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1 **Microclimate Affects the Distribution of Grassland Birds, but not Forest Birds,**
2 **in an Alpine Environment**

3

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29 **Abstract**

30 Predictions derived from species distribution models (SDMs) are strongly influenced by the
31 spatial scale at which species and environmental data (e.g. climate) are gathered. SDMs of
32 mountain birds usually build on large-scale temperature estimates. However, the topographic
33 complexity of mountain areas could create microclimatic refuges which may alter species
34 distributions at small spatial scales. To assess whether fine-scale data (temperature and/or
35 topography) improve model performance when predicting species occurrence, we collected
36 data on presence-absence of bird species, habitat and fine-scale temperature at survey points
37 along an elevational gradient in the Alps (NW Italy). Large-scale temperature data, and both
38 large- and fine-scale topography data, were extracted from online databases for each point.
39 We compared species models (fine-scale vs large-scale) using an information-theoretic
40 approach. Models including fine-scale temperature estimates performed better than
41 corresponding large-scale models for all open habitat species, whereas most forest/ecotone
42 species showed no difference between the two scales. Grassland birds such as Northern
43 Wheatear *Oenanthe oenanthe* and Water Pipit *Anthus spinoletta* were positively associated
44 with warmer microclimates. These results suggest that alpine grassland species are potentially
45 more resistant to the impact of climate change than previously predicted, but that indirect
46 effects of climate change such as habitat shifts (forest- and shrub encroachment at high
47 elevations) pose a major threat. Therefore, active management of alpine grassland is needed
48 to maintain open areas and to prevent potential habitat loss and fragmentation. SDMs based
49 solely on large-scale temperatures for open habitat species in the Alps should be re-assessed.

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52 **Key words:** information-theoretic approach, mountains, species distribution models,
53 temperature, topography.

54

55 **Introduction**

56 Species distribution models (henceforth SDMs) are a widely used tool in conservation (Guisan
57 and Thuiller 2005, Rodríguez et al. 2007, Franklin 2013) for a range of taxa (Ongaro et al.
58 2018, Lewthwaite et al. 2018, Hof and Allen 2019). In the face of climate change, SDMs have
59 become particularly important in predicting current and/or future distributions of species under
60 different climate change scenarios (Avalos and Hernández 2015, Jackson et al. 2015,
61 Lehtikainen and Virkkala 2016). These studies usually rely on macroclimate data, which
62 describe climatic conditions at a relatively large scale (approximately one square kilometre or
63 more; Zellweger et al. 2019) derived from national networks, weather stations or online
64 databases (e.g Worldclim; Hijmans et al. 2005).

65 However, mountain environments are often poorly represented by conventional climate
66 station data, and uncertainty for interpolated climatic values is high (Hijmans et al. 2005).
67 Furthermore, local temperature can vary substantially due to the topographic complexity in
68 mountain areas (Scherrer and Körner 2010, Gunton et al. 2015), thus creating a mosaic of
69 microclimatic conditions over small spatial scales. Depending on discipline, microclimates
70 have been defined in various ways. In this study, we adopt the definition by Bramer et al. (2018)
71 who defined microclimate as fine-scale climate variations at spatial resolutions of < 100m,
72 which are influenced by fine-resolution biotic and abiotic variations (topography, soil type and
73 vegetation). Topographic variables like aspect and slope can markedly alter microclimate by
74 influencing the amount of incoming solar radiation between different exposed slopes. Between
75 north and south exposed slopes, temperature can differ by approximately 1°C if slopes are
76 gentle (<5°) but can increase up to 5°C if slopes are steep (40°; Gubler et al. 2011). Moreover,
77 these differences could subsequently influence snow accumulation processes and thus the
78 rate of snow melt in spring (Gubler et al. 2011).

79 There is mounting evidence of the importance of microclimate in influencing habitat
80 selection. For example, Bramblings *Fringilla montifringilla* tend to rest in higher densities in
81 areas with warm microclimatic conditions (Zabala et al. 2012). In Mountain Chickadees *Poecile*
82 *gambeli*, microclimates influence the selection of foraging sites (Wachob 1996). Microclimates

83 can also act as thermal refuges, which enable individuals to persist despite unfavourable
84 ambient conditions (Wilson et al. 2015). This has been shown in Northern Bobwhites *Colinus*
85 *virginianus*, which mitigated thermal stress by seeking thermally-buffered microclimatic sites
86 during hot days (Carroll et al. 2015). Furthermore, Northern Bobwhite nest site selection was
87 proven to be influenced by microclimate: Individuals nested in cooler and moister microclimatic
88 conditions compared to surrounding non-nesting locations (Tomecek et al. 2017, Carroll et al.
89 2018).

90 Only a few studies have investigated the role of microclimate within a mountain context.
91 Frey et al. (2016) showed that fine-scale temperature metrics were strong predictors of bird
92 distributions, with temperature effects being larger than vegetation effects on occupancy
93 dynamics in mountain forests (but see Viterbi et al. 2013). In the Alps, the habitat of the alpine
94 Rock Ptarmigan *Lagopus muta helvetica* is characterised by a wide variety of microclimates
95 over small spatial scales with individuals choosing colder sites in summer (Visinoni et al. 2015).

