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## Vegetation maps based on remote sensing are informative predictors of habitat selection of grassland birds across a wetness gradient

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1 **Vegetation maps based on remote sensing are informative**  
2 **predictors of habitat selection of grassland birds across a wetness**  
3 **gradient**

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5 **Running title:** Vegetation mapping highlights habitat selection

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22           Keywords: floodplain, vegetation mapping, SPOT 5, phytosociology, agri-environmental scheme,

23 Whinchat, Corncrake, Yellow Wagtail, Corn Bunting, Reed Bunting.

## 24 **Abstract**

25       Vegetation is a major environmental factor influencing habitat selection in bird species. High  
26 resolution mapping of vegetation cover is essential to model the distribution of populations and  
27 improve the management of breeding habitats. However, the task is challenging for grassland birds  
28 because microhabitat variations relevant at the territory scale cannot be measured continuously over  
29 large areas to delineate areas of higher suitability. Remote sensing may help to circumvent this  
30 problem. We addressed this issue by using SPOT 5 imagery and phytosociological data. We mapped  
31 grassland vegetation in a floodplain using two methods. We (i) mapped the continuous Ellenberg  
32 index of moisture and (ii) identified 5 vegetation classes distributed across the wetness gradient.  
33 These two methods produced consistent output maps, but they also provided complementary  
34 results. Ellenberg index is a valuable proxy for soil moisture while the class approach provided more  
35 information about vegetation structure, and possibly trophic resources. In spite of the apparent  
36 uniformity of meadows, our data show that birds do not settle randomly along the moisture and  
37 vegetation gradients. Overall birds tend to avoid the driest vegetation classes, i.e. the highest  
38 grounds. Thus, vegetation maps based on remote sensing could be valuable tools to study habitat  
39 selection and niche partition in grassland bird communities. It is also a valuable tool for conservation  
40 and habitat management.

41

## 42 **Highlights**

- 43       • We mapped grassland vegetation in a floodplain using two methods
- 44       • The Ellenberg index proves to be a valuable proxy for soil moisture
- 45       • Vegetation classes provided more information about vegetation structure

- 46 • Grassland birds do not settle randomly along the vegetation gradient
- 47 • Vegetation maps based on remote sensing are useful tools to study habitat selection

## 49 **1. Introduction**

50 Delimiting zones of protection is a major issue of conservation programs (McNeely, 1994;  
51 Moilanen et al., 2009). In order to identify core protection areas and optimize management, policy  
52 makers need robust background information like precise ecological requirements for target species.  
53 Grasslands present an interesting case in that respect because they often appear to human eyes as  
54 large expanses of uniform vegetation. For this reason, designing efficient protection areas in  
55 grasslands may seem challenging but this objective needs to be met. Due to anthropogenic changes,  
56 grassland birds are threatened in several part of the World (Azpiroz et al., 2012; Brennan and  
57 Kuvlesky, 2005; Tryjanowski et al., 2011; Tucker et al., 1994). Agri-Environmental Schemes (AES) were  
58 implemented in the 1990's within the European Union to subsidize grassland management  
59 compatible with breeding but many species have continued to decline (Kleijn et al., 2006). Precise  
60 knowledge of habitat selection for target species is therefore crucial to design new and more  
61 ecologically oriented AES measures in areas where conservation objectives partly failed.

62 Although their breeding habitat may seem homogeneous, grassland species do not settle at  
63 random in meadows. Spatial variations in density are frequently observed. For instance, many  
64 species are area-sensitive and avoid small fragments of habitats (Besnard and Secondi, 2014; Davis  
65 and Brittingham, 2004; Helzer and Jelinski, 1999). Even in larger patches, they tend to avoid  
66 landscape features like hedges because of higher predation risk (Morris and Gilroy, 2008). Vegetation  
67 itself offers various level of suitability for nesting. Vegetation structure is a major feature that  
68 influences the settlement of grassland birds (Fisher and Davis, 2010; Jacobs et al., 2012). Plant  
69 community largely determines arthropod assemblages (Schaffers et al., 2008) and therefore the  
70 quantity and quality of available trophic resources (Britschgi et al., 2006). Grassland birds tend to

71 prefer areas with higher densities of flowers during the breeding season (Fischer et al., 2012). This  
72 preference may reflect higher prey availability to feed the young (Oppermann, 1990). Vegetation  
73 cover also determines predation risk (Ejsmond, 2008), particularly the ability of birds to hide their  
74 nests under the canopy (Whittingam and Evans, 2004). Therefore, grassland birds tend to select nest  
75 site with taller swards and denser vegetation (Davis, 2005). In addition, some species need  
76 herbaceous perches for foraging and territorial defence (Fischer et al., 2012; Oppermann, 1990).

77 Soil moisture is a major factor of grassland ecology (Price, 2002; Suzuki et al., 2006). It is  
78 considered as the main driver of vegetation patterns in most regions (Moeslund et al., 2013). Flood  
79 is a recurrent phenomenon that generates a wetness gradient and structures vegetation  
80 communities (Martinez and Letoan, 2007). However, wetness is also influenced by local  
81 environmental conditions like altitude, microtopography, or soil. Fortunately, vegetation has the  
82 property to integrate all the components of wetness (Goward et al., 1991). Mapping vegetation in  
83 relation to its affinity for moisture is expected to provide informative predictors to analyse habitat  
84 selection in grassland birds and improve the management of these habitats. Satellite remote sensing  
85 techniques are promising tools in this regard. They provide vegetation data with a spatial resolution  
86 high enough to analyse habitat selection in birds across ecological gradients. Furthermore, satellite  
87 images often cover geographical ranges large enough to delineate areas with different levels of  
88 conservation priority (Guo, 2004; Poulin et al., 2010).

89 We assessed two methodological approaches to describe the variation of grassland vegetation  
90 across the wetness gradient in floodplains. We used the Ellenberg moisture index that attributes a  
91 value to each vegetal species, corresponding to its affinity for soil moisture (Ellenberg et al., 1992).  
92 We computed a continuous wetness gradient based on the mean Ellenberg index of the local  
93 vegetation community to map the wetness gradient across a floodplain. In addition, we tested a

94 discrete method to map vegetation classes as defined by the phytosociological approach (Tichý,  
95 2002). A vegetation class is “a system of vegetal organisms with a floristic composition that is  
96 statistically repetitive” (Biondi, 2011). Each class may offer a specific level of suitability for birds  
97 depending on its physical properties and the various resources it provides. In grasslands, these  
98 vegetation classes may therefore be an informative proxy to describe habitat requirements of bird  
99 species. This approach may be easier to apply for managers since habitats are determined and their  
100 conservation prioritized according to vegetation associations, for instance in the European Union  
101 (Davies et al., 2004). Finally, AES are implemented in our study area to protect grassland and birds.  
102 We tested if AES types were related to vegetation community, i.e. the hydrological functioning of the  
103 floodplain, and if the spatial distribution of AES matched habitat selection of birds as described by  
104 vegetation.



