Interchangeable sets of complementary habitat variables and target values allow for flexible, site-adapted wildlife habitat management in forest ecosystems

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Abstract

1	Integrating biodiversity conservation into forest management is a major goal in
2	sustainable forestry. Hence, target values for forest structural and compositional
3	stand characteristics are required to ensure wildlife habitats of sufficient extent
4	and quality. Yet, the possibility to meet these targets depends on the patch
5	conditions, notably their initial state and future trajectory. Shaped by succession,
6	site conditions and management regime, not all forest stands can be readily
7	converted into a particular state, which calls for flexible management
8	prescriptions. Using the example of two forest grouse species, capercaillie and
9	hazel grouse, we sought complementary variable combinations - with quantitative
10	thresholds for any given crucial habitat feature – which would likewise offer
11	suitable habitat. Habitat variables were mapped in sampling plots within occupied
12	and non-occupied 1 km ² grid cells distributed across three Swiss mountain
13	regions. Generalized Linear Mixed Models (GLMM) were combined with
14	Conditional Inference Trees (CIT) to identify species-relevant variable
15	combinations and variable thresholds. Important features for both species were the
16	proportion of bilberry (Vaccinium myrtillus) and the number of basal-branched
17	trees, as well as a low proportion of beech (Fagus sylvatica) in the canopy layer.
18	Hazel grouse additionally favoured rowans (Sorbus aucuparia) as feeding trees
19	and a high percentage of herbs in the ground layer, while the presence of inner
20	forest edges was additionally important for capercaillie. Thresholds were not
21	clear-cut: different values applied for a particular variable depending on other,
22	functionally similar habitat variables present at the site. By delivering information
23	about relevance, interactions and the required amount of crucial variables, we
24	provide alternative options for flexible species habitat management which allows
25	accounting for the prevailing stand conditions.

26 Zusammenfassung

27	Die Integration von Naturschutzzielsetzungen in die Waldbewirtschaftung ist
28	wesentliches Ziel einer nachhaltigen Waldwirtschaft. Um Wildtierlebensräume in
29	ausreichendem Umfang und Qualität zu gewährleisten werden waldstrukturelle
30	Zielwerte benötigt. Die Möglichkeit diese Zielwerte zu erreichen hängt jedoch
31	maßgeblich von den Ausgangsbedingungen und dem Entwicklungspotential eines
32	Waldbestandes ab. Je nach Sukzessionsstadium, Standortsbedingungen und
33	Bewirtschaftungsform können nicht alle Bestände gleichermaßen in einen
34	gewünschten Zustand überführt werden. Dies macht flexible
35	Managementvorgaben erforderlich. Am Beispiel von zwei sympatrischen
36	Raufußhuhnarten, Auerhuhn und Haselhuhn, ermittelten wir Kombinationen
37	komplementärer Habitatvariablen und zugehöriger Schwellenwerte, die
38	gleichermaßen geeignete Lebensraumbedingungen bieten. Hierfür wurden
39	Flächen mit und ohne Artvorkommen in drei Bergregionen der Schweiz
40	verglichen und artrelevante Variablen, Variablenkombinationen sowie
41	Schwellenwerte durch Generalisierte Lineare Gemischte Modelle und Conditional
42	Inference Trees (CIT) identifiziert. Wichtige Lebensraummerkmale für beide
43	Arten waren der Anteil der Heidelbeere (Vaccinium myrtillus) sowie die Anzahl
44	tiefbeasteter Bäume und ein geringer Anteil Buche (Fagus sylvatica) in der
45	Baumschicht. Das Vorkommen des Haselhuhns wurde zusätzlich durch die
46	Anzahl an Ebereschen (Sobus aucuparia) und einen hohen Anteil an krautigen
47	Pflanzen in der Bodenvegetation bestimmt, Randlinien zu offenen Flächen im
48	Wald waren ein wichtiger, zusätzlicher Habitatfaktor für das Auerhuhn. Die
49	ermittelten Schwellenwerte für Habitatvariablen waren meist nicht klar definiert,
50	vielmehr galten unterschiedliche Werte abhängig davon, welche anderen,
51	funktional ähnlichen Habitatmerkmale in einer Fläche vorhanden waren. Neben

52	der Identifikation artrelevanter Habitatvariablen kann die Bereitstellung
53	alternativer Variablenkombinationen und kombinationsabhängiger
54	Schwellenwerte eine wichtige Grundlage dafür liefern, Managementmaßnahmen
55	flexibel an die in einem Waldbestand gegebenen Ausgangsbedingungen
56	anzupassen.
57	
58	Keywords: Bonasa bonasia, complementary habitat variables, Conditional
59	Inference Tree, habitat management, mountain forests, Tetrao urogallus,
60	thresholds
61	

62 Introduction

63	In the human-dominated landscapes of Central Europe, where suitable wildlife
64	habitat is limited, conservation management needs quantitative and spatially
65	explicit prescriptions for biodiversity preservation and habitat restoration. In
66	forest ecosystems, where species occurrence and diversity largely depends on
67	characteristics of forest composition and structure (Bollmann et al., 2009;
68	Brombacher, 1999), enhancing or restoring forest structural diversity is a prime
69	goal of wildlife habitat management (Bergman et al., 2012; Lindenmayer & Luck,
70	2005). Yet, evidence-based, quantitative targets with regard to the amount, size
71	and configuration of crucial habitat features (e.g. Müller & Bütler, 2010) are still
72	rare. Moreover, even if quantitative management prescriptions exist, they are
73	often not equally applicable to all site conditions: Most forests are commercially
74	used ecosystems, characterized by a slow vegetation succession. Stand
75	composition and structure differ greatly depending on site conditions and mode of
76	exploitation (Bürgi, 1998), and thus provide variable conditions for habitat
77	management. Possibilities for habitat management are further constrained by the
78	objectives of commercial forestry, which may interfere with habitat management
79	goals (Bollmann & Braunisch 2013). While some measures can readily be
80	implemented, e.g. removing trees to create gaps, alter light conditions and
81	promote ground vegetation, other structural components such as tree species
82	composition or age structure can only be modified within long time frames, and in
83	strict consideration of the initial state and local site conditions. Given these
84	limitations, achieving the multiple functionalities of forests through integrative
85	management remains a big challenge. This is particularly true when the
86	requirements of different species with diverging ecological needs have to be met