96 Beside the direct impact on birds, microclimate also plays a crucial role in habitat selection
97 in insects. It has been demonstrated that in *Parnassius apollo*, a mountain specialist butterfly,
98 larval habitat selection is related to ambient temperature. Larvae selected warm microclimates
99 when ambient temperatures fell below a threshold of 27°C, whereas cold microclimates were
100 selected when this threshold was exceeded (Ashton et al. 2009). Microclimate can further
101 influence oviposition (Stuhldreher et al. 2012), and the precise microclimatic conditions for
102 thermoregulation are actively sought by montane species of the genus *Erebia* (Kleckova et al.
103 2014). In this respect, microclimate won't only shape the distributions of these butterfly species,
104 but it will also indirectly influence bird species which rely on caterpillars as a food source for
105 chick rearing.

106 Microclimate thus has the potential to influence many aspects of an organism's life cycle.
107 It could help to buffer or to compound the effects of climate change (Spasojevic et al. 2013).
108 To assess the impact of climate change on current or future distributions of species it is crucial
109 to gather climate data at the most appropriate scale in order to increase model accuracy
110 (Barton et al. 2018, Randin et al. 2009). However, predictions for future geographic

111 distributions of mountain birds under a range of climate change scenarios have thus far been
112 based on models which have considered climate variables measured at large scales, usually
113 ca. 1 km² (Chamberlain et al. 2013, 2016, Brambilla et al. 2016, 2017a). Given the potential
114 for bird responses to microclimatic conditions in mountains (Frey et al. 2016, Visoni et al.
115 2014), it may be more appropriate to consider the role of climate measured at finer spatial
116 resolutions in determining mountain bird distributions. This is particularly important given that
117 environmental conditions in mountains typically change over very small spatial scales thanks
118 to steep elevation gradients (Scherrer and Körner 2010, Gunton et al. 2015).

119 In this study, we investigated the role of microclimate for a range of Alpine ecotone and
120 open habitat species. There were two specific aims. First, to evaluate if models including a
121 microclimatic variable (in this case temperature) show better performance than models using
122 large-scale climate estimates. This will inform future modelling studies, and should help to
123 improve predictions of future impacts of climate change on Alpine birds where microclimatic
124 effects are evident. Second, to assess if models including topographic variables (slope and
125 aspect) in combination with climatic variables (fine and large scale) increase model
126 performance. This will assess the extent to which topographic variables should be included in
127 SDMs of alpine bird species. Based on previous studies, which showed that microclimate can
128 influence bird distributions within mountain habitats (Frey et al. 2016, Visoni et al. 2015), we
129 hypothesise that models using fine-scale temperature estimates will show better model
130 performance than models using large-scale temperature estimates.

131

132 **Methods**

133 Study area and point selection

134 The study was carried out in Val Troncea Natural Park (44°57'28" N; 6°56'28" E) in the western
135 Italian Alps. At lower elevations, the area is dominated by larch *Larix decidua*. The natural
136 treeline is typically found at around 2200 m asl, but varies depending on local conditions.
137 Typical shrub species are *Juniperus nana* (henceforth Juniper) and *Rhododendron*
138 *ferrugineum* (henceforth Rhododendron) which rapidly encroached wide areas of grasslands

139 after the decline of agro-pastoral activities. Grasslands are mainly dominated by *Festuca*
140 *curvula*, *Carex sempervirens*, and *Trifolium alpinum*. Scree and rocky areas occur
141 predominantly at higher elevations, above approximately 2700 m asl.

142 Point counts were carried out along an elevational gradient ranging from 1750 m to 2820
143 m encompassing forest, ecotone and open habitats. Point count locations coincided with the
144 centroids of a pre-existing grid at a scale of approximately 150 x 150 m (there was some
145 variation, due to access constraints for example; Probo et al. 2014) along the western facing
146 slope of the valley. All points were spaced a minimum of 200 m apart.

147

148 Bird surveys

149 Point counts (n = 221) were carried out from mid-May to mid-July 2017 following the methods
150 of Bibby et al. (2000), using a 10 minute count period. At each point count location, all individual
151 birds seen or heard were recorded within a 100 m radius (estimated with the aid of a laser
152 range finder). Point counts commenced 1-1.5 h after sunrise and continued until 1200 h.
153 Surveys did not take place in excessively wet or windy conditions. Each point count location
154 was visited once.

155

156 Habitat data collection

157 At each point count location, habitat data were collected through the visual estimation of the
158 percentage cover of canopy (i.e. vegetation above head height), the dominant shrub species,
159 open grassland and bare rock (including scree and unvegetated areas) within a 100 m radius
160 of the point's centre. The dominant shrub species were defined into four groups:
161 Rhododendron, Juniper, bilberry (*Vaccinium myrtillus* and *V. gaultherioides*) and other (e.g.
162 Green Alder *Alnus viridis*, Willow *Salix spp*, and also including young trees less than two
163 meters in height, mostly European Larch *Larix decidua*). Furthermore, the number of mature
164 trees (greater than c. 20 cm in diameter at breast height) within a 50 m radius of a point count
165 location was counted. These estimates have been shown to correlate well with estimates of

166 land cover derived from remote sensing and have been used as the basis of predictive models
167 for several species considered here (Chamberlain et al. 2013, 2016, Jähnig et al. 2018).

