

# Permanent grassland classifications predict agronomic and environmental characteristics well, but not ecological characteristics

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1	Title
2 3	Permanent grassland classifications predict agronomic and environmental characteristics well, but not ecological characteristics
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20	Colour
21	Figure 1, Figure 2 and Figure 3 require colour.
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#### 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
- north-eastern France to predict 16 characteristics: nine ecological, three agronomic and four
   environmental. We used statistical model selection to identify the classification or
- environmental. We used statistical model selection to identify the classification or
   combination of classifications that best predicted each characteristic. Our results showed great
- 35 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.
- Key words: phytosociology; agricultural type; functional type; management; biodiversity;
   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
- 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
- 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
- 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-

- 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
- ecosystems worldwide (e.g. Cheng et al., 2013; Rodríguez-Rojo et al., 2017, 2001; Setubal
- and Boldrini, 2012), vegetation classes are arranged into a hierarchical system, and their
- names follow scientific rules (Dengler et al., 2008). Once developed, the use of
   phytosociological classifications requires only a complete botanical relevé and less than a
- phytosociological classifications requires only a complete botanical relevé and less than an
   hour in each field. Phytosociology can also be used to predict agronomic characteristics, such
- as forage quality, and environmental characteristics by using indicator species (Petrovic et al.,
- 77 as longe quarty, and chynomicilia characteristics by using indicator species (i cuovie 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
- its prevalence in an animal's diet (Diquélou et al., 2003), but classification approaches may
   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,

90 of grassfands but are closery fied 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

- 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
- 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
- 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
- nutrients, development of plant structure) that express themselves when exposed to
- 126 environmental variation. We hypothesised that each classification could predict certain
- characteristics well: phytosociological for ecological characteristics, agronomic for agronomic
   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,
- 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
- accuracy provided by combinations of classifications. We hypothesised that although each
- classification has strengths and weaknesses, combined classifications would create a new
   classification that was more polyvalent and accurate at predicting grassland characteristics.
- 146 Using a sample of 250 permanent grasslands, we determined a phytosociological, agronomic
- 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
- 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
- and their relative biomass (%) in 25 circles of  $0.2 \text{ m}^2$  randomly placed in the homogeneous
- 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
- to the IUCN Red List, distributed in 30 grasslands. We used this dataset to attribute an
- 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
- 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%
- 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,
- we attributed 20 functional classes, with 1-41 grasslands per class (Table 1). The mean (±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
- farms.
- 224 Normally, phytosociological classes are attributed directly in the field. For this study,
- however, we had to attribute phytosociological classes to the 250 grasslands *a posteriori*,
- from a dataset of existing botanical relevés. Therefore, we developed a new key to determine
- phytosociological classes. We used a statistical regression tree to design the new key, using
- the complete set of 550 relevés (Ferrez et al. 2017) and the mypart package of R software v.
- 3.4.2 (R Core Team, 2019; Therneau and Atkinson, 2014). The key, based on 48 botanical
- genera, determines phytosociological classes easily. We verified the key's percentage of good
   classification for the dataset (550 grasslands) using a confusion matrix. According to the
- classification for the dataset (550 grasslands) using a confusion matrix. According to t confusion matrix, the key had an agreement of  $810^{4}$
- 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
- the field sampling from 2001-2013, we attributed a phytosociological class to each of the 250
- studied grasslands. All of the following analyses were performed for these 250 grasslands.

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
- Table 1. Number of grasslands (n = 250) attributed to 17 phytosociological classes, 25
- agronomic classes and 20 functional classes when attributing one phytosociological, one
- 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	С	41
Phy_05	25	BV_01	17	VN_07	13	А	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	В	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	СВ	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
						Е	1

