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1 Title

2 Permanent grassland classifications predict agronomic and environmental characteristics well,  
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15

16 Declaration of interest

17 None

18

19

20 Colour

21 Figure 1, Figure 2 and Figure 3 require colour.

22

## 23 Abstract

24 Permanent grasslands produce highly diverse ecosystem goods and services, which need to be  
25 easily assessed by decision makers. Naturalists and agronomists classify grasslands in  
26 different ways to predict ecological, agronomic and environmental characteristics of the  
27 grasslands. However, few studies have compared the prediction abilities of these different  
28 classifications using the same botanical relevés, and none has explored the utility of  
29 combining classifications. In this study, we attributed a grassland class from each of three  
30 classifications (phytosociological, agronomic and functional) to 250 permanent grasslands in  
31 north-eastern France to predict 16 characteristics: nine ecological, three agronomic and four  
32 environmental. We used statistical model selection to identify the classification or  
33 combination of classifications that best predicted each characteristic. Our results showed great  
34 prediction ability of agronomic classification, which created the best models for predicting  
35 agronomic (yield) and environmental (management, elevation) characteristics. We also  
36 identified a strong prediction ability of combining two or all three classifications to predict  
37 seven other grassland characteristics. However, grassland classifications did not predict most  
38 of the ecological characteristics well. We can assume that phytosociological classification,  
39 despite its mainstream use, predicts grassland characteristics less well than agronomic  
40 classification. We recommend combining grassland classifications to improve rapid  
41 prediction abilities. This study provides new knowledge useful for developing grassland  
42 classifications which meet the needs of agronomists and naturalists.

43 Key words: phytosociology; agricultural type; functional type; management; biodiversity;  
44 typology

45

## 46 1 Introduction

47 Worldwide, permanent grassland is the main terrestrial ecosystem, covering 26% of the world  
48 land area (FAO, 2019) and 28% of UE total utilised agricultural area in 2013 (Eurostat, 2017).  
49 Permanent grasslands provide diverse ecosystem goods and services of global importance,  
50 such as forage production, species habitat, pollination, water purification, flood prevention  
51 and mitigation of global warming through carbon storage (D'Ottavio et al., 2017). Provision  
52 of these services is threatened by four main dangers: disappearance of grasslands (cultivation,  
53 degradation), underuse (abandonment), agricultural intensification and climate change (Biró  
54 et al., 2013; Muller et al., 1998; WallisDeVries et al., 2002; Young et al., 2005).

55 Conservation of grasslands and associated goods and services requires strong policy, but  
56 grasslands differ and do not need equal protection. Indeed, agronomic and ecological services  
57 provided by grasslands are complex consequences of management choices, environmental  
58 constraints and botanical composition (Dumont et al., 2018; Michaud et al., 2012). Decision-  
59 makers need simple tools such as grassland classifications to assess or predict the levels of  
60 grassland services provided. At local scales, farmers and agronomists mainly need to predict  
61 forage yield and quality, while naturalists are interested in ecological values of grasslands. At  
62 regional, national and international scales, policy makers and administrators need to assess  
63 trade-offs between economics and the environment, and to design best policies. To solve these  
64 issues, naturalists and agronomists have developed different grassland classifications, using  
65 divergent methods. These classifications simplify prediction of grassland characteristics,  
66 which depend on the viewpoint and method of study.

67 Naturalists have used phytosociology since the early 20th century to classify vegetation  
68 communities and assess habitat conservation. The development of phytosociological

69 classification required botanical relevés of all vascular species and a coefficient of abundance-  
70 dominance for each species of each relevé (Braun-Blanquet, 1964). Phytosociology is the  
71 mainstream method for classifying vegetation communities as it can be applied to all  
72 ecosystems worldwide (e.g. Cheng et al., 2013; Rodríguez-Rojo et al., 2017, 2001; Setubal  
73 and Boldrini, 2012), vegetation classes are arranged into a hierarchical system, and their  
74 names follow scientific rules (Dengler et al., 2008). Once developed, the use of  
75 phytosociological classifications requires only a complete botanical relevé and less than an  
76 hour in each field. Phytosociology can also be used to predict agronomic characteristics, such  
77 as forage quality, and environmental characteristics by using indicator species (Petrovic et al.,  
78 2013); however, coefficients of abundance-dominance correlate only weakly with each  
79 species' percentage of total grassland biomass (i.e. relative biomass), which can skew  
80 assessment of agronomic characteristics (Daget and Poissonet, 1971; Pittarello et al., 2018).  
81 Naturalists use phytosociology frequently worldwide; in the European Union, it is used to  
82 assess habitat conservation and define priority habitats to protect faunal and floral  
83 biodiversity.

84 Agronomists have developed agronomic classifications since the 1950s to quickly assess  
85 forage yield and quality, as well as impacts of practices on forage production and the  
86 environment (Michaud et al., 2013). Complete knowledge of botanical diversity is needed to  
87 develop a classification because effects of each plant species on animal production depend on  
88 its prevalence in an animal's diet (Diquélou et al., 2003), but classification approaches may  
89 vary. Agronomic classifications provide accurate information about agronomic performances  
90 of grasslands but are closely tied to the areas for which they were developed. Once developed,  
91 agronomic classifications can often be used without botanical knowledge, but they do require  
92 knowledge about agronomic practices, which needs to be collected when the classifications  
93 are developed. Doing so requires time, but can begin a discussion between farmers and  
94 agricultural advisors. Moreover, agronomic classifications can be used to predict ecological  
95 characteristics such as species richness and pollinator value (Hulin et al., 2011; Launay et al.,  
96 2011), but not all classifications have been developed for this purpose. Several agronomic  
97 classifications have been developed, especially in western Europe, and they are used by a  
98 wide range of decision makers, including agricultural advisors and farmers (Michaud et al.,  
99 2013).

100 More recently, during the 1990s, ecologists attempted to explain the functioning of grassland  
101 ecosystems using functional traits of plants (e.g. Lavorel and Garnier, 2002; Mouillot et al.,  
102 2013; Violle et al., 2007). A functional trait is "any morphological, physiological or  
103 phenological feature measurable at the individual level, ... without reference to the  
104 environment or any other level of organization" (Violle et al., 2007). Agronomists applied this  
105 knowledge to permanent grasslands to develop functional classifications, which are used to  
106 predict grassland agronomic characteristics such as forage quality, earliness and management  
107 flexibility. Dominant grass (Cruz et al., 2010; Durante et al., 2012) and forb species have been  
108 classified by their functional traits, which are then used to classify grasslands. Functional  
109 ecology has brought a fresh perspective to ecology and agronomy, improved prediction of  
110 ecosystem goods and services, such as fodder production or carbon and nitrogen cycling  
111 (Carol Adair et al., 2018; Lavorel, 2013), and been particularly useful for characterising  
112 community response to environmental change (Lavorel and Garnier, 2002; Nock et al., 2016).  
113 Unlike agronomic classifications, functional classifications are not restricted to the areas for  
114 which they were developed (Cruz et al., 2010) and, once developed, do not require great  
115 botanical knowledge: the relative biomass of the grass and forb species classified is sufficient  
116 to classify the grassland and predict its agronomic characteristics. Developing functional  
117 classifications, however, requires knowledge about functional traits of plant species. These

118 classifications are already used in France to help farmers manage grasslands (Carrère et al.,  
119 2012).

