 populations in the Western Palearctic, even though dispersal limitations might hinder the  
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36 45 colonization of newly suitable breeding areas. In-situ climate refugia were mainly identified  
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38 46 outside protected areas, particularly in Northern Africa and the Middle East. Therefore, we  
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40 47 advocate targeted actions in climate refugia to promote the conservation of this and other  
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42 48 steppe-land species under global environmental change.  
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55 50 **Keywords:** arid environment, shorebird, farmland, Maxent, habitat suitability, species  
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57 51 distribution models.  
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## 52 1. INTRODUCTION

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2 53 Anthropogenic global change exerts a strong influence on organisms' distribution, life-history,  
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4 54 population viability, and thus, on their likelihood of extinction (Chen et al., 2011; Parmesan,  
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6 55 2006; Román-Palacios and Wiens, 2020; Selwood et al., 2015). One example is the shift in the  
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8 56 distribution range following climate change (VanDerWal et al., 2013). Such distributional  
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10 57 shifts have been described both for sessile and highly mobile animals (Williams and Blois,  
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12 58 2018). Birds, in particular, are excellent model organisms to understand the response of  
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14 59 organisms to climate change, due to the presence of long-term datasets covering wide spatial  
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16 60 scales (Brlík et al., 2021). Furthermore, in birds it has been shown that climate change can  
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18 61 affect habitat suitability (Barbet-Massin et al., 2012a), which in turn affects population trends  
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20 62 (Green et al., 2008). Steppe-land species are particularly sensitive to global change. In fact,  
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22 63 such species experienced particularly dramatic declines, which were primarily linked to both  
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24 64 agricultural intensification and afforestation following land abandonment (Burfield, 2005;  
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26 65 Onrubia and Andrés, 2005; Silva et al., 2024). Previous studies using species distribution  
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28 66 models (SDMs, Guisan and Zimmermann, 2000) to derive habitat suitability for steppe-land  
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30 67 birds reported poleward range shifts and the persistence of large suitable areas according to  
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32 68 global change scenarios (Estrada et al., 2016; Kiss et al., 2020). The Eurasian Stone-curlew  
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34 69 *Burhinus oedicanus* (Linnaeus, 1758; hereafter Stone-curlew) is a wide-ranging steppe-land  
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36 70 species occurring in (pseudo-)steppes and farmlands in the Palearctic (Vaughan and Vaughan  
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38 71 Jennings, 2005). This species is considered both an umbrella and flagship species (Caro, 2010;  
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40 72 Hunter Jr et al., 2016), and its conservation can therefore benefit steppe-land species and, more  
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42 73 generally, steppe-land ecosystems (Hawkes et al., 2019). The Stone-curlew suffered a severe  
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44 74 population decline (>30%) in the second half of the 20<sup>th</sup> century, mainly due to agricultural  
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46 75 intensification (BirdLife International, 2018), but in recent decades positive trends have been  
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48 76 reported in some areas of its range such as France (BirdLife International, 2017). It is now  
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50 77 classified as Least Concern by the IUCN (BirdLife International, 2021), but information on the  
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78 status of its populations is limited, and positive trends might be biased by the increased  
79 monitoring effort (Gaget et al., 2019). Indeed, the species is still considered of European  
80 conservation concern (SPEC3) and ongoing declines are reported for many regions of its range  
81 (BirdLife International, 2017; Gaget et al., 2019). Huntley et al. (2007) used SDMs to forecast  
82 the future distribution of the Stone-curlew under climate change scenarios, highlighting a  
83 northward shift of suitable areas. Still, their European-level analysis was limited to a coarse  
84 scale ( $\sim 50$  km), hence preventing fine-scale applications such as comparisons with the current  
85 distribution of protected areas. To establish effective conservation practices, state-of-the-art  
86 habitat suitability scenarios for the focal species are required (McShea, 2014; Miller-Rushing  
87 et al., 2010). Rigorous analyses of prospective suitability dynamics are essential to reveal a  
88 species' sensitivity to climate change and to guide conservation efforts (Stiels et al., 2021). In  
89 the spatial planning of the conservation of a species it is also important to define the areas  
90 currently suitable and predicted to remain so under all future climate scenarios, so-called 'in-  
91 situ climate refugia' (Brambilla et al., 2022). The identification of refugia, combined with a  
92 gap analysis, allows to detect areas critical for biological conservation that have been  
93 overlooked and/or ineffectively managed and is pivotal for planning conservation actions  
94 (Maiorano et al., 2006). Therefore, we aimed to: 1) describe the current availability of suitable  
95 breeding habitats, 2) provide a range of future breeding habitat suitability scenarios considering  
96 climatic changes, 3) identify in-situ climate refugia, and 4) assess the proportion of refugia  
97 within the current network of protected areas (gap analysis).

## 98 2. METHODS

### 99 2.1. Stone-curlew occurrences

100 We obtained a dataset of Stone-curlew occurrences during the breeding season (May-July;  
101 Vaughan and Vaughan Jennings, 2005) spanning twenty years (1996-2015). We retrieved data  
102 for the Western Palaearctic (*sensu* Snow et al., 1998) and excluded the two insular, genetically-  
103 distinct Macaronesian subspecies (*B. o. distinctus*, *B. o. insularum*). We downloaded data from  
104 eBird, Global Biodiversity Information Facility (gbif.org; <https://doi.org/10.15468/dl.zxc278>),  
105 ornitho.it, ornitho.cat and xeno-canto.org, as these proved useful in previous SDM studies  
106 (Avalos and Hernández, 2015; Coxen et al., 2017; Engelhardt et al., 2020; Ramellini et al.,  
107 2019). We also included survey data from the British Trust for Ornithology (in agreement with  
108 BTO's data policy), data for Greece from the Ornithotopos database, the second European  
109 Breeding Bird Atlas (hereafter EBBA) and 2 × 2 km surveys in Greece (in formal agreement  
110 with the Hellenic Ornithological Society), and data for the Deux-Sèvres department from the  
111 Nature79 database (provided by Alexis Martineau). Finally, we considered nest points from  
112 Northern Italy collected by Dimitri Giunchi and collaborators in the period 2012-2015. We  
113 discarded observations outside the species' current range (BirdLife International, 2022;  
114 Hagemeyer and Blair, 1997; Keller et al., 2020) to exclude vagrant individuals in non-breeding  
115 areas (Figure 1). We used point occurrences with a maximum spatial uncertainty of 5.5 km,  
116 which roughly approximates the species' breeding home range size (Caccamo et al., 2011;  
117 Hawkes et al., 2021). This value (5.5 km) was also used to define the linear size of grid cells  
118 for all models developed in this study. Indeed, a model grain approaching home range or  
119 territory size is particularly desirable to obtain ecologically more meaningful models  
120 (Brambilla et al., 2024). Moreover, to reduce the spatial autocorrelation among occurrences  
121 and limit the effect of possibly biased sampling effort across space, we subsampled the dataset  
122 considering a minimum distance between occurrence points of 16 km, so that there were no

123 occurrence points in adjacent cells. The final dataset consisted of 816 presences spread across  
124 the species' range in the Western Palearctic (Figure 1).

## 125 ***2.2. Variable selection and preparation***

126 We used an expert-based approach (Santini et al., 2021) to derive eleven biologically  
127 meaningful environmental predictors representing climate, land use and land cover (LULC).  
128 Climate is a major determinant of Stone-curlew's distribution at the broad scale (Vaughan and  
129 Vaughan Jennings, 2005), as the species selects warm and dry areas to reproduce (Green et al.,  
130 2000; Keller et al., 2020; Vaughan and Vaughan Jennings, 2005). We therefore included three  
131 variables describing temperature (annual mean temperature, temperature of the warmest  
132 quarter, temperature seasonality) and three describing precipitation (annual precipitation,  
133 precipitation of the warmest quarter, precipitation seasonality). Climatic variables were  
134 obtained from CHELSAcruts (Karger and Zimmermann, 2018) at one year resolution. As  
135 ensuring a temporal match between predictors and occurrences increases the reliability of  
136 species-environment relationship (Gavrutenko et al., 2021), we computed the averages of  
137 climatic variables over the twenty-years period covered by observations (1996-2015). Climate  
138 stability can significantly affect the distribution of species, being one of the major drivers of  
139 diversification processes and endemism patterns (Rangel et al., 2018). We accounted for  
140 climate stability using the CSI (Climate Stability Index) index (Herrando-Moraira et al., 2022).  
141 LULC change has been shown to affect the distribution and abundance of the Stone-curlew  
142 (Burfield, 2005; Onrubia and Andrés, 2005). Stone-curlews exploit agricultural areas with low  
143 vegetation density for breeding and foraging (Caccamo et al., 2011; Vaughan and Vaughan  
144 Jennings, 2005). Arid and steppic grasslands are among the elective habitats for the species  
145 (Green et al., 2000; Hume and Kirwan, 2013; Teyar et al., 2021; Vaughan and Vaughan  
146 Jennings, 2005) as well as low shrubs, often mixed with grass and bare ground (Traba et al.,  
147 2013; Vaughan and Vaughan Jennings, 2005). Finally, breeding attempts in urbanized areas

148 are increasingly reported (Biondi et al., 2015; Cutini et al., 2007; Giovacchini et al., 2017). We  
149 hence derived the percentage cover for the following classes: 1) agricultural, 2) grass, 3) shrub,  
150 and 4) urban. These predictors adequately represent the main LULC drivers of habitat  
151 suitability for the species previously described (Giovacchini et al., 2017; Vaughan and  
152 Vaughan Jennings, 2005). LULC variables were computed as the percentage cover of each  
153 class on the total surface of a raster grid cell, using the global land cover developed by the  
154 European Space Agency (European Space Agency, 2019) and computing the mean over the  
155 same twenty-years period of species' occurrences (1996-2015). We tested for correlation  
156 among these variables using the Pearson linear correlation coefficients (Supplementary  
157 Materials S1) and excluded four climatic variables (temperature of the warmest quarter,  
158 temperature seasonality, precipitation of the warmest quarter, precipitation seasonality) to  
159 obtain a set of seven uncorrelated predictors with Pearson's coefficient always below 0.7.

### 160 **2.3. Future scenarios**

161 We retrieved future climatic layers for five Intergovernmental Panel on Climate Change  
162 General Circulation Models (GCMs) that gained the minimum score in interdependence  
163 (Sanderson et al., 2015): CESM1-CAM5, FIO-ESM, IPSL-CM5A-MR, MIROC5 and MPI-  
164 ESM-MR. We considered three carbon emission scenarios corresponding to the IPCC's  
165 Representative Concentration Pathways 2.6, 4.5 and 8.5 (RCP 2.6, 4.5 and RCP 8.5). This suite  
166 of RCPs is often selected as it represents a full spectrum of scenarios, including an optimistic  
167 (2.6), a moderate (4.5) and a pessimistic (8.5) scenario (Waynat et al., 2009). We produced  
168 bioclimatic variables for every GCM × RCP combination from the climatic variables available  
169 in the CHELSA CMIP-5 timeseries (Karger et al., 2017). Future variables represented  
170 predicted mean conditions over a twenty-years period (2041-2060). The future CSI index (a  
171 single raster for the future) was obtained from Herrando-Moraira et al., 2022. LULC variables  
172 were kept at their 2016 values, due to the extremely low correspondence between the dataset



173 used to train models and any dataset of future LULC available to our knowledge. We also note  
174 that incorporating fixed LULC variables in future projections of species distributions increases  
175 their reliability as LULC is expected to change more slowly compared to climate and therefore  
176 it is useful to constrain suitable areas to those with LULC values within the niche of the species  
177 (Stanton et al., 2012). All variables were computed or resampled at the  $5.5 \times 5.5$  km grid  
178 resolution, under the equal-area projection World Mollweide (ESRI: 54009).