#### 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
- 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,
- family richness, Shannon heterogeneity index, Simpson diversity index), functional diversity
- (life form abundance, pollinator value, richness and weighted mean of the Ellenberg root
   system depth index) and patrimonial functions (oligotrophic species richness, which can be
- used as a proxy for species of high ecological value, threaten by the homogenization and
- 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
- 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
- the sensitivity of classification to natural and human factors (Ellenberg humidity and fertility
- 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
- (Plantureux and Amiaud, 2010, 2009). This program calculated information at the vegetation
   community scale: all ecological characteristics, as well as pastoral values and life form
- 270 community scale, an ecological characteristics, as well as pastoral values and me for 271 diversity came from direct observation and calculation by e-FLORA-sys. Using a
- 271 diversity came from direct observation and calculation by C-1 DORA-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
- management ("mown", "grazed" or a "mixture" of both) and estimate yield from the number
- and mass of bales and from livestock stocking rates. On 14 grasslands, vegetation was
- sampled and dried to measured yields without interviews. Finally, grassland elevation was
- collected using BD ALTI dataset and QGIS software (IGN, 2016; QGIS Development Team,
- 278 2019).
- 279
- 280
- Table 2. Methods for determining the 16 characteristics studied for permanent grasslands, in
   ecological, agronomic and environmental categories.

Characteristic		Determination method				
	Species richness	Number of botanical species observed in the grassland				
	Oligotrophic species richness	Number of botanical species observed in the grassland with a Ellenberg nitrogen index of 1-3				
	Family richness	Number of botanical families observed in the grassland				
	Shannon heterogeneity index	- $\Sigma(Yk \times log_2 Yk)$ , where Yk is the relative biomass of species k (0 <yk≤1)< td=""></yk≤1)<>				
al	Simpson diversity index	$1-(\Sigma \ Yk^2),$ where Yk is the relative biomass of species k $(0{<}Yk{\leq}1)$				
cologic	Pollinator value	Relative biomass (% of total biomass) of entomophilous botanical species observed in the grassland				
н	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	$\Sigma(Yk \times individual root index)$ , where Yk is the relative biomass of species k (0 <yk<math>\leq1)</yk<math>				
	Life form abundance	Relative biomass (% of total biomass ) of each life form: grasses (Cyperaceae, Juncaceae, Liliaceae, Poaceae), legumes (Fabaceae) and forbs				
	Yield	Estimated from the number of bales and livestock stocking rate, or measured in the field				
Agronomic	Pastoral value	$\Sigma$ (Yk × individual pastoral value), where Yk is the relative biomass of species k (0 <yk≤100). each="" for="" pastoral<br="" species,="">value is estimated by expert opinion from potential yield, nutritive value, appetence and digestibility (Daget and Poissonet, 1971)</yk≤100).>				
	Fodder earliness	Relative biomass (% of total biomass) of early, middle and late species, according to Cruz et al. (2010) and Theau et al. (2017)				
II	Ellenberg humidity index	$\Sigma$ (Yk × individual humidity index), where Yk is the relative biomass of species k (0 <yk≤100)< td=""></yk≤100)<>				
onmenta	Ellenberg fertility index	$\Sigma$ (Yk × individual fertility index), where Yk is the relative biomass of species k (0 <yk≤100)< td=""></yk≤100)<>				
nvirc	Elevation	Mean elevation of the grassland				
Щ	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
- 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 206 possible submodels including an intersect only model (sull model) (Burnham and Anderson
- possible submodels, including an intercept-only model (null model) (Burnham and Anderson,
   2002; Grueber et al., 2011). We then repeated this methodology from a model containing the
- 2002; Grueber et al., 2011). We then repeated this methodology from a model containing the 2008 interactions of all the classifications ( $A \times P \times F$ ). Thus, a set of 12 models could be created,
- 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
- 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
- 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
- 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
- Criterion (AIC) itself, calculated using the qpcR package and R software (Spiess, 2014),
- 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
- better the model is. If only one model had a high weight (> 0.8), we assumed it was the best,
- but if several models had similar weight, we examined them more closely. We verified the
- 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
- 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
- each best model. First, model quality informed about the accuracy of each characteristics
- model. Then we could compare the accuracy of models selected for several characteristics: if
- 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<sup>2</sup>, because R<sup>2</sup> 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<sup>2</sup>
- 348 (Cox and Snell, 1989), which is the easiest to use because it expresses R<sup>2</sup> in terms of log-
- 349 likelihood (Tjur, 2009). Because the Cox and Snell pseudo- $R^2$  is not optimal for generalised
- linear models from the binomial family or for multinomial logit models (Cox and Snell,
- 1989), we calculated McFadden's pseudo-R<sup>2</sup> for these models, which is also based on the
   likelihood of the model (Hoetker, 2007). We used the DescTools package and R software to
- 353 calculate pseudo-R<sup>2</sup> (Signorell, 2017). Finally, we calculated generalised variance-inflation
- factors to check for collinearity among models, using the car package (Fox and Sanford,
- 2011). We assumed that models with pseudo-R<sup>2</sup> > 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.
- 2). Among these 15 models, four of them had a weak weight <0.8 and required a closer look
- 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
- index, phytosociological classification (P) alone had the highest weight (0.66), but it did not
- 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