120 The first objective of our study was to compare how phytosociological, agronomic and  
121 functional classifications assess grassland characteristics, as they use different methods and  
122 have different objectives. Phytosociological classification's main aim is to describe botanical  
123 associations, while agronomic classification focuses on predicting forage yield and quality. In  
124 comparison, functional classification predicts mechanisms (e.g. strategy for acquiring  
125 nutrients, development of plant structure) that express themselves when exposed to  
126 environmental variation. We hypothesised that each classification could predict certain  
127 characteristics well: phytosociological for ecological characteristics, agronomic for agronomic  
128 characteristics and functional for agronomic and environmental characteristics.

129 Classifications are used to predict grassland ecosystem goods and services, but usually only  
130 one classification approach is used to do so. However, differences in classification objectives  
131 lead to divergent methods for constructing classifications, which can cause classifications'  
132 predictions of grassland characteristics to differ despite having similar prediction potentials.  
133 From this perspective, the second objective of this study was to investigate prediction  
134 capacities of combined grassland classifications. To our knowledge, few studies have  
135 combined classification approaches. Carrère et al. (2012) combined phytosociological class,  
136 agronomic management and functional class to study potential evolution from one grassland  
137 class to another (e.g. due to modifying fertilisation or earliness of first use). Macedo et al.  
138 (2010) compared the species prediction abilities of three classifications of dune plants:  
139 phytosociological, dominant-strategy (Grime's CSR theory) and functional. They found that  
140 these classifications predicted plant species similarly but differed in their predictions of plant  
141 response to disturbance. However, Macedo et al. (2010) predicted ecological characteristics of  
142 dune communities only, and neither of these two studies assessed the increase in prediction  
143 accuracy provided by combinations of classifications. We hypothesised that although each  
144 classification has strengths and weaknesses, combined classifications would create a new  
145 classification that was more polyvalent and accurate at predicting grassland characteristics.

146 Using a sample of 250 permanent grasslands, we determined a phytosociological, agronomic  
147 and functional class for each. We analysed the prediction accuracy of each of the three  
148 classifications and explored whether combining two or all three of them improved prediction  
149 of each of 16 ecological, agronomic and environmental characteristics. Finally, we  
150 determined whether one classification alone or a combination of classifications could predict  
151 all 16 of the characteristics well.

152

## 153 2 Materials and methods

### 154 2.1 Site

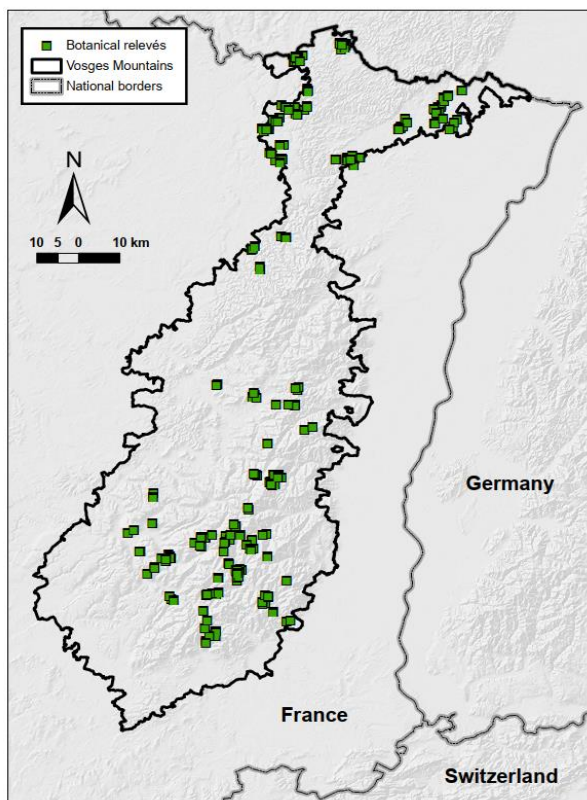
155 The dataset consisted of 250 grasslands in the Vosges Mountains (north-eastern France,  
156 7000+ km<sup>2</sup>) (Fig. 1). Their elevations vary greatly (170-1424 m a.s.l.), as does their geology:  
157 from limestone and sandstone in the north to plutonic volcanic rock in the south. The climate  
158 is under oceanic and semi-continental influences, and can be polar at mountain summits.  
159 According to climate normals (1981-2010), mean monthly temperatures vary from -4 to  
160 +12°C, and mean annual precipitation varies greatly (700-2300 mm) under complex  
161 latitudinal, longitudinal and elevational gradients (Ferrez et al., 2017). Finally, the Vosges  
162 Mountains cover a large gradient of agricultural practices: 26 % of the grasslands were  
163 exclusively mown, 38% were exclusively grazed, and nitrogen fertilisation ranged from 0-277

164 kg nitrogen/ha (69% organic (manure applied or directly deposited during grazing) and 31%  
165 synthetic, by mass ).

## 166 2.2 Attribution of grassland classes

167 Three studies were performed from 2001-2013 (Bayeur et al., 2013; Collectif, 2006; Launay  
168 et al., 2011) of 250 permanent grasslands on commercial farms (Fig. 1). They focused on the  
169 main homogeneous vegetation community of each grassland in areas 1000-10,000 m<sup>2</sup> in size  
170 to avoid effects of paddock size on botanical diversity. One botanical relevé per grassland was  
171 performed in the spring (peak biomass production), identifying all vascular botanical species  
172 and their relative biomass (%) in 25 circles of 0.2 m<sup>2</sup> randomly placed in the homogeneous  
173 vegetation community. Finally, homogeneous vegetation community were prospected to  
174 search for species too rare to be found in the 25 samples.

175 353 species were observed in 250 grassland homogeneous vegetation communities. The mean  
176 ( $\pm$ SD) number of species per community was 37.6 ( $\pm$ 8.7) [min-max = 16-65]. Thirty species  
177 formed 80% of the total biomass, with a dominance of red fescue *Festuca rubra* L. (14.9%),  
178 Yorkshire fog *Holcus lanatus* L. (9.1%), perennial ryegrass *Lolium perenne* L. (7.4%) and  
179 sweet vernal grass *Anthoxanthum odoratum* L. (5.6%). 11 threatened or endangered species  
180 were identified (seven vulnerable, two endangered and two critically endangered) according  
181 to the IUCN Red List, distributed in 30 grasslands. We used this dataset to attribute an  
182 agronomic, functional and phytosociological class to each of the 250 grasslands.