105

## 106 **2. Methods**

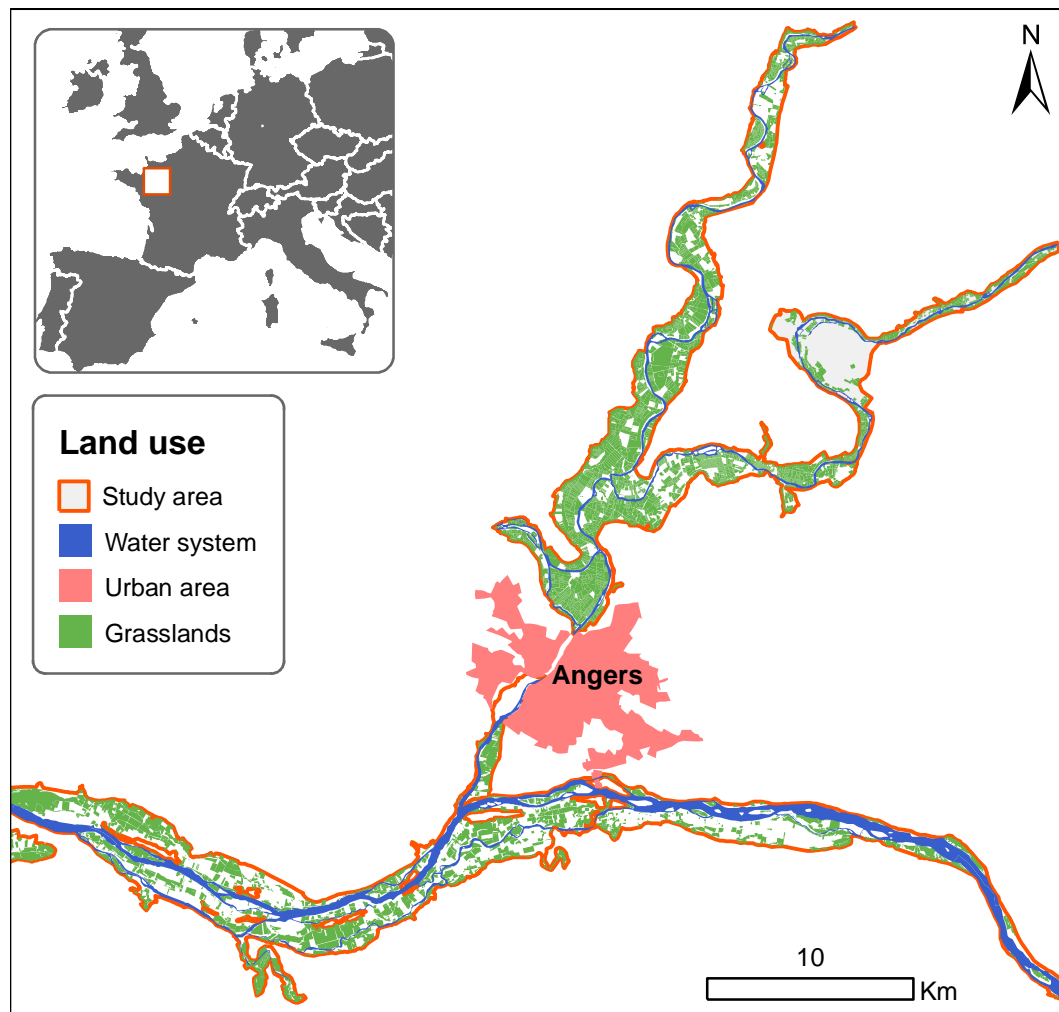
### 107 *2.1 Study area*

108 The study area covers the floodplains of the Loire River and its main tributaries around Angers  
109 city in France (47.48, -0.56) (Fig. 1). Hydrological flow is relatively undisturbed by anthropogenic  
110 developments in contrast to other floodplains of similar size in Western Europe (Hesselink et al.,  
111 2003). Due to frequent floods, extensively managed grasslands still represent the main land cover  
112 type. Agricultural practices consist in mowing meadows once a year in June-July and in allowing low  
113 intensity grazing by cattle during vegetation regrowth. Considering the shallow slope of the ground,  
114 plant community mainly depends on soil wetness and submersibility. Owing to their management,  
115 these grasslands still host several patrimonial bird species, like the Corncrake (*Crex crex*), known to  
116 be highly sensitive to intensive agriculture (Green et al., 1997a). Many grassland bird species  
117 collapsed in the second part of 20<sup>th</sup> century, mainly due to the intensification of practices (more  
118 efficient machinery, fertilisation, advanced mowing schedule). Agri-environmental schemes (AES)  
119 that were implemented locally mainly consisted in delaying hay mowing. The proportion of grassland  
120 under AES is quite high in the study area (45% in 2011). Several levels of AES measures are present in  
121 the study area, differing mainly by the earliest mowing date. For clarity, we aggregated parcels in two  
122 sets: those mown in June (3 540 ha) and those mown in July (1 571 ha). Mowing before July causes  
123 high mortality in broods (Broyer, 2007; Green et al., 1997b). Therefore, we considered that meadows  
124 mown in June were not suitable for the sustainable breeding of grassland birds.

125

126

**Figure 1:** Map of grassland distribution in the study area. The inset shows the location in Europe.



128

129

## 130 *2.2 Vegetation relevés and phytosociological classification*

131 We conducted phytosociological relevés on 107 plots to describe vegetation community across  
 132 the whole study area. Survey was carried out from May 16<sup>th</sup> to June 10<sup>th</sup> 2011 to ensure the reliable  
 133 identification of plant species. A plot was defined by the standard 16m<sup>2</sup> quadrat method (Chytrý and  
 134 Otýpková, 2003). Quadrats were selected in a larger zone of homogeneous vegetation to limit the  
 135 environmental effects of other land cover bordering the pixel of the relevé during the remote sensing

136 process. We sampled as many contrasting situations along the flooding gradient as possible basing  
137 on our knowledge of the study area. Sampling plots were positioned using a Differential Global  
138 Positioning System (DGPS), through a Trimble<sup>®</sup> Juno<sup>®</sup> SB. The estimated georeferencing error after  
139 post-processing was 6 m maximum. However it was lower than 4m for 93% of plots. All species in the  
140 quadrat were identified using either a local specific flora (Corillon, 1981) or a vegetative flora  
141 (Eggenberg and Möhl, 2013) when necessary. Area covered by each species was evaluated using a  
142 Braun-Blanquet coefficient (Braun-Blanquet, 1964). We then classified relevés with JUICE software  
143 (Tichý, 2002), using the TWINSpan method (Hill, 1979), including standard relevés from a previous  
144 study conducted in the same area (Foucault, 1984) as referentials for the classification. This method  
145 classifies relevés according to their similarity in order to identify phytosociological taxa. We identified  
146 five taxa along the wetness gradient in the area: 1. Phalaridion arundinaceae, Kopecky 1961; 2.  
147 Gratiolo officinalis-Oenanthetum fistulosae inferior, De Foucault, 1984 nom. Ined; 3. Gratiolo  
148 officinalis-Oenanthetum fistulosae superior, De Foucault 1984 nom. Ined; 4. Senecio aquatici-  
149 Oenanthetum mediae, Bournerias et al. 1978; 5. Arrhenaterion elatioris, Hoch, 1926. The wettest  
150 and the driest have been considered at the alliance level owing to the diversity of associations  
151 encountered in the field for these two taxa. The three intermediate classes (2-4) have been specified  
152 to the association level because their observed compositions matched the original descriptions.  
153 However, the Gratiolo officinalis-Oenanthetum fistulosae was split in two due to the wide area it  
154 covered and named in accordance with the type relevés described by De Foucault (1984). We tested  
155 the significance of those partitions with a non-parametric multivariate analysis of variance  
156 (Anderson, 2001) using *adonis* from the *vegan* R-package (Oksanen, 2013).

157

158 *2.3 Wetness Ellenberg index*

159 In order to quantify the wetness gradient, we used the wetness Ellenberg index. Ellenberg  
160 indexes determine the affinity of each species for environmental parameters like light, temperature,  
161 or nitrogen in soil (Ellenberg et al., 1992). We used here moisture affinity scores which are available  
162 for each species (Hill et al., 1999). A value of 1 is given to a specialist of the driest habitats and a  
163 value of 12 for a specialist of the wettest habitats. The indicator value of Ellenberg scores has been  
164 evaluated by a field study that concluded that they were very good descriptors of the local  
165 environment (Schaffers and Sýkora, 2000). For each plot, we averaged Ellenberg values of all species,  
166 regardless of their cover, to obtain a single value. We considered this value as a proxy of soil wetness  
167 at the plot scale. We computed average Ellenberg scores weighted by species cover and unweighted.  
168 The unweighted method gave more realistic outputs. This is because cover depends mainly on the  
169 sociability, for example the cover of grasses species is often high whereas sparse species like  
170 *Fritillaria meleagris* can have a more informative value. In addition, weighted average penalize rare  
171 species that often display narrow niches and are informative indicators.

172

#### 173 *2.4 Mapping*

174 A SPOT 5<sup>®</sup> satellite image 2.5m colour, correction level 2B (allocation accuracy less than 10m),  
175 was acquired on May 5<sup>th</sup> 2011. These scenes are provided with three bands: B1 (green: 0.50 to 0.59  
176  $\mu\text{m}$ ), B2 (red: 0.61 to 0.68  $\mu\text{m}$ ), B3 (near-infrared NIR: 0.79 to 0.89  $\mu\text{m}$ ). A mask of all the meadows  
177 within the floodplains was applied on this scene (60 km long x 60 km wide) to delineate the whole  
178 study area using in ARCGIS version 10 (Environmental Systems Research Institute, Meudon France).  
179 All analyses were conducted with this mask. Conditions of image acquisition were optimal with a low  
180 incidence angle (4.77°) and cloud cover less than 10%. Spring 2011 was relatively dry so all the study  
181 area was emerged but a small 41-ha zone that is kept flooded to provide spawning sites for fishes. A

182 vector layer of vegetation plots (quadrats) was created using their GPS coordinates. Circular buffers  
 183 (diameter 4 m) centred on each point were drawn to get a vector layer of polygons of the vegetation  
 184 plots. Then, we used the Spatial Analyst module to extract the mean radiance values of every  
 185 sampling plot for each spectral band. We then calculated for each plot multispectral indices (Table 1)  
 186 adapted for SPOT bands (see the method from Davranche *et al.* (2010 and 2013)).

187

188 **Table 1** Multispectral indices used in this study.