168

169 Temperature measurements

170 At each point count location, temperature was measured with hygro buttons (Plug & Track™),
171 using methods based on Frey et al. (2016). Each button was stuck on the bottom of a small
172 plastic cup, which was attached upside down to a bamboo stick to protect the button against
173 wind, direct sunlight and water. Mean button height was 40.89 cm (min = 28 cm, max = 47
174 cm). Hygro buttons were programmed to record temperature every 5 minutes. They were
175 placed 24 hours before a point count commenced and were collected 24 hours after the point
176 count ended, which resulted in a total recording time of 48 hours. At every hygro button
177 location, button height, distance to slope, substrate and canopy presence/absence was
178 recorded.

179

180

181 Statistical analysis

182 *Temperature modelling*

183 For each point count location, minimum, maximum and mean temperatures were derived over
184 the 48 hour recording period. All temperature measurements were checked for collinearity by
185 calculating Pearson's correlation coefficient. Mean temperature was strongly correlated with
186 both minimum ($r = 0.80$) and maximum temperature ($r = 0.73$) over the recording period.
187 Therefore, temperature modelling was undertaken with mean temperature values. The same
188 procedure was repeated for night-time temperatures. Minimum, maximum and mean night-
189 time temperatures were obtained for the time period between 23.00 pm and 03.00 am over the
190 same recording period at each point. There was a strong positive correlation of mean night-
191 time temperature between minimum ($r = 0.97$) and maximum night-time temperature ($r = 0.89$).

192 The objective of the first analysis was to model temperature in relation to date and
193 elevation. This model was then used to predict a standardised temperature at each point count

194 location, set at a fixed date, which was representative of the fine-scale temperature at that
195 point controlling for seasonal effects. This procedure provided data which was analogous to
196 the larger scale temperature data (see below). This standardised temperature was then used
197 subsequently as a variable in species distribution models. Note that all subsequent modelling
198 steps were performed separately for mean temperature and mean night-time temperature.
199 However, models with night-time temperature were very similar to those using mean
200 temperature, so we focus on the latter. Further details on night-time temperature models are
201 given in the Electronic Supplementary Material (ESM) Table S1.

202 First, to investigate if temperature recording was influenced by characteristics of the hygro
203 button's position, it was analysed using a generalised linear model in relation to button height,
204 distance to slope, substrate underneath the button and canopy presence/absence, specifying
205 a normal error distribution. None of the variables showed a significant effect on mean
206 temperature ($p > 0.05$), therefore they were not considered further in the analysis.

207 In the next modelling step, standardised temperature estimates were derived separately
208 for open Alpine grassland and forest/ecotone habitat, i.e. models were used to estimate
209 temperature for a given elevation whilst accounting for seasonal variation. Points were
210 classified as Alpine grassland if there was no canopy within 100m radius of the point count
211 centre (following Chamberlain et al. 2013). For open habitat points ($n = 93$), temperature was
212 modelled in relation to date and elevation. Date was described as the number of days passed
213 since the start of the field season, where day 1 = 27-May-2017. Canopy cover was added to
214 the model structure for points located in forest and ecotone habitat ($n = 128$). In both cases, a
215 normal distribution was specified. Prior to modelling, all variables were scaled and centred
216 using the scale function in R. Collinearity was assessed using Variance inflation factors (VIFs),
217 calculated using the 'corvif' function (package 'AED', Zuur et al. 2009), and by considering
218 Spearman correlations between continuous variables. All variables had $VIF < 3$, and no pair of
219 variables showed a correlation > 0.7 , indicating low levels of inter-correlation. These models
220 were used to derive a standardised temperature for each point, based on the elevation at that
221 point, the canopy cover (for forest/ecotone habitat) and for a date fixed at 15th June.

222

223 *Species distribution models*

224 Birds detected within a 100-m radius of a point count location were used to analyse species
225 distribution (presence/absence of individual species). Bird species were considered in the
226 modelling process if they were present on at least 15 % of the points; below this threshold
227 model performance is consistently poor (Chamberlain et al. 2013).

228 The commonest species were modelled in relation to four different variable sets: (i) habitat
229 (HABITAT), (ii) habitat + temperature (TEMP), (iii) habitat + topography (TOPO), (iv) habitat +
230 temperature + topography (COMB; Table 2). Temperature and topographic variables were
231 used at two different scales (large-scale/ fine-scale). Fine-scale temperature estimates were
232 derived from the temperature modelling approach described above, whereas large-scale
233 temperature data for each point were extracted from the Worldclim database (Hijmans et al.
234 2005) by calculating the average temperature within a 1000 m radius of the point count centre.
235 Topographic variables (aspect and slope) were derived from a Digital Elevation Model (DEM)
236 at a spatial resolution of 10 metres. Aspect was transformed as $x = -1 * \cos[\varnothing(\pi/180)]$, where \varnothing
237 is measured in degrees. Values ranged from 1 where solar insolation was higher (south-facing
238 slopes) to -1 (north-facing slopes) where it was lower.

239 The mean aspect (transformed values) and slope was calculated within a 100 m (fine-
240 scale) and a 1000 m (large-scale) radius of the point count centre for the analysis. Habitat
241 variables were kept at a constant scale in the models (as the objective was to test scale effects
242 in temperature and topography).

243 Habitat models of Lesser Whitethroat *Sylvia curruca* and Dunnock *Prunella modularis*
244 were tested for non-linear relationships with Rhododendron and Juniper cover as suggested
245 by previous work (Jähnig et al. 2018). Habitat models with and without quadratic terms for shrub
246 species cover were compared using AIC. Lesser Whitethroat models showed lower AIC values
247 for the habitat model without quadratic terms. Therefore these were omitted in further modelling
248 steps. The addition of the quadratic term for Rhododendron cover reduced the AIC of the
249 habitat model for Dunnock by $\Delta AIC > 2$, hence it was included in the next modelling steps.