- of agronomic classification (A) and the null model (0.52 and 0.35, respectively) were too similar to identify one best model.
- 375 The main effects of two or three classifications predicted six characteristics the best:
- 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
- heterogeneity index and pastoral value; and all three classifications (A+P+F) for fodder
- argue argue and a 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
- 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
- less than 0.7 for the Shannon heterogeneity index, pollinator value and Ellenberg fertility
- 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- $R^2 = 0.87$ , 0.83 and 0.54,
- respectively). We identified ten grassland characteristics whose models had goodness of fit > 25 (Fig. 2).
- 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
- 402 fertility and humidity, elevation and management (environmental). Unlike these ten grassland403 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

Goodness of fit			
4ull		888	<u></u>
V×P×F N			
P×F		888	
A×F			
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₽+F		888	
A+F			
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٩			
A		<b>8</b> 88	
	Species richness Shannon heterogenetiy index Simpson diversity index Aimport species richness Family richness Life form abundance Pollinator value Ellenberg root system depth index veighted mean	Yield Pastoral value Fodder earliness	Management Elenberg humidity index Ellenberg fertility index Elevation

413

- 414 Figure 2. Akaike weights and goodness of fit (pseudo- $R^2$ ) 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  $A \times F$ ,  $P \times F$  and  $A \times P \times F$ ) 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

Figure 3. Representation of which phytosociological, agronomic and functional classifications (or combinations of them) were needed to predict ten grassland characteristics well (goodness

422 (of combinations of them) were needed to predict ten grassiand characteristics were (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
- 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
- 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

- 462 oligotrophic species richness was predicted best by the combination of phytosociologi 463 functional classifications.
- 464 Among ecological characteristics, only pollinator value and the weighted mean of Ellenberg
- to system depth needed species relative biomass in their calculations. However, they are
- based on traits (pollinator attractiveness traits and root system depth, respectively) not
- 467 included in the functional classification studied nor in other classifications. Agronomic468 classification has been used to estimate pollinator value (Bayeur et al., 2013; Hulin et al.,
- 468 Classification has been used to estimate pointator value (Bayeur et al., 2013, Hum 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- $R^2 = 0.20$ ) 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).
- The landscape also influences pollinator diversity and abundance strongly, but it is not
- included in grassland classifications (Sutter et al., 2017). Finally, our modelling of root
  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
- Three grassland characteristics elevation, management and yield were predicted best by agronomic classification alone, which was the only classification that could predict grassland characteristics well by itself (Fig. 3). Management and elevation predict species composition well (Rodríguez-Rojo et al., 2017; van Oijen et al., 2018), and agronomic classification predicted management and elevation well with high weights and model qualities. We can assume that botanical associations developed from taxonomic relative biomass are good 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
- 519 taxonomic (Critchey et al., 2002; Ments et al., 2018; wang et al., 2007) and functional (Cop 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 dependent
- 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×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 betanical families: lagungs belong to Fabaassa while areas a help
- 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
- 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
- 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
- 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
- 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 grassland characteristics. Phytosociology diverges into two approaches: Braun-Blanquet and, 602
- 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.
- Of the 16 characteristics studied, five were calculated using Ellenberg indices, whose use may 607
- 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
- correlations between indices and field measurements diverges among studies (Diekmann, 610
- 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
- predict other characteristics. Classifications have been used to predict organoleptic 614
- 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,
- regulation of water flows and landscape heritage (D'Ottavio et al., 2017). Moreover, a more 617
- 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.
- Our study raises questions about the use of phytosociological classification alone to identify 621 622 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
- to conservation of key grasslands, while identification of agronomic characteristics could
- 625
- 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
- characteristics. Our results show that agronomic classification has great potential to predict 636

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
- do not predict agronomic and ecological characteristics at the same time.
- 651
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