183  
184 Figure 1. Location of the 250 botanical relevés performed in the Vosges Mountains, France,  
185 from 2001-2013 (Bayeur et al., 2013; Collectif, 2006; Launay et al., 2011). Coordinate  
186 system: RGF93-Lambert93

187

188

### 189 2.2.1 Agronomic class attribution

190 Previous studies identified 25 agronomic classes for homogenous grassland based on species  
191 presence and relative biomass (Bayeur et al., 2013; Collectif, 2006). To this end, they  
192 performed multivariate analyses of grassland composition: Correspondence Analysis (CA)  
193 and Hierarchical Cluster Analysis (HCA) of species presence and Principal Component  
194 Analysis (PCA) and HCA of relative biomass. Thus, by combining CA and PCA, they  
195 attributed one agronomic class to each grassland based on the presence and relative biomass  
196 of its botanical species (Table S1). The number of grasslands per agronomic class varied from  
197 4-24 (Table 1).

198 This classification is called “agronomic” because its main aim is not to predict botanical  
199 associations, but to use these associations to predict forage yield and quality.

### 200 2.2.2 Functional class attribution

201 Cruz et al. (2010) attributed one class (A, B, b, C and D) to 38 of the most common French  
202 grasses (Poaceae), based on a combination of functional traits for leaves (dry matter content,  
203 specific leaf area, longevity, resistance to breakage) and plants (flowering date, maximum  
204 height) (Table S2). Then, Cruz et al. (2010) attributed functional classes to grasslands  
205 according to the percentage of each grass class in them.

206 We adapted their method of functional class attribution to reduce the number of grassland  
207 classes containing only one grassland. If one grass class represented more than 60% of  
208 grassland grasses, the grassland was defined as that class (e.g. 76% of grasses of class A, 3%  
209 of B and 21% of C yielded grassland class A), as proposed by Cruz et al. (2010). Otherwise,  
210 grassland was defined by the two main grass classes, in decreasing order (e.g. 28% of A, 30%  
211 of B, 10% of b and 32% of C yielded grassland class CB).

212 We then attributed one functional class to each permanent grassland based on the Cruz et al.  
213 (2010) grass classifications and the relative biomass of these grasses in each grassland. Thus,  
214 we attributed 20 functional classes, with 1-41 grasslands per class (Table 1). The mean ( $\pm$ SD)  
215 percentage of Poaceae in relevés was  $64.8 \pm 13.5\%$  [min-max = 24.0-96.7%], while that of  
216 other families was  $35.2 \pm 13.5\%$  [3.3-76.0%].

### 217 2.2.3 Phytosociological class attribution

218 Ferrez et al. (2017) developed a phytosociological classification for the entire Vosges  
219 Mountain range using 1628 relevés performed from 1993-2015 following the Braun-Blanquet  
220 method. They identified 35 phytosociological classes and selected the 22 of them that had the  
221 highest appearance rates and most important agronomic and ecological roles in the Vosges  
222 Mountains (Table S3). These 22 classes are based on 550 grassland relevés on commercial  
223 farms.

224 Normally, phytosociological classes are attributed directly in the field. For this study,  
225 however, we had to attribute phytosociological classes to the 250 grasslands *a posteriori*,  
226 from a dataset of existing botanical relevés. Therefore, we developed a new key to determine  
227 phytosociological classes. We used a statistical regression tree to design the new key, using  
228 the complete set of 550 relevés (Ferrez et al. 2017) and the mvpart package of R software v.  
229 3.4.2 (R Core Team, 2019; Therneau and Atkinson, 2014). The key, based on 48 botanical  
230 genera, determines phytosociological classes easily. We verified the key’s percentage of good  
231 classification for the dataset (550 grasslands) using a confusion matrix. According to the  
232 confusion matrix, the key had an agreement of 81%.

233 Using this key and the presence of botanical genus that we observed in each grassland during  
 234 the field sampling from 2001-2013, we attributed a phytosociological class to each of the 250  
 235 studied grasslands. All of the following analyses were performed for these 250 grasslands.

236 Thus, we attributed 17 phytosociological classes to the 250 grasslands, with 3-61 grasslands  
 237 per class (Table 1). As 22 classes could have been attributed at most, five classes were not  
 238 observed in the set of grasslands.

239

240 Table 1. Number of grasslands (n = 250) attributed to 17 phytosociological classes, 25  
 241 agronomic classes and 20 functional classes when attributing one phytosociological, one  
 242 agronomic and one functional class to each grassland (Table S1, S2 and S3).

Phytosociological classes		Agronomic classes				Functional classes	
Phy_12	61	BV_02	24	VN_09	14	C	41
Phy_05	25	BV_01	17	VN_07	13	A	40
Phy_01	24	BV_10	13	VN_12	11	AC	38
Phy_02	21	BV_06	12	VN_13	11	CA	31
Phy_11	20	BV_07	11	VN_05	9	AB	26
Phy_20	20	BV_08	11	VN_08	9	Ab	15
Phy_07	14	BV_03	10	VN_14	9	B	10
Phy_09	12	BV_04	10	VN_01	8	BA	8
Phy_25	9	BV_09	10	VN_02	8	Cb	8
Phy_04	8	BV_11	6	VN_06	8	CB	6
Phy_06	8	BV_05	5	VN_03	6	CD	6
Phy_08	8			VN_11	6	BC	5
Phy_16	6			VN_10	5	Bb	4
Phy_18	5			VN_04	4	bB	3
Phy_29	3					DC	3
Phy_30	3					bC	2
Phy_31	3					AE	1
						b	1
						bA	1
						E	1

243

244



245 2.3 Grassland characteristics

246 We chose to analyse ecological, agronomic and environmental characteristics of grasslands.  
247 Some of them were ecosystem services, which are benefits that people obtain from  
248 ecosystems (Millennium Ecosystem Assessment, 2005); however, this definition is still  
249 debated, and goods can be separated from services (Fisher et al., 2009). In addition, goods and  
250 services can be delivered by both the ecosystem and human practices; for example, grassland  
251 yield can be increased by applying synthetic fertilisers. Because we assessed a variety of  
252 goods and services delivered by the ecosystem and by human practices, we referred to them  
253 collectively as “grassland characteristics”.

254 We selected nine ecological characteristics to assess taxonomic diversity (species richness,  
255 family richness, Shannon heterogeneity index, Simpson diversity index), functional diversity  
256 (life form abundance, pollinator value, richness and weighted mean of the Ellenberg root  
257 system depth index) and patrimonial functions (oligotrophic species richness, which can be  
258 used as a proxy for species of high ecological value, threaten by the homogenization and  
259 intensification of agricultural management). We selected three agronomic characteristics to  
260 assess actual forage quantity (yield), potential forage quality and quantity (pastoral value) and  
261 phenology (fodder earliness). Finally, we selected four environmental characteristics to assess  
262 the sensitivity of classification to natural and human factors (Ellenberg humidity and fertility  
263 indices, elevation and management). We used a variety of methods (e.g. calculation, farmer  
264 interviews) to determine the 16 characteristics (Table 2, S4 and S5).