#### 179 ***2.4. Species distribution modelling workflow***

180 Considering the inherent spatial bias in the Stone-curlew point occurrences, we opted for a  
181 machine learning algorithm using a maximum entropy (Maxent) approach (Phillips et al.,  
182 2006). In fact, this is considered among the best suited and robust methods for modelling  
183 species distribution as it allows to fine-tune models, while contextually balancing power and  
184 complexity (Radosavljevic and Anderson, 2014; Warren and Seifert, 2011). Maxent requires  
185 background points to describe the suite of environmental conditions found in the study area  
186 and compare them with conditions at occurrence points (Merow et al., 2013). Therefore, we  
187 considered 10000 background points randomly generated over the study area (Barbet-Massin  
188 et al., 2012b). Tuning is essential to reduce overfitting and identify appropriate  
189 hyperparameters (Brambilla et al., 2022; Radosavljevic and Anderson, 2014). Therefore, we  
190 tuned the regularization multiplier (beta, a penalty of all parameters included in Maxent models  
191 that affects model complexity) comparing eight values (from one to eight at incremental steps  
192 of one), and features, testing two different combinations: linear and quadratic (LQ) or linear,  
193 quadratic, and hinge (LQH). Linear and quadratic features have often been proved to be the  
194 most biologically meaningful (Anderson and Gonzalez, 2011; Syfert et al., 2013), whereas  
195 hinge features allow to account for more complex species-environment relationships (Merow  
196 et al., 2013). To compare the performance of different models we used the following metrics:  
197 1) Area Under the Curve (AUC) (Fielding and Bell, 1997) of the Receiver Operating

198 Characteristic (ROC) plot on a test dataset ( $AUC_{test}$ ), a measure of the predictive ability of a  
199 model that is threshold-independent, 2) the difference between the training and test AUC  
200 ( $AUC_{diff}$ ) (Radosavljevic and Anderson, 2014), as a measure of overfitting (with higher values  
201 indicating model overfitting), and 3) Continuous Boyce Index (CBI) (Boyce et al., 2002), a  
202 measure that is independent of species prevalence. Spatial autocorrelation can strongly bias  
203 inference on the factors determining species' distribution, often leading to overfitting and  
204 overrated predictive performance of machine-learning algorithms (Ploton et al., 2020; Roberts  
205 et al., 2017). Therefore, in all tests of model performance, we used a four-fold spatial cross  
206 validation (Muscarella et al., 2014). This procedure splits the occurrences and background  
207 points in four spatial blocks maximising spatial independence, and then uses three blocks for  
208 model training and the remaining one for testing, iterating four times. We estimated  
209 environmental variable contribution in the best-performing model computing permutation  
210 importance, i.e., randomly permuting the values of a variable while keeping the others at their  
211 mean values and evaluating the drop in  $AUC_{test}$ , expressed as percentage (Thuiller et al., 2009).  
212 After tuning the models, the one showing the best trade-off among performance metrics was  
213 used to predict current and future (2041-2060) breeding habitat suitability for the Stone-curlew  
214 in the Western Palearctic. For the choice of the model representing the best trade-off, even if  
215 we checked all metrics, we gave priority to models with a low overfitting given the need to  
216 extrapolate to future conditions. When projected to new time periods, SDMs might encounter  
217 environmental conditions that are not found in the calibration area (Elith et al., 2010; Zurell et  
218 al., 2012), producing spurious predictions (Owens et al., 2013). This occurs when: 1) a variable  
219 is outside the range found when training (i.e., strict extrapolation), or 2) each variable is within  
220 the calibration range, but the combination of predictors is new (i.e., combinatorial  
221 extrapolation) (Elith et al., 2010; Zurell et al., 2012). We used the environmental overlap mask  
222 to identify the areas where strict and combinatorial extrapolation occur (Zurell et al., 2012).

## 223 2.5. Gap analysis

224 Areas predicted as suitable under both current and future conditions (i.e., *in situ* climate  
225 refugia) are fundamental to plan conservation actions (Estrada et al., 2016; Thuiller et al.,  
226 2019). We binarized each habitat suitability map considering as suitable the cells with a  
227 suitability above the maximum training sensitivity plus specificity (habitat suitability > 0.3031)  
228 of the cloglog model output as this binarization is considered robust and reliable (Liu, 2012).  
229 These maps were then used to identify cells predicted to remain suitable under future scenarios  
230 (i.e., in-situ climate refugia). Then, we computed the percentage of climate refugia found within  
231 the World Database on Protected Areas, [www.protectedplanet.net](http://www.protectedplanet.net) (downloaded on April 10<sup>th</sup>,  
232 2023). From this database we removed protected areas considered as “proposed”, retaining  
233 only those currently established.

## 234 2.6. R packages

235 All analyses were performed in the R environment (version 4.3.1; R Core Team 2023) with the  
236 packages: ‘usdm’ v. 1.1-18 (Naimi, 2013), ‘humboldt’ v. 1.0.0 (Brown and Carnaval, 2019),  
237 ‘dismo’ v. 1.3.14 (Hijmans et al., 2017), ‘raster’ v. 3.6.20 (Hijmans, 2018), ‘ecospat’ v. 4.0.0  
238 (Di Cola et al., 2017), ‘ENMeval’ v. 0.2.1 (Muscarella et al., 2014), ‘rmaxent’ v. 0.8.5  
239 (<https://github.com/johnbaums/rmaxent>), ‘mecofun’ v. 0.5.1 ([https://gitup.uni-](https://gitup.uni-potsdam.de/macroecology/mecofun)  
240 [potsdam.de/macroecology/mecofun](https://gitup.uni-potsdam.de/macroecology/mecofun)).

## 241 3. RESULTS

### 242 3.1. Species distribution modelling

243 Based on the tuning of regularization multipliers and features, we selected as best the model  
244 with linear and quadratic features and beta = 1, as it showed the lowest overfitting ( $AUC_{diff} =$

245 0.057 ± 0.088 SD) while retaining excellent  $AUC_{test}$  (0.872 ± 0.081 SD) and CBI (0.990 ±  
1 246 0.008 SD) metrics (Table 1). The tuned model provided a reliable description of the ecological  
2 247 niche of the Stone-curlew (Figure 2) and the current habitat suitability of the Western Palearctic  
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4 248 for this species (Figure 3). The variable with the highest permutation importance was annual  
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6 249 mean temperature, followed by agricultural cover, annual precipitation and climate stability  
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8 250 (Table 2). Response curves (Figure 2) showed a unimodal relationship between the probability  
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10 251 of Stone-curlew occurrence and annual mean temperature (with a peak between 15 and 20 °C),  
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12 252 annual precipitation (with a peak between 800 and 1200 mm), and a quadratic relationship with  
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14 253 agricultural cover. Maps of predicted habitat suitability for the year 2050 showed an increase  
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16 254 of the suitable areas towards north-east under all scenarios, particularly under more severe  
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18 255 scenarios (Figure 3). Slight decreases of breeding habitat suitability were predicted under all  
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20 256 RCPs at the southern range border, e.g., in Northern Africa (Figure 3). The agreement between  
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22 257 GCMs for future predictions was consistently high except for a band across Central Europe  
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24 258 where uncertainty was higher under all scenarios (Figure 3). Strict extrapolation was extremely  
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26 259 low under current conditions, whereas combinatorial extrapolation was slightly higher,  
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28 260 although still confined to a few areas (Figure S1). Strict extrapolation was low under future  
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30 261 scenarios for all GCMs but higher compared to the current, and it increased under more severe  
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32 262 scenarios (Figures S2-S7). This mainly concerned the southern border of the Western Palearctic  
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34 263 (Figures S2-S7). Combinatorial extrapolation had a similar pattern although it also occurred  
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36 264 more consistently in the Middle East and Northern Europe (Figures S7-S11).

### 50 265 *3.2 Gap analysis*

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53 266 The 26.48 % of in-situ climate refugia for the Stone-curlew fell within the World Database on  
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55 267 Protected Areas. In particular, such areas mostly overlapped with the currently suitable  
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57 268 breeding areas (Figure 4: see also Figure 3 for the currently suitable areas). Large patches of  
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59 269 in-situ climate refugia with a scarce cover of protected areas were mainly located in Northern  
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270 Africa (Morocco, Algeria, Tunisia) and the Middle East (Israel, Turkey; Figure 4).

## 271 **4. DISCUSSION**

272 Relying on spatially independent Stone-curlew's occurrences, we developed a robust predictive  
273 framework for the species under climate change, based on the explicit tuning of Maxent  
274 models. The tuned model predicted an expansion of suitable breeding areas for the species  
275 towards the North-East under all future scenarios and allowed the identification of in-situ  
276 climate refugia, which fall mostly outside the current system of protected areas.

### 277 **4.1. Environmental niche**

278 Response curves showed results consistent with the knowledge on the autecology of species.  
279 The preference of the species for mild/warm climates is known from literature (Keller et al.,  
280 2020). The higher suitability at mid/high precipitation levels might be linked to the numerous  
281 breeding areas found in Mediterranean areas, that are rather arid sites despite relatively high  
282 annual precipitation due to a strong seasonality, with precipitations occurring primarily in  
283 autumn (Deitch et al., 2017). The very little permutation importance of urban cover suggests  
284 that urban areas are used mainly for occasional foraging and breeding by Stone-curlews, despite  
285 more frequent sightings in peri-urban settings, such as the area of Fiumicino Airport in Rome  
286 (Biondi et al., 2015). The choice of breeding sites primarily depends on the presence of  
287 extensive agricultural or natural areas nearby (forse è opportuna una citazione). Notably, the  
288 use of agricultural areas for breeding is increasingly documented (Issa and Muller, 2015), and  
289 agricultural areas might be good surrogates of natural open habitats (Figure 2). Stone-curlews  
290 have been reported to forage in agricultural areas with very different characteristics, but they  
291 require specific conditions for nesting that are not provided by areas with intensive agricultural  
292 practices (MacDonald et al., 2012). This calls for the adoption of agricultural practices  
293 compatible with Stone-curlew conservation needs, especially in areas close to where the

294 species breeds and that are predicted to become suitable in the future. Furthermore, a Common  
1  
2 295 Agricultural Policy that benefits specialised taxa instead of generalist one (Assandri et al.,  
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4 296 2019) and that does not support intensive farming would benefit the conservation of the Stone-  
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#### 10 298 **4.2. Future breeding habitat suitability**

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14 299 The northward shift of suitable areas predicted by our model is consistent with previous  
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16 300 projection for the species (Huntley et al., 2007; Keller et al., 2020), and with results obtained  
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18 301 for other pseudo-steppic species, such as Great *Otis tarda* and Little Bustard *Tetrax tetrax*  
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20 302 (Estrada et al., 2016) and European Roller *Coracias garrulus* (Kiss et al., 2020). The loss of  
21  
22 303 suitable areas in the southern Mediterranean region (e.g., Northern Africa) is not surprising as  
23  
24 304 the Mediterranean biogeographical region represents a hotspot of global change, and extensive  
25  
26 305 biodiversity losses have been predicted here (Sala et al., 2000). Dispersal ability, biotic  
27  
28 306 interactions and the carrying capacity of suitable habitats might determine whether a  
29  
30 307 stable/increasing mean breeding habitat suitability translates into a stable/increasing population  
31  
32 308 size (Bateman et al., 2013; Holloway et al., 2016). Habitat suitability has been linked to  
33  
34 309 population size and trends in birds (Green et al., 2008; Stiels et al., 2021). We showed that  
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36 310 large areas of the Western Palearctic are predicted to remain or become suitable in the future.  
37  
38 311 Hence, the species may be able to maintain viable populations in the region. However, models  
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40 312 predicted decreases of breeding suitability for the species at the southern edge of its  
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42 313 distribution, so that marginal populations might need to track their niche in the future. On the  
43  
44 314 one hand, evidence of the ability of animals to track their niche is contrasting (Chen et al.,  
45  
46 315 2011; Devictor et al., 2008) and many terrestrial organisms have been shown to shift their  
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48 316 distribution at a sufficient pace to track recent temperature changes (Chen et al., 2011). On the  
49  
50 317 other side, species can also respond to global change persisting under unfavourable conditions  
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52 318 being phenotypically plastic and becoming locally adapted (Valladares et al., 2014). An  
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319 important aspect to consider is the effect of the length of night on the ability to successfully  
320 forage, as the Stone-curlew forages primarily during night (Caccamo et al., 2011) and the  
321 shorter length of nights at northern latitudes during breeding seasons can limit the ability to  
322 forage. A successful northward expansion would therefore imply a plastic shift towards  
323 foraging in daily hours or increased productivity to offset the limited foraging time. Finally,  
324 biological interactions and movement/dispersal constraints might prevent Stone-curlews from  
325 colonizing newly suitable areas (Bateman et al., 2013; Brambilla et al., 2020; Holloway et al.,  
326 2016). However, the observed variability in large-scale movements both within and between  
327 Mediterranean populations (Falchi et al., 2023) might suggest a significant potential of the  
328 species for colonizing new suitable areas.