within the same area. Yet, species rarely require similar habitat conditions
throughout their range, but avail themselves of a mosaic of different habitat
features and resources that offer complementary functionalities, such as food
supply, cover against predators, roosting or breeding sites. Thereby, different
habitat features may be interchangeable across a species' home range. Identifying
sets of important and complementary variables is thus a key for a flexible multispecies habitat management.

94 In Europe, the hazel grouse (Bonasa bonasia) and the capercaillie (Tetrao *urogallus*) are two forest grouse species of conservation concern (Storch, 2000) 95 which often occur sympatrically. Being considered as indicators for structural 96 97 diversity of boreal and mountain forest ecosystems (Pakkala et al., 2003; Suter et 98 al., 2002), they have suffered from habitat loss and degradation during the last century mainly due to changes in forest management (Klaus, 1991). While 99 100 qualitative habitat requirements for these two tetraonids have been well described 101 (e.g. Glutz von Blotzheim et al., 1973; Müller, 1973), recent studies also provide 102 quantitative target values for particular habitat features, including variable 103 thresholds, which allow for targeted habitat management (Mathys et al., 2006; 104 Müller et al., 2009; Sachot et al., 2003; Schäublin & Bollmann, 2011; Suchant & 105 Braunisch, 2004). However, habitat recommendations vary considerably between 106 studies and areas, providing evidence for their limited generality.

In this study we analyse the habitat requirements of the two species from a novel perspective: using multivariate classification and regression trees, we seek for different combinations of habitat variables as well as quantitative thresholds thereof that similarly promote species presence at the forest stand scale. In this context we explore if and to what extent the required amount of one habitat

variable depends on the occurrence and amount of another, complementary habitat
feature. Thereby we hypothesize that different threshold values apply for a given
habitat feature which vary within the range of threshold-values found in literature.
The quantitative prescriptions drawn for our analyses provide refined guidance for
a flexible management and restoration of suitable forests for declining populations
of the two tetraonids.

118

119 Materials and methods

120 Study area

121 The study was conducted in Switzerland, with the study sites distributed across

three mountain ranges representing a broad gradient of bioclimatic conditions: the

123 Jura Mountains (47°00' N 6°40' E - 47°30' N 8°00' E), Northern Prealps (46°30'

124 N 7°15' E - 47°00' N 9°30' E) and Inner Alps (46°30' N 9°00' E - 47°00' N

125 10°30' E) (Fig. 1A). The Jura Mountains are characterized by a moderate climate

126 with mild, dump summers and cold winters (MeteoSchweiz 2013,

127 http://www.meteoschweiz.admin.ch). The mean annual ambient temperature is

128 5.5°C with 180 frost days and, on average, 2000 mm of rain and 4 m of snow

annually at an altitude of 1200 m (MeteoSchweiz 2013). The tree line is around

130 1400 m a.s.l. (Steiger, 1994). The Northern Prealps are characterized by an

131 Atlantic climate with high precipitation (2000-3000 mm/yr), cold-temperate

132 winters and wet summers (MeteoSchweiz 2013). The tree line is at an elevation of

approximately 2000 m (Steiger, 1994). The open and diversely structured forests

are often adjacent to pastures and interspersed with mires. In the Inner Alps, the

135 prevailing climate conditions are continental, with low precipitation (800-

136 2000mm/yr), cold winters and warm and dry summers (MeteoSchweiz 2013).

Large, continuous forests belts are found along the valley slopes with the tree line
being located at 2300m a.s.l. (Steiger, 1994). The altitudinal-climatic gradient is
also reflected in the tree species composition, consisting of European beech
(*Fagus sylvatica*), silver fir (*Abies alba*) and Norway spruce (*Picea abies*) in the
montane zone with larger proportions of larch (*Larix decidua*) and Swiss stone
pine (*Pinus cembra*) present in the most continental conditions of the subalpine
zone.

144

145 Model species

The capercaillie is declining throughout its European distribution range (Storch
2007), being classified as "endangered" in Switzerland (Keller et al. 2010) where
the number of displaying males was estimated between 450 and 500 in 2001 (half
the size of the population in 1968/71; Mollet et al., 2003; Müller, 1973).

150 Capercaillie prefers mature, open, coniferous or conifer-dominated mixed stands with an intermediate canopy cover (Bollmann et al., 2005; Suchant & Braunisch, 151 2004) and a rich ground vegetation cover, ideally including a high proportion of 152 153 bilberry (Storch, 1993a). The species is considered to be an indicator for structural 154 diversity in boreal and mountain forests, and plays the role of an umbrella species 155 for some associated animal communities, as its presence is positively associated 156 with the diversity and abundance of highly specialized mountain forest birds and forest-dwelling mammals (Pakkala et al., 2003; Suter et al., 2002). The hazel 157 158 grouse is a territorial forest bird which requires semi-natural forests with young seral stages and old-growth stands with gaps (Desbrosses, 1997; cited in: Sachot, 159 Perrin & Neet 2003). In the year 2001, 7500-9000 breeding pairs were estimated 160 for Switzerland (Maumary et al., 2007). The hazel grouse is not threatened in 161