265 The botanical relevés of 250 grasslands and interviews of 52 farmers were performed in  
266 previous studies, which were used to develop the agronomic classification (Bayeur et al.,  
267 2013; Collectif, 2006; Launay et al., 2011). Botanical relevés allowed the collection of species  
268 composition and relative biomass, which we entered into the e-FLORA-sys program  
269 (Plantureux and Amiaud, 2010, 2009). This program calculated information at the vegetation  
270 community scale: all ecological characteristics, as well as pastoral values and life form  
271 diversity came from direct observation and calculation by e-FLORA-sys. Using a  
272 questionnaire to avoid bias, farmers were interviewed to obtain information about yield and  
273 grassland management. Knowledge from the interviews were extracted to deduce grassland  
274 management (“mown”, “grazed” or a “mixture” of both) and estimate yield from the number  
275 and mass of bales and from livestock stocking rates. On 14 grasslands, vegetation was  
276 sampled and dried to measured yields without interviews. Finally, grassland elevation was  
277 collected using BD ALTI dataset and QGIS software (IGN, 2016; QGIS Development Team,  
278 2019).

279

280

281 Table 2. Methods for determining the 16 characteristics studied for permanent grasslands, in  
282 ecological, agronomic and environmental categories.

Characteristic		Determination method
Ecological	Species richness	Number of botanical species observed in the grassland
	Oligotrophic species richness	Number of botanical species observed in the grassland with an Ellenberg nitrogen index of 1-3
	Family richness	Number of botanical families observed in the grassland
	Shannon heterogeneity index	$-\sum(Y_k \times \log_2 Y_k)$ , where $Y_k$ is the relative biomass of species $k$ ( $0 < Y_k \leq 1$ )
	Simpson diversity index	$1 - (\sum Y_k^2)$ , where $Y_k$ is the relative biomass of species $k$ ( $0 < Y_k \leq 1$ )
	Pollinator value	Relative biomass (% of total biomass) of entomophilous botanical species observed in the grassland
	Ellenberg root system depth index richness	Number of different Ellenberg root system depth indices observed in the grassland
	Ellenberg root system depth index weighted mean	$\sum(Y_k \times \text{individual root index})$ , where $Y_k$ is the relative biomass of species $k$ ( $0 < Y_k \leq 1$ )
	Life form abundance	Relative biomass (% of total biomass) of each life form: grasses (Cyperaceae, Juncaceae, Liliaceae, Poaceae), legumes (Fabaceae) and forbs
Agronomic	Yield	Estimated from the number of bales and livestock stocking rate, or measured in the field
	Pastoral value	$\sum(Y_k \times \text{individual pastoral value})$ , where $Y_k$ is the relative biomass of species $k$ ( $0 < Y_k \leq 100$ ). For each species, pastoral value is estimated by expert opinion from potential yield, nutritive value, appetite and digestibility (Daget and Poissonet, 1971)
	Fodder earliness	Relative biomass (% of total biomass) of early, middle and late species, according to Cruz et al. (2010) and Theau et al. (2017)
Environmental	Ellenberg humidity index	$\sum(Y_k \times \text{individual humidity index})$ , where $Y_k$ is the relative biomass of species $k$ ( $0 < Y_k \leq 100$ )
	Ellenberg fertility index	$\sum(Y_k \times \text{individual fertility index})$ , where $Y_k$ is the relative biomass of species $k$ ( $0 < Y_k \leq 100$ )
	Elevation	Mean elevation of the grassland
	Management	“Mown”, “grazed”, or a “mixture” of both, obtained from farmer interviews

## 285 2.4 Statistical analyses

286 We first identified the classification or combination of classifications that predicted each  
287 characteristic the best. We then assessed the quality of the best models to identify the most  
288 polyvalent classification or combination of classifications for all 16 characteristics. The  
289 specific method used depended on the grassland characteristic.

### 290 2.4.1 Modelling each characteristic with classifications

291 We used statistical model selection to calculate the probability that each classification alone  
292 (phytosociological (P), agronomic (A) or functional (F)), or a combination of classifications,  
293 yielded the best model, using R software. We modelled each characteristic as a function of  
294 each classification or combinations of classifications. To this end, we generated a model  
295 containing the main effects of all the classifications (A+P+F), and we then derived all  
296 possible submodels, including an intercept-only model (null model) (Burnham and Anderson,  
297 2002; Grueber et al., 2011). We then repeated this methodology from a model containing the  
298 interactions of all the classifications (A×P×F). Thus, a set of 12 models could be created,  
299 based on classifications alone and combinations of classifications. The sets of models  
300 generated to predict each characteristic are presented in Table S6.

301 Combining agronomic and phytosociological classifications yielded 116 combinations (e.g.  
302 agronomic class BV\_01 with phytosociological class Phy\_05 for the same grassland).  
303 Similarly, we identified 136 combinations of agronomic and functional classifications, 93  
304 combinations of phytosociological and functional classifications, and 202 combinations of all  
305 three classifications. The large number of combinations of classifications demonstrated that  
306 classifications differed in how they classified grasslands.

307 We modelled each continuous variable (species richness, oligotrophic species richness, family  
308 richness, Shannon heterogeneity and Simpson diversity indices, pollinator value, Ellenberg  
309 root system depth richness and root system depth index weighted mean, yield, pastoral value,  
310 Ellenberg humidity and fertility indices and elevation) using generalised linear models from  
311 the gamma family. We modelled each characteristics by 12 models.

312 We also fitted life form abundance and fodder earliness using generalised linear models.  
313 However, as we used only one model for life form (grass, legume and forb) and one model for  
314 earliness (early, middle and late), models were created from the binomial family. Here again,  
315 we modelled each characteristics by 12 models.

316 Grassland management was a categorical variable, so we created multinomial logit models  
317 using the mlogit package (Croissant, 2015). As logit models do not support interactions  
318 (Croissant, 2015), we fitted only eight models to grassland management.

### 319 2.4.2 Identification of the best model

320 After creating the models, we selected the best one for each characteristic. Except for  
321 grassland management models, the best model was that with the lowest second-order Akaike  
322 Information Criterion (AICc), calculated using the MuMIn package and R software (Barton,  
323 2018). Grassland management models were ranked according to the Akaike Information  
324 Criterion (AIC) itself, calculated using the qpcR package and R software (Spiess, 2014),  
325 because AICc cannot be calculated for logit models (Barton, 2018).

326 During model selection, an Akaike weight (hereafter, “weight”) is attributed to each model  
327 tested. This weight is the probability that a given model is the best, and the sum of the weights  
328 of all models tested equals 1 (Symonds and Moussalli, 2011). For each analysis, we compared

329 the weight of each model to those of other models: the closer a model's weight is to 1, the  
330 better the model is. If only one model had a high weight ( $> 0.8$ ), we assumed it was the best,  
331 but if several models had similar weight, we examined them more closely. We verified the  
332 quality of the model selection by ensuring that the null model had a weight close to zero  
333 (Symonds and Moussalli, 2011).

#### 334 2.4.3 Identification of a reliable polyvalent classification

335 Best model do not mean good model: the best among poor quality models remain a poor  
336 quality model. Moreover, the best model for a given characteristic may not be the best model  
337 for multiple characteristics together. To solve these two issues, we calculated the quality of  
338 each best model. First, model quality informed about the accuracy of each characteristics  
339 model. Then we could compare the accuracy of models selected for several characteristics: if  
340 a model would be selected as best model for several characteristics and its accuracy would be  
341 sufficient, we could assume it is a polyvalent and reliable model.