### 329 ***4.3. Gap analysis***

330 The Stone-curlew is philopatric in the breeding areas (Green, 1990) and this might delay  
331 habitat-tracking under environmental change. Therefore, in-situ climate refugia might act as a  
332 stronghold for the species, and anticipatory conservation efforts should primarily focus on these  
333 areas (Thuiller et al., 2019). Alongside, ensuring high connectivity conditions for the species  
334 in areas predicted to become unsuitable might contribute to maintain viable populations and  
335 facilitate niche tracking (Heller and Zavaleta, 2009). This is especially true considering that  
336 habitat fragmentation contributed to the species' decline in the '90s (Tucker and Evans, 1997).  
337 Finally, enhanced monitoring efforts in areas predicted to become suitable might increase  
338 early-detection probability and allow to define and implement strategies to mitigate the  
339 negative effects of biotic interactions. For instance, our model evidenced the importance of  
340 agricultural areas, a LULC class heavily affected by farming and harvesting activities. Many  
341 in-situ climate refugia are located in intensively cultivated areas, corresponding to the 'core of  
342 EU continental agriculture' (D'Amico et al., 2013), namely England and the Po Plain, and  
343 extensively influenced by the Common Agricultural Policy reforms (Assandri et al., 2019).

344 Furthermore, in France, over 60% of breeding pairs are found in the Central/Western region  
345 within arable crops (Issa and Muller, 2015; Malvaud and Blanchon, 1996). In these ecosystems,  
346 *ad hoc* management interventions on a local scale can be effectively used to favour Stone-  
347 curlew's presence (Hawkes et al., 2021). A rather low percentage of the in-situ climate refugia  
348 are located within the framework of protected areas. Despite the predicted increase of suitable  
349 areas, due to the heavy reliance of the Stone-curlew on ecosystems affected by humans, it is  
350 critical to implement conservation measures and secure natural strongholds of the species  
351 towards colder climates (e.g., in northern France or Great Britain). Besides, pseudo-steppic  
352 species at large may benefit from protected areas (Santana et al., 2014) and thus an increased  
353 protection of in-situ climate refugia for the Stone-curlew, especially in areas with large gaps  
354 (North Africa, Middle East), might have a positive impact on other species.

#### 355 ***4.4. Study limitations and future developments***

356 The use of correlative species distribution models may present some limitations. First, SDMs  
357 assume an equilibrium condition between the species and the environment (Araújo and  
358 Pearson, 2005). Areas that have been abandoned by the Stone-curlew during the last decades  
359 of the past century may be recolonized, as happened in the UK following the targeted  
360 conservation efforts of the LIFE11INF/UK000418 'Securing the future of the Stone-curlew  
361 throughout its range in the UK'. This suggests that suitable climate and LULC conditions at  
362 the relatively coarse scale of our study exist in those areas. Thanks to constant improvements  
363 in climate and LULC scenarios, in the future, our workflow might be applied at a finer temporal  
364 scale for the Stone-curlew and, more generally, for steppic species and might include scenarios  
365 of LULC besides standard climatic change scenarios. Finally, we limited our study to the  
366 breeding period: understanding the drivers and changes of habitat suitability for the Stone-  
367 curlew across migratory and wintering grounds might provide further insights for its  
368 conservation.



369 **5. CONCLUSIONS**

1  
2 370 This study refines current knowledge on the effects of climate change for the Stone-curlew,  
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4 371 providing robust predictions of breeding habitat suitability for the species at an ecologically  
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7 372 relevant spatial resolution, and conservation planners might benefit from our results by  
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9 373 incorporating indications on the most relevant conservation areas in the development of action  
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11 374 plans for the species. Our results might as well apply to steppe-land birds in general, and we  
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13 375 advocate the use of a similar framework to model future habitat suitability for other sensitive  
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15 376 species.  
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21 **377 ACKNOWLEDGEMENTS**

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23  
24 378 We thank Diego Rubolini and Luca Forneris for technical help, Danae Portolou and Nikos  
25  
26 379 Tsiopelas (Hellenic Ornithological Society) for providing aggregated occurrence data from  
27  
28 380 Greece. D. Giunchi thanks all the students and collaborators who helped him in the field. We  
29  
30 381 also thank Saverio Gatto for granting us the permission to use his Stone-curlew's photograph  
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33 382 in Figure 1 of the paper.  
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383 **SUPPLEMENTARY MATERIALS, DATA AND CODE**

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2 384 The supplementary materials, data and variables used to perform analyses, together with the R  
3  
4 385 code to replicate them and the knitted document generated by R Markdown are found at:  
5  
6 386 <https://doi.org/10.5281/zenodo.11097919>. Please note that occurrences from the UK provided  
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8 387 by the British Trust for Ornithology are not included in the data as requested by the signed  
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10 388 agreement of data concession.  
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389 **TABLES**

1  
2 390 **Table 1.** Evaluation of Maxent species distribution models for the Eurasian Stone-curlew  
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4 391 (*Burhinus oedicnemus*) in the Western Palearctic. Different values of beta (regularization  
5  
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7 392 multiplier) and different combinations of features were tested to tune model hyperparameters.  
8  
9 393 The following metrics from a four-fold spatial block cross validation are reported: Area Under  
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11 394 the ROC (Receiver Operating Characteristic) Curve of the test dataset ( $AUC_{test}$ ), the difference  
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13 395 between AUC on the training dataset and  $AUC_{test}$  ( $AUC_{diff}$ ); Continuous Boyce Index (CBI).  
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16 396 Standard deviations are reported in the adjacent columns. Results are ordered based on  
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19 397 increasing overfitting ( $AUC_{diff}$ ). The model representing the best compromise among  
20  
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22 398 evaluation metrics is shown in bold.

ID	Features	Beta	$AUC_{test}$	SD	$AUC_{diff}$	SD	CBI	SD
<b>1</b>	<b>LQ</b>	<b>1</b>	<b>0.872</b>	<b>0.081</b>	<b>0.057</b>	<b>0.088</b>	<b>0.990</b>	<b>0.008</b>
2	LQ	3	0.861	0.087	0.060	0.093	0.977	0.022
3	LQH	4	0.874	0.090	0.060	0.097	0.989	0.008
4	LQH	2	0.877	0.089	0.061	0.095	0.994	0.004
5	LQH	5	0.872	0.091	0.062	0.098	0.991	0.006
6	LQH	6	0.869	0.091	0.063	0.098	0.993	0.005
7	LQH	6	0.869	0.091	0.063	0.098	0.993	0.005
8	LQH	7	0.867	0.091	0.063	0.098	0.992	0.006
9	LQH	8	0.865	0.089	0.064	0.096	0.993	0.003
10	LQH	8	0.865	0.089	0.064	0.096	0.993	0.003

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11	LQ	5	0.840	0.091	0.074	0.091	0.971	0.020
12	LQ	5	0.840	0.091	0.074	0.091	0.971	0.020
13	LQ	6	0.837	0.091	0.076	0.088	0.969	0.018
14	LQ	7	0.834	0.090	0.077	0.085	0.971	0.015
15	LQ	7	0.834	0.090	0.077	0.085	0.971	0.015
16	LQ	8	0.832	0.089	0.077	0.083	0.966	0.015

400 **Table 2.** Environmental variables included in the tuned model used to predict current and future  
 401 breeding habitat suitability for the Eurasian Stone-curlew (*Burhinus oedicnemus*) in the  
 402 Western Palearctic, and their permutation importance. Permutation importance for a given  
 403 variable is equivalent to the drop in AUC (Area Under the ROC - Receiver Operating  
 404 Characteristic - Curve) after removing the variable and is expressed as percentage.

ID	Variable	Permutation importance (%)
1	Annual mean temperature (°C)	77.0
2	Agricultural cover (%)	9.5
3	Annual precipitation (mm)	9.0
4	Climate Stability Index	2.2
5	Grassland cover (%)	1.6
6	Urban cover (%)	0.7
7	Shrubland cover (%)	0.0

405

406 **FIGURE CAPTIONS**

407 **Figure 1. Data used to model Eurasian Stone-curlew (*Burhinus oedicephalus*) distribution.**

408 Occurrence and background points used to model breeding habitat suitability for the Eurasian  
409 Stone-curlew (*Burhinus oedicephalus*) in the Western Palearctic. Occurrences (red dots) and  
410 10000 randomly selected background points (small dark dots) are shown. Data for the UK  
411 provided by the British Trust for Ornithology are not shown due to sharing restrictions to  
412 protect nesting sites. The projection used is World Mollweide (ESRI: 54009). The species'  
413 range in the Western Palearctic, excluding the Macaronesian archipelago, is shown in dark grey  
414 and was obtained from the BirdLife International website (<https://www.datazone.birdlife.org>).  
415 Inset photo by Saverio Gatto.

417 **Figure 2. Response curves for a distribution model of Eurasian Stone-curlew (*Burhinus*  
418 *oedicephalus*).** Response curves for the three variables with the highest permutation importance  
419 in a Maxent species distribution model for the Eurasian Stone-curlew (*Burhinus oedicephalus*)  
420 in the Western Palearctic.

422 **Figure 3. Current and future habitat suitability for the Eurasian Stone-curlew (*Burhinus*  
423 *oedicephalus*).** Maps of current and future (2041-2060) breeding habitat suitability for the  
424 Eurasian Stone-curlew (*Burhinus oedicephalus*) in the Western Palearctic, under three  
425 Representative Concentration Pathways (RCP 2.6, RCP 4.5, RCP 8.5). The mean predicted  
426 suitability between five General Circulation Models (GCMs: CESM1-CAM5, FIO-ESM,  
427 IPSL-CM5A-MR, MIROC5, MPI-ESM-MR) is shown for each RCP, together with standard  
428 deviation between predictions according to the different GCMs. The projection used is World  
429 Mollweide (ESRI: 54009).