250 The occurrence probability of each species was modelled in relation to the different
251 variable sets using a binomial logistic regression, after controlling for potential collinearity (as
252 above). In the case of open habitat species, we found high VIFs for the variables rock and
253 grass cover. After the removal of rock cover, all VIFs were below the threshold of three. As a
254 result, rock cover was removed from all models for open habitat species.

255 Data were analysed using an information theoretic approach with the MuMIn package in
256 R version 3.5.2; (R Development Core Team 2018, Bartón 2013). This entailed deriving full
257 models for each variable set at each scale (except habitat which was kept constant in all
258 models) using generalised linear models (R package lme4; Bates et al. 2015). This approach
259 served two goals. First, model-averaged parameter estimates were derived for all
260 combinations of variables in each full model set in order to identify variables that were most
261 closely associated with bird distribution. p -values derived from the model-averaged parameter
262 estimates and their SEs were considered to represent significant effects when $p < 0.05$.
263 Second, the Akaike information criterion corrected for small sample size (AICc) was
264 determined for each individual model and was used to assess model performance for different
265 variable combinations at different scales in the full model. In this way it was possible to assess
266 which combination of the four different variable sets produced the best models, and at which
267 scale.

268 At each scale, the residuals for all full models were extracted and tested for spatial
269 autocorrelation using Moran's I (Moran 1950). Significant spatial autocorrelation was found for
270 models of Eurasian Skylark *Alauda arvensis*, Tree Pipit *Anthus trivialis* and Water Pipit. For
271 these species, spatial effects were incorporated by modelling their distributions using
272 Generalized Additive Models (GAMs) from the mgcv package (Wood 2011) by fitting smoothed
273 terms for latitude and longitude in the model, following Wood (2017).

274

275 **Results**

276 In total, 862 individuals of 40 species were recorded in 221 point counts over an elevational
277 range of 1750 – 2800 m a.s.l. There were seven species that were recorded on at least 15%

278 of the points within forest and ecotone habitat: Dunnock, Lesser Whitethroat, Chaffinch
279 *Fringilla coelebs*, Mistle Thrush *Turdus viscivorus*, Coal Tit *Parus ater*, rock bunting *Emberiza*
280 *cia*, Tree Pipit and three species within open habitat: Eurasian Skylark, Water Pipit and
281 Northern Wheatear.

282 The best model to predict rock bunting occurrence was always the null model for each
283 model set at each scale, with no model-averaged parameter estimates being significant.
284 Therefore, this species was not considered further in the analysis.

285

286 Forest and ecotone species

287 Habitat variables such as trees and shrubs were the variables most commonly associated with
288 species occurrence within the HABITAT model for forest and ecotone species. In general, the
289 results of the HABITAT models were in line with previous findings by Jähnig et al. (2018).
290 Juniper showed a positive relationship with Coal Tit, Dunnock and Lesser Whitethroat, but was
291 negatively related to Tree Pipit presence. Rhododendron was positively associated with Mistle
292 Thrush and Lesser Whitethroat presence, whereas it showed a non-linear relationship with
293 Dunnock presence. The number of mature trees showed a positive relationship with forest
294 species (Chaffinch, Mistle Thrush and Coal Tit). Habitat associations among the species
295 remained mostly constant in TEMP, TOPO and COMB models (for full details see ESM Table
296 S2, S4).

297 Each variable set at each scale performed equally well for Lesser Whitethroat, Mistle
298 Thrush and Coal Tit (Table 3). (Note that full details of all models are given in ESM Table S3).
299 Large-scale temperature and topographic variables were included in the best performing
300 model for Dunnock, temperature being negatively associated with Dunnock presence (Table
301 4, Fig. 1). In contrast, large-scale temperature showed a positive relationship with Chaffinch
302 presence in models including only large-scale temperature (Table 4, Fig. 1), or in models
303 including a combination of large-scale temperature and topographic variables. In both species,
304 large-scale model sets performed better than their fine-scale equivalents. Large-scale models
305 for TOPO and COMB were the best performing models for Tree Pipit, whose presence was

306 more closely associated with large-scale topographic variables such as aspect, for which it
307 showed a strong negative relationship indicating a preference for westerly over southerly
308 slopes (Fig. 2). Beside Tree Pipit, only Mistle Thrush showed a negative association with
309 aspect. No other species showed any association with slope or aspect. Furthermore, Tree Pipit
310 was the only species that showed better model performance ($\Delta AICc \leq 2$) for the large-scale
311 TOPO model compared to all fine-scale models and the large-scale TEMP model. All other
312 species showed better (Chaffinch) or equal model performance of TEMP models compared to
313 TOPO models at both scales.

314

315 Open habitat species

316 The HABITAT model for each open species did not show any habitat associations among the
317 recorded variables. However, all fine-scale models (TEMP, TOPO and COMB) showed a
318 positive association between grass cover and Skylark presence while Juniper cover was only
319 positively associated in the TEMP and COMP models.