Europe (IUCN 2012, http://www.iucnredlist.org), however it is considered to be 162 163 "near threatened" in Switzerland (Keller et al., 2010). Probably due to major differences in body size and mating system, home range and habitat preferences 164 165 (in terms of forest structure and stand density) diverge between the two focal species. Distinct winter feeding habits also lead to discrepancies between the 166 167 trophic niches, especially as regards resource trees. Local sympatric occurrence 168 might arise from a patchy distribution of suitable hazel grouse habitat being embedded within a suitable capercaillie habitat matrix. 169

170

171 Species data

172 The presence data of the two focal species were drawn from the database of the Swiss Ornithological Institute (http://www.ornitho.ch) which compiles the data of 173 the Swiss National Bird Monitoring programme. Direct (sightings) and indirect 174 175 (feathers, faeces) species observations are collected year-round by a dense and 176 area-wide network of species specialists and ornithologists, validated by experts of the Swiss Ornithological Institute, and allocated to the respective 1 km^2 cell of 177 the Swiss National Grid. This cell size also corresponds to the size of a small 178 179 capercaillie home range (100-1000 ha; Storch, 1995a) and to the double or triple 180 of the home range of a hazel grouse (30-40 ha; Rhim & Lee, 2001). A pairwise 181 sampling scheme was applied, selecting pairs of grid cells with species presence or absence (Table 1). Presence grid cells were chosen according to the following 182 183 selection criteria: (1) there were at least three observations of the species within the years 2007 - 2010, (2) the sample contained different types of cells, namely 184 cells with both single and sympatric occurrence of the two species, (3) the grid 185 cells were distributed as evenly as possible within the respective study area and 186

187 along the altitudinal gradient (Fig. 1A). Absence grid cells with a forest cover of 188 at least 50% were randomly selected within 1 km up to maximum 4 km distance to the corresponding presence cells to make sure that they could potentially be 189 190 reached by the species. Although absence cells were only selected when there were no species records (indirect or direct) within the last 10 years, species 191 192 presence could not be entirely ruled out, so that absence grid cells were in fact 193 pseudo-absences. Yet, for reasons of simplicity they are referred to as "absence" 194 here.

195

196 Habitat variables

197 Habitat variables were collected from June to August 2011 at 16 sampling plots of 30 x 30 m in size, regularly distributed within each grid cell (Fig. 1B,C, Table 1). 198 The variables included information on stand structure, successional stage, tree 199 200 species composition, ground vegetation and species-specific habitat features 201 (Table 2). Depending on the spatial extent required to capture the respective 202 structural attribute in sufficient detail, habitat variables were mapped at different 203 reference areas within the sampling plot. Whereas variables describing stand 204 structure and tree species composition in the canopy (≥ 5 m) and shrub layer (\geq 205 1.3 and < 5 m) were collected across the whole plot area, special resources like 206 rowans (Sorbus aucuparia) and anthills were quantified within a 15 x 15 m nested square located around the plot centre (Fig. 1C), the two diagonal corners of which 207 208 were used to assess the ground vegetation.

209

210 Statistics

211 Habitat selection

212	Habitat selection was analysed using Generalized Linear Mixed Models
213	(GLMMs, R-package lme4; Bates et al., 2014) with a binomial error distribution
214	(logit link) and "grid cell pair" as random factor. First, univariate models were run
215	with all potentially relevant variables. From pairs of correlated explanatory
216	variables (Spearman's $r_s \geq 0.7 $) the variable with the higher predictive
217	performance in univariate models was retained. Multivariate models were then
218	generated with the remaining set of significant variables, using a backward
219	selection procedure until the model was reduced to twelve variables. Then, the
220	"dredge" function (R-package MuMIn; Barton, 2012) was applied to identify the
221	most parsimonious model from all possible combinations of the remaining
222	variables according to Akaike's Information Criterion (AIC) (Burnham &
223	Anderson, 2002). In case of non-significant differences between the top-ranked
224	candidate models ($\Delta AIC \text{ of } \leq 2$), model averaging was applied. The models were
225	evaluated by assessing their discrimination ability using the area under the
226	receiver operating characteristic (ROC) curve (AUC) (R-package pROC, Robin et
227	al., 2011) as well as their calibration, i.e. the extent to which the observed
228	proportion of species presence equates to the model's estimated presence
229	probabilities (sensu Jiménez-Valverde et al., 2013).

230

231 Variable thresholds

Conditional Inference Trees (CIT) were used for the identification of variable
thresholds explaining species presence. This method, similar to classification and
regression trees, uses recursive partitioning to select significant predictor variables
in a hierarchical way and to identify the best cut-off values that split the dataset so
as to predict species presence and absence (Hothorn et al., 2006). It is therefore a

valuable tool for deriving quantitative variable thresholds for habitat management
(Müller & Bütler, 2010). The model starts with univariately testing for
independence between the response and each of the predictor variables. If this
hypothesis cannot be rejected, the calculation stops - otherwise the split for the
variable with the strongest association is applied. The procedure is recursively
repeated with each of the remaining subsets until no significant split is found. A
Bonferroni correction was used to account for multiple testing.

Variable thresholds were first calculated univariately for all variables that had
been identified as being significant in the GLMMs. The 95% confidence interval
of each threshold value was quantified by bootstrapping and the obtained valueranges compared to the threshold values provided by other studies.