342 AIC and AICc indicate model quality, but as they are relative to the dataset for each  
343 characteristic we could not use them to compare best models for multiple characteristics  
344 (Burnham and Anderson, 2002). We used each best model to predict all 16 characteristics and  
345 calculated a goodness of fit among the predictions using pseudo- $R^2$ , because  $R^2$  cannot be  
346 calculated for generalised linear models (Tjur, 2009).

347 For generalised linear models for the gamma family, we calculated Cox and Snell pseudo- $R^2$   
348 (Cox and Snell, 1989), which is the easiest to use because it expresses  $R^2$  in terms of log-  
349 likelihood (Tjur, 2009). Because the Cox and Snell pseudo- $R^2$  is not optimal for generalised  
350 linear models from the binomial family or for multinomial logit models (Cox and Snell,  
351 1989), we calculated McFadden's pseudo- $R^2$  for these models, which is also based on the  
352 likelihood of the model (Hoetker, 2007). We used the DescTools package and R software to  
353 calculate pseudo- $R^2$  (Signorell, 2017). Finally, we calculated generalised variance-inflation  
354 factors to check for collinearity among models, using the car package (Fox and Sanford,  
355 2011). We assumed that models with pseudo- $R^2 > 0.5$  had a satisfactory goodness of fit.

356

### 357 3 Results

#### 358 3.1 Identification of the best classification

359 The model with the highest weight for 15 of the 16 grassland characteristics contained one or  
360 more classifications, as root system depth richness was predicted best by the null model (Fig.  
361 2). Among these 15 models, four of them had a weak weight  $< 0.8$  and required a closer look  
362 to identified best models: Shannon heterogeneity index (0.66), pollinator value (0.52),  
363 Ellenberg root system index weighted mean (0.73) and Ellenberg fertility index (0.59).

364 One classification alone was sufficient to predict four characteristics the best. Three  
365 characteristics were predicted best by agronomic classification alone (A): yield (agronomic),  
366 grassland management (environmental) and elevation (environmental). One characteristic was  
367 predicted best by phytosociological classification alone (P): species richness (ecological).

368 For two characteristics, the model with the highest weight contained only one classification,  
369 but the weight was not high enough to select it as the best model. For Shannon heterogeneity  
370 index, phytosociological classification (P) alone had the highest weight (0.66), but it did not  
371 differ enough from the second highest weight (0.25), which was for the main effects of  
372 phytosociological and functional classifications (P+F). Similarly, for pollinator value, weights

373 of agronomic classification (A) and the null model (0.52 and 0.35, respectively) were too  
374 similar to identify one best model.

375 The main effects of two or three classifications predicted six characteristics the best:  
376 agronomic and phytosociological (A+P) for family richness; agronomic and functional (A+F)  
377 for Ellenberg humidity index; phytosociological and functional (P+F) for Simpson  
378 heterogeneity index and pastoral value; and all three classifications (A+P+F) for fodder  
379 earliness. Ellenberg root system index weighted mean highest weight was associated to the  
380 P+F model, but was <0.8. However, the second highest weight was different enough to  
381 assume Ellenberg root system index weighted mean was best model by the main effects of  
382 phytosociological and functional classifications.

383 On the other hand, weights of the A+P+F and A+P models for the Ellenberg fertility index  
384 were too similar (0.59 and 0.41, respectively), we could not identify which one was best.  
385 Finally, two best models contained an interaction: that between agronomic and  
386 phytosociological classifications (A×P) for life form abundance, and between  
387 phytosociological and functional classifications (P×F) for oligotrophic species richness.

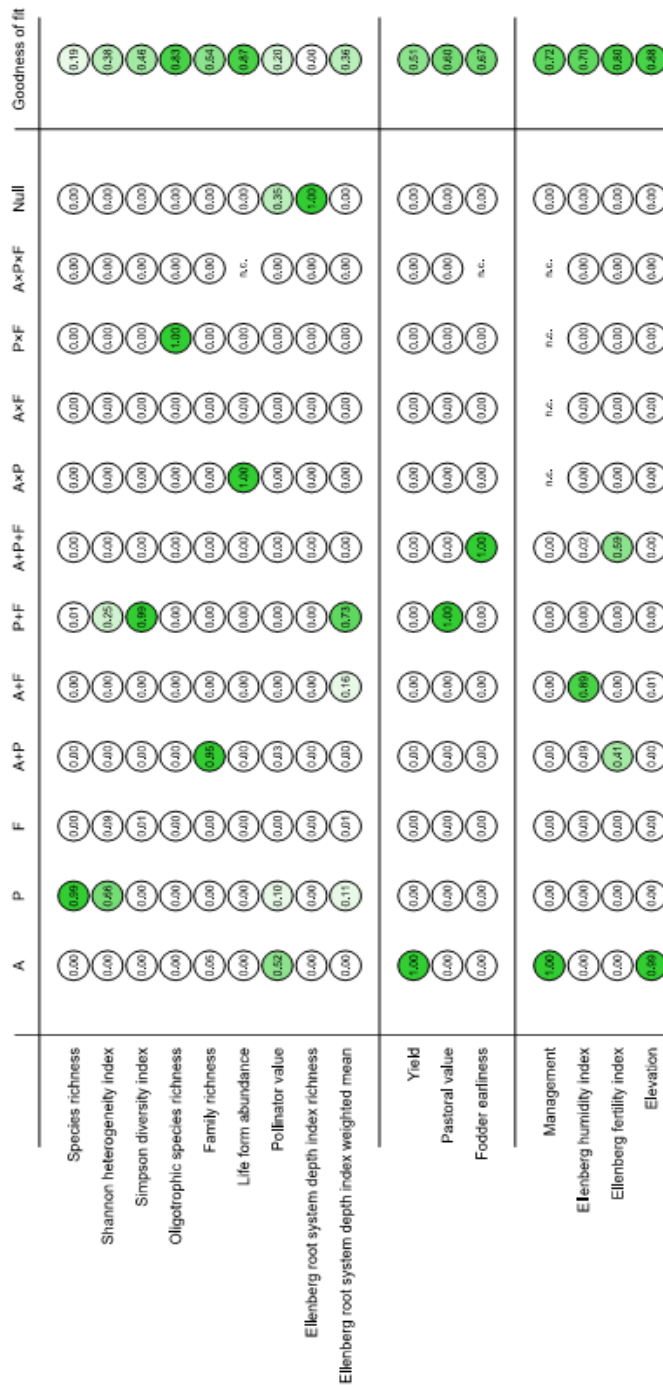
388 The highest weights equalled 1.0 for seven characteristics, 0.7-1.0 for six characteristics, and  
389 less than 0.7 for the Shannon heterogeneity index, pollinator value and Ellenberg fertility  
390 index. Null model weights equalled zero, except for those for pollinator value (0.35) and root  
391 system depth richness (1.0).

