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1	Incorporating phylogeographic information in alien bird distribution models				
2	increases geographic extent but not accuracy of predictions				
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5	Laura Cardador ^{1,2} , Pedro Abellán ³ , Tim M. Blackburn ^{1,4}				
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7					
8	¹ Centre for Biodiversity and Environment Research, Department of Genetics, Evolution,				
9	and Environment, University College London, London WC1E 6BT, United Kingdom				
10					
11	² Ecological and Forestry Applications Research Centre, Campus de Bellaterra				
12	(UAB) Edifici C, 08193 Cerdanyola del Vallès, Spain				
13					
14	³ Department of Zoology, Universidad de Sevilla, Facultad de Biología, 41012 Seville,				
15	Spain				
16					
17	⁴ Institute of Zoology, Zoological Society of London, Regent's Park, London, NW1 4RY,				
18	UK				
19					
20					
21	*Corresponding author.				
22	Email: <u>l.cardador@creaf.uab.cat; lcardador81@gmail.com</u>				
23					
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ABSTRACT

Species distribution models (SDM) have been proposed as valuable first screening tools for predicting species responses to new environmental conditions. SDMs are usually conducted at the species level, assuming that species-environment relationships are a species-specific feature that do not evolve and show no variability across a species' range. However, broad environmental tolerances at the species level can encompass narrower and different environmental tolerances for specific lineages or populations. In this study, we evaluate whether SDMs that account for within-taxon niche variation in climate and human-habitat associations provide better fits between projected distributions and real occurrence data for alien bird species than species-level SDMs. Our study focuses on eight alien bird species with established alien populations for which detailed phylogeographic information was available. Similarity in climates and human disturbance conditions occupied by different phylogenetic groups within species was low and not greater than random expectations. Accounting for intraspecific niche variation in SDMs modified the distribution and extent of suitable habitat predicted as susceptible to invasion, but did not result in more accurate model predictions in alien ranges. Until more accurate information on intraspecific variability is available, species-level models can be reasonable candidates. When phylogeographic information is available, the use of the most conservative criterion (i.e. to model both species and lineages on the basis of the actual range) is recommended. **Keywords:** alien species, birds, climate, human disturbance, intraspecific niche variation, invasion risks, species distribution models

101 INTRODUCTION

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103 Human activities are accelerating the rate and magnitude of changes in species geographic ranges worldwide. Climate change, land-use transformations, habitat 104 105 fragmentation or environmental pollution, among others, threaten the persistence of 106 several species in formerly suitable locations, leading to species range contractions or extinctions, or pushing species to track new suitable environmental conditions beyond 107 former range limits (Pimm et al. 1995; Vitousek 1997; Parmesan et al. 1999). The 108 109 increase and development of trade and transport infrastructures, in turn, have accelerated the dispersal, and subsequent establishment, of alien species in places far 110 away from their native range (Blackburn et al. 2009; Hulme 2009). Such changes have 111 notably altered the distribution of species worldwide, homogenizing species 112 113 assemblages (McKinney and Lockwood 1999; Capinha et al. 2015; Sayol et al. 2021), with detrimental effects on biodiversity and ecosystems. 114

Although biotic interactions and dispersal are important in constraining species 115 116 ranges, environmental factors can exert a primary role (Gaston 2003; Huntley et al. 2007). Species distribution models (SDMs; models that statistically relate observed 117 species occurrences to environmental variables) have thus been proposed as valuable 118 119 first screening tools for predicting species responses to new environmental conditions in new geographic areas (e.g. invasion risk assessments) or under future environmental 120 121 scenarios (e.g. global climate-change) based on current species occurrence-environment 122 relationships (Guisan and Thuiller 2005; Araújo and Peterson 2012). SDMs rely on ecological niche theory, which predicts that for relatively recent events such as 123 biological invasions, the environmental niche is expected to be conserved (Peterson 124 125 2011). SDMs often focus on macroclimatic variables. Additionally, accounting for environmental factors other than climate, such as habitat characteristics and human 126 disturbance, can substantially improve model predictions (Strubbe et al. 2015; Cardador 127 and Blackburn 2020). 128