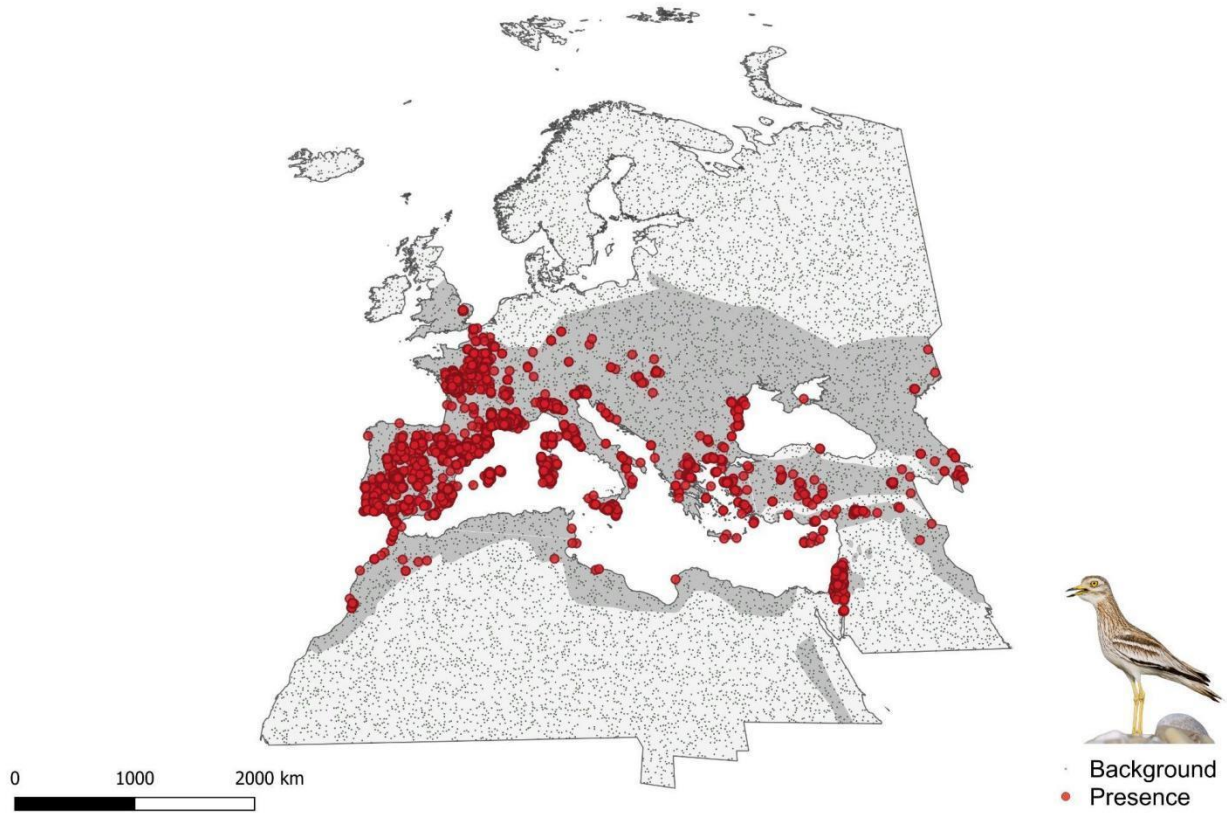
431 **Figure 4. Coverage of in-situ climate refugia for the Eurasian Stone-curlew (*Burhinus***

432 *oediconemus*) by **protected areas**. In-situ climate refugia are areas predicted as suitable under  
1  
2 433 both current and all future scenarios by a tuned Maxent species distribution model. Climate  
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4 434 refugia inside the World Database on Protected Areas ([www.protectedplanet.net](http://www.protectedplanet.net)) are shown in  
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6 435 dark green, those outside in light green. The projection used is World Mollweide (ESRI:  
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437 **FIGURES**

438 **Figure 1.**

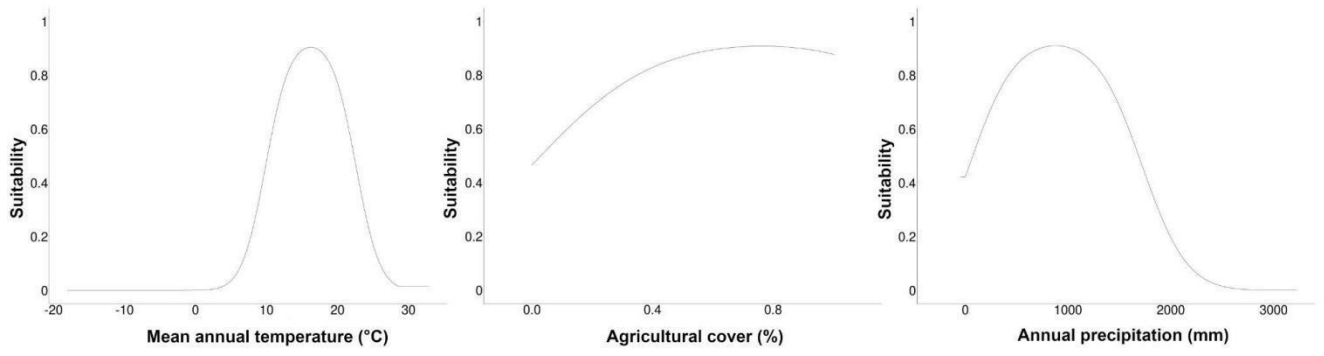


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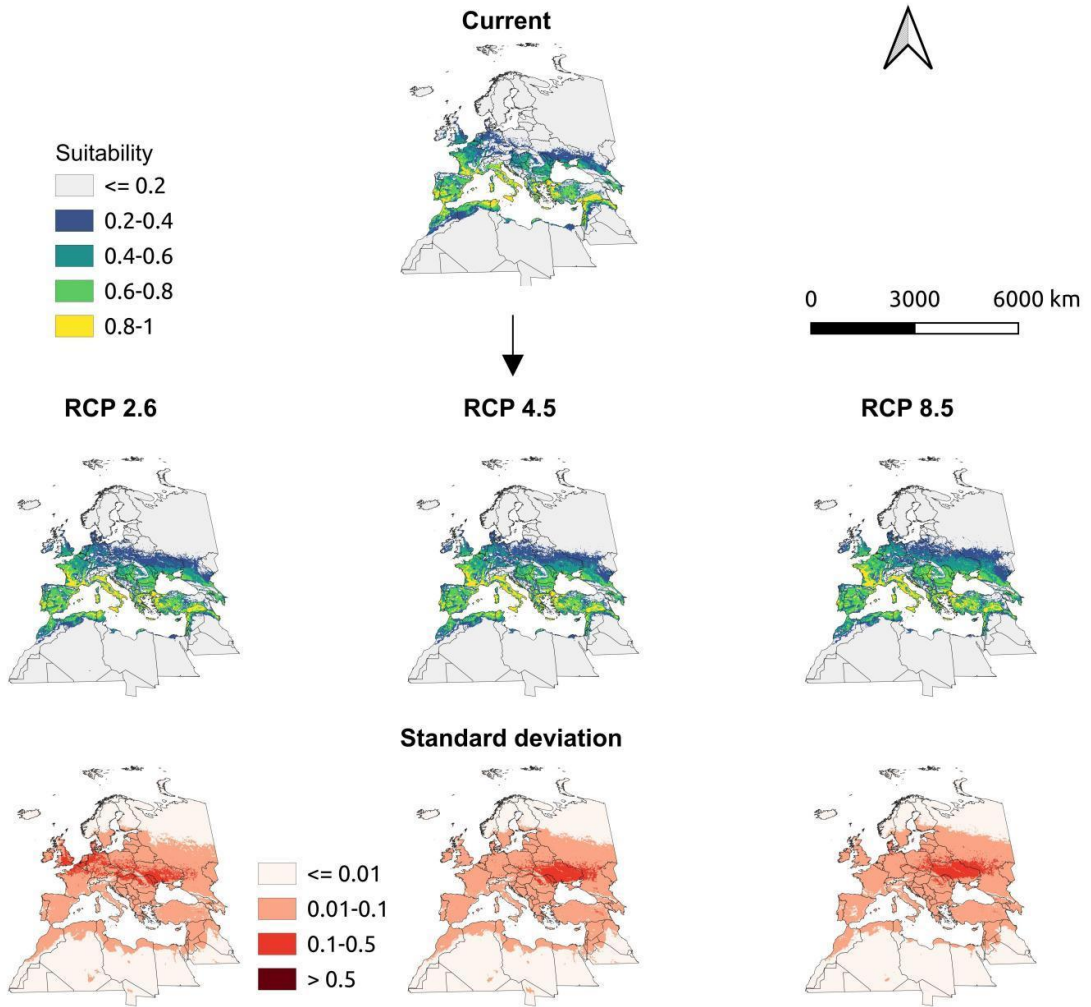
440 **Figure 2.**



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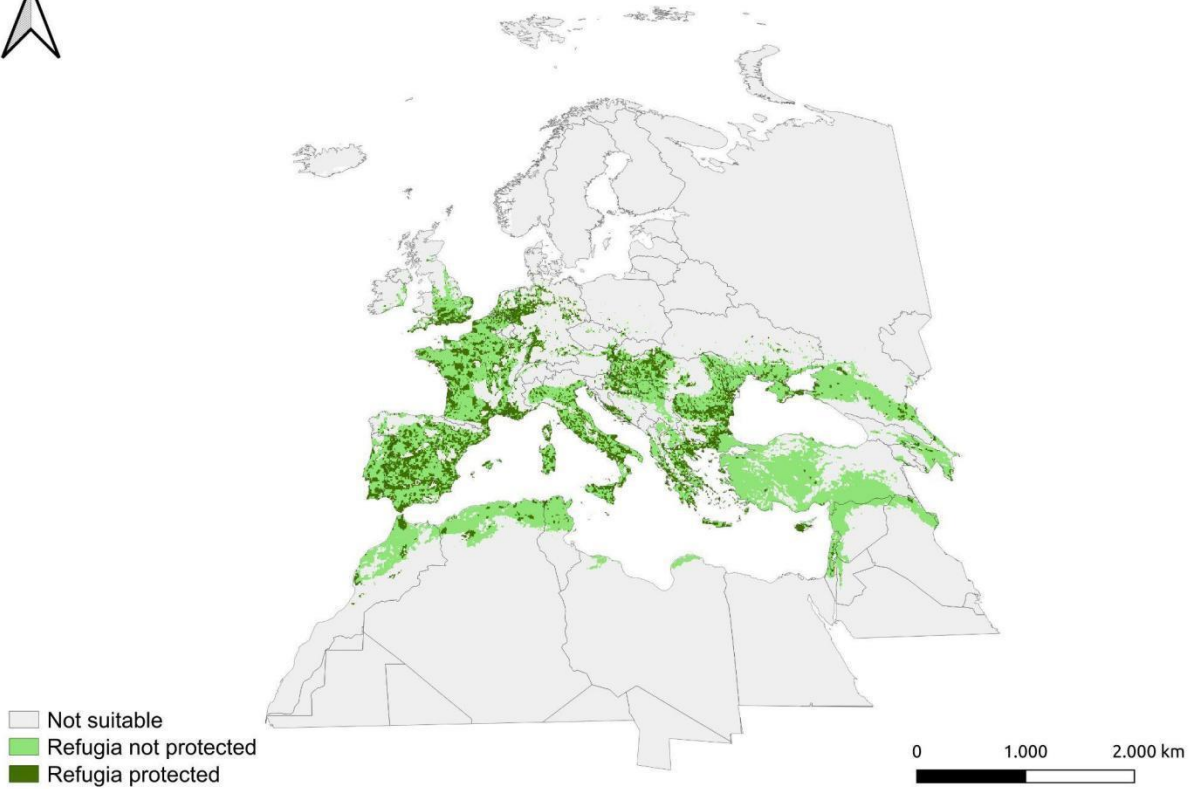


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444 **Figure 4.**

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446 **AUTHOR CONTRIBUTIONS**

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447 AS: conceptualization, data curation, formal analysis, investigation, methodology, supervision,  
448 writing - original draft, writing - review & editing, SR: conceptualization, data curation, formal  
449 analysis, investigation, methodology, writing - original draft, writing - review & editing, MF:  
450 formal analysis, methodology, writing - review & editing, MB: formal analysis, methodology,  
451 writing - review & editing, AMar: data curation, writing - review & editing, AMas:  
452 conceptualization, formal analysis, investigation, methodology, supervision, writing - review  
453 & editing, DG: conceptualization, data curation, formal analysis, investigation, methodology,  
454 supervision, writing - review & editing.