248 Multivariate CIT were then generated to identify variable combinations and 249 threshold thereof that provide suitable structural conditions at the plot-level so as to guide the management of forest stands. Based on the results, we also calculated 250 the percentage of suitable plots per grid cell (i.e. plots with a predicted probability 251 252 of species' presence > 0.5) to obtain information about the required proportion of suitable habitat in the stand mosaic. Conditional Inference Trees were calculated 253 254 with the R-package party (Hothorn et al., 2011) setting the minimum sum of weights for splitting (minsplit-criterion) to 100. The models' predictive 255 performance and consistency were evaluated by calculating AUC (package 256 257 pROC, (Robin et al., 2011)) and calibration. All statistical analyses were done with the Software R (R Development Core Team 2011). 258

259

260 **Results**

261 Habitat selection

262 The important habitat variables identified for both grouse species resembled those 263 of former studies: The probability of capercaillie occurrence was best explained by the following variables: The number of basal-branched trees, the cover of 264 265 ground vegetation, particularly of bilberry, as well as the presence of inner forest edges positively influenced the occurrence probability of capercaillie, while the 266 267 proportion of fir and beech in the canopy layer was negatively related to species 268 presence (Table 3). The presence probability of hazel grouse was positively 269 affected by the number of basal-branched trees, the number of rowans (Sorbus sp.), the bilberry cover and the proportion of herbs and ferns in the ground 270 271 vegetation. A high proportion of beech and deciduous trees other than feeding trees (s. Table 2) in the canopy layer, as well as outer forest edges negatively 272 273 affected the presence probability (Table 4). With an AUC of 0.85 and 0.86 for 274 capercaillie and hazel grouse, respectively, and a consistent calibration (Fig. 2) both models performed very well in predicting species presence (Hosmer & 275 276 Lemeshow, 2000).

277

278 Variable thresholds

The two target species showed a similar selection pattern for several crucial
habitat variables. Confidence intervals largely overlapped between species and
mostly encompassed the species-specific threshold values provided by other
studies (Table 5):

283 The canopy cover threshold for capercaillie indicated an upper limit at 81% (95%

confidence interval [CI] of the threshold: 60 - 83%) which was rather high

compared to the values of 25 - 70% obtained in other studies (Bollmann et al.,

286 2008; Bollmann et al., 2005; Lieser & Roth, 2001; Storch, 1993a). For hazel

grouse this threshold was lower with 60% (CI: 60 - 81%), but still exceeded the results of Mathys (2000)(40 - 50%).

289 The canopy layer on sites with capercaillie presence was composed of spruce by at least 5 % (CI: 1 - 11%) which corresponded roughly to the lower limit of 10 -290 291 33% indicated by Suchant and Braunisch (2004). For hazel grouse, a minimum value of 10% (CI: 5-16%) was found. Furthermore, there was an upper limit for 292 deciduous trees other than beech for both species, at 19% (CI: 12-28%) for 293 capercaillie and 14% (CI: 0 - 18%) for hazel grouse. While these trees are rarely 294 295 used as food resource and provide neither sight nor thermal protection in winter, 296 the beech buds represent an important food resource in late winter and spring. 297 Nevertheless, in our model both grouse species showed only little tolerance 298 towards beech in the canopy (upper threshold of 3%) although the confidence intervals suggest that higher amounts of beech in the canopy layer are accepted. 299 Both grouse species required a minimum of 60% of ground vegetation cover (CI: 300 301 28 - 60% for capercaillie; 38-60% for hazel grouse) which corresponded to literature specifications (Bollmann et al., 2008; Bollmann et al., 2005; Lieser & 302 303 Roth, 2001; Storch, 1993a). For the hazel grouse, herbs covering the ground 304 ideally exceeded 18 % (CI: 13 - 38 %); slightly higher values but with a greater 305 variance were obtained for capercaillie (38 %, CI: 0 -62%). Very low threshold 306 values were obtained for important food resources like bilberry cover and the 307 proportion of resource trees in the shrub and the canopy layer (1% for both species and variables). Moreover, a minimum of one rowan (≥ 3 m tall) and of one 308 basal-branched tree was required per plot (900 m^2) , the former being a little lower 309 than what Schäublin and Bollmann (2011) found for hazel grouse (2 rowans/900 310

311 m²). While outer forest edges were avoided, both species showed a preference for
312 inner forest edges which is in accordance with Bollmann (2006).

313

- 314 Complementary variable combinations
- The multivariate CIT for capercaillie (Fig. 3A) and hazel grouse (Fig. 3B) showed

that suitable habitat (defined here as sites with a probability of species presence

317 $p \ge 0.5$) can be obtained by different variable combinations.

The multivariate tree for capercaillie provided four possible combinations of 318 319 explanatory variables that resulted in a probability of species occurrence greater 320 than 50% (see Fig. 3A). If, in a given plot, bilberry is available, the ground vegetation cover exceeds 53%, and at least one basal-branched tree per $900m^2$ is 321 322 present, the probability that capercaillie occurs is 83% (option 1). In the absence 323 of basal-branched trees this probability decreases to 68% (option 2), and with a ground vegetation cover of less than 53%, the presence probability is further 324 325 reduced to 50% (option 3). With no bilberry present, at least three basal-branched 326 trees have to be available to obtain a 61% probability of capercaillie presence. The model showed a good ability to correctly discriminate between species presence 327 and absence (AUC = 0.75). 328

To obtain a probability of hazel grouse presence of at least 50%, again four possible variable combinations could be prescribed according to the multivariate CIT (see Fig. 3B): if bilberry cover is present, and at least one basal-branched tree is present, the probability of hazel grouse occurrence is 83% (option 1); without such a tree but with bilberry cover of more than 31% there is still a 79% probability that the hazel grouse occurs under such habitat conditions (option 2). In sites with a lower or no bilberry cover a probability of presence of 57% will

still be reached (options 3 and 4). With an AUC of 0.76, this CIT showed gooddiscrimination ability

The probability of capercaillie occurrence was over 70% in grid cells of 1 km² with sampling plots having of suitable habitat in more than 63% (CI: 0.33 - 0.91) (Fig. 4A). More than 75 % (CI: 0.25 - 0.90) of the plots within a grid cell had to be suitable for hazel grouse in order to increase its probability of presence from 30% to almost 80% (Fig. 4B).