129 SDMs are usually conducted at the species level, assuming that speciesenvironment relationships are a species-specific feature that does not evolve and shows 130 no variability across a species' range. However, widely distributed species often 131 132 encompass different taxonomic or evolutionary units, which can reflect the existence of 133 ecotypes and locally adapted populations (Smith et al. 2019). Spatial heterogeneity in environments coupled with reduced gene flow can encourage local adaptation and 134 135 functional differences, leading to divergence in niches among closely related lineages. 136 In fact, recent work has suggested that broad environmental tolerances at the species level usually encompass narrower and different environmental tolerances for specific 137 138 lineages or populations within the species (Peterson and Holt 2003; Pearman et al. 2010). Hence, modelling a species as a single undifferentiated entity may obscure the 139 possibility that these lineages occupy distinct niches and, as a consequence, miss the 140 141 idiosyncratic response of intraspecific lineages to changing environmental conditions (Pearman et al. 2010; Lecocq et al. 2019). Accounting for intraspecific niche variation 142 in SDMs has thus been highlighted as important for forecasting species range shifts 143 144 under changing environmental conditions, particularly under global climate change 145 (Pearman et al. 2010; Peterson et al. 2019). In particular, phylogeographic structures 146 have been proposed as a useful proxy to incorporate intraspecific differentiation in SDMs. However, the efficiency of using these proxies in SDMs remains largely 147 148 unknown, in part because spatiotemporally independent data to test the accuracy of model predictions are often unavailable (Peterson et al. 2019). 149

Biological invasions represent unique, large-scale biogeographical experiments 150 for evaluating model transferability (Liu et al. 2020). Large numbers of alien species 151 have been introduced well outside their native ranges, resulting in geographically 152 independent datasets. However, the relevance of including intraspecific niche variation 153 in invasion risk assessments has not often been addressed (but see exceptions, Strubbe 154 et al. 2015; Godefroid et al. 2016). Many alien species currently arrive at new areas 155 because they are imported as trade commodities (Hulme et al. 2008; Abellán et al. 2016; 156 Cardador et al. 2017, 2019). If individuals coming from different geographic origins 157 belong to different lineages that have particular ecological niches (in terms of climate or 158 159 human tolerances), their invasion success is also likely to differ across different recipient environments. The omission of intraspecific niche structure from niche 160 modelling exercises may lead to some lineages having little representation in the 161 162 resulting species models (Pearman et al. 2010; D'Amen et al. 2013). This can lead to underestimation of the climate tolerances of alien species and, as a consequence, their 163 potential for establishment and spread in new environments. 164

165 Here, we assess the key assumption of distribution modelling theory – that the environmental niche remains conserved across species native ranges – as applied to the 166 bird invasion process. For this, we focused on eight alien bird species with established 167 168 alien populations, selected because of the availability of robust phylogeographic information, and for which different phylogenetic lineages (i.e., phylogroups) have been 169 170 identified in previous studies. We explored niche variation in the climatic and human disturbance spaces occupied by the different lineages in the native range in order to 171 assess whether the different phylogeographic lineages or genetic units occupy different 172 niches. It should be noted that the niches considered here relate to the realized niche 173 174 (occupied niche) and the Grinnellian niche concept: that is, the response of species to a set of non-consumable environmental variables that influence their large-scale 175 geographical distribution (Soberón 2007). As evidence of niche conservatism was not 176 found, we assessed how accounting for intraspecific niche variation in SDMs influences 177 predictions about potential distributions in adventive regions for the whole species. 178 179 Accounting for intraspecific variation is expected to improve the representation of different phylogroups in models (particularly the scarcest and narrowly distributed in 180 181 the native range), and thus to produce better fits between projected distributions and real occurrence data for alien bird species than species-level models not considering within-182 taxon niche structure. 183

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186 METHODS

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188 Phylogenetic and occurrence data