455 **6. CITED LITERATURE**

- 1  
2 456 - Anderson, R.P., Gonzalez, I., 2011. Species-specific tuning increases robustness to  
3  
4 457 sampling bias in models of species distributions: An implementation with Maxent.  
5  
6  
7 458 Ecol. Model. 222, 2796–2811. <https://doi.org/10.1016/j.ecolmodel.2011.04.011>  
8  
9 459 - Araújo, M.B., Pearson, R.G., 2005. Equilibrium of species' distributions with climate.  
10  
11 460 Ecography 28, 693–695.  
12  
13  
14 461 - Assandri, G., Bogliani, G., Pedrini, P., Brambilla, M., 2019. Toward the next Common  
15  
16 462 Agricultural Policy reform: Determinants of avian communities in hay meadows reveal  
17  
18 463 current policy's inadequacy for biodiversity conservation in grassland ecosystems. J.  
19  
20 464 Appl. Ecol. 56, 604–617. <https://doi.org/10.1111/1365-2664.13332>  
21  
22  
23 465 - Avalos, V.D.R., Hernández, J., 2015. Projected distribution shifts and protected area  
24  
25 466 coverage of range-restricted Andean birds under climate change. Glob. Ecol. Conserv.  
26  
27 467 4, 459–469. <https://doi.org/10.1016/j.gecco.2015.08.004>  
28  
29  
30 468 - Barbet-Massin, M., Thuiller, W., Jiguet, F., 2012a. The fate of European breeding birds  
31  
32 469 under climate, land-use and dispersal scenarios. Glob. Change Biol. 18, 881–890.  
33  
34 470 <https://doi.org/10.1111/j.1365-2486.2011.02552.x>  
35  
36  
37 471 - Barbet-Massin, M., Jiguet, F., Albert, C.H., Thuiller, W., 2012b. Selecting pseudo-  
38  
39 472 absences for species distribution models: how, where and how many? Methods Ecol.  
40  
41 473 Evol. 3, 327–338. <https://doi.org/10.1111/j.2041-210X.2011.00172.x>  
42  
43  
44 474 - Bateman, B.L., Murphy, H.T., Reside, A.E., Mokany, K., VanDerWal, J., 2013.  
45  
46 475 Appropriateness of full-, partial- and no-dispersal scenarios in climate change impact  
47  
48 476 modelling. Divers. Distrib. 19, 1224–1234. <https://doi.org/10.1111/ddi.12107>  
49  
50  
51 477 - Biondi, M., Pietrelli, L., Meschini, A., Giunchi, D., 2015. L'Occhione: ricerca,  
52  
53 478 monitoraggi, conservazione di una specie a rischio. Belvedere, Latina.  
54  
55  
56 479 - BirdLife International, 2022. Species distribution maps. Available at:  
57  
58 480 <http://datazone.birdlife.org/species/requestdis>.  
59  
60  
61  
62  
63  
64  
65

- 481 - BirdLife International, 2021. Species factsheet: *Burhinus oedicnemus*.
- 1  
2 482 - BirdLife International, 2018. *Burhinus oedicnemus*. IUCN Red List Threatened  
3  
4 483 Species.
- 5  
6 484 - BirdLife International, 2017. European birds of conservation concern: Populations,  
7  
8  
9 485 trends and national responsibilities.
- 10  
11 486 - Boyce, M.S., Vernier, P.R., Nielsen, S.E., Schmiegelow, F.K.A., 2002. Evaluating  
12  
13 487 resource selection functions. *Ecol. Model.* 157, 281–300.  
14  
15 488 [https://doi.org/10.1016/S0304-3800\(02\)00200-4](https://doi.org/10.1016/S0304-3800(02)00200-4)
- 16  
17  
18 489 - Brambilla, M., Bazzi, G., Ilahiane, L., 2024. The effectiveness of species distribution  
19  
20 490 models in predicting local abundance depends on model grain size. *Ecology* 105, e4224.  
21  
22 491 <https://doi.org/10.1002/ecy.4224>
- 23  
24  
25 492 - Brambilla, M., Rubolini, D., Appukuttan, O., Calvi, G., Karger, D.N., Kmecl, P.,  
26  
27 493 Mihelič, T., Sattler, T., Seaman, B., Teufelbauer, N., Wahl, J., Celada, C., 2022.  
28  
29 494 Identifying climate refugia for high-elevation Alpine birds under current climate  
30  
31 495 warming predictions. *Glob. Change Biol.* 28, 4276–4291.  
32  
33 496 <https://doi.org/10.1111/gcb.16187>
- 34  
35  
36 497 - Brambilla, M., Scridel, D., Bazzi, G., Ilahiane, L., Iemma, A., Pedrini, P., Bassi, E.,  
37  
38 498 Bionda, R., Marchesi, L., Genero, F., Teufelbauer, N., Probst, R., Vrezec, A., Kmecl,  
39  
40 499 P., Mihelič, T., Bogliani, G., Schmid, H., Assandri, G., Pontarini, R., Braunisch, V.,  
41  
42 500 Arlettaz, R., Chamberlain, D., 2020. Species interactions and climate change: How the  
43  
44 501 disruption of species co-occurrence will impact on an avian forest guild. *Glob. Change*  
45  
46 502 *Biol.* 26, 1212–1224. <https://doi.org/10.1111/gcb.14953>
- 47  
48  
49 503 - Brlík, V., Šilarová, E., Škorpilová, J., Alonso, H., Anton, M., Aunins, A., Benkő, Z.,  
50  
51 504 Biver, G., Busch, M., Chodkiewicz, T., Chylarecki, P., Coombes, D., De Carli, E., Del  
52  
53 505 Moral, J.C., Derouaux, A., Escandell, V., Eskildsen, D.P., Fontaine, B., Foppen, R.P.B.,  
54  
55 506 Gamero, A., Gregory, R.D., Harris, S., Herrando, S., Hristov, I., Husby, M.,  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

- 507 Ieronymidou, C., Jiquet, F., Kålås, J.A., Kamp, J., Kmecl, P., Kurlavičius, P.,  
1 508 Lehikoinen, A., Lewis, L., Lindström, Å., Manolopoulos, A., Martí, D., Massimino, D.,  
2  
3  
4 509 Moshøj, C., Nellis, R., Noble, D., Paquet, A., Paquet, J.-Y., Portolou, D., Ramírez, I.,  
5  
6 510 Redel, C., Reif, J., Ridzoň, J., Schmid, H., Seaman, B., Silva, L., Soldaat, L., Spasov,  
7  
8  
9 511 S., Staneva, A., Szép, T., Florenzano, G.T., Teufelbauer, N., Trautmann, S., Van Der  
10  
11 512 Meij, T., Van Strien, A., Van Turnhout, C., Vermeersch, G., Vermouzek, Z., Vikstrøm,  
12  
13  
14 513 T., Voříšek, P., Weiserbs, A., Klvaňová, A., 2021. Long-term and large-scale  
15  
16 514 multispecies dataset tracking population changes of common European breeding birds.  
17  
18  
19 515 Sci. Data 8, 21. <https://doi.org/10.1038/s41597-021-00804-2>  
20  
21 516 - Brown, J.L., Carnaval, A.C., 2019. A tale of two niches: methods, concepts, and  
22  
23 517 evolution. *Front. Biogeogr.* 11.  
24  
25  
26 518 - Burfield, I., 2005. The conservation status of steppic birds in Europe. *Ecol. Conserv.*  
27  
28 519 *Steppe-Land Birds* 119–140.  
29  
30  
31 520 - Caccamo, C., Pollonara, E., Emilio Baldaccini, N., Giunchi, D., 2011. Diurnal and  
32  
33 521 nocturnal ranging behaviour of Stone-curlews *Burhinus oedicnemus* nesting in river  
34  
35 522 habitat. *Ibis* 153, 707–720.  
36  
37  
38 523 - Caro, T., 2010. Conservation by proxy: indicator, umbrella, keystone, flagship, and  
39  
40 524 other surrogate species. Island Press.  
41  
42  
43 525 - Chen, I.-C., Hill, J.K., Ohlemüller, R., Roy, D.B., Thomas, C.D., 2011. Rapid range  
44  
45 526 shifts of species associated with high levels of climate warming. *Science* 333, 1024–  
46  
47 527 1026.  
48  
49  
50 528 - Coxen, C.L., Frey, J.K., Carleton, S.A., Collins, D.P., 2017. Species distribution models  
51  
52 529 for a migratory bird based on citizen science and satellite tracking data. *Glob. Ecol.*  
53  
54 530 *Conserv.* 11, 298–311.  
55  
56  
57 531 - Cutini, S., Campedelli, T., Tellini Florenzano, G., 2007. Nidificazione di Occhione  
58  
59 532 *Burhinus oedicnemus* in un'area urbanizzata della Piana Fiorentina (Toscana). *Riv. Ital.*  
60  
61  
62  
63  
64  
65

533 Ornitol. 76, 171–174.

1  
2 534 - D'Amico, M., Coppola, A., Chinnici, G., 2013. Agricultural systems in the European  
3  
4 535 Union: an analysis of regional differences. *New Medit* 4, 28–34.

5  
6 536 - Deitch, M., Sapundjieff, M., Feirer, S., 2017. Characterizing precipitation variability  
7  
8  
9 537 and trends in the world's mediterranean-climate areas. *Water* 9, 259.  
10  
11 538 <https://doi.org/10.3390/w9040259>

12  
13  
14 539 - Devictor, V., Julliard, R., Couvet, D., Jiguet, F., 2008. Birds are tracking climate  
15  
16 540 warming, but not fast enough. *Proc. R. Soc. B Biol. Sci.* 275, 2743–2748.  
17  
18 541 <https://doi.org/10.1098/rspb.2008.0878>

19  
20  
21 542 - Di Cola, V., Broennimann, O., Petitpierre, B., Breiner, F.T., D'Amen, M., Randin, C.,  
22  
23 543 Engler, R., Pottier, J., Pio, D., Dubuis, A., Pellissier, L., Mateo, R.G., Hordijk, W.,  
24  
25 544 Salamin, N., Guisan, A., 2017. ecospat: an R package to support spatial analyses and  
26  
27 545 modeling of species niches and distributions. *Ecography* 40, 774–787.  
28  
29 546 <https://doi.org/10.1111/ecog.02671>

30  
31  
32  
33 547 - Elith, J., Kearney, M., Phillips, S., 2010. The art of modelling range-shifting species.  
34  
35 548 *Methods Ecol. Evol.* 1, 330–342. <https://doi.org/10.1111/j.2041-210X.2010.00036.x>  
36  
37  
38 549 - Engelhardt, E.K., Neuschulz, E.L., Hof, C., 2020. Ignoring biotic interactions  
39  
40 550 overestimates climate change effects: The potential response of the spotted nutcracker  
41  
42 551 to changes in climate and resource plants. *J. Biogeogr.* 47, 143–154.  
43  
44 552 <https://doi.org/10.1111/jbi.13699>

45  
46  
47  
48 553 - Estrada, A., Delgado, M.P., Arroyo, B., Traba, J., Morales, M.B., 2016. Forecasting  
49  
50 554 large-scale habitat suitability of European Bustards under climate change: The role of  
51  
52 555 environmental and geographic variables. *PLoS ONE* 11, e0149810.  
53  
54 556 <https://doi.org/10.1371/journal.pone.0149810>

55  
56  
57  
58 557 - European Space Agency, 2019. Land cover classification gridded maps from 1992 to  
59  
60 558 present derived from satellite observations. *Copernic. Clim. Change Serv.* 7–9.