ID index	Multispectral index	References
1	Differential Vegetation Index (DVI)	Richardson & Everitt, 1992
2	Index of free water (IFW)	Adell & Puech, 2003
3	Normalized Difference Vegetation Index (NDVI)	Rouse <i>et al.</i> , 1973
4	Normalized difference water index (NDWI)	Mc Feeters, 1996
5	Optimized Soil Adjusted Vegetation Index (OSAVI)	Rondeaux <i>et al.</i> , 1996
6	B3	Spot image
7	B2	Spot image
8	B2/B1	This study
9	Soil Adjusted Vegetation Index (SAVI)	Huete, 1988
10	Brightness index (BI)	Kauth and Thomas, 1976
11	Simple ratio (SR)	Pearson & Miller, 1972
12	B1	Spot image
13	B1-B2	This study
14	$(B1-B2)/(B1+B2)$	This study
15	$B1^2/B2$	This study
16	Vegetation indice (VI)	Lillesand & Kiefer, 1987
17	Water index (WI)	Davranche et al, 2013
18	Water impoundment index (WII)	Caillaud <i>et al.</i> , 1987

189

190

191 Classification of the 5 vegetation classes was performed using a decision tree with a dichotomous  
192 partitioning (Breiman et al., 1984). It was performed for each class using a binary coding: presence or  
193 absence. We also tested a multiple-class classification, where we attempted to identify all classes in  
194 the same analysis, but this method gave poor results. The Rpart package (Recursive PARTitioning,  
195 Therneau and Atkinson, 1997) in the R software version 2.15.2 software (Rdevelopment core team,  
196 2012) was used. This method is based on the cost complexity parameter (cp) for pruning. As  
197 described in Davranche et al. (2010) for unbalanced samples, we used the cross-validation procedure  
198 called CV-1SE (Esposito et al., 1999) for pruning with 10 subsets and iterative runs of the algorithm  
199 (Breiman et al., 1984) to select the cp and the prior parameter. Cross-validation is well suited to small  
200 samples (Breiman et al., 1984), so it can be recommended when no additional independent sample  
201 is available.

202 The distribution of wetness Ellenberg index was checked for normality. We used linear models to  
203 test whether index values obtained from field relevés could be predicted from remote sensing  
204 variables). Models with all combinations of predictors were computed with the 'lm' function from  
205 the R-package 'stats'. Model selection was carried out using the 'dredge' function of the R-package  
206 'MuMIn' (Barton, 2013). The best model was selected according to the lowest AICc value (Burnham  
207 and Anderson, 2002) (Appendix 1 in Supplementary material). As advised by Symonds and Moussali  
208 (2011), we assessed the goodness-of-fit of this best AICc model, by calculating the coefficient of  
209 determination ( $R^2$ ) and the normalized root-mean-square error (NRMSE) between the predicted and  
210 observed values.

211

212 *2.5 Bird census*

213 The study area host several breeding grassland species, some of which have been declining for  
214 several decades in Western Europe (Tucker et al., 1994). We sampled the 4 dominant passerine  
215 species in this small avian community: the Whinchat *Saxicola rubetra*, the Yellow Wagtail *Motacilla*  
216 *flava*, the Corn Bunting *Emberiza calandra* and the Reed Bunting *Emberiza schoeniclus* (Noël, 2003).  
217 We scanned every hay meadows of the study area during the 2011 breeding season to locate birds.  
218 We used binoculars (10x42) and a spotting scope (20x-60x, 66mm) to detect and identify species.  
219 Fieldwork was performed from April 13th to June 17th 2011 in good weather conditions (no  
220 precipitation and low wind) to optimize bird detection and avoid the recording of migrating birds.  
221 The time of day was not considered to maximize the area surveyed during the breeding season.  
222 However, the detection rate of these species remains relatively high throughout the day, even in the  
223 late afternoon when males rest on the top of vegetation. All occurrences were located on a map  
224 (IGN© 1:25 000), and reported on a GIS software (ArcGIS© 10) by the same observer. We also used  
225 the Corncrake database from LPO France (French official BirdLife partner). These data were collected  
226 in 2011 by volunteer ornithologists who located singing males at night. Like for passerines, Corncrake  
227 data were compiled in a GIS dataset. Overall, we observed 451 Whinchats, 151 Yellow Wagtails, 114  
228 Corn Buntings, 174 Reed Buntings, and we used 479 occurrences of Corncrake across the study area.

229

## 230 2.6 Statistical analyses

231 In order to compare Ellenberg index values on bird locations with background values, we defined  
232 1 501 background plots distributed across a 250m-grid. We created a buffer zone of 100m around  
233 each bird location and background plot. We extracted the average wetness index for all pixels  
234 included in the buffer area. For each bird species, we then compared mean wetness values on  
235 location buffers and background plots using a Wilcoxon test based on bootstrap (1000 iterations of

236 background values with  $n \geq 114$  corresponding to the sample size of each species) with the R software  
237 (version 3.0.2).

238 Similarly, we extracted the mean area covered by each vegetation class within 100m-buffers  
239 around each bird location. Knowing that each class was calculated independently, a pixel can be  
240 assigned to several classes. We compared values for each class to the area covered by the same class  
241 in the whole study area, and tested the differences between the two variables using a Wilcoxon test.  
242 We measured selection or avoidance by birds for each class by calculating the difference in the  
243 distributions of vegetation classes between bird and random location using background plots  
244 described above ( $n=1\ 501$ ).

245 In order to compare the two methods (Ellenberg wetness index and vegetation classes), we used  
246 44 transects of 500m long surrounded with a 100m-buffer (i.e. 13.1 ha). These transects were  
247 distributed across the floodplain in open meadows selected for their suitable landscape for grassland  
248 birds. These were previously used with success to investigate the interest of the topographic  
249 wetness index as a predictor of grassland bird distribution (Besnard et al., 2013). For the two  
250 vegetation maps, we extracted mean values (Ellenberg index and vegetation class) on these transects  
251 and we fitted a linear model between these two datasets. We also used Chi-squared tests to test  
252 whether vegetation classes and bird distributions were randomly distributed across mowing dates.  
253 All tests were carried out using R software (version 3.0.2). Finally, we could determine the pattern of  
254 flooding susceptibility in 35 plots spread across the study area during a spring flood (April-June) in  
255 2013. We sampled these plots twice a week before, during and after the flood, and derived a flood  
256 index which corresponds to the number of times the plots were flooded. To determine whether  
257 Ellenberg index was related to submersibility, we fitted a linear model between flood index and  
258 mean Ellenberg index on plots.



259

### 260 3. Results

261 Using remote sensing method we could map the wetness gradient based on Ellenberg moisture  
262 index across the hay meadows of the study area (Fig. 2; Best model :  $df = 7$ ,  $\text{LogLik} = 110.97$ ,  $\text{AICc} =$   
263  $237.08$ ,  $\text{weight} = 0,00048$ ,  $R^2 = 0.41$ ,  $\text{NRMSE} = 19\%$ ;  $Y = 114,10 + 0,19 * \text{DVI} + 49,73 * \text{NDWI} + 1,65 * \text{B2} +$   
264  $164,96 * \text{B2} / \text{B1} + 0,65 * \text{B1}^2 / \text{B2}$  (More details on model selection in Table S2 in Supplementary  
265 material). The map was consistent with the observed flood susceptibility pattern ( $F_{1,33} = 25.09$ ;  
266  $p < 0.001$ , adjusted  $R^2 = 0.43$ ) (Fig. 3a). The resulting trees for the classification of vegetation classes  
267 provided the following error rates  $C_1$ : 9%,  $C_2$ : 14%,  $C_3$ : 16%,  $C_4$ : 16%,  $C_5$ : 10%. Plant species  
268 composition was significantly different between classes as defined by Twinspan ( $F_{1,106} = 5.62$  ;  
269  $p = 0.001$ ). Using transect data, we found that average vegetation class was strongly correlated with  
270 Ellenberg moisture index ( $F_{1,42} = 116.1$ ;  $p < 0.001$ ; adjusted  $R^2 = 0.73$ ) (Fig. 3b) confirming the value of  
271 these two methods to map wetness gradients. We noticed that the cover of class 5 is probably  
272 overestimated on a part of the wettest area. This area was submerged by water several weeks before  
273 the image capture and vegetation reflectance was modified by alluvium deposits. It was classified as  
274 belonging both to the wettest classes (1-3) and class 5 but field data confirm that this latter class was  
275 not observed there. This classification error causes an underestimation of avoidance of class 5 by  
276 birds because this area exhibit high bird densities. Nevertheless, we detected an avoidance of this  
277 class for 4 species. Thus, this limit does not alter the conclusion of this study.