### 392 3.2 Identification of a reliable and polyvalent classification

393 The goodness of fit (pseudo-R<sup>2</sup>) varied greatly among the best models for characteristics  
394 (0.20-0.88) (Fig. 2). The goodness of fit of the model for the Ellenberg root system index  
395 weighted mean equalled zero, due to the selection of the null model. Models for agronomic  
396 and environmental characteristics had high weights and/or quality. In contrast, most models  
397 for ecological characteristics had low quality, except for life form abundance, oligotrophic  
398 species richness and, to a lesser extent, family richness (pseudo-R<sup>2</sup> = 0.87, 0.83 and 0.54,  
399 respectively). We identified ten grassland characteristics whose models had goodness of fit >  
400 0.5 (Fig. 3): oligotrophic species richness, family richness and life form abundance  
401 (ecological); yield, pastoral value and fodder earliness (agronomic); and Ellenberg indices for  
402 fertility and humidity, elevation and management (environmental). Unlike these ten grassland  
403 characteristics, the other six, all ecological, had best models of low quality despite having  
404 high weights: species richness, Shannon heterogeneity index, Simpson diversity index,  
405 pollinator value and richness and weighted mean of Ellenberg root system depth

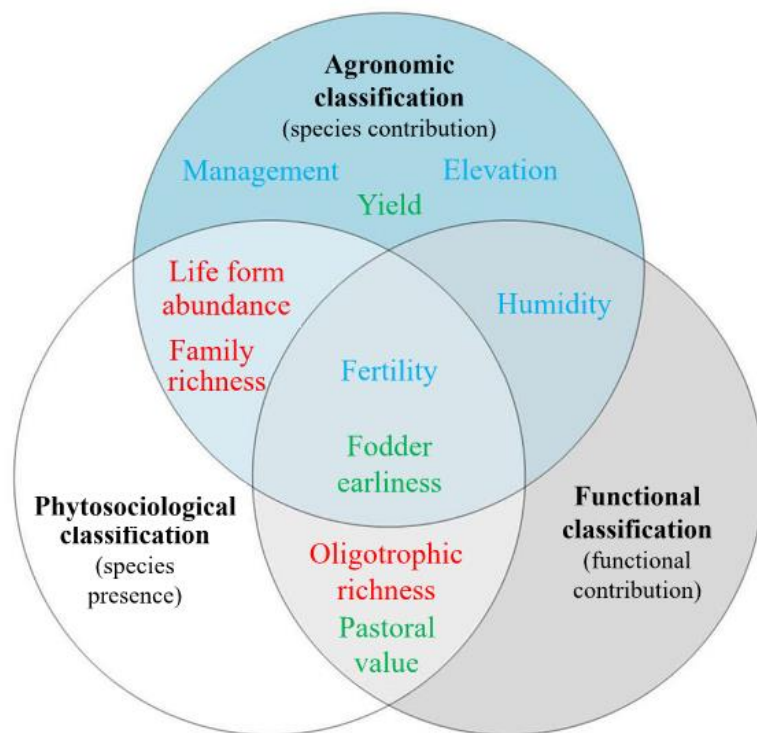
406 We could not identify one polyvalent and reliable classification or combination of  
407 classifications that could predict ecological, agronomic and environmental characteristics  
408 well. Only agronomic classification could predict characteristics the best when alone, with  
409 high quality models. Moreover, most of the characteristics predicted well were predicted  
410 totally or partially by agronomic classification. The combination of phytosociological and  
411 functional classifications predicted oligotrophic species richness and pastoral value well.

412



413

414 Figure 2. Akaike weights and goodness of fit (pseudo-R<sup>2</sup>) of the 16 grassland characteristics  
 415 modelled using agronomic (A), phytosociological (P) or functional (F) classification, the main  
 416 effects of two or all three of them (A+P, A+F, P+F and A+P+F), their interactions (A×P,  
 417 A×F, P×F and A×P×F) and a null model (Null). The term “n.c.” (“not considered”) indicates  
 418 characteristics that could not be modelled with interactions. The goodness of fit shown is that  
 419 of the model with the highest weight for each grassland characteristic.



420

421 Figure 3. Representation of which phytosociological, agronomic and functional classifications  
 422 (or combinations of them) were needed to predict ten grassland characteristics well (goodness  
 423 of fit > 0.5). Red, green and blue text identify ecological, agronomic and environmental  
 424 characteristics, respectively.

425

## 426 4 Discussion

### 427 4.1 Prediction of grassland characteristics

#### 428 4.1.1 Quality of prediction models

429 Four of the six characteristics whose models had goodness of fit < 0.5 involved species or  
 430 trait richness and equitability. This poor prediction of ecological characteristics is not  
 431 surprising for agronomic and functional classifications, which were not designed to predict  
 432 them and rely mainly on relative biomass rather than presence of species. The best models for  
 433 each of these characteristics are built in part on phytosociological classification, except those  
 434 for pollinator value and Ellenberg root system index weighted mean. However, the poor  
 435 quality of these ecological characteristics highlights the lack of a relationship between  
 436 ecological characteristics and phytosociological classification, which is more surprising.  
 437 While grasslands in the same phytosociological class have species in common (a  
 438 “characteristic combination”), they also have some different species among them, which gives  
 439 them different values of species richness and may help explain our result. Bias in relevés  
 440 could also be a reason: Chytrý (2001) showed that botanists increase the area sampled in  
 441 species-poor grasslands to increase the number of species, which could bias attribution of  
 442 class and calculation of richness.

443 Despite its common use and importance for estimating total biodiversity, species richness is  
 444 not a key characteristic to predict because of its high variability in similar grasslands  
 445 (Brunbjerg et al., 2018). These limits to biodiversity measurements have led researchers and  
 446 decision-makers to use diversity indices such as the Shannon heterogeneity index and

447 Simpson diversity index (Bello et al., 2010; Mauchamp et al., 2014). In our study, we could  
448 not identify models that predicted diversity indices well, but ecological indices were predicted  
449 best by phytosociological classification alone or a combination of phytosociological and  
450 functional classifications. These indices provide different types of information: the Shannon  
451 heterogeneity index describes species equitability, while the Simpson diversity index  
452 describes both species equitability and richness. One way to predict grassland plant diversity  
453 well could be to use disturbance intensity: Vujnovic et al. (2002) showed that intermediate  
454 disturbance by grazing, trampling or soil management maximised grassland biodiversity,  
455 while Rodríguez-Rojo et al. (2017) observed that management intensity had more influence  
456 on grassland biodiversity than management practices. However, biodiversity measurement,  
457 through species richness or ecological indices, is not necessary a useful indicator. Indeed,  
458 these measurements do not take into account vegetation characteristics as proportion of rare  
459 species, which is not correlated to total richness (Pykälä et al., 2005). Assessment of  
460 biodiversity should be implemented with proxy for species of high ecological value like  
461 oligotrophic species richness (Michaud et al., 2012; Muller, 2002). In the present study,  
462 oligotrophic species richness was predicted best by the combination of phytosociological and  
463 functional classifications.