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Our study focuses on 8 alien bird species that have established alien populations in 190 191 different regions of the world and for which detailed phylogeographic information derived from analyses of mitochondrial and/or nuclear DNA sequences was available 192 from the literature (Table 1). We only considered studies reporting a clear definition of 193 194 intra-specific phylogenetic divisions and covering substantial parts of species' native ranges. Thissen polygons were applied to locations with available phylogenetic data to 195 delimit geographic boundaries of different phylogroups (Figs. 1a and S1 in Supp. Info.) 196 197 (Strubbe et al. 2015). Thissen polygons define an area of influence around each 198 sampled point (points with genetic data in our study), where every location of the study 199 area (species ranges in our case) is nearer to this point than to all the others. Thiessen

polygons derived from sampled points where a given phylogroup was identified were 200 merged together to obtain the phylogroup geographic boundaries. We used ArcGIS 10.5 201 202 for those analyses. Note that for most species, different phylogroups were allopatric (Fig. S1), although cases of partial overlap in geographic ranges also occur. For each 203 species, occurrence data for niche and modelling analyses were compiled from the 204 205 Global Biodiversity Information Facility (GBIF, GBIF.org, 2017, Table S1). GBIF records spanned the years 1744 to 2017 (Table S2). Compiled records were classified as 206 pertaining to the native breeding range or alien established range according to range 207 208 maps provided by the BirdLife International & NatureServe (2014) and the Global Avian Invasions Atlas (Dyer et al. 2017), respectively. Note that in the case of 209 Copsychus saularis, BirdLife International & NatureServe (2014) provided separate 210 maps for Copsychus saularis and Copsychus mindanensis. Based on the phylogenetic 211 data available, we considered these two taxa as the same species and considered their 212 range maps jointly (Sheldon et al. 2009). Species occurrences in the native range were 213 then assigned to different phylogroups according to geographic boundaries defined by 214 215 Thiessen Polygons (Figs. 1a and S1 in Supp. Info.). Occurrence data were aggregated at 5-arcminute resolution, which corresponds approximately to 10×10 km. This 216 resolution was considered to be representative of the size of the smallest cities, and thus 217 218 adequate to capture the main responses of bird species to humanized environments with acceptable computing time. Samples with reported geographical issues, location 219 uncertainty above 5 km, or with central grid coordinates of atlases of >10 km resolution, 220 221 were removed from analyses. Duplicate samples at the 5-arcminute resolution were handled as single observations. Final sample sizes ranged from 3,156 to 32,052 for 222 different species in the native range, and from 2 to 2,368 in the alien range (Table 1). 223

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225 Environmental variables

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227 We considered eight bioclimatic variables (obtained from WorldClim 1, 228 http://www.worldclim.org/) (Hijmans et al. 2005), which are known to affect bird distributions (Strubbe et al. 2015; Cardador et al. 2016): annual mean temperature, 229 temperature seasonality (standard deviation $\times 100$), maximum temperature of the 230 warmest month, minimum temperature of the coldest month, annual precipitation, 231 232 precipitation of the driest month, precipitation of the wettest month and precipitation seasonality (coefficient of variation). However, annual mean temperature, temperature 233 seasonality and annual precipitation were highly correlated with other climate variables 234 across the world ($r \ge 0.90$) and thus removed from analyses (Cardador and Blackburn 235 2019). We considered two variables as descriptors of human transformed environments: 236 i) the Global Human Influence Index, which provides a weighed composite map of 237 anthropogenic impacts including urban extent, population density, land cover, night 238 lights and distance to roads, railways, navigable rivers and coastlines (Sanderson et al. 239 2002), and ii) the percentage of urban habitats, as a more specific descriptor of 240 urbanization. The percentage of urban habitats at the 5-arcminute resolution was derived 241 from MODIS-based global land cover climatology data at 500m resolution (Broxton et 242 243 al. 2014).

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245 Niche analyses

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We compared the climatic and human disturbance niches of different phylogroups of a
given species in its native range using the framework proposed by Broennimann et al.
(2012). These analyses involved four steps: (1) definition of a two-dimensional gridded

environmental space, (2) calculation of the density of occurrences along the two-250 251 dimensional environmental space using kernel smoothers (3) measurement of niche 252 overlap between occurrence densities of two given groups along the environmental space and (4) statistical tests of niche similarity using a randomization approach. For 253 climatic niche analyses the gridded environmental space was that formed by the first 254 255 two axes of a PCA on the five climatic variables considered (see above) in 5-arcminute pixels across the world. These axes explained 78% of the inertia. The first PCA axis 256 (45%) predominantly represented temperature gradients (with higher values 257 258 representing warmer climates) while the second axis (33%) represented precipitation gradients (with higher values representing drier climates with higher precipitation 259 seasonality, Table S3). For the human space, the two axes represented the two human-260 related variables considered (i.e., the Global Human Influence Index and the percentage 261 262 of urban environments - see above). Niche similarity was assessed using the Schoener's D metric, calculated from the occupancies in the environmental space depicted by the 263 two first axes of the PCA. This metric indicates the overall match between two niches 264 265 over the whole climatic or human spaces and ranges from 0 (no overlap) to 1 (complete overlap). We calculated niche similarity between each phylogroup of a species and all 266 the other phylogroups using one-to-one comparisons. 267