343

344 Discussion

345 Similar habitat associations of the two species

Even if this study overall corroborates previous findings about habitat selection of

347 capercaillie and hazel grouse, it indicates less contrasting habitat associations than

348 previously established. The novelty of our research lies in the finding of

349 combinations of habitat variables that all provide acceptable if not suitable habitat

350 conditions for both grouse species. This increases the flexibility of managers in

351 developing area-specific solutions for species conservation.

352 A previously established major difference in the ecological association of the two

353 grouse species is a preference for different seral stages. While hazel grouse is

considered to prefer younger forests (Klaus, 1991; Mathys et al., 2006),

capercaillie is generally associated with old growths (Rolstad & Wegge, 1987).

We could not find a clear cut preference for any given successional stage, neither

- 357 for hazel grouse nor for capercaillie. This might be due to the fact that our study
- 358 sites mainly consisted of multi-aged stands without extended old growths. The
- 359 variable with the strongest association with capercaillie presence was bilberry
- 360 cover. Another important variable was ground vegetation cover, which decreases

as the canopy becomes denser. A well-developed field layer provides shelter 361 362 against predators to chick-rearing hens and food supply in the form of buds and berries (e.g. Vaccinium myrtillus, Lakka & Kouki, 2009). When the field layer 363 was limited, basal-branched trees took over as shelter and vice versa. According 364 to Bollmann et al. (2005) and Lanz and Bollmann (2008), basal-branched Norway 365 366 spruce *Picea abies* typically represent the favourite resting trees for capercaillie, 367 especially when these trees are situated in forest stands with two or more aisles as this eases soaring and landing (Lanz & Bollmann, 2008). Therefore it is also not 368 surprising that capercaillie preferred the presence of inner forest edges. There is a 369 370 trade-off, however, between woodland openness and closure due to an increased predation risk when the habitat is too open, as demonstrated for other grouse 371 372 species (Signorell et al., 2010). Especially the hazel grouse avoided outer forest 373 edges. Edge effects typically caused by increased habitat fragmentation have been shown to augment the risk of egg-predation in grouse that nest on the ground 374 375 (Storch, 1995b). Moreover, the hazel grouse is the poorest disperser among grouse 376 species, which renders it very vulnerable to patch isolation (Åberg et al., 1995; Sahlsten, 2007): gaps larger than 150 - 250 m in diameter already represent a 377 serious obstacle to dispersal (Åberg et al., 1995; Montadert & Léonard, 2006; 378 379 Sahlsten, 2007). While both species' avoidance of beech-dominated stands was 380 not surprising, capercaillie presence was also negatively related to the proportion of white fir (Abies alba). This is in contrast with previous studies demonstrating a 381 382 preference for this tree species, particularly as food resource in winter (e.g., Lanz & Bollmann, 2008), although preferences for particular conifer species (Storch, 383 384 1993b) have been found to vary greatly between regions (Lanz & Bollmann, 2008; Lieser, 1996; Siano, 2011; Storch, 1993b). Across our study area the 385 386 abundance of white fir was overall low and frequently associated with beech-

387 dominated stands in the lower altitudes otherwise representing structurally 388 suboptimal habitat conditions, which may explain this result. Hazel grouse has been shown to prefer mixed or coniferous stands over pure deciduous stands 389 (Klaus, 1991; Montadert & Léonard, 2006), which is corroborated in this study. 390 Although several deciduous trees act as important resource trees, coniferous trees 391 392 in the shrub layer remain essential as they provide better sight protection from 393 predators and enhanced thermal benefits, especially in winter (Swenson et al., 1995; Swenson & Olsson, 1991). Yet, despite explaining species presence very 394 well, our variable set may not fully represent the two species' requirements, since 395 396 large-scale habitat characteristics such as stand mosaic heterogeneity, forest gaps and linear structural elements cannot be sufficiently captured by a plot-based 397 sampling design. Area-wide structural variables obtained from remote sensing, 398 399 such as Airborne Laser Scanning, aerial or satellite images have been shown add valuable complementary information which can substantially improve the 400 401 predictive performance of habitat models (Zellweger et al., 2014) and - in our case 402 - may have revealed greater species-specific differences in habitat selection.

403

404 Variable thresholds

While the threshold-ranges obtained for most variables encompassed the values
found in literature, for some relevant habitat variables our thresholds were
strikingly lower. This concerns for instance the proportion of bilberry in the field
layer, a feature relevant for both species. Former studies indicated 15 – 70%
bilberry cover for capercaillie and 40% for hazel grouse (Baines et al., 2004;
Schäublin & Bollmann, 2011), which contrasts with our > 0% for capercaillie and
>1% for hazel grouse. Regional variation in both food supply and diet (i.e. the

availability and use of other, complementary food resources), can explain this 412 413 divergence. For example, in the dry Eastern part of the study area the abundance of bilberry is generally low and replaced by other food items (Bollmann et al. 414 415 2005). Still, methodological issues cannot entirely be ruled out: Small patches 416 with locally high proportions of Vaccinium myrtillus may be sufficient within an individual's home range, but may have been missed by our plot-based sampling. 417 418 Differences in variable thresholds may further result from different statistical 419 methods (Manel et al., 2001), sampling resolutions, study regions as well as varying seasons (Table 5). Moreover, most of the studies were conducted within 420 421 small study regions with limited representativeness (Braunisch & Suchant, 2010; 422 Graf et al., 2006).

423 The effects of grain and extent upon the generality of habitat selection analyses have been subject to several studies (Braunisch & Suchant, 2010; Graf et al., 424 425 2006; Thuiller et al., 2004). It is widely acknowledged that increasing the spatial 426 extent of the study area generally increases the representativeness of the results because one then encompasses a greater proportion of a species' distribution and 427 428 environmental gradient. In practice, however, the unavoidable trade-off between 429 sampling resolution and extent persists, mostly due to time constraints and limited 430 manpower. Braunisch and Suchant (2010) showed that coarse-grained data, 431 sampled over a wide representative area, outperform very precise data 432 systematically collected from a restricted, less representative region. As our data was collected over three Swiss mountain ranges at a 1 km² resolution, we are 433 confident about the generality of our results despite its fairly coarse resolution. In 434 addition, particularly in highly mobile species, a coarse sampling resolution 435 436 matching the species-specific home ranges, can even be advantageous for

437 appraising habitat selection, as the required habitat mosaic is also be taken into438 account (Braunisch & Suchant, 2010).