320 Models including fine-scale temperature and topography performed best ($\Delta AICc \leq 2$) for
321 Northern Wheatear. The best performing models of Skylark and Water Pipit included both fine-
322 scale TEMP and COMB models. Fine-scale temperature was positively associated with Water
323 Pipit and Northern Wheatear presence, whereas Eurasian Skylark presence was negatively
324 associated (Table 4, Fig. 3).

325 At a fine scale, TEMP models showed better model performance than TOPO models for
326 Northern Wheatear and Water Pipit, whereas on a large scale, model sets for TEMP and TOPO
327 were overlapping (Northern Wheatear, Water Pipit). The large-scale TOPO model showed
328 equal model performance compared to the large-scale TEMP model for Skylark, but AIC_c was
329 still higher compared to fine-scale COMB. In addition, aspect showed a positive relationship
330 with Northern Wheatear (Fig.2, fine-scale COMB model) and Skylark presence (large-scale
331 TOPO model) while slope was positively related to Skylark presence in the fine-scale TOPO
332 model.

333

334 **Discussion**

335 Models including fine-scale temperature estimates (TEMP, COMB) showed better model
336 performance ($\Delta AIC_c < 2$) than corresponding large-scale models for all three open habitat
337 species. Northern Wheatear and Water Pipit were both positively associated with warm
338 microclimates while Skylark presence was negatively associated with fine-scale temperature.
339 These results contrast with previous findings from the same region of the Alps (Chamberlain
340 et al. 2013, 2016), where model predictions were based on large-scale climatic variables. In
341 these studies, SDMs (based on temperature change and assuming no change in habitat)
342 suggested that under warmer conditions, Skylark and Northern Wheatear would show an
343 increase in their distribution whereas Water Pipit distribution would decrease. Therefore, for
344 Water Pipit and Skylark distributions, our findings suggest opposite associations between fine-
345 scale and large-scale temperature.

346 Differences in model predictions at different spatial scales have been reported for a range
347 of studies, and thus identifying the appropriate scale represents a major problem when
348 forecasting suitable habitat in order to inform conservation planning (Elith and Leathwick 2009,
349 Randin et al. 2009, Franklin et al. 2013, Logan et al. 2013, Scridel et al. 2018). To improve
350 SDMs, it is therefore necessary to carefully select predictors (e.g. temperature variables) and
351 their spatial resolution. In the case of microclimate, local topography could create areas with
352 suitable climatic conditions under which it would still be possible for a species to persist under
353 the impact of climate change. Through the use of large-scale climate data, these areas might
354 not be recognised by SDMs (Austin et al. 2011). Besides affecting the future distribution of a
355 species, microclimate can also influence many other aspects of a species' life cycle.

356 There is evidence that microclimate can be important in influencing habitat selection in
357 mountain birds which may explain our findings. For example, it has been shown that Horned
358 Larks *Eremophila alpestris* adjusted the amount of incubation time in response to microclimatic
359 conditions (Camfield and Martin 2009) by spending less time on the nest as temperatures in
360 the nest surrounding increased, which may imply energy savings in warmer microclimates.
361 Furthermore, microclimate and aspect strongly influenced nestling survival in Water Pipits

362 (Rauter et al. 2002). Nests which were located at ENE-facing slopes (temperature maximum
363 in the morning) had more fledglings than those on WSW-facing slopes (temperature maximum
364 in the afternoon). In contrast, foraging habitat selection by alpine White-winged Snowfinches
365 *Montifringilla nivalis*, a high altitude specialist, was influenced by solar radiation (Brambilla et
366 al. 2017b). Snowfinches preferred to forage at colder sites (low solar radiation) throughout the
367 season. These studies illustrate that behaviour, foraging habitat selection and choice of nest
368 sites could be driven by microclimatic conditions thereby affecting bird species distributions.
369 Therefore, we would strongly recommend considering microclimate as a predictor in future
370 SDMs for open habitat Alpine species.

371 In contrast to the open habitat species considered, forest and ecotone species showed no
372 association with fine-scale temperature. One possible reason might be the buffering effect of
373 vegetation. Körner et al. (2007) showed that temperature can vary strongly between forest and
374 open alpine grassland along the elevation gradient with intermediate values at the treeline
375 ecotone. Furthermore, canopies can buffer the diurnal amplitude of air temperature in the forest
376 (Chen et al. 1999).

377 For two species (Dunnock and Chaffinch) large-scale models including temperature (TEMP,
378 COMB) performed better than fine-scale models. The probability of occurrence of Chaffinch
379 was positively associated with large-scale temperature, whereas the probability of Dunnock
380 presence was negatively affected. A future increase in temperature could therefore affect the
381 distribution of Chaffinches by expanding its range towards higher elevations. In contrast, the
382 distribution of Dunnocks might be severely limited. Bani et al. (2019) demonstrated that
383 Dunnock distribution experienced a lower range contraction along the elevational gradient
384 during the last 35 years, but a simple dispersal into higher elevations as a response to
385 environmental change might not be possible because it's preferred nesting habitat in our study
386 area, *Rhododendron*, has a slow rate of colonisation to the extent that treeline shifts towards
387 higher elevations are likely to be more rapid than upwards shifts in this species (Komac et al.
388 2016).

389 The mismatch between temperature and available future habitat can also affect open
390 habitat species considered in this study. Due to increasing temperatures, shifts in major habitat
391 types (i.e. forest and shrub encroachment; Harsch et al. 2009) may lead to habitat
392 fragmentation and/or loss of open alpine grassland at higher elevations. This process might
393 even be exacerbated by the abandonment of pastoral activities which formerly have
394 maintained the forest limit at lower elevations than would be possible under climatic constraints
395 only (Gehrig- Fasel et al. 2007).