268 We assessed niche conservatism by conducting niche similarity tests, whereby each obtained value of niche similarity was compared against a null distribution of 100 269 simulated similarity values (obtained when comparing the observed niche of one 270 271 phylogroup with niches obtained by drawing occurrences at random within available habitats and vice versa) (Warren et al. 2008; Broennimann et al. 2012). Note that the 272 niche similarity test is thus bidirectional, and two tests were conducted for each 273 274 comparison between two phylogroups. As available habitat for each phylogroup in species' native ranges for analyses, we considered two alternative approaches. First we 275 considered all ecoregions (Olson et al. 2001) occupied by each species in its native 276 range (Figs. 1b and S2), as this might represent the complete gradient of climatic and 277 278 human conditions that the study species could have reasonably encountered considering that dispersal is expected to be mainly limited by major biogeographical barriers in 279 native ranges (Soberon and Peterson 2005). Second, we accounted for potential spatial 280 281 constraints limiting the access of different phylogroups to available habitat for the 282 whole species. For this, we repeated the niche similarity tests considering as available habitat for each phylogroup that present within the geographic range actually occupied 283 284 by that particular phylogroup: i.e., that limited by the geographic boundaries derived from Thiessen polygons (Fig.S1). The results of both analyses were highly consistent 285 (Table S4), and for simplicity we thus only provide those for the former approach in the 286 main manuscript. All analyses were conducted using the 'ecospat' library in R software 287 (Broenniman et al. 2014). The minimum sample size for analyses was five occurrences 288 289 (Broennimann et al. 2012).

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291 Species distribution models

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We fitted SDMs calibrated on occurrences of different phylogroups (single-phylogroup models) and for the species as a whole (species-level model) to generate global
predictions of species potential distributions outside their native ranges. For robustness of analyses only phylogroups with more than 50 occurrence locations (exceptions: 1
phylogroup for the northern cardinal *Cardinalis cardinalis*, 1 for the oriental magpie-robin *Copsychus saularis* and 9 for the ring-necked parakeet *Psittacula krameri*) were
retained for single-phylogroup models (Stockwell and Peterson 2002). Data from

phylogroups with fewer than 50 occurrence locations were also disregarded from 300 species-level models, to avoid biases in model comparisons related to differences in the 301 302 data used. Predictions were derived from an ensemble model of three techniques generalized linear models, MAXENT and random forest - using R library 'biomod2'. 303 Both the linear and quadratic terms of the climate and human predictors were 304 305 considered, to account for positive or negative responses to intermediate values of the variables. All models were run with a single set of a maximum of 10,000 pseudo-306 absences randomly drawn from all ecoregions occupied by each species across its native 307 308 range as with niche analyses (Figs. 1b and S2). Presences and pseudoabsences were weighted as such to ensure neutral (0.5) prevalence. 309

To reduce the potential effect of sampling biases in the data, a bias file was 310 created by retrieving from GBIF occurrence data at the family level for each species 311 (Elith et al. 2010; Cardador and Blackburn 2019). We derived a kernel density map of 312 sampling bias at a 5-arcminute resolution using ArcMap 10.5 to be included as a fixed 313 effect in model training. Occurrence data from species in the same taxonomic family are 314 315 expected to suffer from the same detection limitations, reducing the effect of sampling biases in observed distribution patterns. To further account for potential effects of the 316 data selection, we conducted 10 replicates for each model by using random samples 317 318 (70%) of the complete datasets. Final ensemble model predictions for each species and phylogroup were generated as averaged means of all model replicates conducted (Fig. 319 1c-e). Sampling bias was set to its maximum value for model predictions. For each 320 321 species, a composite model prediction integrating information on all single-phylogroup models was then developed (phylogroup-composite model) (Fig. 1f). For this, single-322 phylogroup predictions were first standardized to a maximum value of 1 to make them 323 comparable. We then calculated the mean probability of occurrence of at least one of 324 the related phylogroups using the multiplicative probability method described in 325 Pearman et al. (2010). We converted continuous model predictions into binary 326 presence-absence maps by implementing a threshold for species presence that 327 328 maximized sensitivity plus specificity (Liu et al. 2005) in the training region (Fig. 1g). 329 In the case of composite models, binary maps were obtained by assigning species presence to each cell that was predicted suitable for at least one single-phylogroup 330 331 model (Fig. 1h). To reduce problems related to model extrapolation, model projections were adjusted using multivariate environmental similarity surfaces (MESSs) (Mateo et 332 al. 2014) (Fig. S3). Environmental suitability in dissimilar areas (MESS <0) was 333 334 considered to be zero. However, analyses using non-adjusted model projections were 335 highly concordant (see results).