278 All bird species except the Corn bunting settled in meadows with Ellenberg values higher than  
279 random locations in the study area (Bootstrap based on Wilcoxon test;  $p < 0.001$ ) (Fig. 4 and Table 2).  
280 Yet, this species also tended to select plots with high Ellenberg values ( $p = 0.10 \pm 0.16$ ). Generally,  
281 birds selected wetter hay meadows than available in the study area (Fig. 4 and Table 2). The analysis

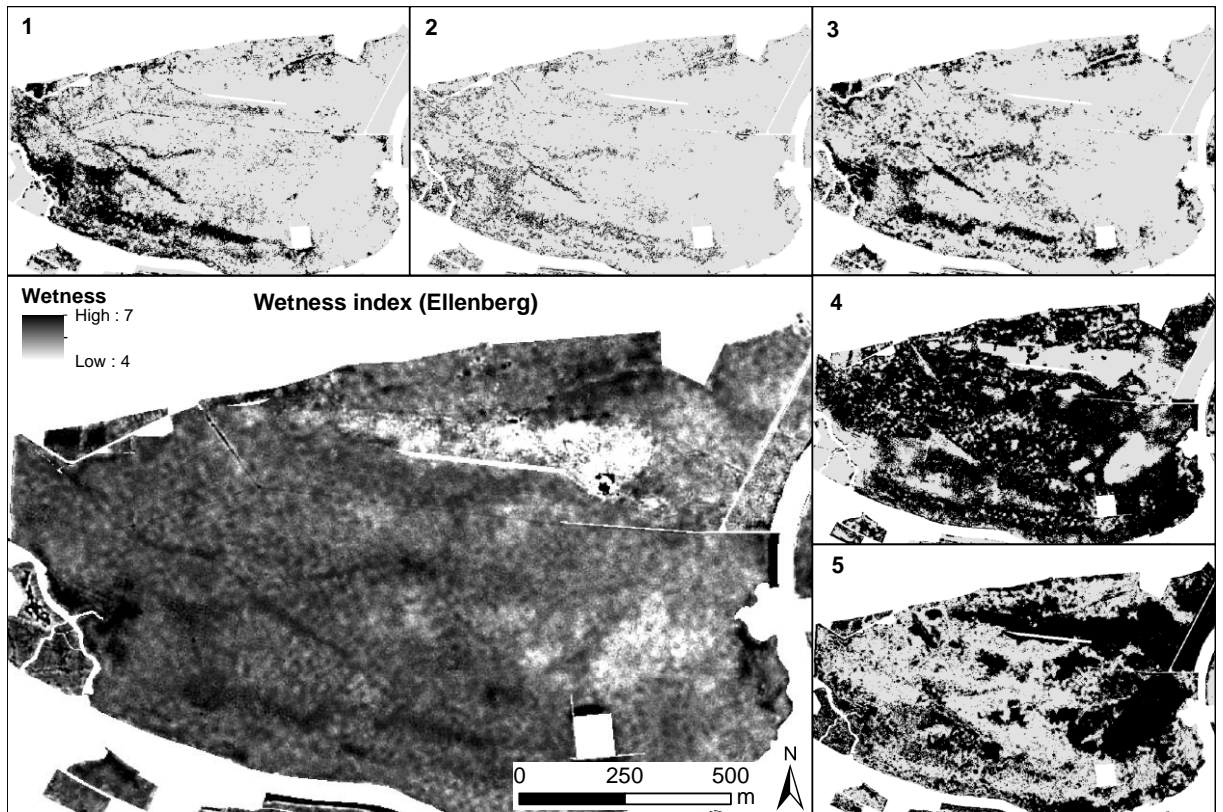
282 of vegetation classes provided supplementary information (Fig. 5). Except for the Corn Bunting, the  
283 three wettest vegetation classes represented a larger proportion of the buffers around bird locations  
284 than available (Table 3). For all species but the Whinchat, the driest vegetal class (5) represented a  
285 smaller proportion of the buffer area around bird locations than expected by chance. For all species,  
286 vegetation class 3 was more represented around bird location than available. Results were more  
287 contrasting for vegetation class 4. It was more represented around bird locations for the Corn  
288 Bunting and the Whinchat, whereas it was less represented for the Reed Bunting and the Corncrake.  
289 More globally, the pattern of habitat selection for vegetation classes was different between species

290 The proportion of area covered by each vegetation class differed between AES contract types  
291 ( $\text{Chi}^2 = 350.75$ ,  $\text{df} = 4$ ,  $p < 0.001$ ) (Fig.5). The driest vegetal classes (5) covered a larger proportion of  
292 the meadows available for mowing in June (47 %) than in July (23%). Logically, we observed the  
293 reverse pattern for the wettest vegetal classes 1, 2 and 3 which represented a lower proportion of  
294 the meadows mown in June (31%) than in July (55%). The proportion of the area covered by  
295 vegetation class 4 was constant between both periods (22 %). Regarding mowing date, birds of all  
296 species settled more frequently in parcels available for mowing in July than expected by chance ( $\text{Chi}^2$   
297  $= 521.10$ ,  $\text{df}=4$ ,  $p < 0.001$ ). In the study area only 22 % of meadow area was mown in July whereas  
298 between 45 % and 66 % of birds settled in this parcels (Fig.5).

299

300 **Figure 2:** Maps extract of the study area representing with the wetness gradient as determined  
301 by Ellenberg moisture index and vegetation classes (1 the wettest and 5 the driest). Grassland areas  
302 were used as a mask prior to mapping.

303



304

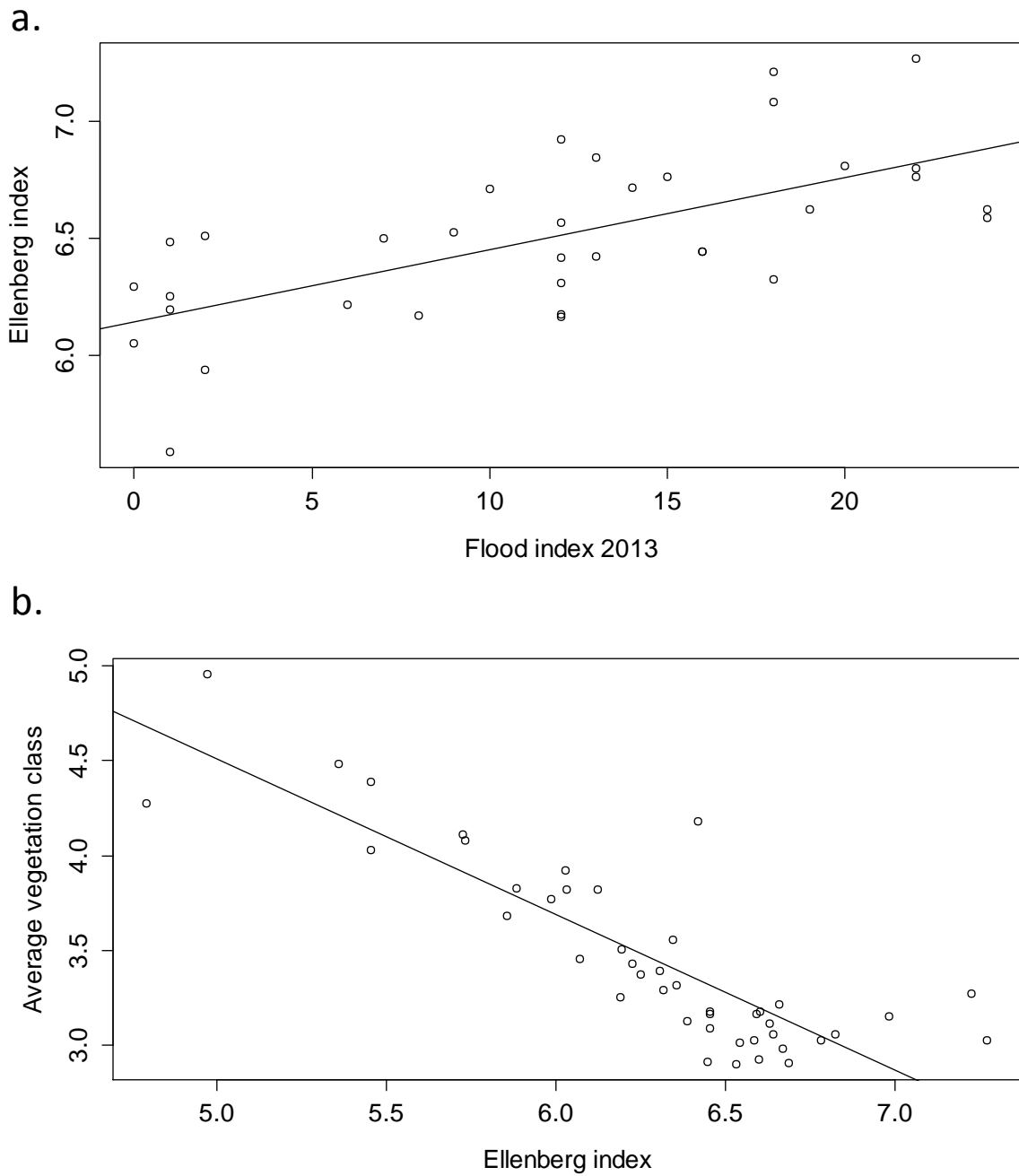
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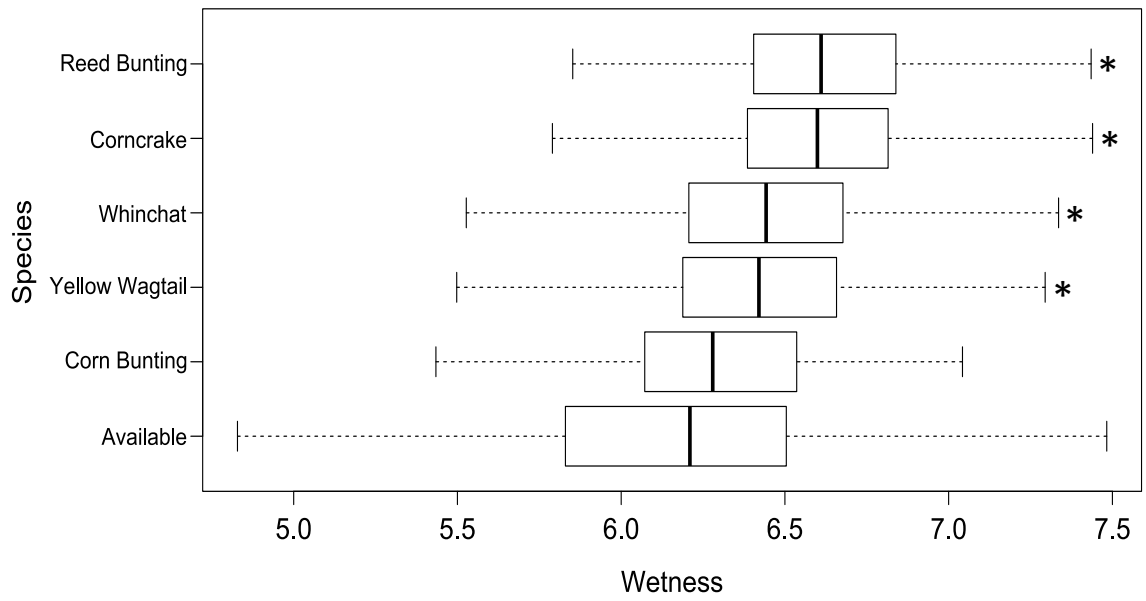
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**Figure 3:** a. Linear relationship between Ellenberg moisture index and flood susceptibility index as measured on 35 plots during a flood event in 2013. b. Linear relationship between Ellenberg moisture index and average vegetation class (1 is the driest, 5 the wettest class) in hay meadows (n=44).