396

397 Topography

398 For the majority of species, COMB models performed equally well in comparison with TEMP
399 models at both spatial scales. Combining temperature with topographic variables increased
400 model performance only for Northern Wheatear and Skylark at a fine scale. For the former
401 species, occurrence was more closely related with south-facing slopes. At a large scale, the
402 probability of Tree Pipit presence was higher on westerly slopes. However, in general
403 topographic variables were rarely associated with species occurrence. The influence of aspect
404 on the occurrence of some species could be explained by its effect on snow melt patterns
405 during spring. Thermal differences among slopes with different exposition, which are caused
406 by the amount of received solar radiation, could lead to an early snow melt on south-exposed
407 slopes whereas north-exposed slopes might stay snow covered for a longer period (Keller et
408 al. 2005). These early snow free areas could potentially benefit Northern Wheatears by making
409 suitable nesting sites available earlier. Furthermore, it has been shown that differences in
410 temperature among slopes can influence plant species diversity in temperate mountains
411 (Winkler et al. 2016) with south-exposed slopes favouring a higher degree of species richness
412 and diversity which may in turn influence insect availability.

413

414 Conservation implications

415 Previous studies from the Italian Alps have indicated that increasing temperatures could have
416 detrimental effects for certain Alpine species in the future (Chamberlain et al. 2013), with some

417 species being potentially impacted by both temperature and habitat shifts (Water Pipit), while
418 for others, loss of habitat due to forest and shrub encroachment will likely be more important
419 (Northern Wheatear, Skylark).

420 However, our results have shown that species such as Water Pipit and Northern
421 Wheatear are positively associated with warm microclimates which could indicate that both
422 species are potentially more resistant to the impact of a warming climate than previously
423 emphasised by large-scale temperature modelling (e.g. Chamberlain et al. 2013). As a
424 consequence, our results imply that changes in habitat in the form of advancing treelines and
425 the encroachment of formerly open areas by shrubs and trees (Gehrig-Fasel et al. 2007,
426 Leonelli et al. 2011) are currently the major threat to those Alpine species, rather than direct
427 effects of temperature. Therefore, it becomes particularly important to actively manage open
428 areas within mountain environments. This could be achieved by targeted grazing techniques
429 such as mineral mix supplements (Pittarello et al. 2016) or temporary night camp areas (Tocco
430 et al.2013). Both techniques lead to the mechanical damage of shrubs (including saplings) and
431 eventually result in a reduction of shrub cover (Probo et al. 2013, 2014).

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435 **Acknowledgements**

436 We thank all rangers and staff of Val Troncea Natural Park for their great help and we are
437 grateful to Nadja Schäfer and Riccardo Alba for help with the field work.

438

439 **Figure legends**

440

441 **Fig. 1** Relationship between large-scale temperature and the probability of occurrence of
442 Dunnock and Chaffinch based on the large-scale COMB model. Shading indicates the 95%
443 confidence interval.

444

445 **Fig. 2** Relationship between aspect and the probability of occurrence for Tree Pipit and
446 Northern Wheatear for the large-scale TOPO and the fine-scale COMB model, respectively.
447 Note that aspect was modelled as an index from 1 (south-facing) to -1 (north facing), but here
448 we present the axis as the equivalent cardinal direction for ease of interpretation. Shading
449 indicates the 95% confidence interval.

450

451 **Fig. 3** Relationship between fine-scale temperature and probability of occurrence for open
452 habitat species for the fine-scale COMB model. Shading indicates the 95% confidence interval.

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Table 1 Variables considered in the analysis, and the scale at which they were measured.

| Parameter | Scale | Description |
|-----------|-------|---|
| Canopy | fine | Percentage cover of canopy (above head height) within a radius of 100 m of the point count centre |
| Rod | fine | Percentage cover of Rhododendron within a radius of 100 m of the point count centre |
| Jun | fine | Percentage cover of Juniper within a radius of 100 m of the point count centre |
| Vac | fine | Percentage cover of bilberry within a radius of 100 m of the point count centre |
| Oth | fine | Percentage cover of shrubs different from Juniper, Rhododendron and bilberry within a radius of 100 m of the point count centre |
| Grass | fine | Percentage cover of grass within a radius of 100 m of the point count centre |
| Rock | fine | Percentage cover of rock within a radius of 100 m of the point count centre |
| Trees | fine | Number of mature (greater than ca. 20 cm in diameter) trees within a radius of 50 m of the point count centre |
| Temp | fine | Modelled fine-scale standardised average temperature of the point count centre |
| Temp | large | Large-scale average temperature within 1000 m of the point count centre extracted from WorldClim. |
| Aspect | fine | The average direction a slope is facing within a 100 m radius of the point count centre transformed as $x = -1 \cdot \cos[\varnothing(\pi/180)]$, where \varnothing is measured in degrees. |
| Aspect | large | The average direction a slope is facing within a 1000 m radius of the point count centre transformed as $x = -1 \cdot \cos[\varnothing(\pi/180)]$, where \varnothing is measured in degrees. |
| Slope | fine | The average inclination of the surface within a 100 m radius of the point counts centre measured in degrees. |
| Slope | large | The average inclination of the surface within a 1000 m radius of the point counts centre measured in degrees. |