Model accuracy of phylogroup-composite and species-level models in predicting 336 337 species occurrences in the native range were evaluated using the Boyce index (which ranges from -1 to 1, with higher values indicating higher match (Hirzel et al. 2006)) and 338 AUC (which ranges from 0 to 1, with values up to 0.5 representing models not better 339 than random (Phillips et al. 2006)), using the libraries 'pROC' and 'ecospat' in R. 340 Sensitivity (i.e., the proportion of correctly classified presences) was also computed 341 using the binary maps derived from continuous predictions. Potential differences in 342 343 accuracy metrics among species-level and phylogroup-composite models in native 344 ranges were evaluated using non-parametric paired Wilcoxon signed rank tests.

- 344 345
- 346 Geographic extent of SDM predictions
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We calculated the extent of predicted suitable habitat in km² for each species at a global
 scale according to binary map projections of single-phylogroup, phylogroup-composite

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and species-level models, using the library 'raster' from R. Accounting for intraspecific 350 variation is expected to improve the representation of different phylogroups in models 351 352 (particularly the most scarce and narrowly distributed in the native range), and thus to increase the geographical distribution of habitat conditions predicted as suitable for 353 alien birds: environments occupied by rarer phylogroups are expected to be marginal, 354 355 and thus result in low probabilities of occurrence in those environments when distribution is modelled at the species level. Differences in the extent of phylogroup-356 composite and species-level model predictions in alien ranges were evaluated using 357 358 one-tailed paired t-tests. We also tested the hypothesis that the niches occupied by the most narrowly distributed phylogroups in the native range are little represented in 359 species-level models. For this, we assessed the relationship between the percentage of 360 habitat predicted as suitable by single-phylogroup models also predicted as suitable by 361 362 species-level models and phylogroup relative range size (i.e., the proportion of species native range covered by a given phylogroup). We used general linear models (GLM) for 363 364 those analyses.

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366 Accuracy of SDM predictions

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368 SDM-based predictions were tested against real occurrence data in alien ranges using the Boyce index, AUC and sensitivity using the libraries 'pROC' and 'ecospat' in R as 369 in native ranges. As background for AUC and Boyce calculations, we followed the 370 371 framework proposed by (Strubbe et al. 2013, 2015) to estimate the area that could have been effectively accessible to introduced birds. We buffered each 5-arcminute alien 372 373 locality with a distance equal to the minimum invasion speed recorded for birds (i.e. 374 4.59 km year, derived from (Blackburn et al. 2009)) multiplied by the number of years since introduction (Fig. S4). For localities with duplicate records the oldest year was 375 used in analyses. When the specific year of introduction was not provided ($\leq 4\%$ of total 376 alien localities for each species), we were conservative and only considered that locality 377 378 (not a buffer around it) for background calculations. Buffers were only allowed to cover areas effectively outside species native breeding ranges. Both occurrence localities in 379 regions where the species has effectively established (see 'Phylogenetic and occurrence 380 381 data' section) and known introduction localities (compiled from (Redding et al. 2019)) 382 were used. Differences in the accuracy of phylogroup-composite and species-level model predictions in alien ranges were evaluated using one-tailed paired t-tests (AUC) 383 384 and one-tailed paired Wilcoxon signed rank tests (Boyce and sensitivity) according to fit of normality and homoscedasticity assumptions. 385

386

387 **RESULTS**

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389 Intraspecific climatic and human niche variation