439

440 Threshold ranges

Some of the habitat variable thresholds have broad confidence intervals. One may 441 argue that this is merely due to the variation between plots within the 1 km² grid 442 cells, and that narrower confidence intervals would have been obtained if 443 444 variables would have been mapped at a higher resolution (e.g. just around bird sighting location). Actually, we tested for such an effect, mapping the habitat at a 445 446 25 x 25 m resolution within a subregion of 1772 ha (Forest Reserve Amden, 447 Northern Prealps, 1040 m a.s.l., 47°10'N 9°13'E): similar thresholds with equally broad confidence intervals were obtained (Appendix A). Therefore, our large 448 confidence intervals indicate that there is not one clear-cut quantitative threshold, 449 450 but rather a "threshold zone" (Huggett, 2005) that may serve for habitat management. The multivariate CIT finally show how, depending on the local 451 conditions (i.e. differences in presence and abundance of other variables), a single 452 variable can exhibit different threshold values, all falling within the confidence 453 intervals obtained from univariate CIT. A good example is provided by the 454 455 multivariate tree for capercaillie occurrence (Fig. 3A). Here, the variable "number of basal-branched trees" has two thresholds: with a higher ground vegetation 456 cover, a lower number of such trees is required, and vice versa. Both thresholds 457 typically contribute to a capercaillie presence probability greater than 50% under 458 different conditions, which delivers flexible guidance for habitat management. 459

460

461 Combined habitat variable sets

Multivariate CITs enable visualizing, under the form of a classification tree, the 462 463 information about the importance and interaction of different variables. It therefore provides a promising user-friendly tool that can deliver pragmatic, 464 465 flexible quantitative management criteria to practitioners by presenting different pathways for receiving a favoured goal (e.g. a probability of species presence of at 466 least 50%). The probability of species presence resulting from a specific 467 468 combination of habitat variables is graphically depicted by branches of the tree, which facilitates interpretation (Fig. 3). 469

Yet, one drawback of conditional inference trees is that one cannot account for 470 data clustering, e.g. by including spatial random factors in the models. Although 471 our species data were recorded for 1 km^2 grid cells, we applied the CIT to the 472 473 plot-data to capture the full variety of different variable combinations within an individuals' home range, without smoothing out the heterogeneity between 474 475 sampling plots, e.g. by averaging the variable values across the grid cell. 476 Averaging all the plot values per grid cell and calculating the thresholds from the averaged values may have biased the results towards intermediate values. Hence, 477 important information about species' preferences, for instance under more 478 marginal circumstances, would have been lost. This was possible as the variance 479 between the plots of the same grid cell did not differ from those between 480 randomly chosen plots of different grid cells of the same category 481 482 (presence/absence). Moreover, our grid cells do not correspond to the presence of a single individual but rather an area where the species occurs. The area is hosting 483 484 at least one but most likely several individuals, with the plots in a grid cell thus representing the gradient of species-specific environmental conditions. Our dual 485 486 approach, using a GLMM to pre-select the important habitat variables that were entered in the CIT, nevertheless accounts for spatial clustering in the first analysis 487

488 step, which makes us confident that the plot-based results provide a useful

489 approximation of the variable thresholds at the forest stand level.

490

491 Conclusions

Our approach generates complementary, interchangeable habitat variable sets and 492 variable thresholds at both the forest stand (conditions per plot) and the forest 493 494 mosaic (proportion of suitable habitat per grid cell) scale that all deliver suitable 495 conditions for our model species. With that we provide applicable quantitative prescriptions for habitat management that allow practitioners to take the local 496 497 conditions into accountand to find a good solution for integrating timber 498 production and biodiversity preservation and restoration in multi-functional forests. Our findings revealed that the two model species have less contrasting 499 500 habitat requirements as expected. This could be an indicator of their behavioural 501 and ecological congruence which may allow them to exploit similar habitats and greatly simplifies management in areas of sympatric occurrence. Accompanied by 502 analyses of landscape suitability at the meta-population level, which allow priority 503 504 areas to be delineated (Bollmann et al., 2011; Braunisch & Suchant, 2007; Graf et 505 al., 2005), the approach used here advances the development of multiple-species 506 conservation strategies.

507

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515

516 Appendix A. Supplementary data

- 517 Supplementary data associated with this article can be found, in the online
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704 Tables

- Table 1. The number of presence and absence grid cells (1 km^2) per species, as
- well as the number of embedded sampling plots (30 x 30 m) (in parentheses) used
- 707 for the analysis.

	Presence	Absence
Capercaillie	50 (609)	50 (526)
Hazel Grouse	72 (771)	71 (627)

708

- Table 2. List of habitat variables with the reference area (R.area) at which they
- 711 were collected: $P = Plot (30 \times 30 \text{ m})$, NS = Nested square (15 x 15 m), GV =
- Nested square quarters (7.5 x 7.5 m) for ground vegetation (see Fig. 1C). DBH:
- stem diameter at breast height, p/a: presence/absence.