464 Among ecological characteristics, only pollinator value and the weighted mean of Ellenberg  
465 root system depth needed species relative biomass in their calculations. However, they are  
466 based on traits (pollinator attractiveness traits and root system depth, respectively) not  
467 included in the functional classification studied nor in other classifications. Agronomic  
468 classification has been used to estimate pollinator value (Bayeur et al., 2013; Hulin et al.,  
469 2011; Launay et al., 2011). Our study confirms that agronomic classification predicts  
470 pollinator value the best, but its low model quality (weight = 0.52, pseudo-R<sup>2</sup> = 0.20) raises  
471 questions about the reliability of the prediction. Beyond our study, phytosociological  
472 classification may help predict pollinator species or traits, which are particularly related to  
473 flower diversity (Hegland and Totland, 2005; Warzecha et al., 2017). However,  
474 entomophilous botanical species relative biomass assesses a potential pollinator value at  
475 grassland scale. To assess a real pollinator service, flowering time and cutting/grazing dates  
476 should be studied because they express the real abundance of flowers (Kleijn et al., 2001).  
477 The landscape also influences pollinator diversity and abundance strongly, but it is not  
478 included in grassland classifications (Sutter et al., 2017). Finally, our modelling of root  
479 system depth is similar to the study of Oram et al. (2018), which found that mean root system  
480 depth was related to other characteristics but root system depth richness was not.

#### 481 4.1.2 Grassland characteristics predicted by one classification alone

482 Three grassland characteristics – elevation, management and yield – were predicted best by  
483 agronomic classification alone, which was the only classification that could predict grassland  
484 characteristics well by itself (Fig. 3). Management and elevation predict species composition  
485 well (Rodríguez-Rojo et al., 2017; van Oijen et al., 2018), and agronomic classification  
486 predicted management and elevation well with high weights and model qualities. We can  
487 assume that botanical associations developed from taxonomic relative biomass are good  
488 indicators of elevation and might be indicators of climate more generally.

489 Prediction of yield is crucial, especially for farmers. As agronomic classifications are  
490 developed mainly to predict agronomic characteristics, we expected a strong relationship  
491 between yield and agronomic classification. Functional classifications are also developed to  
492 predict grassland yields, and this ability was confirmed by Lavorel and Garnier (2002), who  
493 identified strong relationships between nutrient-response traits and traits determining yields.  
494 Plasticity in trait expression (at the species scale) and trait co-occurrence (at the community



495 scale) of grasses and forbs need to be better understood to improve predictions of functional  
496 classification (Roscher et al., 2018). Yield can be estimated easily using Ellenberg fertility  
497 index (Hill and Carey, 1997) or by more complex models based on functional traits, life form  
498 abundance (Michaud et al., 2015) and phytosociological classes (Magiera et al., 2017).  
499 Finally, field measurement also estimates grassland yield well but requires more time and  
500 equipment than using grassland classifications or Ellenberg indices (Ni, 2004).

#### 501 4.1.3 Combining classifications: a solution?

502 To our knowledge, our study is the first to compare three classification approaches using the  
503 same relevés. Carrère et al. (2012) created tool based on phytosociological, agronomic and  
504 functional classifications but did not compare the quality of predictions provided by each  
505 classification to those of the combination of two or three classifications. Macedo et al. (2010)  
506 compared the prediction abilities of three classifications but focused only on predicting  
507 ecological characteristics of dune communities.

508 In our study, seven of the characteristics studied were predicted better by combinations of  
509 classifications than by one classification alone (Fig. 3): oligotrophic species richness, family  
510 richness and life form abundance (ecological), pastoral value and fodder earliness  
511 (agronomic) and Ellenberg humidity and fertility indices (environmental). Notably, among the  
512 goodness of fit  $>0.8$ , three out of four models required combination of classifications: life  
513 form abundance (0.87), oligotrophic species richness (0.83) and Ellenberg fertility index  
514 (0.8). Moreover, despite its weak prediction capacities when used alone, phytosociological  
515 classification is part of these three best models.

516 Both fertility and humidity indices were predicted well (high weight and goodness of fit) by  
517 combining classifications. Humidity and fertility indices have been linked to elevation (de  
518 Almeida Campos Cordeiro and Neri, 2019; Pittarello et al., 2018; Sevruk, 1997) but also to  
519 taxonomic (Critchley et al., 2002; Melts et al., 2018; Wang et al., 2007) and functional (Čop  
520 et al., 2009; Schellberg, 1999; Suding et al., 2005) diversity. We also used the fertility index  
521 to calculate oligotrophic species richness. However, fertility needed all three classifications to  
522 be predicted well, while oligotrophic species richness needed only phytosociological and  
523 functional classifications and was predicted better. This difference could have been due to the  
524 method used: the fertility index is based on relative biomass, unlike oligotrophic species  
525 richness. Ellenberg fertility index is influenced by fertilizer application, but is also dependant  
526 of soil properties like the cation exchange capacity. Thus, the prediction of Ellenberg fertility  
527 index and oligotrophic species richness can bring information about presence of species of  
528 high ecological value, but cannot be used to assess the impact of fertilization at scales larger  
529 than grassland community.

530 Life form abundance, as well as root system depth, was not included in previous  
531 classifications. The latter was not predicted well, but the life form abundance was predicted  
532 well by an interaction between classifications ( $A \times P$ ). This result is particularly interesting  
533 because it shows that grassland classifications can predict characteristics beyond those for  
534 which they were developed. Moreover, family richness was predicted best by a similar  
535 combination of classifications: the main effects of agronomic and phytosociological  
536 classifications ( $A+P$ ). These characteristics are related by the method of calculation. Indeed,  
537 life forms are based on botanical families: legumes belong to Fabaceae, while grasses belong  
538 to Cyperaceae, Juncaceae, Liliaceae and Poaceae. This result could highlight a correlation  
539 between richness and relative biomass of families. Grassland management influences life  
540 form diversity strongly: mowing increases grass and forb relative biomass, while grazing  
541 selects rosettes and creeping plants (Gaujour et al., 2012; Lanta et al., 2009). However,

542 intensification also selects rosettes and creeping plants (Gaujour et al., 2012), and livestock  
543 type also has a strong influence on life form diversity (Tóth et al., 2018). These previous  
544 studies show that knowledge about grassland management could improve prediction of life  
545 form abundance; however, Craine et al. (2001) identified correlations between leaf traits and  
546 life form but no correlation between intensification and life form. The prediction of life form  
547 abundance can be useful for agronomists and naturalists. Indeed, grassland with highest life  
548 form diversity produce higher yields (Bullock et al., 2006), and allow heavier livestock live  
549 weight than grassland with poor life form diversity (Grace et al., 2019). In the present study,  
550 the goodness of fit of life form abundance (0.87) was higher than goodness of fit of yield  
551 (0.51) and fodder quality (0.60). Finally, life form abundance also determines the resistance of  
552 botanical species to drought: life form of weak abundance have more probabilities to  
553 disappear (Tilman and Haddi, 1992). Thus, life form abundance could be an important  
554 characteristic for naturalist who want to assess the risk of extinction of grassland botanical  
555 species.