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Phylogenetic groups within species occupied partially overlapping portions of the 391 392 climate and human spaces available in the native range. However, climatic niche similarity among phylogroups of a species was low (mean \pm SD, D = 0.07 \pm 0.09, N = 393 8) and not more similar than expected by chance for the vast majority of phylogroups 394 within species (95% of 101 reciprocal similarity tests involving 32 phylogroups from 395 396 eight species had P > 0.05, Table S4). Human niche similarity was higher than climatic niche similarity (D = 0.32 ± 0.13), but generally not more similar (97% of tests had P > 397 0.05) than expected by chance for most comparisons. 398

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400 Species distribution models in native ranges

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402 Species-level and phylogroup-composite model predictions showed a good agreement 403 with species occurrences in the native ranges (mean \pm SD, species-level: Boyce = 0.88 \pm 404 0.24, AUC = 0.86 ± 0.11 , sensitivity = 0.78 ± 0.19 ; phylogroup-composite: Boyce = 0.91 ± 0.12 , AUC = 0.84 ± 0.09 , sensitivity = 0.89 ± 0.10). No significant differences in 405 model performance between species-level and phylogroup-composite models were 406 407 observed (one-tailed paired Wilcoxon rank test: Boyce, V = 21.5, P = 0.71; AUC, V =

- 28, P = 0.93; sensitivity, V = 6, P = 0.054). 408
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410 Geographic extent and accuracy of model projections in alien ranges

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412 Species-level and phylogroup-composite models provided similar but not equal predictions of habitat susceptible to invasion (Figs. 1e-h, S5 and S6). Notably, 413 414 phylogroup-composite models projected significantly larger habitat suitability at a global scale than species-level models (Fig. 2a, t = -2.0, df = 7, P = 0.04). On average, 415 only $30 \pm 16\%$ of total pixels predicted as suitable by binary maps derived from both 416 417 species-level and phylogroup-composite models were coincident between both types of models, while $52 \pm 30\%$ of pixels were predicted as suitable only by phylogroup-418 419 composite models and $18 \pm 19\%$ only by species-level models. The capacity of species-420 level models to predict the occurrence of individual phylogroups was significantly related to phylogroup range size (estimate: 0.68 ± 0.13 , P < 0.001, R² = 0.55; Fig. 3). 421

When used to predict occurrences in alien ranges, model accuracy was on average 422 423 good according to different metrics considered (Figs. 2b-d), but high variability was observed among species (Figs. 2b-d; see also Fig S7 for comparisons of models not 424 adjusted by MESS analyses). Accounting for intraspecific niche variation did not 425 improve model accuracy (Boyce, V = 21, P = 0.69; AUC, t = -0.09, df = 7, P = 0.47; 426 427 sensitivity, V = 9, P = 0.22). These result hold when omitting *Platycercus elegans* from analyses (Boyce, V = 14, P = 0.53; AUC, t = -0.29, df = 6, P = 0.39; sensitivity, V = 9, 428 P=0.22), for which sample size in the alien range was very low (Table 1). 429

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DISCUSSION 431

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433 There is a limited number of studies considering intraspecific niche variation in models assessing environmental susceptibility to the colonization by alien birds, and they have 434 rarely compared modelled predictions against independent sets of occurrence data 435 (Peterson et al., 2019). Our results agree with recent evidence suggesting that 436 437 conspecific phylogenetic lineages of a species can differ in the climates and human disturbance conditions they experience in native ranges (Peterson and Holt 2003; 438 439 Pearman et al. 2010; D'Amen et al. 2013): we find little climatic niche similarity among phylogroups of the 8 species in our study. Accounting for intraspecific variation in 440 SDMs modified the distribution and the extent of potential suitable habitat for the whole 441 442 species. However, contrary to our expectations, accounting for intraspecific niche variation did not result in more accurate model predictions, according to current 443 444 distributions of established alien species.

445 The increased extent of phylogroup-composite model predictions, when compared to classical species-level models, suggests that the omission of intraspecific niche 446 structure from species distribution models underestimates intraspecific realized niche 447 448 variation, and thus species-level prediction of habitat susceptible to invasion (Peterson

and Holt 2003; D'Amen et al. 2013; Godefroid et al. 2016). The extents of geographic
areas occupied by different phylogroups of a species in our study were not equivalent
(Fig. S1), and this may lead to some phylogroups (particularly the most scarce and
narrowly distributed in the native range) having little representation in model
predictions obtained by classical species level models (Fig. 3).