Category	Variable Code	Description	Unit	R.area
Successional stage	SUCC_STAGE	Age of the forest stands subdivided into 5 age- classes: 1 = regeneration (<1.3m height) 2 = thicket (<10cm DBH) 3 = pole stage (<30cm DBH) 4 = tree stage (<60cm DBH) 5 = ,,old" forest (\geq 3tr. \geq 60cm DBH) 6 = multi-age stands	categorical (1-6)	Р
Stand structure	STAND_STRU	Vertical structure as number of layers, 1 = one, 2 = two 3 = multi layered	categorical (1-3)	Р
Ground vegetation distribution	GV_DIS	Pattern of ground vegetation: 1=homogeneous, 2=patchy, 3=clumped	categorical (1-3)	Р
	CAN_COV	Canopy (≥5m) cover	%	Р
Vegetation	SHRUB_COV	Shrub (≥ 1.3 m, ≤ 5 m) cover	%	Р
cover	GV_COV	Ground vegetation (<1.3m) cover	%	GV
	CAN_BEE	Percentage of beech (Fagus sylvatica)	%	Р
	CAN_O_DEC	Percentage of deciduous trees (excluding beech and resource trees)	%	Р
	CAN_FIR	Percentage of fir (Abies alba)	%	Р
Canopy	CAN_LAR	Percentage of larch (Larix decidua)	%	Р
composition	CAN_RES_TR	Percentage of resource trees (Sorbus sp., Salix sp., Betula sp., Alnus sp., Corylus sp. and Sambucus sp.)	%	Р
	CAN_SPR	Percentage of spruce (<i>Picea abies</i>)	%	Р
	CAN_PIN	Percentage of pine (Pinus sp.)	%	Р
	SHR_BEE	Percentage of beech	%	Р
	SHR_O_DEC	Percentage of deciduous trees (excluding beech and resource trees)	%	Р
Shruh	SHR_FIR	Percentage of fir	%	Р
composition	SHR_LAR	Percentage of larch	%	Р
	SHR_RES_TR	Percentage of resource trees	%	Р
	SHR_SPR	Percentage of spruce	%	Р
	SHR_PIN	Percentage of pine	%	Р
	GV_HEI	Ground vegetation height	cm	GV
	COV_CON	Cover of coniferous regeneration	%	GV
	COV_DEC	Cover of deciduous regeneration	%	GV
Ground	COV_HERB	Cover of herbs	%	GV
vegetation	COV_FERN	Cover of ferns	%	GV
	COV_GRAS	Cover of grasses	%	GV
	COV_BER	Cover of berry plants	%	GV
	COV_VAC	Cover of bilberry (Vaccinium myrtillus)	%	GV
Special	ROW_TOT	Number of Rowans $\geq 3m$ (Sorbus aucuparia)	n	NS
Ressources	ANT_HILL	Number of ant hills	n	NS

Functional trees	BB_TREE	Basal-branched trees	n	Р
Eastance	E1	Presence/absence of inner forest edge	p/a	Р
Ecotones	E2	Presence/absence of outer forest edge	p/a	Р

716	Table 3. Habitat variables explaining the presence of capercaillie, obtained from a
717	Generalized Linear Mixed Model (GLMM) with "grid cell-pair" as random factor.
718	Variable estimates, as obtained from averaging the four best models according to
719	the AIC-ranking, are presented and the relative variable importance is provided in
720	parentheses. The composition and ranking of the included models is specified in
721	the lower part of the table. Asterisks indicate significance levels with *** p <
722	0.001, ** p < 0.01, * p < 0.05, n.s. = non-significant. Variable codes are explained
723	in Table 2.

No.	Variables (fixed effects)	Estimate	SE	Sign.
1	BB_TREE (1)	0.158	0.041	***
2	CAN_BEE (1)	-0.029	0.009	***
3	CAN_FIR (1)	-0.030	0.012	*
4	COV_HERB (0.81)	0.011	0.006	n.s.
5	COV_VAC(1)	0.045	0.008	***
6	E1 (1)	0.760	0.347	*
7	E2 (0.81)	-0.613	0.326	n.s.
8	GV_COV (1)	0.012	0.005	*
9	ROW_TOT (0.78)	0.056	0.033	n.s.
Groupin	g factor (random effect)	Variance	CI	
1	Pair_ID (Intercept)	1.933	1.339-3.032	
Rank	Incl. Variables (No.)	AICc	ΔAICc	∆AICc weight
1	1/2/3/4/5/6/7/8/9	941.59	0	0.39
2	1/2/3/4/5/6/7/8	942.73	1.14	0.22
3	1/2/3/5/6/7/8/9	943	1.41	0.19
4	1/2/3/4/5/6/8/9	943.05	1.46	0.19

726 Table 4. Habitat variables explaining the presence of hazel grouse, obtained from a Generalized Linear Mixed Model (GLMM) with "grid cell-pair" as random 727 factor. Variable estimates, as obtained from averaging the four best models 728 according to the AIC-ranking, are presented and the relative variable importance 729 730 is provided in parentheses. The composition and ranking of the included models is specified in the lower part of the table. Asterisks indicate significance levels with 731 *** p < 0.001, ** p < 0.01, * p < 0.05, n.s. = non-significant. Variable codes are 732 733 explained in Table 2.

	Variable	Estimate	SE	Sign.
1	BB_TREE (1)	0.268	0.047	***
2	CAN_BEE (1)	-0.023	0.006	***
3	CAN_O_DEC(1)	-0.032	0.012	**
4	COV_DEC (1)	-0.031	0.011	**
5	COV_FERN(1)	0.023	0.009	*
6	COV_HERB (1)	0.022	0.005	***
7	COV_VAC (1)	0.044	0.006	***
8	E2 (1)	-0.911	0.271	***
9	ROW_TOT (1)	0.099	0.035	**
10	SHR_O_DEC (1)	-0.053	0.019	**
11	SHR_RES_TR (0.68)	0.022	0.012	n.s.
Group	ing factor (random effect)	Variance	CI	
	Pair_ID	1.554	1.398-2.243	
Rank	Incl. Variables (No.)	AICc	∆AICc	∆AICc weight
1	1/2/3/4/5/6/7/8/9/10/11	1267.78	0	0.68
2	1/2/3/4/5/6/7/8/9/10	1269.28	1.5	0.32

- Table 5. Thresholds for the variables significantly explaining the occurrence of
- each of the two model species (see Table 3 and 4), calculated using univariate
- 736 Conditional Inference Trees (CIT) and compared to thresholds (indicated by </>
- and optimal variable ranges found in literature. n.s. = no significant split.