61  
62  
63  
64  
65



- 559 - Falchi, V., Cerritelli, G., Barbon, A., Catoni, C., Cutroneo, A., Dell’Omo, G.,  
1 560 Dragonetti, M., Giovacchini, P., Meschini, A., Panzarin, L., Picciau, A., Giunchi, D.,  
2  
3  
4 561 2023. Inter and intra-population variability of the migratory behaviour of a short-  
5  
6 562 distance partial migrant, the Eurasian Stone-curlew *Burhinus oedicnemus*  
7  
8  
9 563 (Charadriiformes, Burhinidae). J. Ornithol. 164, 85–100.  
10  
11 564 <https://doi.org/10.1007/s10336-022-02020-0>
- 12  
13  
14 565 - Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of prediction  
15  
16 566 errors in conservation presence/absence models. Environ. Conserv. 24, 38–49.  
17  
18  
19 567 <https://doi.org/10.1017/S0376892997000088>
- 20  
21 568 - Gaget, E., Fay, R., Augiron, S., Villers, A., Bretagnolle, V., 2019. Long-term decline  
22  
23 569 despite conservation efforts questions Eurasian Stone-curlew population viability in  
24  
25  
26 570 intensive farmlands. Ibis 161, 359–371. <https://doi.org/10.1111/ibi.12646>
- 27  
28  
29 571 - Gavrutenko, M., Gerstner, B.E., Kass, J.M., Goodman, S.M., Anderson, R.P., 2021.  
30  
31 572 Temporal matching of occurrence localities and forest cover data helps improve range  
32  
33 573 estimates and predict climate change vulnerabilities. Glob. Ecol. Conserv. 27, e01569.  
34  
35  
36 574 <https://doi.org/10.1016/j.gecco.2021.e01569>
- 37  
38 575 - Giovacchini, P., Dragonetti, M., Farsi, F., Cianferoni, F., 2017. Winter Diet of Eurasian  
39  
40 576 Stone-curlew, *Burhinus oedicnemus* (L., 1758) (Aves: Charadriiformes) in a  
41  
42  
43 577 Mediterranean Area (Tuscany, Central Italy). Acta Zool. Bulg. 69, 323–326.
- 44  
45 578 - Green, R., 1990. Saving the stone curlew. Sanctuary Bull 19, 37–39.
- 46  
47  
48 579 - Green, R.E., Collingham, Y.C., Willis, S.G., Gregory, R.D., Smith, K.W., Huntley, B.,  
49  
50 580 2008. Performance of climate envelope models in retrodicting recent changes in bird  
51  
52 581 population size from observed climatic change. Biol. Lett. 4, 599–602.  
53  
54  
55 582 <https://doi.org/10.1098/rsbl.2008.0052>
- 56  
57  
58 583 - Green, R.E., Tyler, G.A., Bowden, C.G.R., 2000. Habitat selection, ranging behaviour  
59  
60 584 and diet of the stone curlew (*Burhinus oedicnemus*) in southern England. J. Zool. 250,  
61  
62  
63  
64  
65

585 161–183. <https://doi.org/10.1111/j.1469-7998.2000.tb01067.x>

1  
2 586 - Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in  
3 ecology. *Ecol. Model.* 135, 147–186. [https://doi.org/10.1016/S0304-3800\(00\)00354-9](https://doi.org/10.1016/S0304-3800(00)00354-9)

4 587  
5  
6 588 - Hagemeyer, W.J., Blair, M.J., 1997. The EBCC atlas of European breeding birds.  
7 Poyser Lond. 479.  
8 589

9  
10 590 - Hawkes, R.W., Smart, J., Brown, A., Green, R.E., Jones, H., Dolman, P.M., 2021.  
11 Effects of experimental land management on habitat use by Eurasian Stone-curlews.  
12 *Anim. Conserv.* 24, 743–755. <https://doi.org/10.1111/acv.12678>  
13 591  
14 592

15  
16 593 - Hawkes, R.W., Smart, J., Brown, A., Jones, H., Lane, S., Wells, D., Dolman, P.M.,  
17 2019. Multi-taxa consequences of management for an avian umbrella species. *Biol.*  
18 *Conserv.* 236, 192–201. <https://doi.org/10.1016/j.biocon.2019.05.039>  
19 594  
20 595

21 596 - Heller, N.E., Zavaleta, E.S., 2009. Biodiversity management in the face of climate  
22 change: A review of 22 years of recommendations. *Biol. Conserv.* 142, 14–32.  
23 597  
24 598 <https://doi.org/10.1016/j.biocon.2008.10.006>  
25 599

26 600 - Herrando-Moraira, S., Nualart, N., Galbany-Casals, M., Garcia-Jacas, N., Ohashi, H.,  
27 Matsui, T., Susanna, A., Tang, C.Q., López-Pujol, J., 2022. Climate Stability Index  
28 maps, a global high resolution cartography of climate stability from Pliocene to 2100.  
29 601  
30 602 *Sci. Data* 9, 48. <https://doi.org/10.1038/s41597-022-01144-5>  
31 603

32 604 - Hijmans, R.J., 2018. raster: Geographic data analysis and modeling. R Package Version  
33 2, 8.  
34 605

35 606 - Hijmans, R.J., Phillips, S., Leathwick, J., Elith, J., 2017. dismo: Species distribution  
36 modeling. R Package Version 1, 1–1.  
37 607

38 608 - Holloway, P., Miller, J.A., Gillings, S., 2016. Incorporating movement in species  
39 distribution models: how do simulations of dispersal affect the accuracy and uncertainty  
40 of projections? *Int. J. Geogr. Inf. Sci.* 1–25.  
41 609  
42 610

43 <https://doi.org/10.1080/13658816.2016.1158823>  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

- 611 - Hume, R., Kirwan, G., 2013. Eurasian thick-knee (*Burhinus oedicnemus*). Handb. Birds  
1  
2 612 World Alive Barc. Lynx Edicions.  
3
- 4 613 - Hunter Jr, M., Westgate, M., Barton, P., Calhoun, A., Pierson, J., Tulloch, A., Beger,  
5  
6 614 M., Branquinho, C., Caro, T., Gross, J., 2016. Two roles for ecological surrogacy:  
7  
8 615 Indicator surrogates and management surrogates. Ecol. Indic. 63, 121–125.  
9
- 10  
11 616 - Huntley, B., Green, R.E., Collingham, Y.C., Willis, S.G., 2007. A climatic atlas of  
12  
13 617 European breeding birds. Lynx Edicions.  
14  
15
- 16 618 - Issa, N., Muller, Y., 2015. Atlas des oiseaux de France métropolitaine: nidification et  
17  
18 619 présence hivernale. Delachaux et Niestlé.  
19  
20
- 21 620 - Karger, D., Zimmermann, N., 2018. CHELSAcruts—high resolution temperature and  
22  
23 621 precipitation timeseries for the 20th century and beyond. EnviDat.  
24  
25
- 26 622 - Karger, D.N., Conrad, O., Böhner, J., Kawohl, T., Kreft, H., Soria-Auza, R.W.,  
27  
28 623 Zimmermann, N.E., Linder, H.P., Kessler, M., 2017. Climatologies at high resolution  
29  
30 624 for the earth’s land surface areas. Sci. Data 4, 170122.  
31  
32 625 <https://doi.org/10.1038/sdata.2017.122>  
33  
34
- 35 626 - Keller, V., Herrando, S., Voříšek, P., Franch, M., Kipson, M., Milanesi, P., Martí, D.,  
36  
37 627 Anton, M., Klvaňová, A., Kalyakin, M.V., 2020. European breeding bird atlas 2:  
38  
39 628 distribution, abundance and change. European Bird Census Council & Lynx Edicions,  
40  
41 629 Barcelona.  
42  
43
- 44 630 - Kiss, O., Catry, I., Avilés, J.M., Barišić, S., Kuzmenko, T., Cheshmedzhiev, S.,  
45  
46 631 Marques, A.T., Meschini, A., Schwartz, T., Tokody, B., Végvári, Z., 2020. Past and  
47  
48 632 future climate-driven shifts in the distribution of a warm-adapted bird species, the  
49  
50 633 European Roller *Coracias garrulus*. Bird Study 67, 143–159.  
51  
52 634 <https://doi.org/10.1080/00063657.2020.1784842>  
53  
54
- 55 635 - Liu, X., 2012. Classification accuracy and cut point selection. Stat. Med. 31, 2676–  
56  
57 636 2686. <https://doi.org/10.1002/sim.4509>  
58  
59  
60  
61  
62  
63  
64  
65

- 637 - MacDonald, M.A., Maniakowski, M., Cobbold, G., Grice, P.V., Anderson, G.Q.A.,  
1 638 2012. Effects of agri-environment management for stone curlews on other biodiversity.  
2 639 Biol. Conserv. 148, 134–145. <https://doi.org/10.1016/j.biocon.2012.01.040>  
3  
4  
5  
6 640 - Maiorano, L., Falcucci, A., Boitani, L., 2006. Gap analysis of terrestrial vertebrates in  
7 641 Italy: Priorities for conservation planning in a human dominated landscape. Biol.  
8  
9 642 Conserv. 133, 455–473. <https://doi.org/10.1016/j.biocon.2006.07.015>  
10  
11  
12  
13 643 - Malvaud, F., Blanchon, R., 1996. L'œdicneme criard en France (*Burhinus oedicephalus*):  
14 644 résultats d'une enquête nationale (1980-1993) importance et distribution des  
15  
16 645 populations, biologie, exigences écologiques et conservation de l'espèce. Groupe  
17  
18  
19 646 Ornithologique Normand.  
20  
21  
22  
23 647 - McShea, W.J., 2014. What are the roles of species distribution models in conservation  
24  
25 648 planning? Environ. Conserv. 41, 93–96. <https://doi.org/10.1017/S0376892913000581>  
26  
27  
28 649 - Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling  
29  
30 650 species' distributions: what it does, and why inputs and settings matter. Ecography 36,  
31  
32 651 1058–1069. <https://doi.org/10.1111/j.1600-0587.2013.07872.x>  
33  
34  
35 652 - Miller-Rushing, A.J., Primack, R.B., Sekercioglu, C.H., 2010. Conservation  
36  
37 653 consequences of climate change for birds, in: Effects of Climate Change on Birds.  
38  
39 654 Oxford University Press, p. 311.  
40  
41  
42 655 - Muscarella, R., Galante, P.J., Soley-Guardia, M., Boria, R.A., Kass, J.M., Uriarte, M.,  
43  
44 656 Anderson, R.P., 2014. ENMeval: An R package for conducting spatially independent  
45  
46 657 evaluations and estimating optimal model complexity for Maxent ecological niche  
47  
48 658 models. Methods Ecol. Evol. 5, 1198–1205. <https://doi.org/10.1111/2041-210X.12261>  
49  
50  
51 659 - Naimi, B., 2013. Package “usdm”: Uncertainty analysis for species distribution models,  
52  
53 660 R package Version 1: 1–12. R Found. Stat. Comput.  
54  
55  
56 661 - Onrubia, A., Andrés, T., 2005. Impact of human activities on steppic-land birds: a  
57  
58 662 review in the context of the Western Palearctic, in: Ecology and Conservation of  
59  
60  
61  
62  
63  
64  
65

- 663 Steppe-Land Birds. Lynx Edicions, Barcelona, pp. 185–210.
- 1  
2 664 - Owens, H.L., Campbell, L.P., Dornak, L.L., Saupe, E.E., Barve, N., Soberón, J.,  
3  
4 665 Ingenloff, K., Lira-Noriega, A., Hensz, C.M., Myers, C.E., Peterson, A.T., 2013.  
5  
6 666 Constraints on interpretation of ecological niche models by limited environmental  
7  
8  
9 667 ranges on calibration areas. *Ecol. Model.* 263, 10–18.  
10  
11 668 <https://doi.org/10.1016/j.ecolmodel.2013.04.011>
- 12  
13  
14 669 - Parmesan, C., 2006. Ecological and evolutionary responses to recent climate change.  
15  
16 670 *Annu. Rev. Ecol. Evol. Syst.* 37, 637–669.  
17  
18 671 <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>
- 19  
20  
21 672 - Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of  
22  
23 673 species geographic distributions. *Ecol. Model.* 190, 231–259.  
24  
25 674 <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- 26  
27  
28 675 - Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., Dormann,  
29  
30 676 C., Cornu, G., Viennois, G., Bayol, N., Lyapustin, A., Gourlet-Fleury, S., Pélissier, R.,  
31  
32 677 2020. Spatial validation reveals poor predictive performance of large-scale ecological  
33  
34 678 mapping models. *Nat. Commun.* 11, 4540. <https://doi.org/10.1038/s41467-020-18321->  
35  
36  
37  
38 679 *y*
- 39  
40 680 - Radosavljevic, A., Anderson, R.P., 2014. Making better Maxent models of species  
41  
42 681 distributions: complexity, overfitting and evaluation. *J. Biogeogr.* 41, 629–643.  
43  
44 682 <https://doi.org/10.1111/jbi.12227>
- 45  
46  
47  
48 683 - Ramellini, S., Simoncini, A., Ficetola, G.F., Falaschi, M., 2019. Modelling the potential  
49  
50 684 spread of the Red-billed Leiothrix *Leiothrix lutea* in Italy. *Bird Study* 66, 550–560.  
51  
52 685 <https://doi.org/10.1080/00063657.2020.1732864>
- 53  
54  
55 686 - Rangel, T.F., Edwards, N.R., Holden, P.B., Diniz-Filho, J.A.F., Gosling, W.D., Coelho,  
56  
57 687 M.T.P., Cassemiro, F.A.S., Rahbek, C., Colwell, R.K., 2018. Modeling the ecology and  
58  
59 688 evolution of biodiversity: Biogeographical cradles, museums, and graves. *Science* 361,