454 However, contrary to our expectations, accounting for intraspecific niche variation did not improve model accuracy when predicting occurrences in alien ranges. These 455 results could be related to different, not mutually exclusive processes. First, it should be 456 noted that phylogroup separation - in this study and in general - relies on neutral 457 molecular markers. Strong structuring in these markers across populations indicates 458 reduced dispersal and thus increased potential for local genetic adaptation to emerge 459 (Lenormand 2002). Yet, we do not know whether genetic structuring in neutral markers 460 461 really reflects local genetic adaptation to climatic and human environmental conditions experienced (Holderegger et al. 2006), and thus in these species tolerances, or just 462 reflects differences in the realized (i.e., occupied) niche of different phylogroups 463 464 (Guisan et al. 2014; Peterson et al. 2019). In this sense, since most phylogroups within species considered have allopatric distributions, observed realized niche divergence may 465 466 have been driven by different environmental conditions in the range of each 467 phylogroup, rather than by adaptation to different conditions within a shared spatial distribution (Maia-Carvalho et al. 2018). If so, dividing a species' range into several 468 469 groups might have yielded different climate-occupancy relationships for each group 470 even in the absence of local adaptation. In our study, this could explain the larger species range predictions of models considering phylogroup information, but the quite 471 similar prediction performances. For some species it is also possible that local 472 473 adaptation occurs at higher or lower taxonomic levels (Peterson et al. 2019; Smith et al. 474 2019) or geographic scales (Cardador et al. 2016).

Second, lineages little represented in classical species-level models are also those 475 less likely to be introduced and subsequently established in new areas, given the 476 477 positive effects of abundance and geographic range size on introduction and 478 establishment success in alien species (Blackburn and Duncan 2001b, a). If this is the case, accounting for intraspecific niche variation would result in small differences in 479 480 model prediction for the most commonly translocated taxa. At the same time, 481 accounting for intraspecific niche variation might overestimate the potential alien range size, as the environmental tolerances of alien individuals would actually be narrower 482 483 than that of the species as a whole. Under this hypothesis (i.e., the more common phylogroups in native areas are more often introduced and established in alien ranges), 484 higher model accuracy for the more common phylogroups should be expected. 485 However, post-hoc analyses assessing the relationship between accuracy of single-486 phylogroup model predictions and phylogroup relative range size (i.e., the proportion of 487 species native range covered by a given phylogroup) offer little support for this 488 hypothesis (Pearson correlation coefficients between accuracy metrics and phylogroup 489 range size, AUC: r = -0.20, P = 0.33; Boyce: r = -0.01, P = 0.97, N = 25). 490

Third, as most bird introductions are relatively recent, species might not occupy 491 492 all of the potential suitable environments available in the invaded range, due to dispersal 493 limitations (Blackburn et al. 2009; Ascensão et al. 2020). For some species, current 494 alien distributions may thus reflect the characteristics of the new introduction localities 495 rather than optimum environmental conditions, which might be more likely to be moved 496 into during spread (Abellán et al. 2017). Furthermore, while climate and human variables appeared to be major factors shaping alien species distributions (Cardador and 497 Blackburn 2019), omission of other important drivers of bird distributions, such as 498

499 interspecific interactions (Blackburn et al. 2009; Redding et al. 2019), might also produce an overestimate of the projected suitable area for species. Some species might 500 501 even undergo niche shifts in alien ranges, although this seems to be less frequent (Broennimann et al. 2007; Strubbe et al. 2013; Cardador and Blackburn 2020). All of 502 these issues may have contributed to reduce model accuracy for both species-level and 503 504 phylogroup-composite model predictions in alien ranges, masking potential differences.