Table 2 Variable combinations for each model set. Model sets for TEMP, TOPO and COMB were considered at two different scales (fine and large) and included temperature, slope and

| Full models | Parameter |
|-------------|--|
| HABITAT | Rod + Jun + Vac + Oth + Grass + (Rock) + (Trees) |
| TEMP | Rod + Jun + Vac + Oth * Grass + (Rock) + (Trees) + Temp |
| TOPO | Rod + Jun + Vac + Oth * Grass + (Rock) + (Trees) + Slope + Aspect |
| COMB | Rod + Jun + Vac + Oth * Grass + (Rock) + (Trees) + Temp + Slope + Aspect |

aspect at their matching scale. The variables Rock and Trees were omitted from the habitat model for open habitat species (Northern Wheatear, Water Pipit and Skylark).

Table 3 ΔAIC_c value for each model set at each scale for all species. A ΔAIC_c value of zero indicates the best performing model. Note that in some cases, the best performing models were identical in different model sets, hence a value of zero can appear more than once for a given species. Original AIC_c values are listed in ESM Table S3.

| Species | HABITAT | | TEMP | | TOPO | | COMB | |
|---------------------------|----------------|------------|-------------|------------|-------------|------------|-------------|--|
| | fine-scale | fine-scale | large-scale | fine-scale | large-scale | fine-scale | large-scale | |
| <i>Prunella modularis</i> | 3.9 | 2.7 | 0.8 | 3.9 | 3.9 | 2.7 | 0 | |
| <i>Sylvia curruca</i> | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| <i>Parus ater</i> | 1.4 | 1.4 | 0 | 1.4 | 1.4 | 1.4 | 0 | |
| <i>Turdus viscivorus</i> | 1.2 | 1.2 | 1.2 | 0 | 1.2 | 0 | 1.2 | |
| <i>Fringilla coelebs</i> | 13.9 | 6.3 | 0 | 13.1 | 12.9 | 6.3 | 0 | |
| <i>Anthus trivialis</i> | 10 | 8.5 | 10 | 9.8 | 0 | 8.4 | 0 | |
| <i>Oenanthe oenanthe</i> | 7.7 | 3.5 | 7.7 | 5.8 | 6.5 | 0 | 6.5 | |
| <i>Anthus spinoletta</i> | 4.6 | 0.9 | 4.6 | 3.2 | 4.6 | 0 | 4.6 | |
| <i>Alauda arvensis</i> | 6.0 | 0.9 | 2.7 | 2.3 | 4.8 | 0 | 2.7 | |

| Species | Mode | Scale | Parameter | Estimate | SE | z | p |
|----------------------------|----------|-------|-----------|----------|-------|-------|-------|
| <i>Prunella modularis</i> | COM B | large | Rod | 1.285 | 0.618 | 2.068 | |
| | | | Jun | 0.818 | 0.308 | 2.632 | 0.038 |
| | | | Oth | 0.580 | 0.270 | 2.126 | 0.008 |
| | | | Temp | - 0.886 | 0.406 | 2.163 | 0.033 |
| | | | | | | | 0.030 |
| <i>Sylvia curruca</i> * | TEM P | fine | Rod | 1.029 | 0.265 | 3.835 | ≤ |
| | | | Jun | 0.624 | 0.265 | 2.332 | 0.001 |
| | | | Rock | - 1.174 | 0.467 | 2.487 | 0.019 |
| <i>Parus ater</i> * | COM B | large | Jun | 0.677 | 0.333 | 2.017 | |
| | | | Oth | 0.657 | 0.277 | 2.351 | 0.043 |
| | | | Grass | 0.938 | 0.434 | 2.145 | 0.018 |
| | | | Trees | 1.126 | 0.303 | 3.678 | 0.031 |
| | | | | | | | ≤ |
| <i>Turdus viscivorus</i> * | TOP O | fine | Vac | - 1.700 | 0.823 | 2.049 | |
| | | | Aspect | - 0.644 | 0.316 | 2.017 | 0.040 |
| | | | | | | | 0.043 |

| | | | | | | | |
|--------------------------|-----|-------|--------|---------|-------|-------|-------|
| <i>Fringilla coelebs</i> | TEM | large | Trees | 2.453 | 0.809 | 3.004 | |
| | P | | | | | | 0.002 |
| | | | Temp | 1.500 | 0.462 | 3.218 | |
| | | | | | | | 0.001 |
| <i>Anthus trivialis</i> | TOP | large | Jun | - 1.187 | 0.399 | 2.939 | |
| | O | | | | | | 0.003 |
| | | | Aspect | - 2.614 | 0.644 | 4.022 | ≤ |
| | | | | | | | 0.001 |
| <i>Oenanthe oenanthe</i> | COM | fine | Temp | 0.736 | 0.305 | 2.386 | |
| | B | | | | | | 0.017 |
| | | | Aspect | 0.622 | 0.288 | 2.133 | |
| | | | | | | | 0.032 |
| <i>Anthus spinoletta</i> | COM | fine | Temp | 1.336 | 0.577 | 2.281 | |
| | B | | | | | | 0.022 |
| <i>Alauda arvensis</i> | COM | fine | Jun | 0.616 | 0.282 | 2.158 | |
| | B | | | | | | 0.030 |
| | | | Grass | 1.010 | 0.436 | 2.289 | |
| | | | | | | | 0.022 |
| | | | Temp | - | 0.447 | 1.980 | |
| | | | | 0.896 | | | 0.047 |

Table 4 Significant model averaged parameters of the best model for each species. The model type, scale (large or fine), estimate, standard error (SE), test value (z) and *p*-value are given for each parameter. Note that species where there was more than one model in the best model set (i.e. $\Delta AIC_c < 2$) are marked with *. In these cases, the model with the lowest AIC_c is presented, but competing models are shown in ESM, Table S3, along with full details for all species.