689 eaar5452. <https://doi.org/10.1126/science.aar5452>

- 1  
2 690 - Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G.,  
3  
4 691 Hauenstein, S., Lahoz-Monfort, J.J., Schröder, B., Thuiller, W., Warton, D.I., Wintle,  
5  
6 692 B.A., Hartig, F., Dormann, C.F., 2017. Cross-validation strategies for data with  
7  
8  
9 693 temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* 40, 913–929.  
10  
11 694 <https://doi.org/10.1111/ecog.02881>
- 12  
13  
14 695 - Román-Palacios, C., Wiens, J.J., 2020. Recent responses to climate change reveal the  
15  
16 696 drivers of species extinction and survival. *Proc. Natl. Acad. Sci.* 117, 4211–4217.  
17  
18 697 <https://doi.org/10.1073/pnas.1913007117>
- 19  
20  
21 698 - Sala, O.E., Stuart Chapin, F., Iii, Armesto, J.J., Berlow, E., Bloomfield, J., Dirzo, R.,  
22  
23 699 Huber-Sanwald, E., Huenneke, L.F., Jackson, R.B., Kinzig, A., Leemans, R., Lodge,  
24  
25 700 D.M., Mooney, H.A., Oesterheld, M., Poff, N.L., Sykes, M.T., Walker, B.H., Walker,  
26  
27 701 M., Wall, D.H., 2000. Global biodiversity scenarios for the year 2100. *Science* 287,  
28  
29 702 1770–1774. <https://doi.org/10.1126/science.287.5459.1770>
- 30  
31  
32  
33 703 - Sanderson, B.M., Knutti, R., Caldwell, P., 2015. A representative democracy to reduce  
34  
35 704 interdependency in a multimodel ensemble. *J. Clim.* 28, 5171–5194.  
36  
37 705 <https://doi.org/10.1175/JCLI-D-14-00362.1>
- 38  
39  
40 706 - Santana, J., Reino, L., Stoate, C., Borralho, R., Carvalho, C.R., Schindler, S., Moreira,  
41  
42 707 F., Bugalho, M.N., Ribeiro, P.F., Santos, J.L., Vaz, A., Morgado, R., Porto, M., Beja,  
43  
44 708 P., 2014. Mixed effects of long-term conservation investment in Natura 2000 farmland.  
45  
46 709 *Conserv. Lett.* 7, 467–477. <https://doi.org/10.1111/conl.12077>
- 47  
48  
49  
50 710 - Santini, L., Benítez-López, A., Maiorano, L., Čengić, M., Huijbregts, M.A.J., 2021.  
51  
52 711 Assessing the reliability of species distribution projections in climate change research.  
53  
54 712 *Divers. Distrib.* 27, 1035–1050. <https://doi.org/10.1111/ddi.13252>
- 55  
56  
57 713 - Selwood, K.E., McGeoch, M.A., Mac Nally, R., 2015. The effects of climate change  
58  
59 714 and land-use change on demographic rates and population viability. *Biol. Rev.* 90, 837–

715 853. <https://doi.org/10.1111/brv.12136>

1  
2 716 - Silva, J.P., Gameiro, J., Valerio, F., Marques, A.T., 2024. Portugal's farmland bird

3  
4 717 crisis requires action. *Science* 383, 157–157. <https://doi.org/10.1126/science.adn1390>

5  
6 718 - Snow, D.W., Gillmor, R., Perrins, C.M., 1998. *The birds of the Western Palearctic.*

7  
8  
9 719 Oxford University Press.

10  
11 720 - Stanton, J.C., Pearson, R.G., Horning, N., Ersts, P., Reşit Akçakaya, H., 2012.

12  
13 721 Combining static and dynamic variables in species distribution models under climate

14  
15 722 change. *Methods Ecol. Evol.* 3, 349–357. <https://doi.org/10.1111/j.2041->

16  
17 723 210X.2011.00157.x

18  
19 724 - Stiels, D., Bastian, H.-V., Bastian, A., Schidelko, K., Engler, J.O., 2021. An iconic

20  
21 725 messenger of climate change? Predicting the range dynamics of the European Bee-eater

22  
23 726 (*Merops apiaster*). *J. Ornithol.* 162, 631–644. <https://doi.org/10.1007/s10336-021->

24  
25 727 01867-z

26  
27 728 - Syfert, M.M., Smith, M.J., Coomes, D.A., 2013. The effects of sampling bias and model

28  
29 729 complexity on the predictive performance of MaxEnt species distribution models. *PLoS*

30  
31 730 ONE 8, e55158. <https://doi.org/10.1371/journal.pone.0055158>

32  
33 731 - Teyar, Y., Giunchi, D., Baratti, M., Falchi, V., Znari, M., Aourir, M., 2021. Does the

34  
35 732 breeding biology of the Eurasian Stone-Curlew *Burhinus oedicnemus* in South-Western

36  
37 733 Morocco differ between grazed steppe and irrigated farmland? *Acta Ornithol.* 55.

38  
39 734 <https://doi.org/10.3161/00016454AO2020.55.2.007>

40  
41 735 - Thuiller, W., Guéguen, M., Renaud, J., Karger, D.N., Zimmermann, N.E., 2019.

42  
43 736 Uncertainty in ensembles of global biodiversity scenarios. *Nat. Commun.* 10, 1446.

44  
45 737 <https://doi.org/10.1038/s41467-019-09519-w>

46  
47 738 - Thuiller, W., Lafourcade, B., Engler, R., Araújo, M.B., 2009. BIOMOD – a platform

48  
49 739 for ensemble forecasting of species distributions. *Ecography* 32, 369–373.

50  
51 740 <https://doi.org/10.1111/j.1600-0587.2008.05742.x>

52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

- 741 - Traba, J., Acebes, P., Malo, J.E., García, J.T., Carriles, E., Radi, M., Znari, M., 2013.  
1  
2 742 Habitat selection and partitioning of the Black-bellied Sandgrouse (*Pterocles*  
3  
4 743 *orientalis*), the Stone Curlew (*Burhinus oedicnemus*) and the Cream-coloured Courser  
5  
6 744 (*Cursorius cursor*) in arid areas of North Africa. J. Arid Environ. 94, 10–17.  
7  
8 745 <https://doi.org/10.1016/j.jaridenv.2013.02.007>  
9  
10  
11 746 - Tucker, G.M., Evans, M.I., 1997. Habitats for birds in Europe: a conservation strategy  
12  
13 747 for the wider environment. BirdLife International.  
14  
15  
16 748 - Valladares, F., Matesanz, S., Guilhaumon, F., Araújo, M.B., Balaguer, L., Benito-  
17  
18 749 Garzón, M., Cornwell, W., Gianoli, E., Van Kleunen, M., Naya, D.E., Nicotra, A.B.,  
19  
20  
21 750 Poorter, H., Zavala, M.A., 2014. The effects of phenotypic plasticity and local  
22  
23 751 adaptation on forecasts of species range shifts under climate change. Ecol. Lett. 17,  
24  
25 752 1351–1364. <https://doi.org/10.1111/ele.12348>  
26  
27  
28 753 - VanDerWal, J., Murphy, H.T., Kutt, A.S., Perkins, G.C., Bateman, B.L., Perry, J.J.,  
29  
30  
31 754 Reside, A.E., 2013. Focus on poleward shifts in species' distribution underestimates  
32  
33 755 the fingerprint of climate change. Nat. Clim. Change 3, 239–243.  
34  
35 756 <https://doi.org/10.1038/nclimate1688>  
36  
37  
38 757 - Vaughan, R., Vaughan Jennings, N., 2005. The stone curlew: *Burhinus oedicnemus*.  
39  
40 758 Isabelline books.  
41  
42  
43 759 - Warren, D.L., Seifert, S.N., 2011. Ecological niche modeling in Maxent: the  
44  
45 760 importance of model complexity and the performance of model selection criteria. Ecol.  
46  
47 761 Appl. 21, 335–342. <https://doi.org/10.1890/10-1171.1>  
48  
49  
50 762 - Waynat, J., Azar, C., Kainuma, M., Kejun, J., Nakicenovic, N., Shukla, P.R., La  
51  
52 763 Rovere, E., Yohe, G., 2009. Report of 2.6 versus 2.9 Watts/m<sup>2</sup> RCPP evaluation panel.  
53  
54 764 Integrated Assessment Modeling Consortium.  
55  
56  
57 765 - Williams, J.E., Blois, J.L., 2018. Range shifts in response to past and future climate  
58  
59 766 change: Can climate velocities and species' dispersal capabilities explain variation in  
60  
61  
62  
63  
64  
65



767 mammalian range shifts? J. Biogeogr. 45, 2175–2189.

1  
2 768 <https://doi.org/10.1111/jbi.13395>

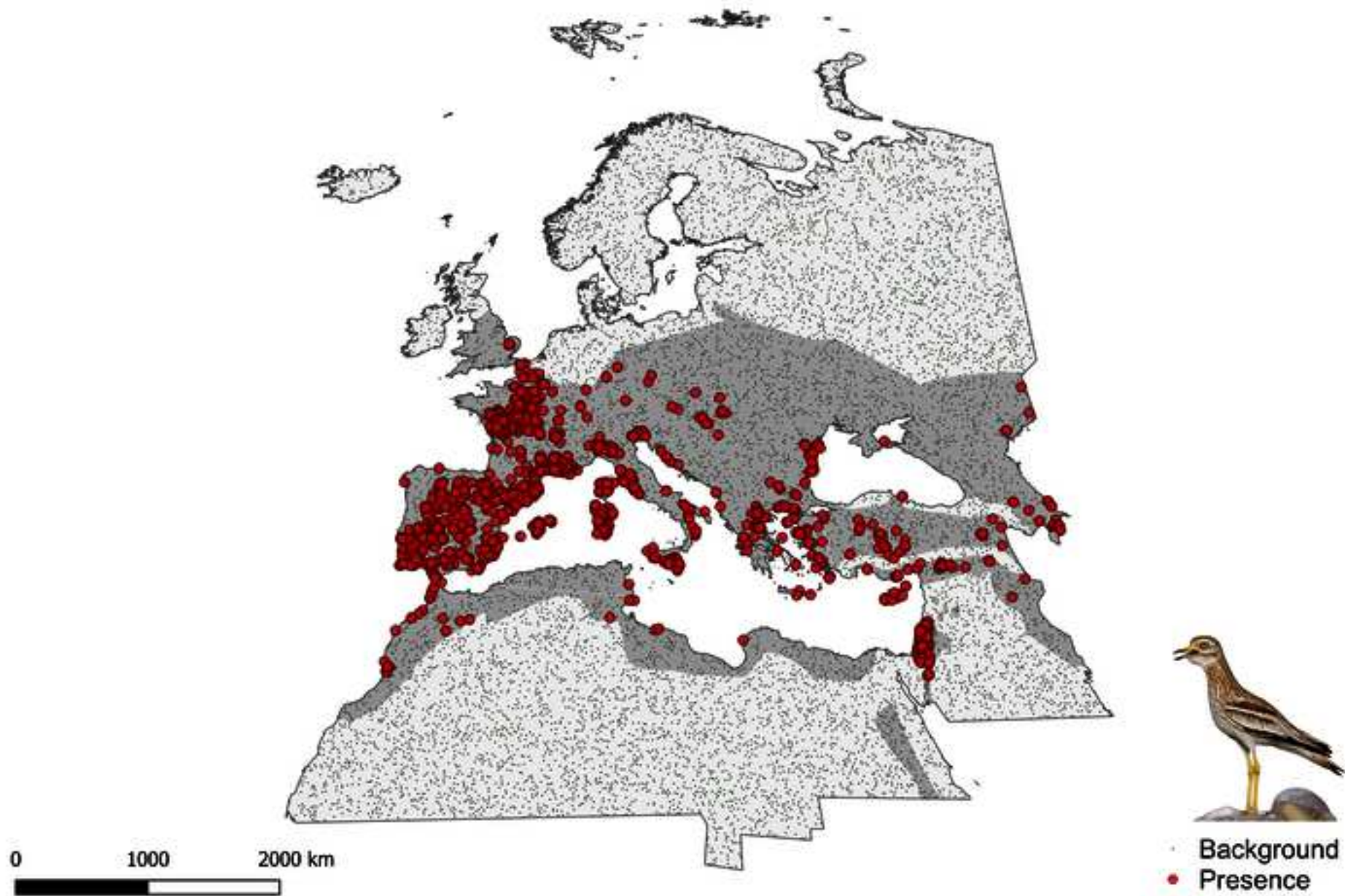
3  
4 769 - Zurell, D., Elith, J., Schröder, B., 2012. Predicting to new environments: tools for