	Thresholds		Literature ^{1,2}			
Explanatory variable	Capercaillie	Hazel grouse	Capercaillie	Hazel grouse		
n(presence/absence)	n(800/593)	n(477/667)				
CAN_COV (%)	≤81 (60-83)	≤60 (60-81)	25-65 [1] 40-60 [2] 50 [3] <60 [5] 50-70 [6]	40-50 [4]		
CAN_SPR (%)	>5 (1-11)	>10 (5-16)	10-33 [6]			
CAN_FIR (%)	≤24 (3-33)	<u>≤10 (1-33)</u>				
CAN_BEE (%)	<u>≤3 (2-26)</u>	<u>≤3(0-11)</u>				
CAN_O_DEC (%)	≤19 (12-28)	≤14 (0-28)				
CAN_RES_TR (%)	>1(0-2)	>1 (0-5)				
SHRUB_COV (%)	n.s.	≤26 (15-40)				
SHR_RES_TR (%)	n.s.	>0 (0-2)		>10 [5]		
SHR_O_DEC (%)	n.s.	≤6 (3-18)				
GV_COV (%)	>60 (28-60)	>60 (38-60)	>40 [6] 50-70 [7] >60 [5] [1] >70 [2] 90-100 [3]	30-45 [5] 60-100 [4]		
COV_VAC (%)	>0 (0-3)	>1 (0-1)	15-20 or more [8] >20 [5] ≥60 [10] >70-100 [7]	40 (+-4) [11]		
COV_HERB (%)	>38 (0-62)	>18 (13-38)				
COV_GRAS (%)	n.s.	>3 (1-17)				
COV_DEC (%)	n.s.	≤13 (8-25)				
ROW_TOT (no./900m ²)	>0 (0-2)	>0 (0-1)		2/900m ² [11]		
BB_TREE (no./900m ²)	>0 (0-1)	>0 (0-5)				
E1 (0;1)	=1	=1	The more the better [9]			
E2 (0;1)	=0	=0				

¹**References:** [1] Bollmann et al. 2005, [2] Bollmann et al. 2008, [3] Storch, I. 1993, [4] Mathys et al. 2006, [5] Lieser and Roth 2001, [6] Suchant and Braunisch 2004, [7] Ehrbahr et al. 2011, [8] Baines et al. 2004, [9] Bollmann, K. 2006,

[10] Müller, F. 1973, [11] Schäublin & Bollmann 2011

²Season and spatial scale of the studies: [1] spring, 25x25m plots; [2] winter&summer 25x25m; [3] plot with r=10m;
[4] autumn, 0.8ha; [5] forest stand scale; [6] summer & winter, forest stand scale (1-50ha); [7] forest stand scale; [8]
forest stand scale; [9] summer, Scotland, 64m²; [10] area not specified; [11] winter, 25x25m

738 **Figure captions**

739	Fig. 1. Sampling design. Distribution of presence grid cells (black: capercaillie
740	presence, white: hazel grouse presence and dark grey: sympatric occurrence)
741	within three biogeographic mountain regions (highlighted in grey) of Switzerland:
742	Jura mountains (JM), Northern Prealps (NPA) and Inner Alps (IA) (A). For each
743	presence grid cell, an absence grid cell (not depicted on this map) was selected
744	within 1 - 4 km distance. In each grid cell, habitat variables were collected in
745	every sampling plot which was located in the forest (maximum 16 per grid cell)
746	(B). In a sampling plot, variables were collected at different reference areas (C):
747	within the entire 30 x 30 m plot, within a nested square (15 x 15 m) (white) or
748	within the two diagonal quarters of the nested square (7.5 x 7.5 m). The variables,
749	their unit and corresponding reference area for sampling are listed in Table 2.
750	

751 Fig. 2. Model evaluation: Calibration plot showing the modelled probabilities of 752 species presence (x-axis) against the observed proportion of presence points (yaxis) for 10 equal-sized probability intervals. Open symbols: capercaillie, filled 753 754 symbols: hazel grouse, squares: Generalized linear mixed models (GLMM), 755 triangles: conditional inference trees (CIT), solid line: perfect calibration. As a 756 classification method, CIT returns probability classes instead of continuous 757 probability values. Consequently, the bins with values correspond to the 758 probability classes shown in Figs 3A and B. In addition, the AUC-values of the 759 corresponding models are indicated.

760

Fig. 3. Multivariate Conditional Inference Trees (CIT) (minsplit=100) explaining
the presence of (A) capercaillie and (B) hazel grouse. The columns at the end of
each branch illustrate the probabilities of species presence (values from 0 to 1 are

764	given on	the right	side of eac	h bar) re	sulting f	from a s	pecific	variable	combinatio	n

Abbreviations of the habitat variables are explained in Table 2.

767	Fig. 4. CIT (minsplit = 10) depicting the thresholds for the proportion of suitable
768	habitat (i.e. proportion of plots with a probability of presence ≥ 0.5) per grid cell
769	explaining the presence of (A) capercaillie and (B) hazel grouse, respectively.
770	Presence probabilities (dark grey) are given in values from 0 to 1. The 95%
771	confidence intervals (CI) of the threshold values based on 1000 bootstrap
772	replicates are as follows: (A) CI: 0.33- 0.91 and (B) CI: 0.25 - 0.90).
773	







Figure 3A Click here to download high resolution image









Supplementary material Click here to download Supplementary material: Appendix A.docx