Figure 1

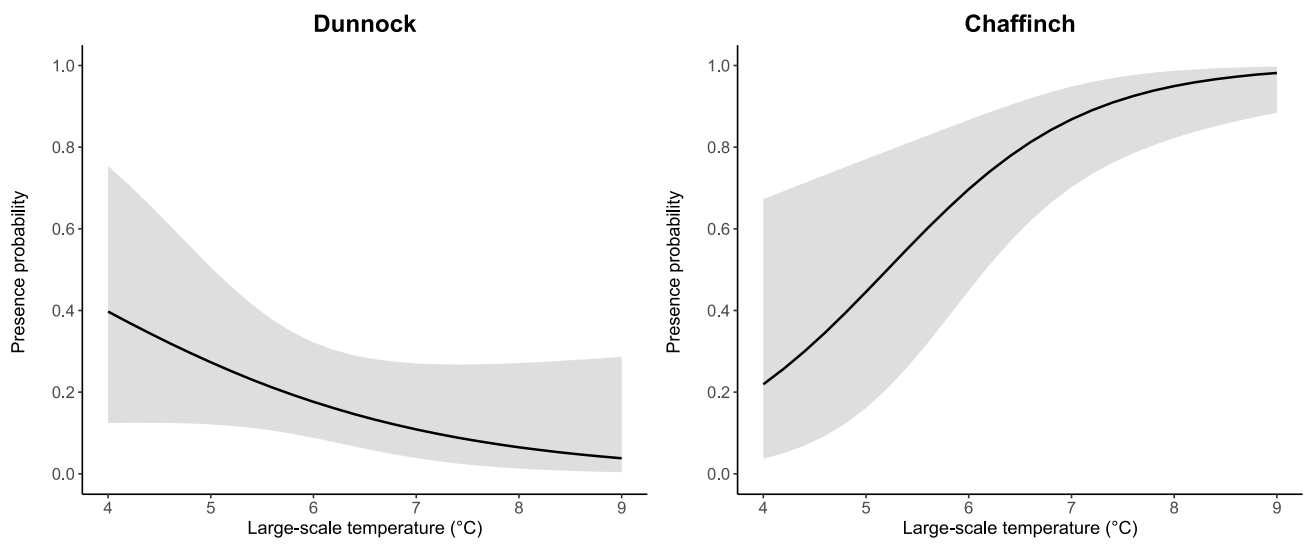


Figure 2

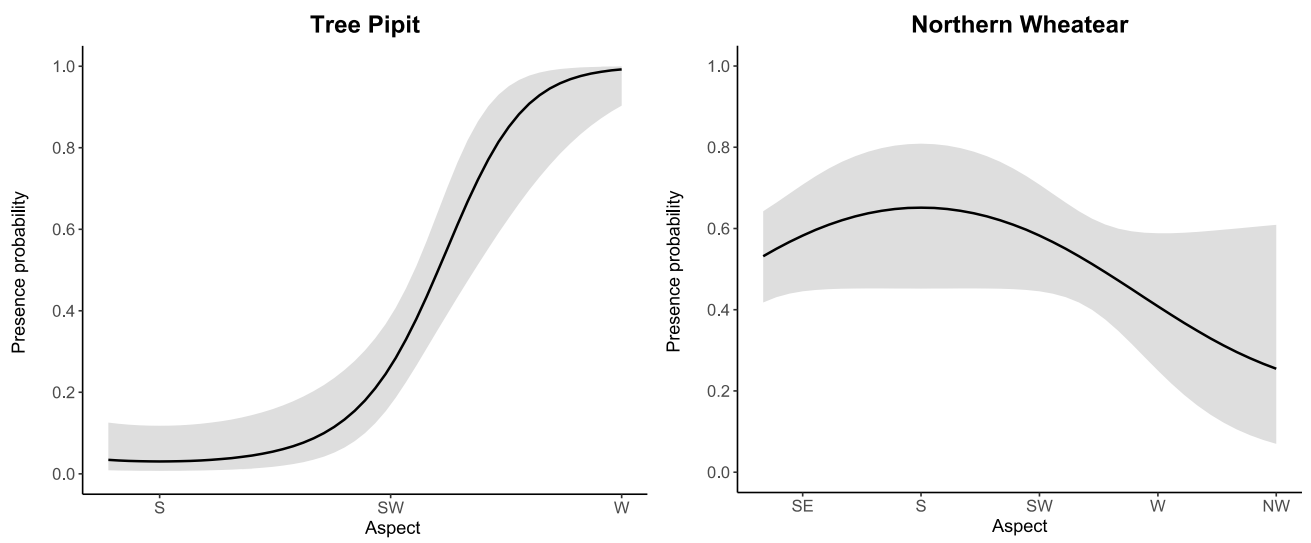


Figure 3