309

310 **Figure 4:** Boxplots of distribution of Ellenberg moisture index calculated for 100m buffers around  
 311 species occurrences and in the study area (available). \* indicates that a species did not settle at  
 312 random across the wetness gradient and significantly preferred wetter meadows (Wilcoxon signed-  
 313 rank test).



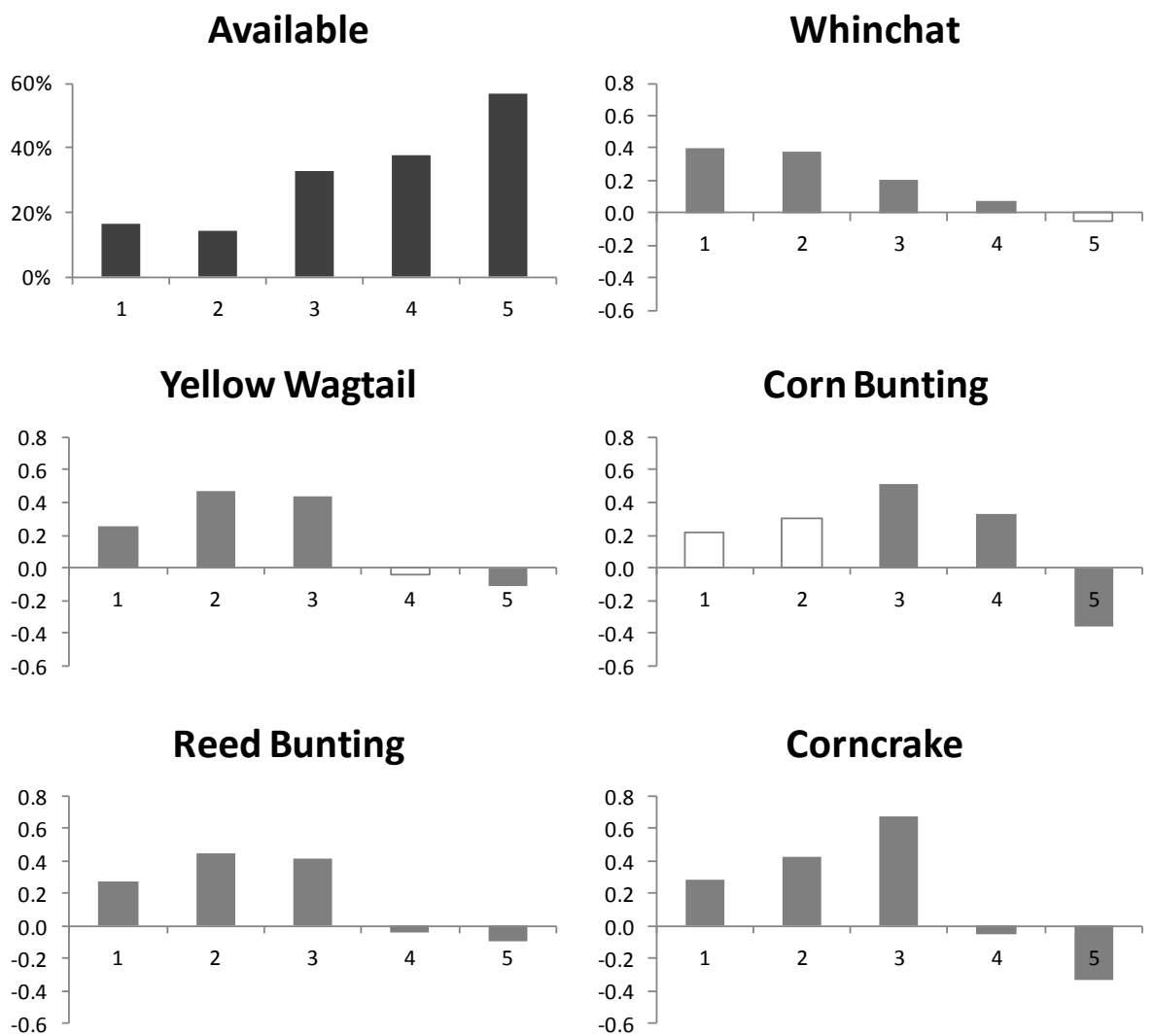
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316

317 **Figure 5:** Distribution of bird occurrences across vegetation classes in floodplain grasslands. The  
 318 first histogram represents the proportion of each class in the study area. All other histograms  
 319 represent the differences between the proportion of each vegetation class available in the study area  
 320 and the proportion of these classes in a 100m-buffer around bird occurrences. Filled symbols indicate  
 321 whether birds significantly selected or avoided this class (Wilcoxon signed-rank tests). Open symbols  
 322 indicate that no selection or avoidance was detected (see values in Table 2). Vegetation classes were  
 323 ranked from the wettest (1) to the driest (5).

324

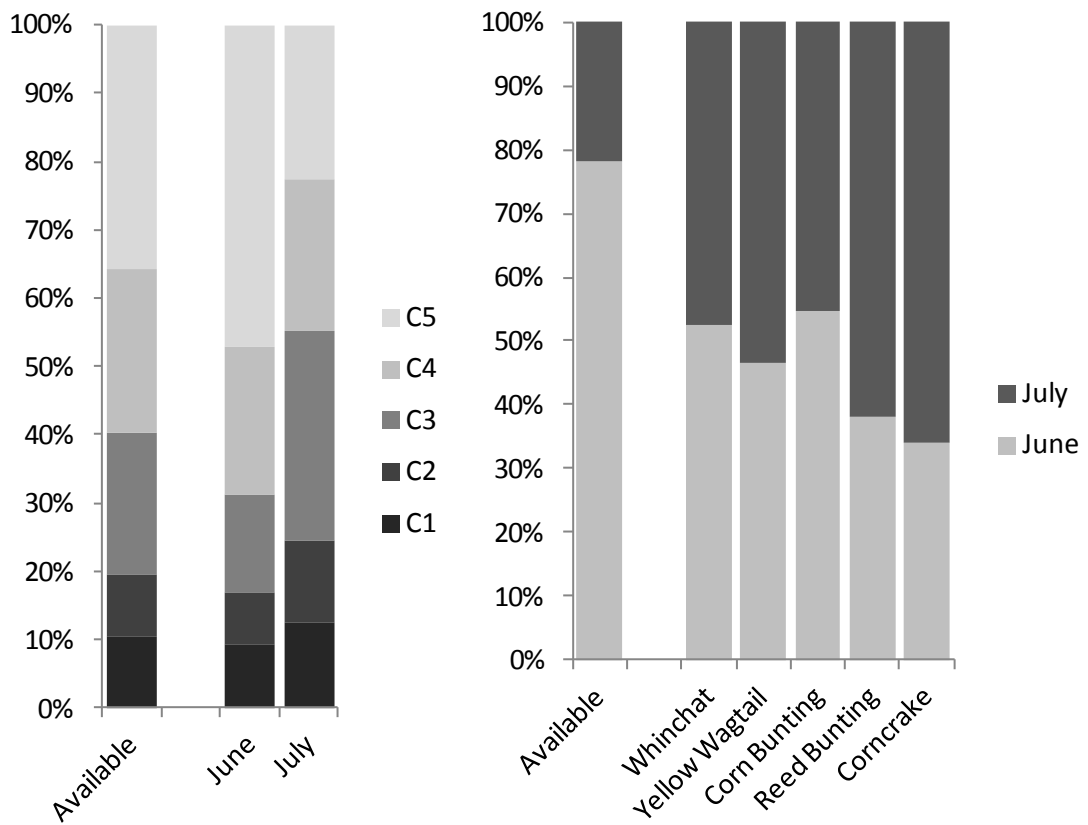


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326

327 **Figure 6:** (left panel) Comparison between the distribution of the five vegetation classes (from C<sub>1</sub>  
328 the wettest to C<sub>5</sub> the driest) observed across the grasslands of the study area and in the parcels  
329 under AES contracts. Mowing dates were allowed either in June or in July. (right panel) Comparison  
330 between the proportion of area available for mowing in June and July, and the proportion of the  
331 population for each bird species on these two management options.

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336 **Table 2:** Test of habitat selection comparing Ellenberg index in 100m buffers around bird  
 337 occurrences and random background locations, and using bootstrap results of Wilcoxon  
 338 tests. Selection is considered to occur when p-value < 0.05, in this case the value is in bold.  
 339  
 340

	p average	2.50%	97.50%
Yellow Wagtail	<b>&lt;0.001</b>	<0.001	<0.01
Corn Bunting	0.10	<0.001	0.62
Reed Bunting	<b>&lt;0.001</b>	<0.001	<0.001
Corncrake	<b>&lt;0.001</b>	<0.001	<0.001
Whinchat	<b>&lt;0.001</b>	<0.001	<0.001

341

342

343 **Table 2:** Cover of each vegetation class within a 100m buffer around species occurrences and  
 344 random background locations. A species is considered to settle more often than by chance in a given  
 345 class when p-value < 0.05 (value in bold). Vegetation classes were classified for the wettest (1) to the  
 346 driest (5). V is the Wilcoxon statistic and p is the corresponding p-value.

	1		2		3		4		5	
	V	p	V	p	V	p	V	P	V	p
Whinchat	62531	<b>p &lt;0.001</b>	72221	<b>p &lt;0.001</b>	66832	<b>&lt;0.001</b>	57279	<b>p &lt;0.05</b>	46081	0.078
Yellow Wagtail	6593	0.112	8265	<b>p &lt;0.001</b>	9339	<b>&lt;0.001</b>	5082	0.223	3786	<b>p &lt;0.001</b>
Corn Bunting	3279	0.998	3615	0.341	4744	<b>&lt;0.001</b>	4404	<b>p &lt;0.01</b>	1297	<b>p &lt;0.001</b>
Reed Bunting	10291	<b>p &lt;0.001</b>	13992	<b>p &lt;0.001</b>	14941	<b>&lt;0.001</b>	6178	<b>p &lt;0.05</b>	3609	<b>p &lt;0.001</b>
Corncrake	68357	<b>p &lt;0.001</b>	94337	<b>p &lt;0.001</b>	108846	<b>&lt;0.001</b>	47725	<b>p &lt;0.01</b>	10081	<b>p &lt;0.001</b>

347

348



349 **4. Discussion**

350 Floodplain grasslands, the location the work was conducted, do not represent a uniform habitat.  
351 Soil moisture gradient generates spatial variation in the composition of plant community (Fig. 2).  
352 Using remote sensing, we characterized Ellenberg index at the pixel scale (2.5 m) so that we could  
353 map the moisture gradient at a high spatial resolution. The ability of this index to represent wetness  
354 was confirmed by the positive relationship with flooding susceptibility, a variable that we could  
355 extract from direct observations in the field during a flood event (Fig 3a.). The vegetation community  
356 showed some discontinuity across the soil moisture gradient though using the TWINSpan method  
357 (Hill, 1979) we could define five phytosociological classes spread across the soil moisture range.  
358 Average level of association in a plot was strongly related to Ellenberg wetness index (Fig 3b.). These  
359 remote sensing data provided us with a layer of an informative predictor, the moisture gradient, to  
360 analyse fine habitat selection of birds.

361 Basing on these data, we found that no bird species settled randomly across the grasslands of the  
362 study area. They rather selected parcels depending on vegetation composition, which itself reflected  
363 the moisture gradient. The wettest meadows (high values of Ellenberg index) hosted generally more  
364 grassland birds in 2011 (Fig. 4), a distribution pattern observed in other years (Noël, 2003, A. Besnard  
365 unpublished data). Even the Corn Bunting, which exploits a large range of open habitats (Donald and  
366 Evans, 1995) showed a tendency to select the wettest meadows. Consistently, birds did not settle  
367 randomly according to vegetation class. This approach provided additional information to the  
368 wetness index. The Reed Bunting and the Corncrake, specialists of grasslands and wetlands with tall  
369 sward (Brickle and Peach, 2004; Green et al., 1997a), settled in areas containing a higher proportion  
370 of the wettest vegetation classes (1-3) than available across the floodplain (Fig. 3b). They also  
371 avoided plots with a high proportion of the driest classes (4-5). Similarly, the Whinchat which is a

372 specialist of extensively managed hay meadows (Müller et al., 2005), and the Yellow Wagtail which  
373 can breed in alternative habitats like crops (Gilroy et al., 2011) preferentially selected the wettest  
374 meadows. Finally, the Corn Bunting selected grasslands with a higher proportion of classes 3 and 4,  
375 and avoided both wettest and driest classes. Overall, no species selected areas covered by a large  
376 proportion of the driest class (5), confirming the results obtained by the method based on Ellenberg  
377 index. Interestingly, this latter class is the most represented in the study area (36%) whereas classes  
378 1, 2 and 3 cover respectively only 10%, 9% and 21%. Species' responses to class 4 were more diverse.  
379 The Corn Bunting settled in areas offering a large cover of this class, and the Whinchat tended to  
380 slightly show the same pattern. In contrast, the Reed Bunting and the Corncrake tended to avoid  
381 areas where this type of vegetation was more abundant than observed in average in the study area.  
382 These results highlight interspecific differences in habitat selection and are consistent with the  
383 ecology of these birds. Yet, differences were usually described for a larger range of ecological  
384 conditions (Jacobs et al., 2012). It is thus particularly interesting to observe that it is possible to  
385 determine species-specific habitat selection profiles within a much narrower ecological range.  
386 Furthermore, species tended to keep their relative position in the wetness gradient with the  
387 restricted ecological range of conditions encountered within the grasslands of these floodplains.

388 Our results suggest that the wettest grasslands (high Ellenberg index and large proportion of  
389 classes 1-3) were the most suitable for birds. Intermediate class (4) were suitable for some species  
390 and avoided by others but selection or avoidance was lower. In contrast, the driest grasslands (class  
391 5) tended to be avoided by all species. We can draw hypotheses to explain this pattern. The wettest  
392 classes can be characterized by a higher forb cover than drier class. We expect trophic resources (e.g.  
393 pollinator insects) (Oppermann, 1990; Pywell et al., 2011) and vegetation structure to depend on the  
394 grass/forbs ratio (Oppermann, 1990). All bird species are mainly insectivorous during the breeding  
395 season (Brickle, 1999; Brickle and Peach, 2004; Britschgi et al., 2006; Davies, 1977; Green et al.,

396 1997a). Therefore, the quantity or quality of trophic resources may be higher on the wet end of the  
397 moisture gradient than on its dry end. Vegetation structure may be of importance too as a higher  
398 proportion of forbs may provide better sites for building nest and more perches for foraging and  
399 social activities as well as reducing predation risk.

400

#### 401 *Flood, meadow management and bird conservation*

402 Vegetation mapping based on remote sensing technique appears as a helpful tool to investigate  
403 habitat selection in grassland habitats and to guide conservation actions. In our study area, the  
404 proportion of any given vegetation class drastically differed between AES contract types (Fig. 5). Early  
405 mown parcels (June) were mostly covered by the driest vegetal classes whereas parcels mown later  
406 (July) were mostly covered by the wettest classes. This is a logical outcome of a scheme based on  
407 volunteering. Farmers tend to select the contract level which minimizes the loss of hay quality. On  
408 the driest meadows, that are mature early, farmers preferentially choose contracts with early  
409 mowing dates. It results that the spatial pattern of mowing dates matches fairly well the wetness  
410 gradient across the study area.

411 It is possible to describe the wetness gradient of an area using only topographical data (Besnard  
412 et al., 2013; Beven and Kirkby, 1979). However, the low altitudinal variation in floodplains may not be  
413 grasped by the resolution of available many digital elevation models, that are the raw data for  
414 computing topographic methods, which limit our ability to map accurately the wetness gradient. Also  
415 pixel size of these models may not be appropriate or relevant in species with small territories for  
416 which small-scale features of the habitat may matter, for their nest site for instance. In contrast, the  
417 high resolution provided by satellite imagery (2.5 m here) allows adjusting the spatial scale of the  
418 analysis to the scale relevant for any bird species. Digital elevation models can be available with very

419 high altitudinal resolution in some areas, in which case it could be interesting to carry out a  
420 comparative assessment of these two methods. However, it is important to outline that unlike  
421 topographical methods the local plant community is an integrative measure of various processes  
422 generating soil moisture (topography, soil composition and climate). Vegetation mapping takes also  
423 into account anthropogenic modifications (like dams or drainages) which cannot be integrated by  
424 topographic methods, for instance in cultivated lands where vegetation depends mainly on  
425 agricultural processes. Finally, the remote sensing method is more ecologically realistic in naturally  
426 sown grasslands where environmental factors, namely flood, largely influence vegetation. This  
427 approach requires more resources for image acquisition, fieldwork, and botanical expertise than  
428 topographical approaches. However, these constraints are balanced by deeper insight into habitat  
429 selection of species, even in homogeneous landscapes, and probably the providing of more robust  
430 information to base on to delineate areas for conservation.

431

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438

439 **References**

- 440 Barton, K., 2013. MuMIn: Multi-model inference, R package version 1.9.13.
- 441 Anderson, M., 2001. A new method for non-parametric multivariate analysis of variance. *Austral*  
442 *Ecol.* 32–46.
- 443 Azpiroz, A.B., Isacch, J.P., Dias, R. a., Di Giacomo, A.S., Fontana, C.S., Palarea, C.M., 2012. Ecology and  
444 conservation of grassland birds in southeastern South America: A review. *J. F. Ornithol.* 83, 217–  
445 246. doi:10.1111/j.1557-9263.2012.00372.x
- 446 Besnard, A.G., Jeunesse, I. La, Pays, O., Secondi, J., 2013. Topographic wetness index predicts the  
447 occurrence of bird species in floodplains. *Divers. Distrib.* 19, 955–963. doi:10.1111/ddi.12047
- 448 Besnard, A.G., Secondi, J., 2014. Hedgerows diminish the value of meadows for grassland birds:  
449 Potential conflicts for agri-environment schemes. *Agric. Ecosyst. Environ.* 189, 21–27.  
450 doi:10.1016/j.agee.2014.03.014
- 451 Beven, K., Kirkby, M.M.J., 1979. A physically based, variable contributing area model of basin  
452 hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin  
453 versant. *Hydrol. Sci. J.* 24, 43–69.
- 454 Biondi, E., 2011. Phytosociology today: Methodological and conceptual evolution. *Plant Biosyst.* - An  
455 *Int. J. Deal. with all Asp. Plant Biol.* 145, 19–29. doi:10.1080/11263504.2011.602748
- 456 Braun-Blanquet, J., 1964. *Pflanzensoziologie: grundzüge der vegetationskunde.*
- 457 Breiman, L., Friedman, J., Stone, C., Olshen, R., 1984. *Classification and regression trees*, Chapman & .  
458 ed. New York.
- 459 Brennan, L., Kuvlesky, W., 2005. North American Grassland Birds: An Unfolding Conservation Crisis? *J.*  
460 *Wildl. Manage.* 69, 1–13. doi:10.2193/0022-541X(2005)069<0001:NAGBAU>2.0.CO;2
- 461 Brickle, N., 1999. Diet of nestling Corn Buntings *Miliaria calandra* in southern England examined by  
462 compositional analysis of faeces. *Bird Study* 46, 319–329.
- 463 Brickle, N.W., Peach, W.J., 2004. The breeding ecology of Reed Buntings *Emberiza schoeniclus* in  
464 farmland and wetland habitats in lowland England. *Ibis (Lond. 1859)*. 146, 69–77.
- 465 Britschgi, A., Spaar, R., Arlettaz, R., 2006. Impact of grassland farming intensification on the breeding  
466 ecology of an indicator insectivorous passerine, the Whinchat *Saxicola rubetra*: Lessons for  
467 overall Alpine meadowland management. *Biol. Conserv.* 130, 193–205.  
468 doi:10.1016/j.biocon.2005.12.013
- 469 Broyer, J., 2007. Définition d'un calendrier des fenaison compatible avec la reproduction des  
470 passereaux. *Alauda* 75, 145–158.

- 471 Burnham, K. P., D. R. Anderson., 2002. Model selection and multimodel inference : a practical  
472 information-theoretic approach. Second edition. Springer, New York, New York, USA.
- 473 Chytrý, M., Otýpková, Z., 2003. Plot sizes used for phytosociological sampling of European  
474 vegetation. *J. Veg. Sci.* 563–570.
- 475 Corillon, R., 1981. Flore et végétation de la vallée de la Loire, Imprimerie. ed. Paris.
- 476 Davies, C.E., Moss, D., Hill, M.O., 2004. EUNIS habitat classification revised 2004.
- 477 Davies, N.B., 1977. Prey selection and social behaviour in wagtails. *J. Anim. Ecol.* 46, 37–57.
- 478 Davis, S., 2005. Nest-site selection patterns and the influence of vegetation on nest survival of mixed-  
479 grass prairie passerines. *Condor* 605–616.
- 480 Davis, S.K., Brittingham, M., 2004. Area sensitivity in grassland passerines: effects of patch size, patch  
481 shape, and vegetation structure on bird abundance and occurrence in southern Saskatchewan.  
482 *Auk* 121, 1130–1145.
- 483 Davranche, A., Lefebvre, G., Poulin, B., 2010. Wetland monitoring using classification trees and SPOT-  
484 5 seasonal time series. *Remote Sens. Environ.* 114, 552–562. doi:10.1016/j.rse.2009.10.009
- 485 Davranche, A., Poulin, B., Lefebvre, G., 2013. Mapping flooding regimes in Camargue wetlands using  
486 seasonal multispectral data. *Remote Sens. Environ.* 138, 165–171.  
487 doi:10.1016/j.rse.2013.07.015
- 488 Donald, P., Evans, A., 1995. Habitat selection and population size of Corn Buntings *Miliaria calandra*  
489 breeding in Britain in 1993. *Bird Study* 42, 190–204.
- 490 Eggenberg, S., Möhl, A., 2013. Flora Vegetativa [Relié], 2th editio. ed. Bern.
- 491 Ejsmond, J., 2008. The effect of mowing on next-year predation of grassland bird nests: experimental  
492 study. *Polish J. Ecol.* 56, 299–307.
- 493 Ellenberg, H., Weber, H.E., Düll, R., Wirth, V., Werner, W., Paulißen, D., 1992. Zeigerwerte von  
494 Pflanzen in Mitteleuropa. *Scr. Geobot* 18, 1–258.
- 495 Esposito, F., Malerba, R.D., Semeraro, G., Tamma, V., 1999. The effects of pruning medods on the  
496 predictive accuracy of indices. *Appl. Stoch. Model. Buisness Ind.* 15, 277–299.
- 497 Fischer, K., Busch, R., Fahl, G., Kunz, M., Knopf, M., 2012. Habitat preferences and breeding success  
498 of Whinchats (*Saxicola rubetra*) in the Westerwald mountain range. *J. Ornithol.* 154, 339–349.  
499 doi:10.1007/s10336-012-0898-z
- 500 Fisher, R.J., Davis, S.K., 2010. From Wiens to Robel: A Review of Grassland-Bird Habitat Selection. *J.*  
501 *Wildl. Manage.* 74, 265–273. doi:10.2193/2009-020

- 502 Foucault, B. De, 1984. Systématique, structuralisme et synsystématique des prairies hygrophiles des  
503 plaines atlantiques françaises. Univ. Rouen.
- 504 Gilroy, J.J., Anderson, G.Q. a., Vickery, J. a., Grice, P. V., Sutherland, W.J., 2011. Identifying  
505 mismatches between habitat selection and habitat quality in a ground-nesting farmland bird.  
506 Anim. Conserv. 14, no–no. doi:10.1111/j.1469-1795.2011.00480.x
- 507 Goward, S.N., Markham, B., Dye, D.G., Dulaney, W., Yang, J.L., 1991. Normalized Difference  
508 Vegetation Index Measurements From The Advanced Very High-Resolution Radiometer.  
509 Remote Sens. Environ. 35, 257–277.
- 510 Green, R., Rocamora, G., Schaffer, N., 1997a. Populations, ecology and threats to the Corncrake *Crex*  
511 *crex* in Europe. Vogelwelt 118, 117–134.
- 512 Green, R., Tyler, G., Stowe, T., Newton, A., 1997b. A simulation model of the effect of mowing of  
513 agricultural grassland on the breeding success of the corncrake (*Crex crex*). J. Zool. 243, 81–115.
- 514 Guo, X., 2004. Measuring Spatial and Vertical Heterogeneity of Grasslands Using Remote Sensing  
515 Techniques. J. Environ. Informatics 3, 24–32. doi:10.3808/jei.200400024
- 516 Helzer, C.J., Jelinski, D.E., 1999. The relative importance of patch area and perimeter-area ratio to  
517 grassland breeding birds. Ecol. Appl. 9, 1448–1458.
- 518 Hesselink, A., Weerts, H., Berendsen, H., 2003. Alluvial architecture of the human-influenced river  
519 Rhine, The Netherlands. Sediment. Geol.
- 520 Hill, M.O., 1979. TWINSpan: A FORTRAN Program for Arranging Multivariate Data in an Ordered  
521 Two-way Table by Classification of the Individuals and Attributes.
- 522 Hill, M.O., Mountford, J.O., Roy, D.B., Bunce, R.G.H., 1999. Ellenberg's indicator values for British  
523 plants. ECOFACT Volume 2 Technical Annex.
- 524 Jacobs, R.B., Thompson, F.R., Koford, R.R., La Sorte, F. a., Woodward, H.D., Fitzgerald, J. a., 2012.  
525 Habitat and landscape effects on abundance of Missouri's grassland birds. J. Wildl. Manage. 76,  
526 372–381. doi:10.1002/jwmg.264
- 527 Kleijn, D., Baquero, R. a, Clough, Y., Díaz, M., De Esteban, J., Fernández, F., Gabriel, D., Herzog, F.,  
528 Holzschuh, a, Jöhl, R., Knop, E., Kruess, a, Marshall, E.J.P., Steffan-Dewenter, I., Tscharrntke, T.,  
529 Verhulst, J., West, T.M., Yela, J.L., 2006. Mixed biodiversity benefits of agri-environment  
530 schemes in five European countries. Ecol. Lett. 9, 243–54; discussion 254–7. doi:10.1111/j.1461-  
531 0248.2005.00869.x
- 532 Martinez, J., Letoan, T., 2007. Mapping of flood dynamics and spatial distribution of vegetation in the  
533 Amazon floodplain using multitemporal SAR data. Remote Sens. Environ. 108, 209–223.  
534 doi:10.1016/j.rse.2006.11.012
- 535 McNeely, J., 1994. Protected areas for the 21st century: working to provide benefits to society.  
536 Biodivers. Conserv. 405, 390–405.

- 537 Moeslund, J., Arge, L., Bøcher, P., 2013. Topographically controlled soil moisture is the primary driver  
538 of local vegetation patterns across a lowland region. *Ecosphere* 4, 1–26.
- 539 Moilanen, A., Wilson, K., Possingham, H., 2009. Spatial conservation prioritization: quantitative  
540 methods and computational tools.
- 541 Morris, A.J., Gilroy, J.J., 2008. Close to the edge: predation risks for two declining farmland  
542 passerines. *Ibis (Lond. 1859)*. 150, 168–177.
- 543 Müller, M., Spaar, R., Schifferli, L., Jenni, L., 2005. Effects of changes in farming of subalpine  
544 meadows on a grassland bird, the whinchat (*Saxicola rubetra*). *J. Ornithol.* 146, 14–23.  
545 doi:10.1007/s10336-004-0059-0
- 546 Noël, F., 2003. Étude de l'avifaune nicheuse des prairies inondables de fauche dans les Basses Vallées  
547 Angevines. *Crex* 7, 53–58.
- 548 Oppermann, R., 1990. Suitability of different vegetation structure types as habitat for the whinchat  
549 (*Saxicola rubetra*). *Vegetatio* 109–116.
- 550 Poulin, B., Davranche, A., Lefebvre, G., 2010. Ecological assessment of *Phragmites australis* wetlands  
551 using multi-season SPOT-5 scenes. *Remote Sens. Environ.* 114, 1602–1609.  
552 doi:10.1016/j.rse.2010.02.014
- 553 Price, E., 2002. *Lowland Grassland and Heathland Habitats (Habitat Guides)*. Routledge.
- 554 Pywell, R.F., Meek, W.R., Hulmes, L., Hulmes, S., James, K.L., Nowakowski, M., Carvell, C., 2011.  
555 Management to enhance pollen and nectar resources for bumblebees and butterflies within  
556 intensively farmed landscapes. *J. Insect Conserv.* 15, 853–864. doi:10.1007/s10841-011-9383-x
- 557 Schaffers, A., Raemakers, I., Sýkora, K., Braak, C. Ter, 2008. Arthropod assemblages are best  
558 predicted by plant species composition. *Ecology* 89, 782–794.
- 559 Schaffers, A., Sýkora, K., 2000. Reliability of Ellenberg indicator values for moisture, nitrogen and soil  
560 reaction: a comparison with field measurements. *J. Veg. Sci.* 11, 225–244.
- 561 Suzuki, R., Xu, J., Motoya, K., 2006. Global analyses of satellite-derived vegetation index related to  
562 climatological wetness and warmth. *Int. J. Climatol.* 26, 425–438. doi:10.1002/joc.1256
- 563 Therneau, T.M., Atkinson, E.J., 1997. *An Introduction to Recursive Partitioning Using the RPART*  
564 *Routines*.
- 565 Tichý, L., 2002. JUICE, software for vegetation classification. *J. Veg. Sci.* 451–453.
- 566 Tryjanowski, P., Hartel, T., Báldi, A., Szymański, P., Tobolka, M., Herzon, I., Goławski, A., Konvička, M.,  
567 Hromada, M., Jerzak, L., Kujawa, K., Lenda, M., Orłowski, G., Panek, M., Skórka, P., Sparks, T.H.,  
568 Tworek, S., & A.W., Żmihorski, M., 2011. Conservation of Farmland Birds Faces Different  
569 Challenges in Western and Central-Eastern Europe. *Acta Ornithol.*  
570 doi:10.3161/000164511X589857



571 Tucker, M., Heath, M.F., Tomialojc, L., Grimmett, R., 1994. Birds in Europe: Their Conservation Status  
572 (Birdlife Conservation). BirdLife International.

573 Whittingam, M.J., Evans, K.L., 2004. The effects of habitat structure on predation risk of birds in  
574 agricultural landscapes. *Ibis* (Lond. 1859). 146, 210–220.

575

576 SUPPLEMENTARY MATERIAL

577 **Table S1.** Model selection for mapping the ewetness index using the MuMin R package. Only models with  $\Delta AICc < 1.5$  are shown.

578 Description of variables are given in Table 1 (1-1\_ refer to ID index.

579

Intercept	Coefficient estimates																		Df	logLik	AICc	$\Delta AICc$	Weight	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18						
114.10	0.19			49.73			1.65	-164.96												7	-110.97	237.08	0.00	0.00048
115.33				49.95		0.19	1.48	-167.03												7	-111.02	237.18	0.10	0.00046
105.32				42.22			1.36	-155.15		0.17										7	-111.13	237.40	0.32	0.00041
107.07		0.17		44.44			1.55	-156.43												7	-111.17	237.47	0.39	0.00040
84.54		-1.12		25.56				-131.68		1.25										7	-111.36	237.85	0.77	0.00033
60.41	3.29	-6.90						-109.44		3.71		-2.71								8	-110.40	238.27	1.19	0.00027
78.70		-1.57				1.67		-159.23			45.54									7	-111.67	238.48	1.40	0.00024
-19.01	5.30	-8.37								2.98		-2.36				-1.57	3.85			8	-110.52	238.51	1.44	0.00023
139.51	1.12	-0.96	-56.04				1.70	-185.53												8	-110.53	238.52	1.45	0.00023
139.25	1.11	-0.95					1.70	-185.38	-37.46											8	-110.53	238.53	1.45	0.00023
139.19	1.11	-0.95			-56.21		1.70	-185.35												8	-110.53	238.53	1.45	0.00023
100.51	0.10				-32.83		1.29	-142.17												7	-111.71	238.54	1.47	0.00023
100.49	0.10						1.29	-142.13	-21.86											7	-111.71	238.55	1.47	0.00023

100.38 0.10

-32.55

1.29 -141.93

-0.43

7 -111.72 238.56

1.49

0.00023

580 Richardson, A. J., & Everitt, J. H. (1992). Using spectra vegetation indices to estimate rangeland  
581 productivity. *Geocarto International*, 1, 63-69.

582 Adell, C., & Puech, C. (2003). L'analyse spatiale des plans d'eau extraits par télédétection satellitale  
583 permet-elle de retrouver la marque cynégétique en Camargue? *Bulletin de la société française*  
584 *de photogrammétrie et de télédétection*, 172, 76-86.

585 Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). Monitoring vegetation systems in the  
586 great plains with ERTS. Third ERTS Symposium, NASA SP-351,1.

587 Rondeaux, G., Steven, & M, Baret, F. (1996). Optimization of Soil-Adjusted Vegetation Indices.  
588 *Remote Sensing of Environment*, 55, 95-107.

589 McFeeters, S. K. (1996). The use of the normalised difference water index (NDWI) in the delineation  
590 of open water features. *International Journal of Remote Sensing*, 17, 1425-1432.

591 Symonds, MRE., & Moussalli, A., (2011). A brief guide to model selection, multimodel inference and  
592 model averaging in behavioural ecology using Akaike's Information Criterion, *Behavioral Ecology and*  
593 *Sociobiology*, 65, 13-21.

594 Huete, A. R. (1988). A Soil-Adjusted Vegetation Index (SAVI). *Remote sensing of Environment*, 25,  
595 295-309.

596 Pearson, R.L., & Miller, L.D. (1972). *Remote mapping of standing crop biomass for estimation of the*  
597 *productivity of the short-grass Prairie, Pawnee National Grasslands, Colorado*. Processing of the  
598 8th International Symposium on Remote Sensing of Environment, ERIM, Ann Arbor, MI, 1357-  
599 1381.

600 Lillesand, T. M., & Kiefer, R. W. (1987). *Remote sensing and image interpretation*, 2e édition, John  
601 Wiley and Sons, New York, 721 p.

602 Caillaud, L., Guillaumont, B., & Manaud, F. (1991). *Essai de discrimination des modes d'utilisation*  
603 *des marais maritimes par analyse multitemporelle d'images SPOT. Application aux marais maritimes*  
604 *du Centre Ouest*. IFREMER report (H4.21) 485, 24 p.

605