556 It was particularly surprising that phytosociological and functional classifications combined  
557 (P+F) predicted pastoral value the best, because i) yield, part of the pastoral value equation, is  
558 predicted well by agronomic classification, and ii) calculating the pastoral value requires the  
559 pastoral value and relative biomass of each species, which is provided by agronomic  
560 classification (Daget and Poissonet, 1971). Functional traits (Tasset et al., 2019) and  
561 phytosociology (Petrovic et al., 2013) can be used to predict forage quality, but our result  
562 shows that combining them improves predictions. Phytosociology alone may not be sufficient  
563 to predict pastoral value due to the inclusion of different facies in the same phytosociological  
564 class (Bagella and Roggero, 2004). Prediction of pastoral value could be improved by using  
565 Ellenberg fertility index and environmental indicators such as elevation and slope (Bagella  
566 and Roggero, 2004; Pittarello et al., 2018).

567 Forage earliness is key information in grassland management, because peak forage quality is  
568 related to plant phenology (Pontes et al., 2007). Moreover, coupled with cutting or grazing  
569 dates, earliness could also be used to assess pollination service (Kleijn et al., 2001). Climate is  
570 the main factor that influences flowering time: temperature (Kudernatsch et al., 2008) and, to  
571 a lesser extent, precipitation (Hovenden et al., 2008) create annual variability. We used degree  
572 days to be free from annual temperature variability. Generally, alpine vegetation needs fewer  
573 heat units to initiate flowering (Heide, 1994), which could create a fodder earliness gradient  
574 according to elevation. Management, expressed indirectly through botanical composition,  
575 creates differences in earliness of French grasslands, but differences are also perceptible  
576 among species from the same community (Ansquer et al., 2009). We conclude that the three  
577 classifications are essential to predict fodder earliness: while the functional classification is  
578 based in part on grass earliness, phytosociological and agronomic classifications could  
579 provide information about other species.

#### 580 4.2 Limits of the study and perspectives

581 It may be possible to extrapolate results of this study. From the viewpoint of environmental  
582 conditions, our study focused on 250 permanent grasslands of the French Vosges Mountains  
583 but covered wide gradients of climates, elevations, soils and agricultural practices. From the  
584 viewpoint of vegetation, we found 17 phytosociological classes out of the 35 identified by  
585 botanists in the Vosges Mountains (Ferrez et al., 2017). However, these 17 classes are the  
586 most representative of commercial farms according to expert opinion and can be found in  
587 many other lowlands and low-elevation mountains in western Europe. Finally, the functional  
588 classification studied can also be used in a wide range of grasslands, as it is representative of  
589 western-European grassland Poaceae (Cruz et al., 2010).

590 All grassland classifications are based in part on arbitrary choices, either of the classification  
591 criteria (here, taxonomic richness, taxonomic relative biomass, or functional relative biomass)  
592 or the number of grassland classes. The method used to attribute functional classes provided  
593 quick and easy classification, but it can also be restrictive and attribute different functional  
594 classes to similar grasslands. This method also creates several functional classes containing  
595 few grasslands: seven classes contained less than five grasslands. Moreover, the functional  
596 classification focused only on Poaceae, even though other families represent a relatively large  
597 percentage of each grassland (mean  $\pm$  SD =  $35 \pm 14\%$ ), which could lead to lower accuracy in  
598 measuring response traits if Poaceae respond differently to disturbances than other plant  
599 families. A new functional classification based not only on Poaceae but also on  
600 dicotyledonous species may improve prediction abilities of functional classification. Finally,  
601 including new classification approaches should also improve knowledge about predicting  
602 grassland characteristics. Phytosociology diverges into two approaches: Braun-Blanquet and,  
603 more recently, numerical (Dengler et al. 2008). In the latter, relevés are grouped into classes  
604 using statistics, based on presence/absence (as in the Braun-Blanquet approach) or relative  
605 biomass (as in agronomic classifications). Classes are not phytosociological classes from the  
606 literature but are instead free from the subjective concept of the vegetation unit.

607 Of the 16 characteristics studied, five were calculated using Ellenberg indices, whose use may  
608 raise some questions. Indeed, some indices are estimated rather than measured, species  
609 response to the environment depends on location and plant stage, and the strength of  
610 correlations between indices and field measurements diverges among studies (Diekmann,  
611 2003; Schaffers and Sýkora, 2000). Nevertheless, Ellenberg weighted mean indices are  
612 considered reliable (Diekmann, 2003).

613 In a more extensive study, we could have analysed the ability of grassland classifications to  
614 predict other characteristics. Classifications have been used to predict organoleptic  
615 characteristics of animal products (Diquélou et al., 2003) and soil carbon stocks (Hulin et al.,  
616 2011), but other services could be studied, such as maintenance of genetic diversity,  
617 regulation of water flows and landscape heritage (D'Ottavio et al., 2017). Moreover, a more  
618 complete dataset of grassland characteristics could improve statistical analyses: the lack of  
619 homogeneity of grasslands per class might induce statistical bias, and it is important to assess  
620 the quality of new models on an external dataset.

621 Our study raises questions about the use of phytosociological classification alone to identify  
622 habitats of interest in Europe. Indeed, we demonstrated that ecological characteristics remain  
623 difficult to predict and, above all, that phytosociological classification alone does not predict  
624 grassland characteristics well. However, identification of ecological characteristics could lead  
625 to conservation of key grasslands, while identification of agronomic characteristics could  
626 improve distribution of economic incentives for ecologically valuable grasslands.  
627 Characteristics can be predicted more accurately by combining classifications, as in this  
628 study, but also by using other methods. Indicator species or life traits such as life forms or  
629 flower colour are also easy to use but might be less accurate or more time consuming (Arnold  
630 et al., 2009; Ellenberg et al., 1992). Finally, models can consider soil and weather variability,  
631 but such models are often difficult for non-specialists to use and do not predict agronomic and  
632 ecological characteristics at the same time (van Oijen et al., 2018).

633

## 634 5 Conclusion

635 Our study focused on the ability of three classification approaches to predict 16 grassland  
636 characteristics. Our results show that agronomic classification has great potential to predict

637 three agronomic and environmental characteristics, which demonstrates that it meets the  
638 needs of farmers and agronomists well. Although phytosociological classification is designed  
639 to assess habitat conservation, it failed to predict the studied ecological characteristics well.  
640 Functional classification appears promising, but it was developed more recently and may  
641 suffer from knowledge gaps. As ecological characteristics remain especially difficult to  
642 predict, naturalists and policy makers should use tools other than phytosociological  
643 classification alone to predict them. Indicator species or life traits such as life forms or flower  
644 colour are also easy to use but might be more time consuming than a phytosociological relevé.  
645 To identify trade-offs between economics and ecology, it may be important to combine  
646 grassland classifications: our results show that combinations of phytosociological, agronomic  
647 and/or functional classification could accurately predict seven ecological, agronomic and  
648 environmental characteristics. Finally, models may improve prediction of characteristics: they  
649 can consider soil and weather variability but are often difficult for non-specialists to use and  
650 do not predict agronomic and ecological characteristics at the same time.

651

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