Overall, our results show variability in model predictions linked to taxonomic 505 506 level considered. However, comparisons of model predictions with current available 507 distribution data in alien ranges do not provide evidence of an improvement in prediction accuracy for models accounting for intraspecific niche variation. This result 508 509 is relevant given the lack of information about the presence and geographical distribution of phylogeographic lineages for many species: according to our results, 510 511 until more accurate information on intraspecific variability is available, species-level models can be reasonable candidates. However, when phylogeographic information is 512 available, the use of the most conservative criterion (i.e. to model both species and 513 514 lineages on the basis of the actual range, e.g. Mori et al. 2019) is recommended, given that the ultimate purpose of such modelling exercises is to reduce invasion risks and 515

- their consequences on biodiversity conservation. 516
- 517 518

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- 527

528 **Conflicts of interest/Competing interests**

529 The authors have no conflict of interest to disclose.

530

531 Availability of data and material

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All data used in this manuscript have already been published or archived and can be 533

accessible via Figshare http://dx.doi.org/10.6084/m9.figshare.4234850 (Dyer et al. 534

2016), GBIF.org (2018 - for a complete list of GBIF occurrence downloads see Table 535

S1), WorldClim database (Hijmans et al. 2005) available for download from 536

http://www.worldclim.org, BirdLife International & NatureServe, (2014) available for 537

538 download from http://datazone.birdlife.org/species/requestdis and terrestrial

ecoregions of the world (Olson et al. 2001) available for download from 539

http://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world. Data on 540

541 geographic extent and accuracy of model projections will be accessible via Figshare 542 should the manuscript be accepted.

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Code availability 545

547 Code associated with this manuscript will be accessible via Figshare should the manuscript

548 be accepted. 549

550	Authors' contributions
551 552	'Not applicable'
552	Ethics approval
554	'Not applicable'
555	Concent to participate
550	(Nat applicable)
557 EE0	Not applicable
550	Consent for publication 544
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561	Not applicable
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Table 1. Bird species selected on the basis of the existing literature on phylogeographic structure. Species name, number of phylogroups per species, source for phylogenetic data and the number of occurrences available in the native and alien ranges according to GBIF (<u>www.gbif.org</u>) are provided. For native occurrences, the minimum and maximum occurrences available for different phylogroups are shown in parentheses.

Species	Phylogroups	References	Native occurrences	Alien occurrences
Alauda arvensis	2	Zink et al. 2008	19789 (232- 19557)	2378
Cardinalis cardinalis	6	Smith et al. 2011	41372 (9-40079)	200
Copsychus saularis	3	Sheldon et al. 2009	3893 (20 - 3726)	36
Corvus frugilegus	2	Haring et al. 2007	7445 (52-7393)	53
Perdix perdix	2	Liukkonen-Anttila et al. 2002	6444 (1804 - 6291)	2316
Pica pica	2	Haring et al. 2007	32052 (782 - 31270)	115
Platycercus elegans	2	Joseph et al. 2008	5046 (79- 4967)	2
Psittacula krameri	17	Strubbe et al. 2015	3156 (1-1834)	701

- 751 Figure Legends

Figure 1. Phylogroup distribution, native occurrences and model predictions for the Eurasian skylark Alauda arvensis. (a) Distribution of two different phylogroups (red and orange) as derived from Thiessen polygons and locations with genetic data (points); (b) native occurrence data (black dots) and background (i.e., all ecoregions occupied by each species in its native range, grey) used for species distribution modelling; (c-d) continuous predictions of single phylogroup models, polygons show the distribution of the phylogroup used in models; (e) species-level model continuous predictions; (f) phylogroup-composite model continuous predictions; (g) species-level model binary predictions; (h) phylogroup-composite model binary predictions. In (g) and (h), green represents habitat predicted as suitable and grey as non-suitable.

Figure 2. Comparisons of (a) extent of suitable habitat and (b - d) model accuracy in alien ranges between species distribution models accounting or not for phylogroup niche variation. Extent of suitable habitat (a) is derived from binary maps using the maximum sensitivity plus specificity threshold. Model accuracy in alien ranges is assessed by the AUC (b), TSS (c) and sensitivity (d). N = 8.

Figure 3. Similarity between single-phylogroup and species-level model predictions in
relation to phylogroup relative range size. Similarity refers to the percentage of pixels
predicted as suitable by a single-phylogroup model also predicted as suitable by
species-level models at a global scale.





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Model comparisons: (a) t = -2.3, df = 7, P = 0.03; (b) V = 21, P = 0.69; (c) t = -0.09, df = 7, P = 0.47; (d) V = 9, P = 0.22