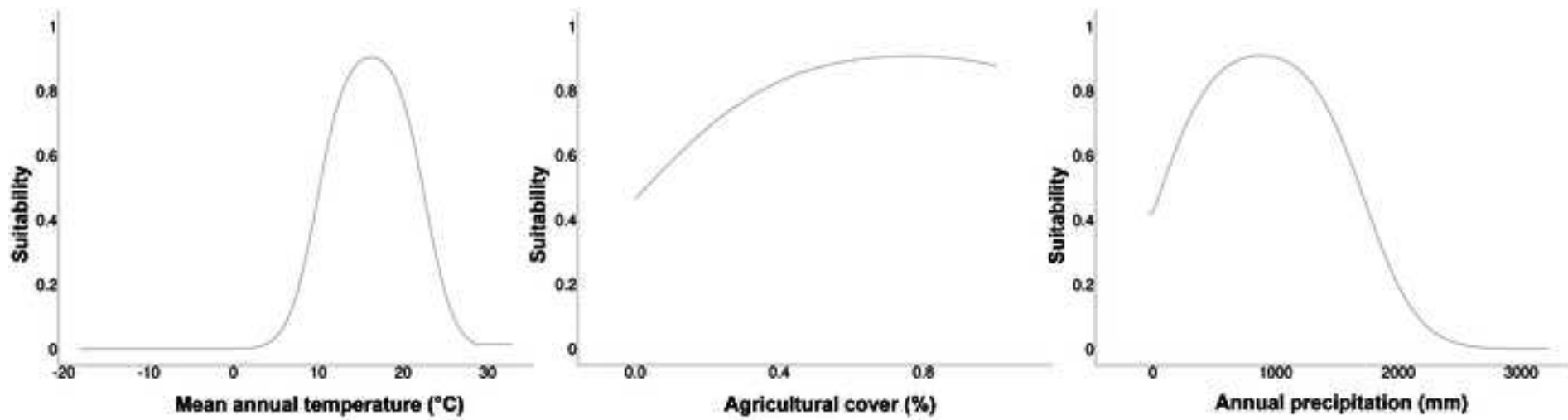
5  
6 770 visualizing model behaviour and impacts on mapped distributions. Divers. Distrib. 18,

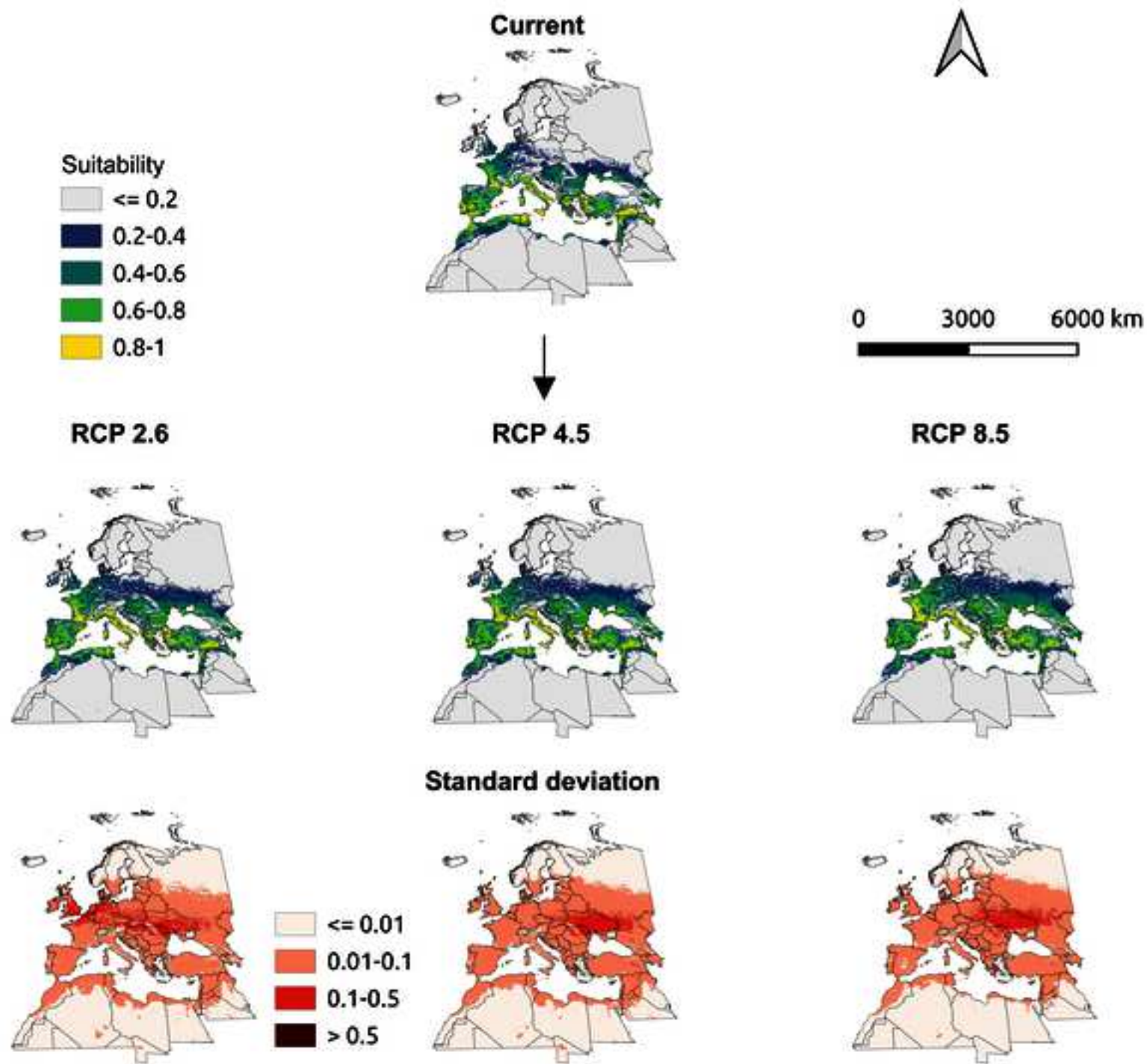
7  
8  
9 771 628–634. <https://doi.org/10.1111/j.1472-4642.2012.00887.x>

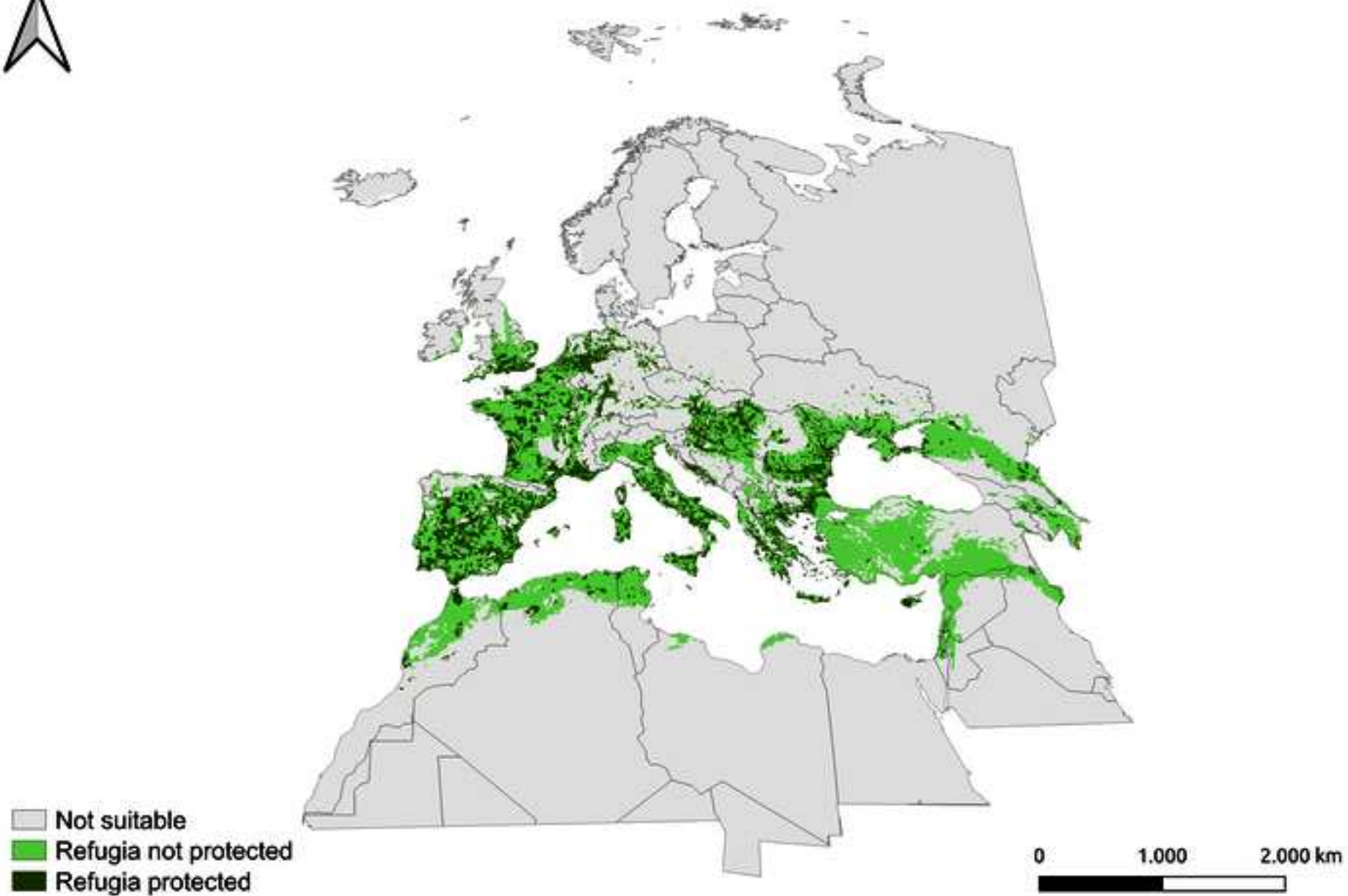
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**Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: